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Digital plant: methods of discrete-event modeling and optimization of production characteristics

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Abstract

This article presents a new approach to the development of a ‘digital twin’ of a manufacturing enterprise, using a television manufacturing plant as the case study. The feature of the proposed approach is the use of hybrid methods of agent-based modeling and discrete-event simulation in order to implement a simulation model of a complex production process for assembling final products from supplied components. The most important requirement for such a system is the integration of all key chains of a digital plant: conveyor lines, warehouses with components and final products (TVs), sorting and conveyor system, assembly unit, technical control department, packing unit, etc. The proposed simulation model is implemented in the AnyLogic system, which supports the possibility of using agent-based and discrete-event modeling methods within one model. The system also supports using

the built-in genetic algorithm to optimize the main parameters of the model: the most important production characteristics (for example, assembly time of a product, the number of employees involved in assembly, quality control and packaging processes). Optimization experiments were completed with the help of the developed model at various intensities of loading conveyor lines with components, various restrictions on labor resources, etc. Three scenarios of the production system behavior are investigated: the absence of the components deficit with the possibility of significantly increasing the labor resource involved, a components deficit while demand for final products is maintained, and the presence of hard restrictions on the number of employees who can be involved in the processes under conditions of components deficit.

Key words: digital plant; production processes; agent-based modeling; discrete-event simulation; genetic algorithm; AnyLogic.

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Introduction

Currently, the problem of rational management of production characteristics in a dynamically changing external environment is becoming highly timely for many industrial enterprises (e.g. in conditions of a sharp decrease in the supply of components, significant increase in the cost of raw materials, lack of labor resources). At the same time, the complexity of production and logistics processes often does not allow enterprises to quickly adapt due to the operational management of their own resources (e.g. to reduce the volume of production without reducing labor resources, change the structure of the production portfolio without significant capital investments). The reason of emerging problems, as a rule, is the unbalanced state of various parts of the production chain (e.g. the deficit of production capacity with a significant turnover rate of warehouse stock). Therefore, there is a need to develop decision-making systems (DMS) based on the construction of ‘digital twins’ of enterprises. Such twins help to determine the best values of the characteristics of the production process in various scenario conditions (e.g. with a sharp

change in demand for final products when there are interruptions with supplies of raw materials and components).

The first works devoted to the problems of rational production planning date back to the mid-20th century. It is necessary to highlight the most important works on rational organization of production activities using the methods of system dynamics [1, 2]. Also, well-known developments of the application of queuing systems theory (QS) [3, 4] to control complex production and logistics processes [5, 6]. The central problem of such methods, developed within the framework of the well-known scientific field of operations research [7], is to optimize the characteristics of the chains for creating the final product. Examples include minimizing costs, maximizing the rate of turnover of stock, optimizing the number and structure of labor resources involved, as well as providing the required quality level and timeliness of finished goods delivery [8].

In modern times, we have methods of system dynamics [9–11], agent-based modeling [12–14], discrete-event modeling [15, 16], heuristic optimization methods for a class of genetic algo-

rithms [17–19] and others. For instance, a simulation model of a vertically integrated oil company, which includes the links of oil production, oil refining, transportation and sales, developed using the methods of system dynamics, is presented in [10]. The advantage of this model is the ability to maximize the shareholder value of an oil company under multiple constraints and take into account the influence of the feedback system arising in the value chain.

The next stage in the development of such intelligent production systems is the creation of so-called ‘digital twins’ [20–24] which are based on simulation models aggregated with databases, data warehouses, optimization modules, etc. For instance, a ‘digital twin’ of an organisation providing financial services is presented in [20], a simulation model of a mining enterprise is proposed in [21], implemented in the Powersim system.

This article develops a methodology for developing ‘digital twins’ of a manufacturing enterprise based on the methods of discrete-event and agent-based modeling with implementations in the AnyLogic system [25]. A new simulation model of the ‘digital plant’ type is proposed with the use of an enterprise that assembles TVs as the case study. The most important parameters of the production system are optimized according with the criteria of the value of the accumulated gross profit at the various scenario conditions.

1. Digital factory concept

Currently, TVs are assembled with the use of ready-made components, the production of which is done at other enterprises using an imported electronic component base (e.g. microprocessors, LCD displays, etc.) at most Russian plants. Despite certain disadvantages (such as complete dependence on the supply of imported components), such an organization of the production process can significantly reduce operating costs, mainly by attracting

less expensive (local) labor, minimizing transport and tax costs.

The conceptual model of a ‘digital plant’ is based on the creation of a number of interacting subsystems, among which the most important are the following:

◆ **simulation modeling subsystem**, providing the ability to calculate the production and financial characteristics of the enterprise, taking into account the detailing of the entire chain of creating the final product for management at the micro level. The simulation model of an enterprise assembling TVs consists of the following important elements:

1. **sources of component supplies** required for the assembly of the final product (in particular, such components include housings, LCD screens, motherboards, video adapters, image processing units, power supplies, etc.) supplied to the factory in accordance with a given intensity;
2. **warehouses of components** which are intended for temporary storage of intermediate products (parts) and their delivery to conveyor lines;
3. **sorting and conveyor system**, designed for automatic synchronization of streams with components having different technical and operational characteristics, e.g. different size of the liquid crystal screen (in particular, varying from 20 to 90 inches), different body sizes, etc.;
4. **assembly unit** ensuring the assembly of final products using the attracted specialists (labor resources);
5. **technical control unit** providing quality control of the final product (testing devices);
6. **packing unit** performing the function of packing, picking and forming batches of final products;
7. **warehouse of final products** that is intended for temporary storage of TVs;
8. **shipping unit** providing the function of shipment of batches of final products by transferring it to a transport company;

- ◆ **data warehouse**, intended for storing the initial data required for simulation modeling and processing the results of optimization experiments;
- ◆ **optimization module** aggregated through objective functions with the simulation model of the enterprise and providing the ability to search for the best values of the characteristics of the production process in various scenario conditions.

An aggregated diagram of the ‘digital twin’ of an enterprise assembling TVs is shown in Figure 1.

Note that an important feature of the system under consideration (Figure 1) is the presence of agents involved in the production process:

- ◆ **agents-components** with their own individual characteristics;
- ◆ **agents-products** varied by their functional characteristics (e.g. TV model, matrix size, cost, etc.);
- ◆ **agents-batches** of final products, which are a grouping of agents-products (by TV-models) for transportation.
- ◆ **agents-resources (humans)** involved in various processes (e.g. assemblers, quality control specialists, packers, etc.).

At the same time, the production system provides a mechanism for automatic transformation of agents-components into final agents-products, as well as grouping of agents-products in the form of batches of final products (TVs).

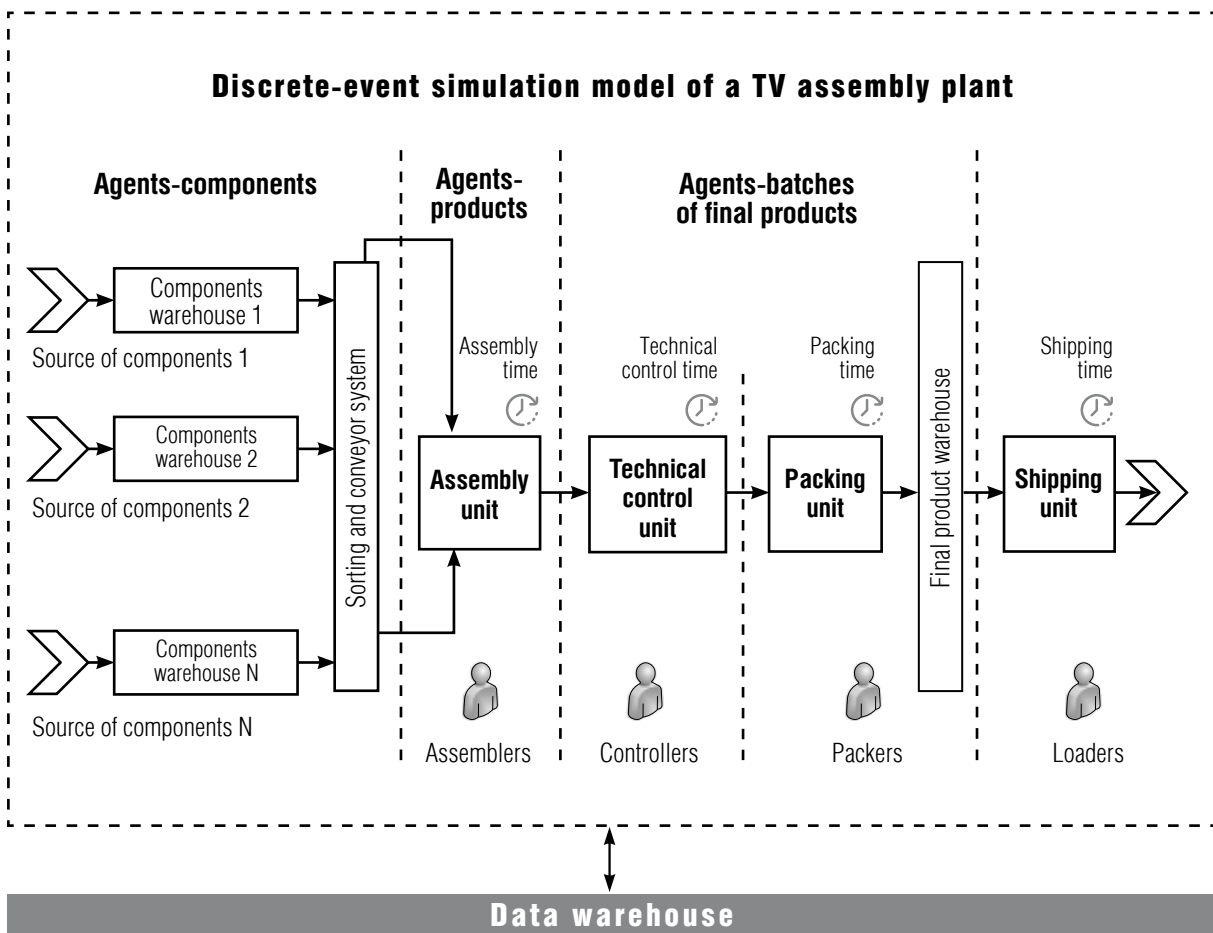


Fig. 1. Aggregated diagram of the ‘digital twin’ of a manufacturing enterprise

2. Simulation model

Earlier, a simulation model of an assembly unit implemented in the AnyLogic system was presented in [21]. Such a model can be considered as a prototype when creating a more complex model of a hybrid type which simultaneously uses the methods of system dynamics, agent-based and discrete-event modeling. Another important difference of the model proposed here is a more complex structure and dynamics of supply of components, characterized by the presence of multiple time gaps. At the same time, the main service characteristics of the production process (in particular, the time of assembly, technical control, shipment, etc.), which significantly affect its effectiveness, are stochastic. As a result, the performance metric of such a system (profit dynamics) belongs to the class of multimodal objective functions with multiple break points, the maximization of which cannot be performed by known analytical methods. Therefore, in order to create a ‘digital twin’ of a production enterprise that assembles TVs, an original simulation model is being developed, aggregated by target functionality with a built-in genetic algorithm that provides the search for the best solutions based on heuristics.

Further, a brief problem statement of optimizing main characteristics of the considered manufacturing enterprise is given.

Here:

- ◆ $t_r \in T$ – is the discrete model time; $T = \{t_1, t_2, \dots, t_{|T|}\}$ – a set of moments of model time; $|T|$ – the total number of moments of model time;
- ◆ $I = \{i_1, i_2, \dots, i_{|I|}\}$ – is the set of indices of models of the assembled TVs (variable by the screen size, different functional characteristics, etc.); $|I|$ – is the total number of assembled TV-models;
- ◆ $J_i = \{j_{i_1}, j_{i_2}, \dots, j_{|J_i|}\}$, $i \in I$ – is the set of indices of components required for assembly i -th television model (e.g. bodies, LCD screens, system boards, etc.); $|J_i|$ – is the total number of components that are necessary for assembling TV sets of i -th type;
- ◆ $\{n_1, n_2, \dots, n_N\}$ – is the number of specialists of various categories (e.g. assemblers of the first and second qualification levels, QM-specialists, packers and loaders) involved in production processes, humans; N is the total number of qualification categories of employees; $\zeta = \{1, 2, \dots, N\}$ – is index of the category of employees and the types of processes in which they are involved;
- ◆ $\{w_1(t_r), w_2(t_r), \dots, w_N(t_r)\}$, $t_r \in T$ – are the daily salaries of specialists of various categories involved in production processes, rubles;
- ◆ $c_{j_i}(t_r)$, $j_i \in J_i$, $i \in I$, $t_r \in T$ – is the cost of components required for assembly the i -th TV model at the moment t_r , rubles;
- ◆ $p_i(t_r)$, $i \in I$, $t_r \in T$ – is the price of a final product (TV) at the moment t_r , rubles;
- ◆ $\{\tau_1, \tau_2, \dots, \tau_N\}$ – the average time for assembling a final product from main and auxiliary parts, technical control time, packing and shipping times per employee involved in the relevant operations;
- ◆ $\delta_{j_i}(t_r)$, $j_i \in J_i$, $i \in I$, $t_r \in T$ – is the endogenous structure of supply of components at the moment t_r , specified using a unit impulse function with random arguments, items;
- ◆ $v_i(t_r)$, $i \in I$, $t_r \in T$ – is the endogenous structure of final product output at the moment determined as a result of simulation and depending on the sets of control parameters $\{n_1, n_2, \dots, n_N\}$, $\{\tau_1, \tau_2, \dots, \tau_N\}$, as well as the dynamics of supply of components $\delta_{j_i}(t_r)$, items.

Daily gross profit of the enterprise at the moment t_r , $t_r \in T$:

$$\pi(t_r) = \sum_{i=1}^{|I|} \left((v_i(t_r) p_i)(t_r) - \sum_{j_i=1}^{|J_i|} \delta_{j_i}(t_r) c_{j_i}(t_r) \right) - \sum_{\zeta=1}^N w_{\zeta}(t_r) n_{\zeta}. \quad (1)$$

Now we can formulate the central task of the manufacturing enterprise to maximize the accumulated gross profit.

The problem. The need to maximize the accumulated gross profit by sets of control parameters $\{n_1, n_2, \dots, n_N\}$ and $\{\tau_1, \tau_2, \dots, \tau_N\}$:

$$\sum_{t_r=1}^{|T|} \pi(t_r) \rightarrow \max_{\{n_1, n_2, \dots, n_N, \{\tau_1, \tau_2, \dots, \tau_N\}\}} \quad (2)$$

s.t.

$$n_{\xi} \leq n_{\xi} \leq \bar{n}_{\xi}, \quad \tau_{\xi} \leq \tau_{\xi} \leq \bar{\tau}_{\xi}.$$

Here $\{n_{\xi}, \bar{n}_{\xi}\}, \{\tau_{\xi}, \bar{\tau}_{\xi}\}$ are known boundary values of control parameters (upper and lower limits).

The proposed simulation model that provides the computation of the objective function (1)–(2) was implemented in the AnyLogic system (Figure 2). The main feature of the

model is the high dimensionality of initial data flows (tens thousands of components involved in the assembly of TVs with their individual characteristics). In particular, it is determined by the presence of a large number of elements of a ‘warehouse’ type used for storing intermediate and final products, and also the use of sorting and conveyor systems for synchronizing the flows of agents-components (Figure 2).

Another important feature of the model shown in Figure 2 is the integration of the module of computing financial and economic indicators with operational sub-models. These sub-models implement the processes of receiving and distributing components through sorting and conveyor systems, assembly unit, technical control unit, packaging and formation of batch units vary-

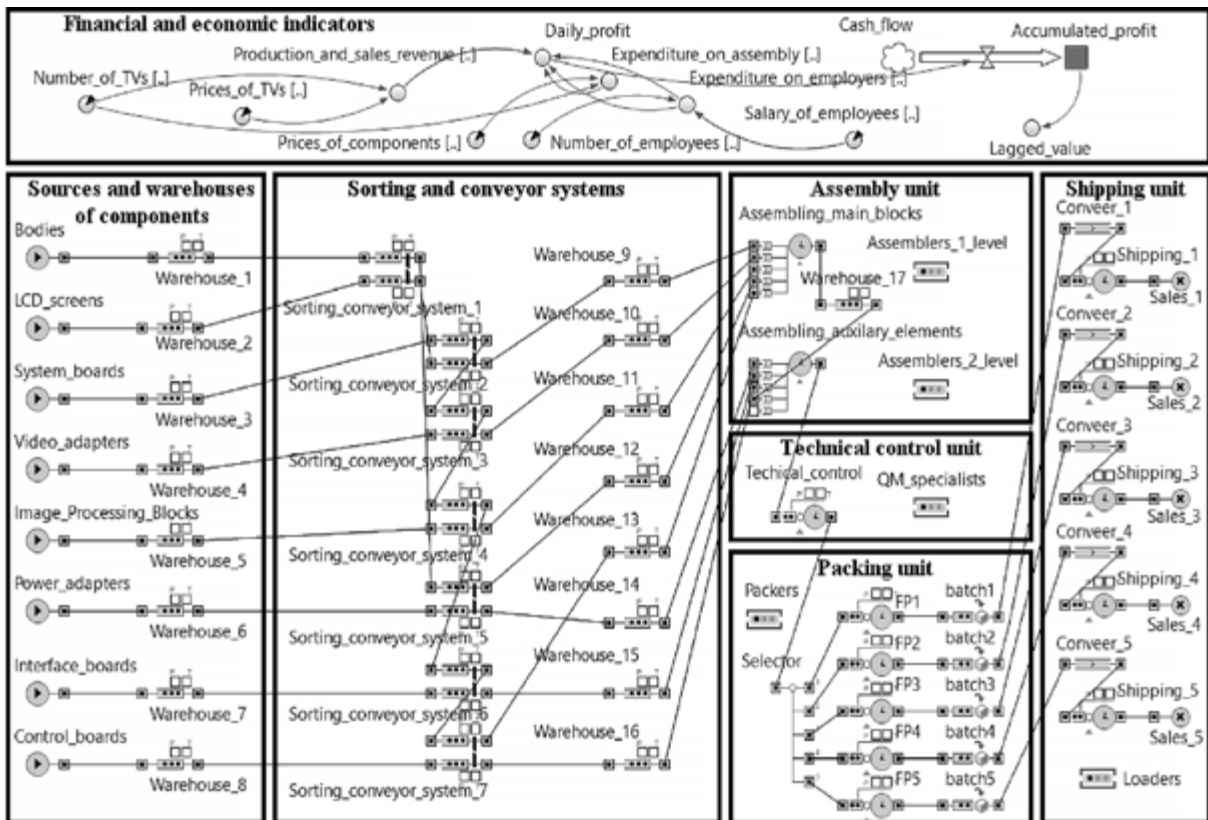


Fig. 2. Simulation model of TV equipment manufacturing plant in AnyLogic

ing by a product type (e.g. depending on the size of the LCD screen and the specified set of functions). The initial data of component (characteristics of elements) are loaded from the system database taking into account a variable number of each type elements, simultaneously arriving in accordance with a given intensity. The software implementation of the simulation model was performed using the Java programming language supported in the AnyLogic system.

To start sequential processing of components in the model, a special object of the **source** type (component source) is used in which the characteristics of each generated agent belonging to the **Components_X** class (components of type **X**) are redefined in a special field – ‘**Actions when approaching the exit**’:

```
((Components_X) entity) .parameter = components_X.get(index_X) .parameter;
index_X = index_X ++;
```

Here, **Components_X** is a population of component agents of type **X** with characteristics whose values are dynamically loaded from the data warehouse (MS SQL Server), **parameter** is one of the possible parameters of the component agent ((**Components_X**) **entity**), e.g. the overall size of the body, **index_X** is the global variable used as an iterator to access the next member of the **Components_X** population (i.e. the agent-component). Note that starting with the AnyLogic of version 8, the simpler form of access to data of an agent participating in the process chain is supported using the **agent** attribute instead of the ((**Components_X**) **entity**). At the same time, when creating multiple requests, the ‘**Actions when approaching the exit**’ method is also performed multiple times for each component agent outgoing from the source (*Figure 3*). The number of agents-

components generated at any given time is set by means of a single impulse function with random arguments determining the expected number of details that will arrive in the case of the arrival of a given batch:

```
(int) pulse(uniform(0, 100), uniform(0, 100))*uniform_discr(1000, 1500);
```

Also, one of the most important elements of the proposed model is the formation of batches of final products by distributing the flow of TVs that have passed technical control into groups depending on the type of an agent-product (i.e. a model of TV) (*Figure 4*).

Because of the prices of the final products depend on the model range of the assembled TVs, computing the revenue and expenditure is possible to use indicators whose values are calculated in the elements of the process diagram (*Figure 2*), e.g. the number of assembled TVs of various types can be set as follows:

```
Number_TV.set (Implementation1.count () * batch1_size, M);
```

Here, **Implementation1.count ()** is the function that computes the number of elements (agents-products of the first type) at the exit from the production process, **batch1_size** is the number of products in a batch, **M** is the index of TV-model.

3. Experimental results

As mentioned earlier, the sources of supplying agents-components provide the generation of the components required for assembly using a single impulse function with stochastic arguments. *Figure 5* shows the dynamics of such deliveries over the model time interval from 1 to 100 days.

Bodies - Source

Name: Show name Ignore

Entity type:

Arrivals defined by:

Arrival rate:

Multiple entities per arrival:

Entities per arrival:

Limited number of arrivals:

New entity:

Location of arrival:

Advanced

Custom time of start:

Add entities to: default population custom population

Forced pushing:

Actions

On before arrival:

On at exit:

On exit:

Advanced

Description

Fig. 3. Properties of a typical source of supply of agent-components

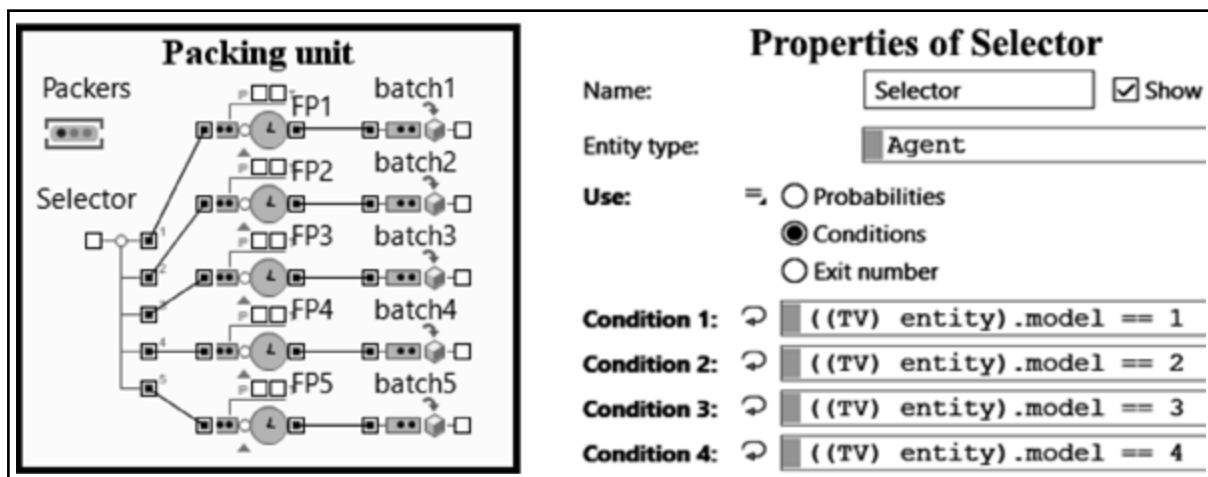


Fig. 4. Distribution of the flow of final products when forming batches

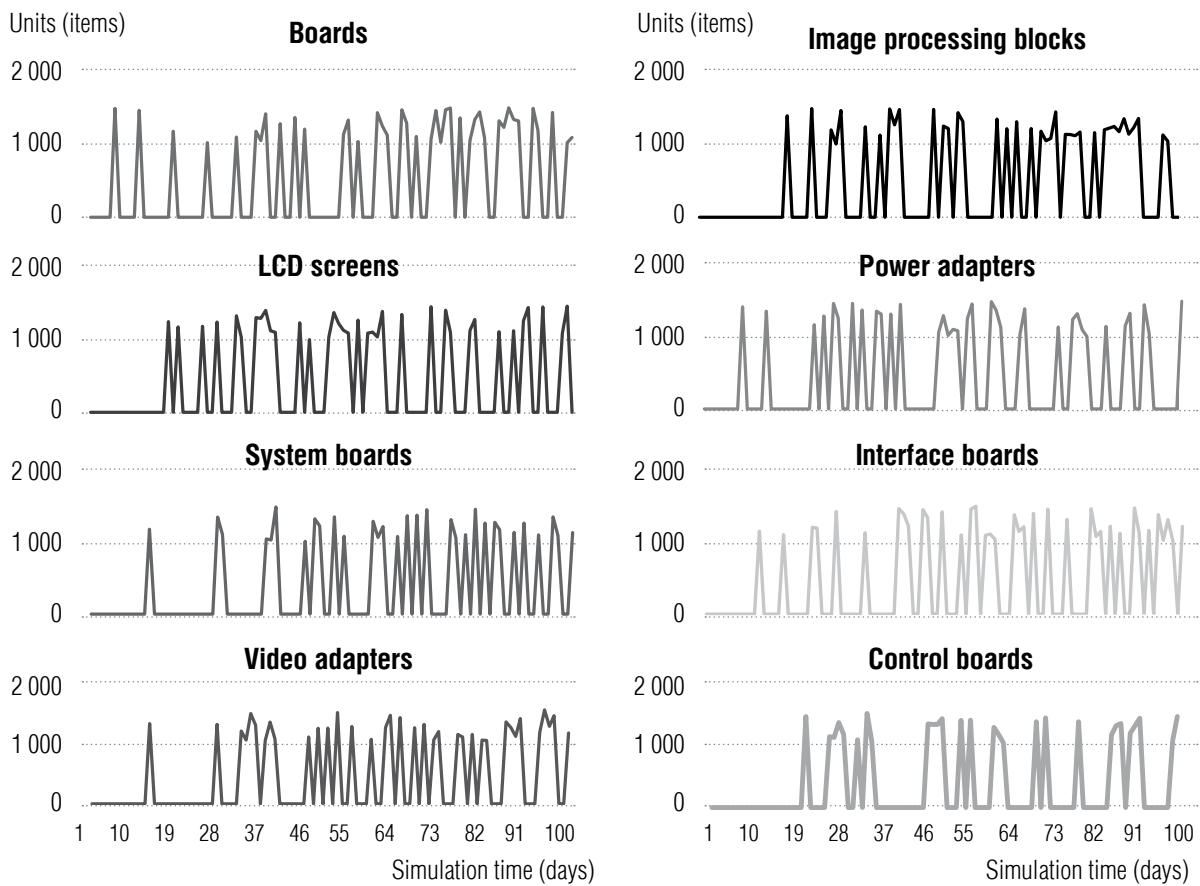


Fig. 5. Model dynamics of supplying the components

As follows from *Figure 5*, there are time gaps between component supplies due to natural logistic disruptions. Therefore, the model provides automatic synchronization of input flows through sorting and conveyor systems that redirect selected and mutually matched elements to the assembly unit.

Figure 6 shows the model dynamics of warehouse stocks of main and auxiliary assemblies, as well as finished products (TVs).

Further, optimization experiments were carried out aimed at maximizing the profit generated because of the assembly and sale of TVs. Optimization experiments were performed using the genetic algorithm embedded in the AnyLogic. At the same time, the following

control parameters of the model were selected as decision variables:

- ◆ **number of agents-assemblers** (humans) of various categories involved in the assembly of main and auxiliary parts;
- ◆ **number of quality control agents** responsible for performing technical control of final products (TVs);
- ◆ **number of agents-packers and agents-loaders** involved in the processes of packaging and shipment of final products, respectively;
- ◆ **average (median) values of assembly time, technical control time, packaging and shipment (sale) times** affecting the speed of execution of the corresponding processes.

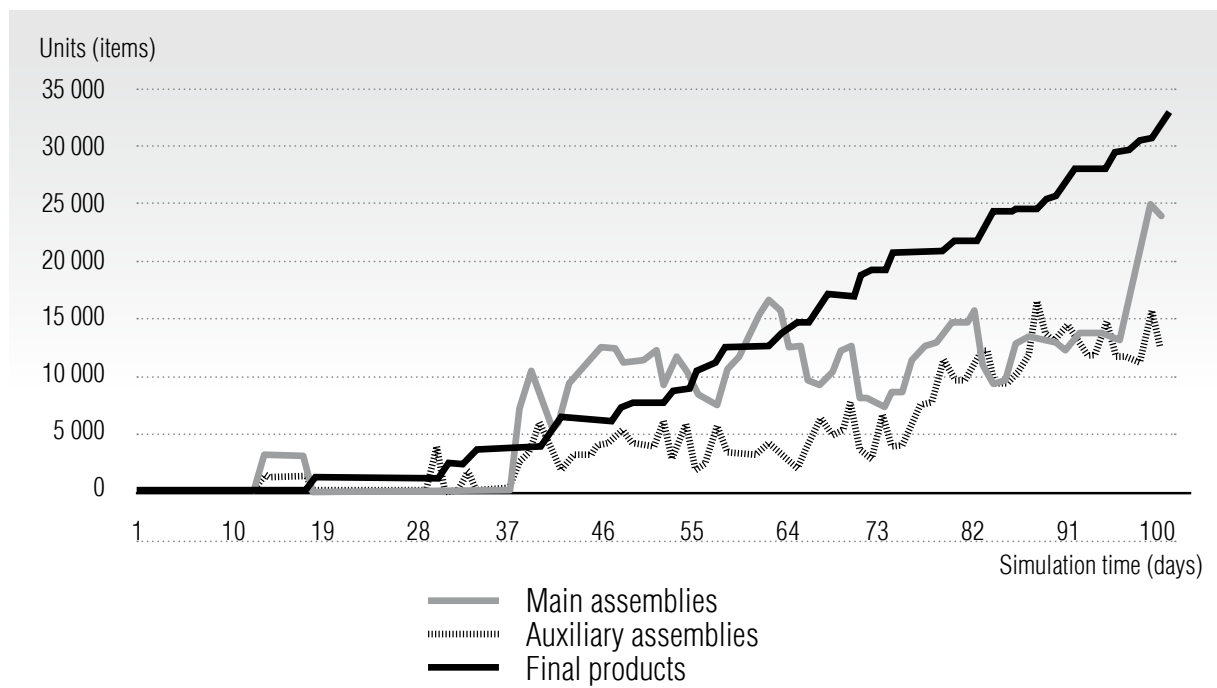


Fig. 6. Model dynamics of warehouse stocks

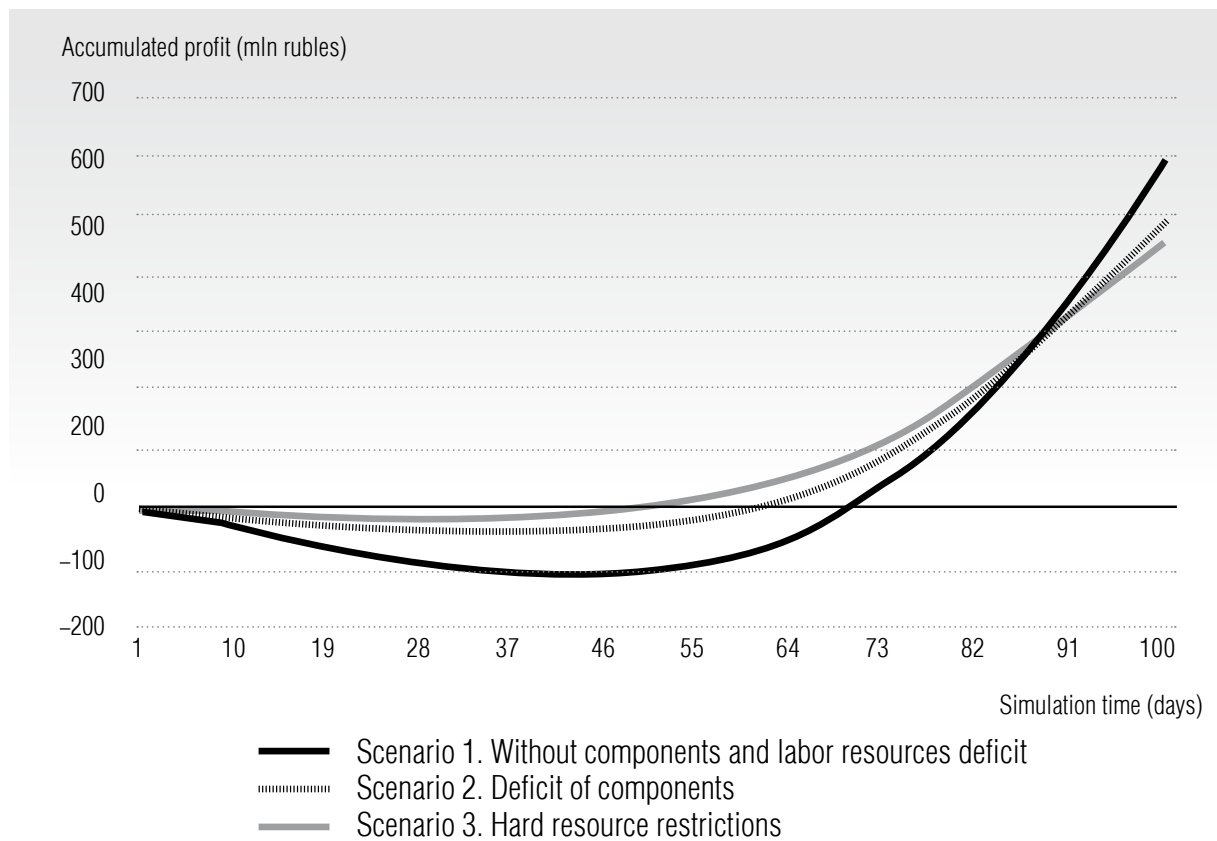


Fig. 7. Results of optimization experiments (accumulated profit)

Table 1.

Values of the sought variables and optimization results

| Model parameter | Scenario 1: Without deficit of components and labor resources | Scenario 2: Deficit of components | Scenario 3: Hard resource restrictions |
|--|--|---|--|
| Number of agents–assemblers of the 1st category, people | 1000 | 430 | 125 |
| Number of agents–assemblers of the 2nd category, people | 500 | 225 | 84 |
| Number of agents– specialists belong to technical control department, people | 100 | 30 | 15 |
| Number of agents– packers, people | 100 | 27 | 13 |
| Number of agents–loaders, people | 50 | 20 | 10 |
| Average assembly time, days | 0.1 | 0.05 | 0.03 |
| Average technical control time, days | 0.01 | 0.01 | 0.008 |
| Average packing time, days | 0.01 | 0.07 | 0.05 |
| Average shipping time, days | 7 | 5 | 4 |
| Accumulated gross profit at time T = 100, million rubles | 619 | 494 | 468 |

At the same time, three scenarios of the behavior of the considered production system were considered:

Scenario 1. Without any deficit of components and with the possibility of a significant increase in the involved labor resources.

Scenario 2. A deficit of components while demand for final products is maintained

Scenario 3. The presence of hard resource restrictions on the number of employees involved in the processes while many of the needed components are missing.

In *Figure 7* the results of optimization experiments are shown.

Table 1 shows the numerical values of the sought variables obtained because of optimization for the three considered scenarios of the behavior of the investigated production system.

As follows from *Figure 7* and *Table 1*, the use of a genetic algorithm to optimize the characteristics of the developed discrete-event simulation model made it possible to determine the best (suboptimal) values of the decision-variables corresponding to three fundamentally different scenarios of the production system

behavior. At the same time, the dynamics of the accumulated gross profit is generally stable in relation to the scenarios under study. Thus, for instance, in conditions of components deficit (Scenario 2) due to a significant reduction in the number of involved labor resources with a simultaneous decrease in the execution time of production operations (i.e. due to increasing labor productivity), a significant level of accumulated profit can be ensured. In addition, the same financial result can be obtained in conditions of hard resources restrictions and the absence of the components deficit (Scenario 3).

Conclusion

This article presents a new approach to the development of a ‘digital twin’ of a manufacturing enterprise (using a TVs assembly plant as the case study) based on the combined use of discrete-event and agent-based simulation methods. A conceptual model of a digital plant is proposed with subsequent software implementation in the AnyLogic simulation system. We formulated and solved the most important problem of maximising the gross accumulated profit of a manufacturing enterprise taking into account the contribution of the operational component, including the dynamics of the volume of finished products, the number of employees involved in various processes, the execution time of production operations, etc.

Numerical studies were completed, in particular, optimization experiments which confirm the possibility of determining the best solutions that ensure the stability of the accumulated gross profit of the enterprise in relation to various characteristics of the external environment (e.g. in conditions of the components deficit and hard resource restrictions).

The simulation results demonstrate the possibility of obtaining an accumulated gross profit of the manufacturing plant that is stable in relation to the scenario characteristics of environment. Thus, for instance, in the appearance of the components deficit (Scenario 2), as well as in conditions of hard resource constraints and the absence of the components deficit (Scenario 3), it is possible to provide a level of accumulated profit close to the financial result of the first scenario with the absence of such restrictions.

Further research will focus on the development of methods for the creating ‘digital twins’ of manufacturing enterprises with a more complex organizational structure and nested (hierarchical, multilevel) processes. ■

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