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Developing digital twins for production enterprises

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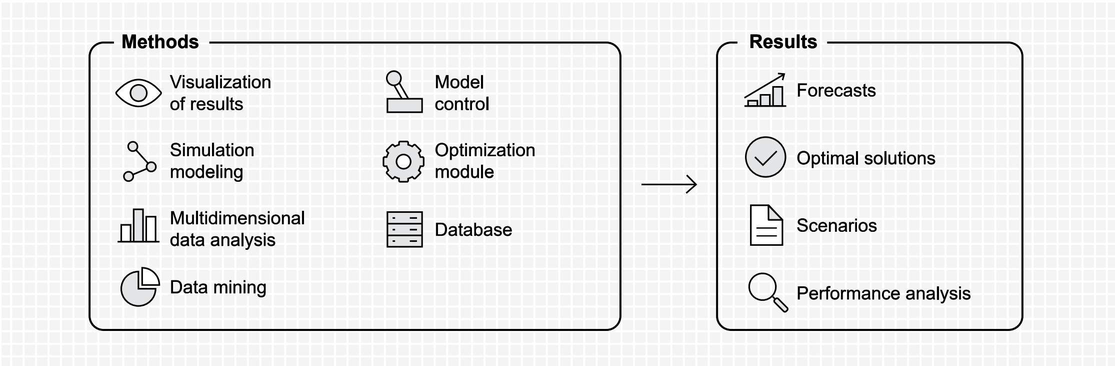
Abstract

This article presents a new approach to developing digital twins of production companies with the use of simulation methods. It describes the concept of digital twins as an integrated system that aggregates simulation models, databases and intelligent software modules of the class of genetic optimization algorithms, subsystems of data mining, etc. The article presents examples of simulation models of different production companies, in particular, a typical assembly plant and a typical oil production enterprise. The first company carries out activities to assembly products from individual components with its own individual characteristics. To describe the behavior of such an enterprise, methods of agent and discrete-event modeling are used. The second enterprise produces raw carbohydrate materials at existing fields with individual characteristics. The integrated simulation models thus developed are integrated with a subject-oriented database and optimization modules that facilitate providing a control of the technological and resource characteristics of the respective production enterprises. The development of these models was performed using AnyLogic and Powersim simulation systems that support agent-based modeling and system dynamics methods. We demonstrate here the possibility of creating 'digital twins' for production companies using modern simulation tools.

Graphical abstract



Key words: digital twins; agent-based modeling; system dynamics; discrete-event simulation; digital economy; production companies.

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Introduction

In modern times, as we transition to the digital economy, a new scientific vector is developing related to the creation of so-called "digital twins" – digital copies of real physical objects (for example, manufacturing enterprises, financial corporations, etc.) that help to optimize the effectiveness of all the main processes. The most important characteristic of digital twins is the existence of a virtual model that is supportive in an actual state, mainly due to continuous updating of data that used for the evaluation of multiple characteristics of the physical object under examination.

The concept of digital twins has been proposed recently [1, 2]. However, researchers point out that the design of digital twins should be based mainly on the use of simulation techniques providing the most realistic representation of a physical object in the virtual environment [3]. In this case, the computer model must support the ability to solve problems of optimizing the multiple characteristics of the simulated object using data updated in real time. A similar approach is applicable to many objects of life as lifeless nature. There are examples of the development of simulation models for the simulation of complex socio-economic systems [4, 5], vertically integrated petroleum companies and financial corporations [6], ecological and business systems [7, 8], modeling human crowd behavior in emergencies [9, 10] and some others. In this study, various methods of simulation modelling are used, in particular, the methods of system dynamics, agent-based and discrete-event modelling, which are supported in Powersim, AnyLogic, etc. [6].

A significant contribution to the development of system dynamics methods has been made in [11–16]. Within the research on agent-based modelling, we should highlight the works [17–20]. Important research in the field of discrete-event simulation is presented in papers [21, 22].

An important feature of modern simulation systems is the ability to integrate the developed models to databases and data warehouses (e.g. MS SQL Server, Oracle, SAP HANA), as well as the ability to integrate with external software modules, usually through a special API (application programming interface). For example, simulation models developed in AnyLogic and written in the programming Java can be integrated with the applications designed with the use of C++ and MPI (message passing interface) for parallelizing the respective computational procedures. As a result, the simulation model can be aggregated with genetic optimizing algorithms through objective functions, providing the ability to optimize characteristics of the simulated object in real time [23–25]. To ensure the software and management pool of available digital twins, it is possible to use an approach based on a service-oriented architecture (SOA).

The purpose of this article is to develop the approach to designing digital twins for a variety of production companies using simulation methods, databases, optimization modules, etc. for the implementation of the rational production management concept in real time and to support strategic and operational decision-making systems.

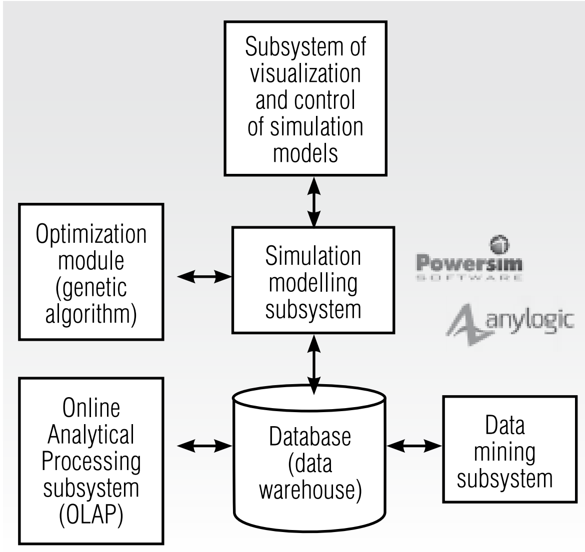

Fig. 1. The integrated system architecture of a digital twin of the manufacturing enterprise

1. The concept of creating digital twins

The suggested concept of creating digital twins is based on the use of an integrated approach combining simulation methods, optimization modules (of a type of genetic algorithms), a database (data warehouse), a multidimensional data analysis subsystem (online analytical processing, OLAP) , etc. (*Figure 1*).

An important feature of the approach being proposed is to ensure continuous integration of the considered subsystems with support for the functioning of all software modules in real time.

Thus, the following interacting subsystems are suggested:

✦ **simulation modelling subsystem** designed to compute the values of multiple characteristics of the enterprise under given scenario conditions;

✦ **optimization module (genetic algorithm)** that is aggregated through the objective functions with simulation models of the production company and provides the possibility to seek the best (rational, suboptimal) decisions with the existing restrictions;

✦ **database (data warehouse)** provides collection and processing of relevant data across the enterprise, as well as initial data for simulation models and saves the results of simulation modelling;

✦ **subsystem of visualization and control of simulation models** integrated with enterprise simulation models (through a special API or using web services technologies – SOA) and allowing access to various functions of simulation models, for example, calling optimization experiments, saving the results of scenario modeling in the database and doing other activities;

✦ **Online Analytical Processing subsystem (OLAP)**, allowing us to analyze the results of simulation and optimization with the drill-down of the corresponding aggregation data (e.g., for the enterprise as a whole, for individual business-directions, by products, customers, etc.);

✦ **data mining subsystem** that provides an analysis of the relationships between the most important characteristics of an information model of production and updates the values of all influencing factors and significance coefficients, followed by saving the results to the system database. Such an approach provides continuous updating of existing interdependencies in the enterprise simulation models.

Next we will consider some examples of simulation models developed for enterprises of various classes, in particular, a typical assembly plant and a typical oil production enterprise.

2. Simulation model of assembly plant

Consider the aggregated simulation model of a typical assembly plant implemented in the AnyLogic system (*Figure 2*).

This assembly plant produces some products using two production lines. The first production line provides the formation of an intermediate product using five separate components supplied in accordance with a given schedule to the assembly system (the element of "Assembly 1"). The second production line provides the formation of the final product (the element of "Assembly 2") using two components, one of which is assembled using the output of the first production line.

In this model, each production component is an agent with its own individual characteristics. For example, if this is a production skeleton, then it has certain sizes and other specified technical characteristics. Based on the variation of the set of inflow agent-components, it ensures manufacture of various types of products at the output of the system (the element of "Exit"). At the same time, for components of individual types with their own individual characteristics, dynamic synchronization is performed using a special element that ensures the placement of agent-components in the queue and seeks the pairs of agents that satisfy a given correspondence criterion (the element of "Synchronizer"). As a result, agent-components corresponding to some specified criteria are being sent to the assembly, while other agent-components remain in the queue, or are forced out of it (for safekeeping).

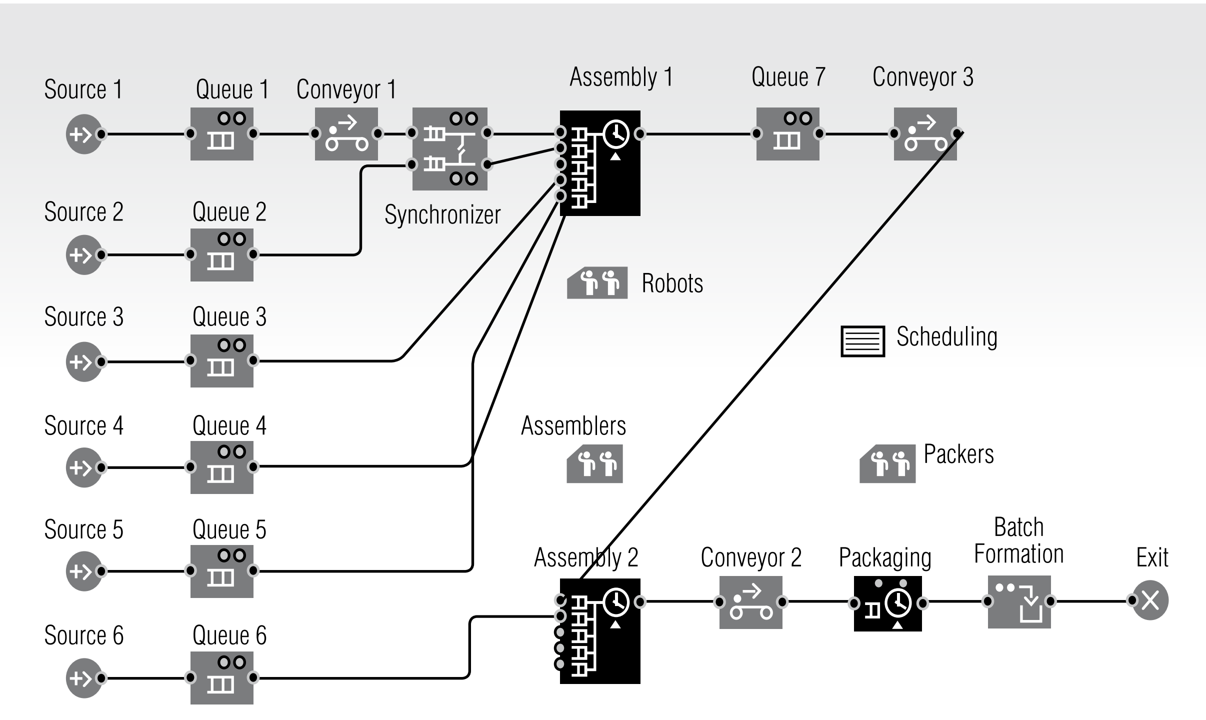

Fig. 2. Simulation model of an assembly plant in AnyLogic

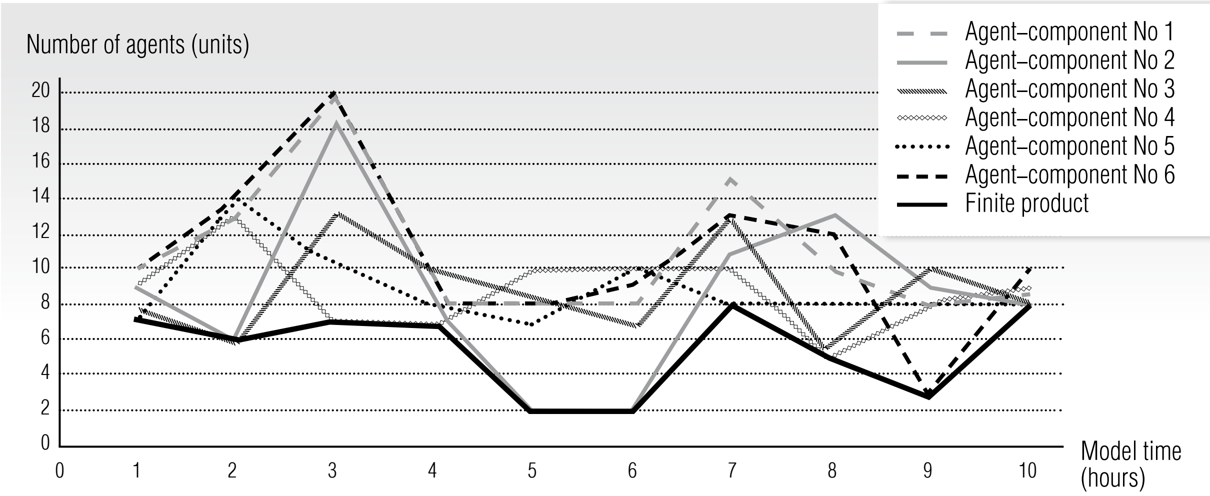

Fig. 3. The dependence of the total number of assembled products on the dynamics of the supply of agent–components

One of the possible examples of analysis of the stability of the production process using the simulation model so developed is the dependence of the total number of assembled products on the dynamics of the supply of agent-components (*Figure 3*).

In *Figure 3* we see that in conditions of the deficit of agent-components No 2 that occurs in the time interval from 5 to 6 hours, the rate of assembly of the finished product is reduced to the minimum level (two products per hour) equaling the value of the supply rate of the most deficit (the second) component.

Thus, the assembly rate of the final product is limited by the rate of supply of the most deficit component needed at the corresponding assembly stage. The rate of assembly and delivery of the final product also significantly depends on the resources involved in the corresponding production processes (elements of "Robots", "Assemblers" and "Packers" in *Figure 2*). In the case of the deficit of resources necessary for the production of a unit of production, the time to complete the corresponding task (product assembly) will be increased in proportion to the value of the availability coefficient of the corresponding resource.

3. Simulation model of an oil production company

Further, we consider the aggregated simulation model of a typical oil production company implemented in the Powersim system (*Figure 4*).

In contrast to the previous discrete-event and agent-based simulation of the assembly plant, this model operates with continuous raw and financial flows and therefore it was developed with the use of system dynamics methods [6]. At the same time, the main assets of the production enterprise, in particular, the set of new wells and the set of old wells, differentiated by fields, are important resource characteristics. The transition of wells from a new set to the old set takes place after a certain time interval (usually five years) with the associated change in a production volume, which is reflected in the production function, taking into account the different contributions of new and old wells in operation, respectively.

On the other hand, the indicators of economic efficiency of the exploited fields and wells depend not only on the volume of extracted raw materials, but also on the operating and investment expenditures differentiated by the respective fields. If a certain field is not oper-

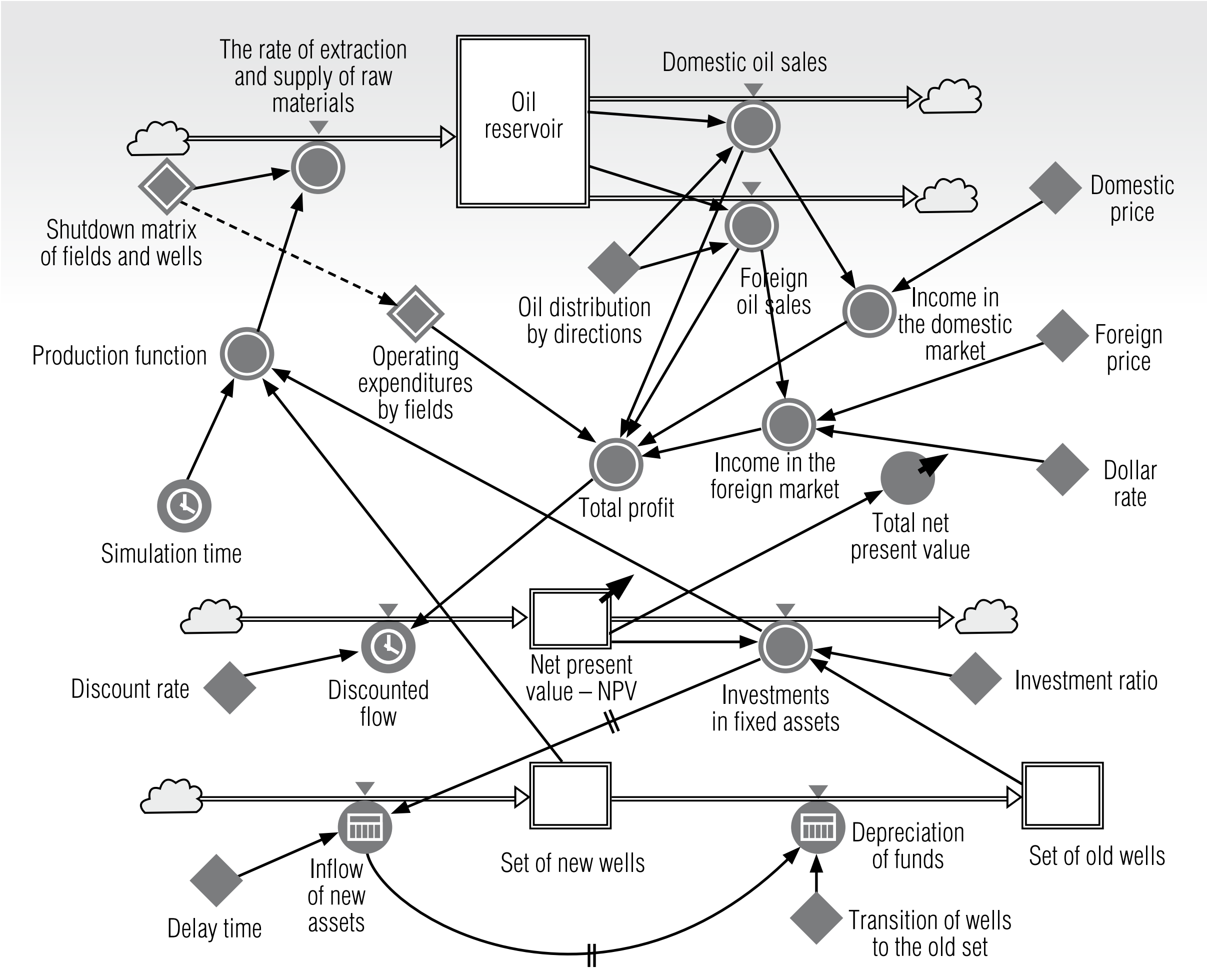

Fig. 4. Simulation model of an oil production company

ated at a certain time (for example, due to the suspension of the respective wells), then material and financial flows, as well as income and expenditure characteristics, cease to be formed on it. Further on, the most important relations of the proposed model will be described.

Here,

✦ $t = 1, 2, ..., T$ is the simulation time (by years), T is the horizon of a strategical planning;

✦ $i = 1, 2, ..., I$ is the indexes of fields, I is the total number of fields;

✦ $a_i(t)$ is the number of new wells (fixed assets of an oil production company) of the i-th field ($i = 1, 2, ..., I$) at the moment t ($t = 1, 2, ..., T$);

✦ $\{b_i(t),\ b_i(1)\}$ is the number of old wells of the i-th field ($i = 1, 2, ..., I$) at the moment t ($t = 1, 2, ..., T$) and the initial number of old wells at the initial moment $t = 1$;

✦ $\chi_i(t) \in \{0, 1\}$ is the shutdown matrix the i-th fields ($i = 1, 2, ..., I$) at the moment t ($t = 1, 2, ..., T$): if $\chi_i(t) = 0$ the i-th field is not operated, if $\chi_i(t) = 1$ the i-the field is operated;

✦ $c_i(t)$ is the rate of production and supply of raw materials (ton per year) of the i-th field ($i = 1, 2, ..., I$) at the moment t ($t = 1, 2, ..., T$);

✦ μ is the coefficient of decreasing of old fields;

✦ $\{v(t),\ \tilde{v}(t)\}$ are average annual production volume of new and old wells, respectively at the moment$t$ $(t = 1, 2, ..., T)$;

✦ $\{p_1(t), p_2(1)\}$ are prices of raw materials supplied in domestic and foreign markets, respectively at the moment t $(t = 1, 2, ..., T)$;

✦ $\{P_{1i}(t),\ P_{2i}(t)\}$ are incomes by i-ths fields $(i = 1, 2, ..., I)$ in domestic and foreign markets, respectively at the moment$t$ $(t = 1, 2, ..., T)$;

✦ $\{\tilde{O}_i(t),\ \tilde{I}_i(t)\}$ are operation and investment expenditures by i-ths fields $(i = 1, 2, ..., I)$, respectively at the moment t $(t = 1, 2, ..., T)$;

✦ $s(t)$ is the dollar rate at the moment t $(t = 1, 2, ..., T)$;

✦ $\lambda(t)$ is s share of supply in a domestic market at the moment t $(t = 1, 2, ..., T)$, $0 \le \lambda(t) \le 1$;

✦ τ is the time period, during of which wells can be classified as news (as a rule, five years);

✦ r is discounted rate.

The number of new and old wells respectively:

$$a_i(t) = \sum_{t=1}^{T} \left(\tilde{a}_i(t) - \tilde{a}_i(t-\tau)\right), \tag{1}$$

$$b_i(t) = b_i(1) + \sum_{t=1}^{T} \tilde{a}_i(t-\tau), \tag{2}$$

$$i = 1, 2, ..., I;\ t = 1, 2, ..., T.$$

The rate of production (and supply) of raw materials:

$$c_i(t) = \chi_i(t)\left(a_i(t)v(t) + b_i(t)\tilde{v}(t)e^{-\mu \cdot t}\right), \tag{3}$$

$$i = 1, 2, ..., I;\ t = 1, 2, ..., T.$$

Revenue in domestic and foreign markets respectively:

$$P_{1i}(t) = p_1(t)c_i(t)\lambda(t), \tag{4}$$

$$P_{2i}(t) = p_2(t)s(t)c_i(t)\left(1 - \lambda(t)\right), \tag{5}$$

$$i = 1, 2, ..., I;\ t = 1, 2, ..., T.$$

The profit of the oil production company:

$$\pi_i(t) = P_{1i}(t) + P_{2i}(t) - \chi_i(t)\tilde{O}_i(t), \tag{6}$$

$$i = 1, 2, ..., I;\ t = 1, 2, ..., T.$$

The discounted cash flow of an oil production enterprise:

$$DCF_i(t) = \frac{\pi_i(t) - \chi_i(t)\tilde{I}_i(t)}{(1+t)^r}, \tag{7}$$

The net accumulated discounted financial flow of the producing enterprise and the total financial flow (net present value) summarized by all fields, respectively:

$$NPV_i = \sum_{t=1}^{T} DCF_i(t), \tag{8}$$

$$NPV^* = \sum_{i=1}^{I} NPV_i. \tag{9}$$

Note that to predict the dynamics of the average daily production (production) rate for new and old wells $\{v(t),\ \tilde{v}(t)\}$, which affects the rate of production and supply of raw materials (3), data mining methods are currently being applied, in particular, artificial neural networks (ANN). Such ANN estimates multiple input characteristics (for example, the level of reserves, data on actually carried out and planned geological and technical measures, the selected production technology, etc.) to predict the average daily production rate of wells and annual volume. Thus, the values of the most important basic characteristics of the suggested simulation model are updated in real time taking into account the physical characteristics of the exploited fields.

One possible example of analysis of the effectiveness of a portfolio of investment projects for the set of exploited fields is the dependence of the discounted financial flow $DCF_i(t)$ on the values of the elements of the matrix of "shutdowns" of fields $\chi_i(t) \in \{0, 1\}$ $(i = 1, 2, ..., I)$ (*Figure 5*).

Figure 5 shows that the "shutdown" of the second field leads to doubling the total financial flow (summarized by all fields) – NPV^*. Such a positive effect results from the fact that the level of operating expenditure for the second field (per unit of production) significantly exceeds the level of costs of other fields with a comparable level of production volume. Nevertheless, if there is a hard restriction on the minimum needed total volume of production and supply of raw materials, then the exclusion of the second field from operation is impossible.

At the same time, if the number of simultaneously evaluated raw materials assets is large (for example, several thousand), then genetic optimization algorithms [23–25], aggregated with the simulation model of a production company, should be used to identify and "turn off" such fields.

Conclusion

The article presents a new approach to the development of digital twins for manufacturing enterprises which is based on the concept of continuous integration of a number of key subsystems, in particular, a simulation modeling subsystem, optimization module, database, data mining subsystem, etc. An important feature of digital twins is updating source data and values of influencing parameters in real time. Thus, digital twins significantly expand the functionality of traditional enterprise simulation models, mainly due to the greater realism and interactivity of the corresponding technology.

Examples of digital twins developed for manufacturing enterprises of different types are presented. In particular, these are the typical assembly plant and an oil production company. The first model, in particular, allows us to study the dependence of the total number of assembled products on the dynamics of the supply of components, taking into account their individual characteristics. The second model allows us to evaluate the impact of the matrix of "shutdowns" of oil fields on the dynamics of the discounted financial flow. It is shown that in the case of an absence of hard restrictions on the minimum required total volume of the raw material production (the production plan),

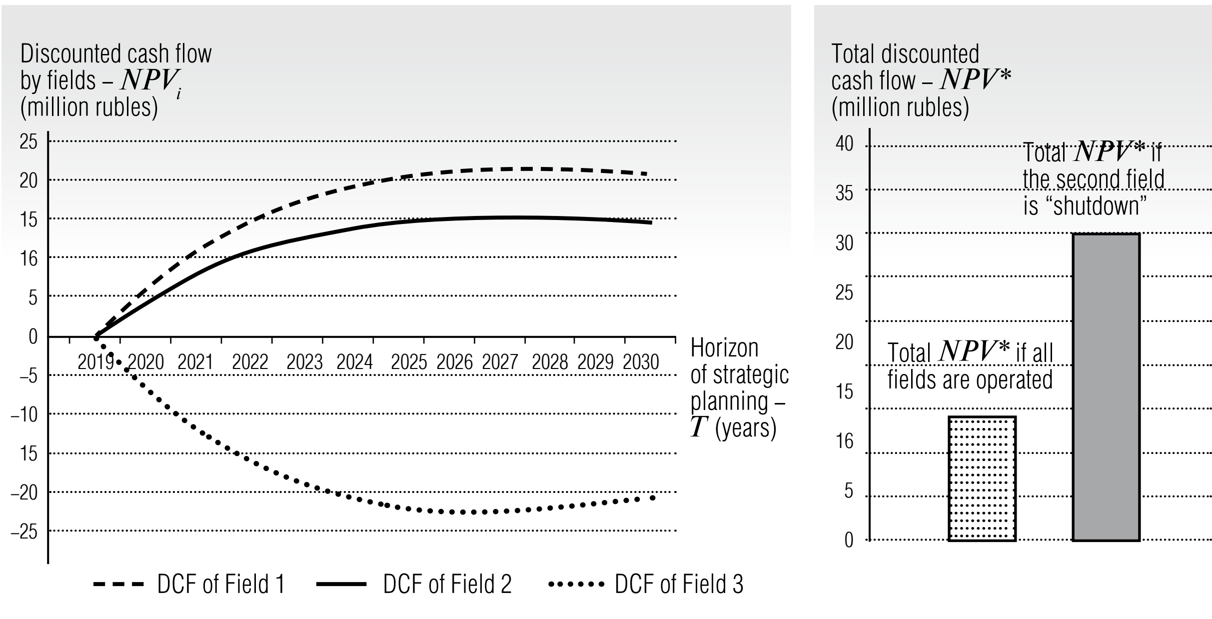

Fig. 5. The dependence of the discounted financial flow on the values of the elements of the matrix of "shutdowns" of fields

a significant increase in the net present value of the portfolio of fields is possible due to the exclusion of low-debit wells and fields with a relatively high level of operating expenditures.

If it is necessary to study the influence of multiple control parameters (for example, thousands of fields and wells, hundreds of components, dozens of production lines, etc. are simulated), then it is possible to use special optimization modules aggregated with simulation models through objective functions. Such an integrated approach is the most promising in terms of the development of the concept of digital twins and can be used in the future at a more detailed level. ■

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References

1. Saddik A.E. (2018) Digital twins: the convergence of multimedia technologies. *IEEE MultiMedia*, vol. 25, no 2, pp. 87–92.
2. Yan X., Yanming S., Xiaolong L., Yonghua Z. (2019) A digital-twin-assisted fault diagnosis using deep transfer learning. *IEEE Access*, vol. 7, pp. 19990–19999. DOI: 10.1109/ACCESS.2018.2890566.
3. Talkhestani B.A., Jung T., Lindemann B., Sahlab N., Jazdi N., Schloegl W., Weyrich M. (2019) An architecture of an intelligent digital twin in a cyber-physical production system. *Automatisierungstechnik*, vol. 67, no 9, pp. 762–782. DOI: 10.1515/auto-2019-0039.
4. Makarov V.L., Bakhtizin A.R., Beklaryan G.L., Akopov A.S. (2019) Development of a software platform for large-scale agent-based modeling of complex social systems. *Program Engineering*, vol. 10, no 4, pp. 167–177 (in Russian). DOI: 10.17587/prin.10.167-177.
5. Makarov V.L., Bakhtizin A.R., Beklaryan G.L., Akopov A.S., Rovenskaya E.A., Strelkovsky N.V. (2019) Aggregated agent-based simulation model of migration flows of the European Union countries. *Economics and Mathematical Methods*, vol. 55, no 1, pp. 3–15 (in Russian). DOI: 10.31857/S042473880004044-7.
6. Akopov A.S. (2017) *Simulation modeling*. Moscow: Urait (in Russian).
7. Akopov A.S., Beklaryan L.A., Saghatelyan A.K. (2019) Agent-based modelling of interactions between air pollutants and greenery using a case study of Yerevan, Armenia. *Environmental Modelling and Software*, vol. 116, pp. 7–25. DOI: 10.1016/j.envsoft.2019.02.003.
8. Akopov A.S., Beklaryan L.A., Saghatelyan A.K. (2017) Agent-based modelling for ecological economics: A case study of the Republic of Armenia. *Ecological Modelling*, vol. 346, pp. 99–118. DOI: 10.1016/j.ecolmodel.2016.11.012.
9. Akopov A.S., Beklaryan L.A. (2015) An agent model of crowd behavior in emergencies. *Automation and Remote Control*, vol. 76, no 10, pp. 1817–1827. DOI: 10.1134/S0005117915100094.
10. Beklaryan A.L., Akopov A.S. (2016) Simulation of agent-rescuer behaviour in emergency based on modified fuzzy clustering. Proceedings of the *2016 International Conference on Autonomous Agents & Multiagent Systems (AAMAS 2016), Singapore, 9–13 May 2016*, pp. 1275–1276.
11. Forrester J. (1969) *Urban dynamics*. Waltham, MT, USA: Pegasus Communications.
12. Forrester J. (1959) Industrial dynamics: A major breakthrough for decision makers. *Harvard Business Review*, vol. 36, no 4, pp. 37–66.
13. Meadows D.H., Randers J. Meadows D.L. (2005) *Limits to growth: The 30-year update*. London: Earthscan.
14. Meadows D.H. (1972) *Limits to growth: A report for the Club of Rome's project on the predicament of mankind*. New York: Universe Books.
15. Sidorenko V.N. (1998) *System dynamics*. Moscow: MSU, TEIS (in Russian).
16. Akopov A.S., Khachatryan N.K. (2014) *System dynamics*. Moscow: CEMI RAS (in Russian).
17. Schelling T.C. (1971) Dynamic models of segregation. *Journal of Mathematical Sociology*, vol. 1, no 2, pp. 143–186.

18. Axelrod R. (1997) *The complexity of cooperation: Agent-based models of competition and collaboration*. Princeton: Princeton University Press.
19. Bakhtizin A.R. (2008) *Agent-based models of economy*. Moscow: Economics (in Russian).
20. Akopov A.S., Khachatryan N.K. (2016) *Agent-based modeling*. Moscow: CEMI RAS (in Russian).
21. MacDougall M.H. (1987) *Simulating computer systems: Techniques and tools*. MIT Press.
22. Delaney W., Vaccari E. (1989) *Dynamic models and discrete event simulation*. New York: Marcel Dekker.
23. Akopov A.S., Beklaryan L.A., Thakur M., Verma B.D. (2019) Parallel multi-agent real-coded genetic algorithm for large-scale black-box single-objective optimization. *Knowledge-Based Systems*, vol. 174, pp. 103–122. DOI: 10.1016/j.knosys.2019.03.003.
24. Akopov A.S., Beklaryan A.L., Thakur M., Verma B.D. (2019) Developing parallel real-coded genetic algorithms for decision-making systems of socio-ecological and economic planning. *Business Informatics*, vol. 13, no 1, pp. 33–44. DOI: 10.17323/1998-0663.2019.1.33.44.
25. Beklaryan G.L., Akopov A.S., Khachatryan N.K. (2019) Optimisation of system dynamics models using a real-coded genetic algorithm with fuzzy control. *Cybernetics and Information Technologies*, vol. 19, no 2, pp. 87–103. DOI: 10.2478/cait-2019-0017.

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