Development of a Hybrid Decision-Making Method Based on a Simulation-Genetic Algorithm in a Web-Oriented Metallurgical Enterprise Information System

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***Abstract*— The modern large industrial enterprises are faced with the problem of collecting, centralized storage and intellectual analysis of a large volume of production data with the goal of timely output of control actions, including in real time. The paper focuses on a web-oriented distributed metallurgical enterprise information system designed to support decision making with the help of data mining and simulation of multi-agent resource conversion processes. In order to support the optimization of production processes, a hybrid decision-making method based on a simulation-genetic algorithm is proposed. The hybrid method is implemented in the modeling subsystem of the metallurgical enterprise information system. The application of the method in solving the problem of the enterprise organizational processes optimization made it possible to develop concrete practical recommendations.

Keywords—decision-making process; web-oriented distributed automated system; hybrid simulation; cloud computing; multi-agent resource conversion process

I. INTRODUCTION

Recently more attention is paid to production management. Large industrial enterprises are implementing MES and ERP-systems, digitizing the metallurgical production, realizing the material tracking, and implementing an analytical study of historical data on production and orders. The development of a system of fully digitized production is relevant. Construction a system of fully digitized production means to allow the use of the maximum amount of information for decision-making in real or limited time. The solution of this task should be integrated: 1) it is necessary to collect and store a large array of digitized data; 2) the stored data should be linked to the units of production (UP), with each of which the production genealogy is connected (a chain of different UP that are obtained from one another during the execution of technological operations); 3) it is necessary to support decision-making on the basis of analysis and simulation of stored and real-time data.

The paper is devoted to the description of a metallurgical enterprise information system (MEI system) [1-5]. The MEI system is solved the problem of fully digitized production. The MEI system is designed for analysis of production using simulation models of multi-agent resource conversion processes (MRCP) [6] and real-time management decisions using BIG DATA technology [7].

We consider the architecture of the MEI system and extension of the MRCP model of the modeling subsystem of the MEI system using the evolutionary modeling method to support the optimization of the company's technological, logistic, and organizational processes.

II. THE METALLURGICAL ENTERPRISE INFORMATION SYSTEM

The architecture of the MEI system is shown in Fig. 1. The data storage (DS, data warehouse) consists of two components: 1) Mongo DB for the operational collection and post-processing of information; 2) Oracle to provide long-term storage and analytical processing of information. The data exchange (DE) module with automated enterprise systems provides the collection and exchange of data with external systems like corporate information systems (CIS), MES-, ERP-systems.

The MEI system consists of two subsystems: a subsystem of the data collection and a modeling subsystem. The subsystem of the data collection includes: data warehouse; the query builder (QB) module [3-5]; the DE module. The modeling subsystem includes: the data preparation (DP) module; the module for creating process models (CM); the module of the processes optimization (PO); the integration module (IM), which solves the problem of using models in decision-making processes in real time. The CM and PO modules have been developed jointly with the Ural Federal University.

Commercial products of the class of simulation systems of technological, logistic, and organizational (business) processes, represented on the market (AnyLogic, Arena, ARIS, G2, Simio), are desktop-applications. In the development of complex simulation models in the team, additional requirements for simulation systems are the following: support for multi-user mode, access to the model and conduct experiments through the Internet.

The MEI system uses an approach that is close to cloud computing.

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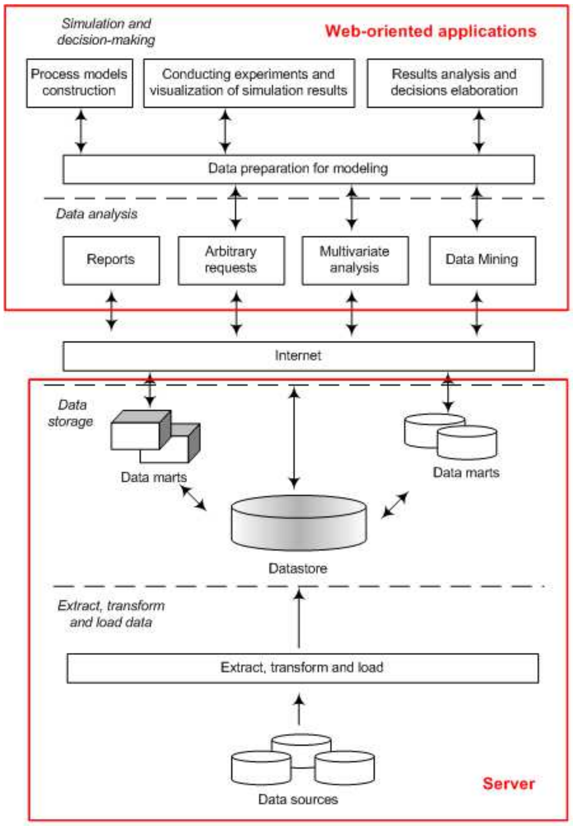

Fig. 1. The architecture of the MEI system.

Cloud computing [8] is a model for providing convenient network access on demand to a common pool of configurable computing resources that can be provided and released with minimal operating costs and calls to the provider.

With such a solution, the client only needs to enter the initial data (whether the model itself, or its elements, or the original experimental data), then data are sent to the server, the server accepts and starts all data processing at their own, so the client does not spends its resources, which is optimal from the point of view of productivity and the organization of multi-user work. The scheme of the work of the modeling subsystem of the MEI system is shown in Fig. 2.

A comparative analysis of the simulation systems is presented in Table 1: ARIS (AR) [9], G2 [10], AnyLogic Cloud (ALC) [11], and modeling subsystem of the MEI-system (MEI). In the direction of distributed multi-user work, only G2 system with Telewindows technology and MEI-system develop.

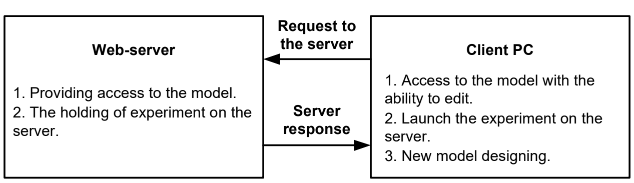

Fig. 2. Organization of remote computing in the modeling subsystem of the MEI system.

TABLE I. COMPARATIVE ANALYSIS OF THE SIMULATION SYSTEMS

№	Criterion	AR	G2	ALC	MEI
1	The language of the resource conversion processes description	+	+	+	+
2	Multi-agent modeling	No	No	+	+
3	Simualtion	+	+	+	+
4	Expert modeling	No	+	No	+
5	Evolutionary modeling	No	No	+	+
6	Organization of distributed multi-user work				
6.1	Multi-user mode	No	+	+	+
6.2	Carrying out experiments on the server via the Internet	No	+	+	+
6.3	Presence of the web interface	No	No	No	+
6.4	Java support	No	+	+	+
7	Orientation to non-programming user	+	No	No	+
8	Means of data exchange with CIS, MES-, ERP-systems	No	+	No	+

The main competitive advantage of the modeling subsystem of the MEI system is the availability of the modules for analysis and data preparation, which with the help of machine learning methods work with a large amount of accumulated data and restore the missed data collected from production sensors. In addition, an important advantage of the MEI system is the ability to exchange data (both input data for simulation and simulation results) with various external information systems using a data bus. The competitive advantage is the orientation of the MEI system to the non-programming user – technologist, logist, etc.

The MEI system also supports the optimization of the company's processes. Optimization implies generation and evaluation various alternatives of the system operation by simulation and choose of the one alternative based on the described criterion (objective function). Integration of evolutionary and simulation modeling allows to narrow the space of a full-factor experiment with the model and obtain an optimal (effective) solution in less time.

We consider the development of a hybrid decision-making method in the MEI system in order to support the optimization of the MRCP processes.

III. DEVELOPMENT OF A HYBRID DECISION-MAKING METHOD IN THE MEI SYSTEM

The MEI system provides an opportunity to build models of MRCP and collective behavior of objects (agents in terms of artificial intelligence) in the conditions of a given system of needs and interests. The basis of the MRCP model is queuing schemes, automata, Petri nets and the agent approach [12-13]. The MRCP model is extended by the application of the genetic algorithm (GA) [14], one of the methods of evolutionary modeling. This opportunity provides a wide range of optimization, decision-making, operational planning and dispatching technological, logistic and business processes.

The use of the integrated evolutionary-simulation algorithm allows to use the natural laws of the development of complex systems for solving optimization problems by generating and evaluating alternative variants of the system functioning. The scheme of integration of GA and simulation is shown in Fig. 3.

This scheme differs from existing schemes by modifying the GA in order to improve the quality of the solution found. The genetic algorithm is modified by the annealing simulation algorithm and the novelty search algorithm. In the novelty search algorithm, the measure of the adaptability of an alternative solution to environmental conditions is the originality of the solution, which is determined by numerical transformations of the Hamming distance matrix between chromosomes-solutions. The originality of solutions and their fitness functions (the values of objective functions at the model output) determine the various strategies for the formation of a new population of alternative solutions (a new search space). The annealing simulation algorithm is designed to implement a combination of proposed strategies for the formation of new populations. A detailed description of the genetic algorithm modification by the annealing simulation algorithm and the novelty search algorithm is given in [15]. Also in [15] the evaluation of efficiency of the hybrid method application for the decision of a project scheduling problem in comparison with a critical path method realized in MS Project is presented.

We consider the stages of the hybrid decision-making method based on a simulation-genetic algorithm implementated in the PO module of the modeling subsystem of the MEI system.

Stage 1. Choice of the method of coding the alternative solution of the problem (phenotype) into a string of symbols that encodes some solution of the optimization problem (genotype).

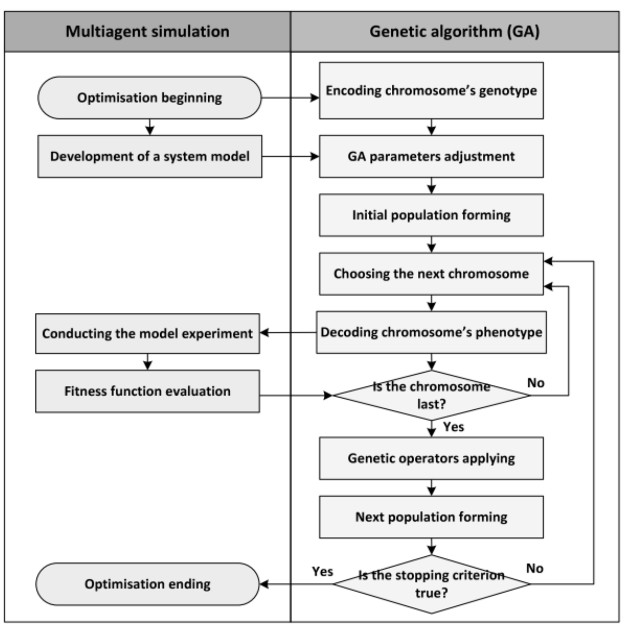

Fig. 3. The scheme of integration of simulation and genetic algorithm in solving of optimization problems.

Stage 2. Development (adjustment and selection) of genetic operators for the problem.

Stage 3. Determination of the laws of solution survival.

Stage 4. Selection of the method of initial population generation and the method of stopping the operation of the algorithm (Fig. 4). Generation of the initial population is realized randomly. The algorithm is stopped when the user-defined number of populations is reached.

Stage 5. Evolutionary simulation.

Stage 6. Transmitting the results of the model.

The CM module subscribes to the parameter with a definite identifier (UUID) when coordinate the input and output parameters of the process model with the the parameters of the actual technological processes and the parameters generated as a result of the operation of other system modules. When coordinated through the DE module, this parameter is a real process parameter obtained by the DE module from external information systems and broadcast by the DE module to all subscribers including the CM module and the data warehouse.

When parameter is coordinated through the IM module, this parameter is the calculated process parameter received by the DE module from the IM module and broadcast by the DE to all subscribers including the CM module. When parameter is coordinated through the QB module, the CM module stores the identifier (UUID) of the request (the request itself is stored in the data warehouse). When simulation is launched, the required request is executed in the QB module and the data generated as a result of the query are fed to the model. This ensures that the incoming data is up-to-date when the simulation starts.

The algorithm of the PO module use is the following.

1. The user enters to the web interface of the PO module by selecting the "Models / Constructor" menu of the workstation.

2. The CM module checks whether the user has the right to execute the model.

3. On the Model Designer page, the user ought to select the subject area and open the model.

4. The user ought to create an experiment plan.

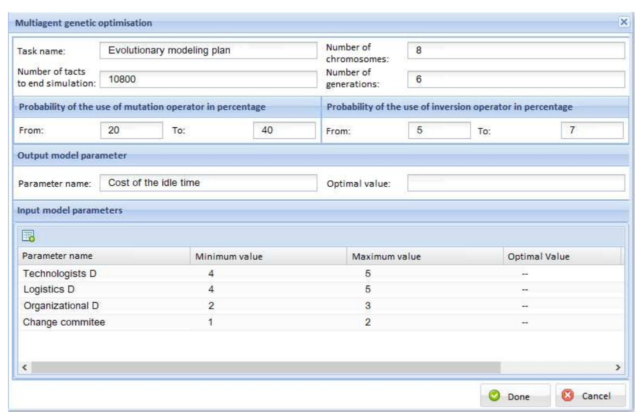

Fig. 4. View of the created plan of evolutionary modeling in the MEI system.

5. Carrying out experiments with the model: the user needs to determine the conditions for simulating and for stopping the work of the model, check the completion of the plan or experiment. When visualizing the work of models, 3D animation is used.

6. Transfer of the results of model execution and report generation.

IV. Testing of the Modeling Subsystem of the MEI System

Consider the development of a model of organizational processes to implement measures aimed at improving metallurgical production and improving the quality of products.

A standard permanent business process of the metallurgical enterprise to change production processes (PBPC) includes the following process groups: a) processes of detection of incidents (technological incidents - TI, logistic incidents - LI, or organizational incidents - OI); b) processes of detection of incidents causes and search of measures to prevent incidents, and c) processes of implementing of incident prevention measures. For simulation, we consider the last group of processes for improving production.

The optimization goal of the processes of implementing of incident prevention measures is to detect the optimal number of employees in the departments so that the percentage of the closed incidents at the end of the simulation will be maximum, and the cost of payment of the idle time for employees of the enterprise will be minimal. Within the research, the following departments are distinguished: department of technologists; the logistics department, the department for resolving of organizational incidents, and the change committee.

In the model (Fig. 5), it is necessary to take into account the fulfillment order of the operations of prevention measures implementing and operations duration as well as the availability of appropriate renewable resources (employees).

The process of the prevention measures implementing consists of eight steps. At the first stage, incidents are distributed to departments with the participation of the change committee. From the second to the fourth stage, various types of incidents in the relevant departments are resolved.

Technological and logistic incidents with exceeded deadline for resolution generate organizational incidents, for which causes are established and measures are being searched for from the fifth to the seventh stage. At the eighth stage, the implemented measures for all types of incidents are approved by the change committee and the incidents are closed.

The model has been developed in the CM module of the MEI system. The model is implemented on the resources, which are the queues of incidents to processing with the help of corresponding operations. When describing the processes of the incident prevention measures implementing, decomposition of the model nodes has been used. The agent "Distribution according to the executors" has been used to distribute operations for the departments and determine the probability of exceeding the estimated time for the operations execution over the actual execution time. The implementation of measures to prevent TI and LI incidents is described with decomposition into two processes: 1) fulfillment of measures with a normal execution time, and 2) fulfillment of measures with an exceeded execution time leading to the organizational encidents emerging. To fulfill these processes in the distribution agent, different execution queues are formed for the fulfillment.

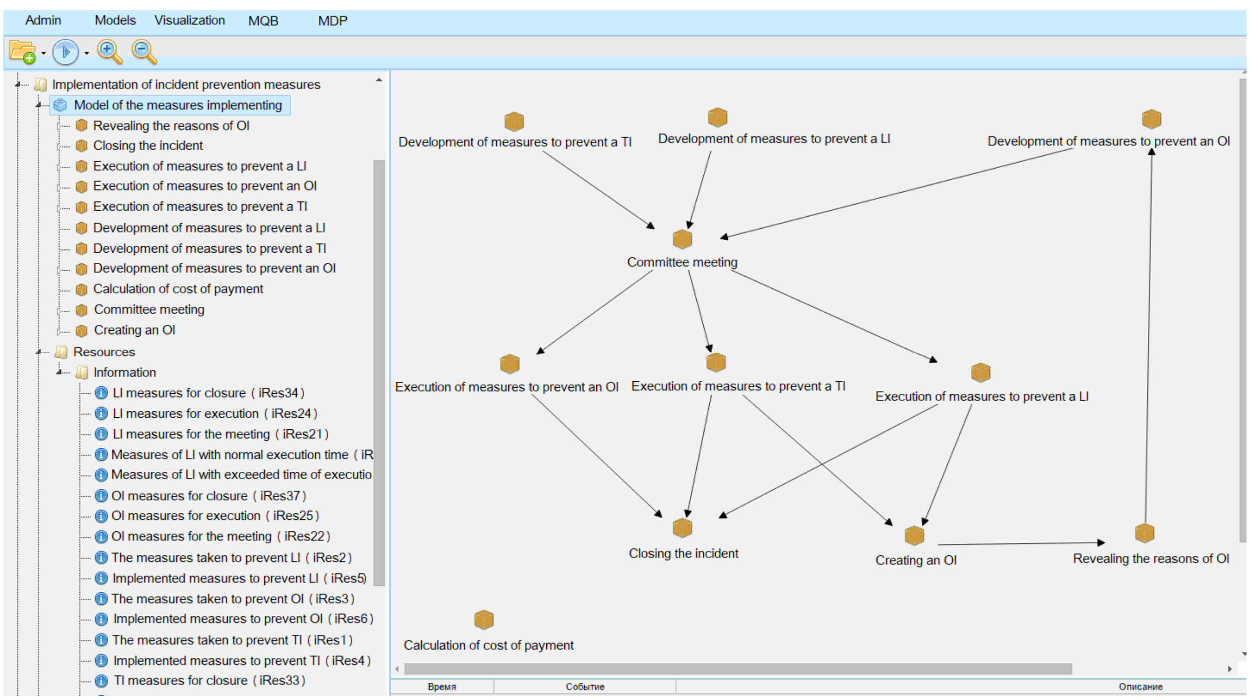

Fig. 5. The structure of the model of the incident prevention measures implementing in the CM module of the MEI system.

Processes in the performance of which several employees of one department participate, are described by means of decomposition and have at the lower level of decomposition the number of operations equal to the number of employees of the department.

With the developed model, experiments have been conducted in the PO module of the MEI system. As input to the simulation, statistical data on the number of incidents of each type, the number of incidents executed on time, and the number of incidents executed beyond the deadline have been used. The statistical data have been obtained from DS module with the help of the QB and DP modules of the MEI system.The DP module view with an example of statistical data analyzed and transmitted to the simulation model is shown in Fig. 6. The percentage of closed incidents for the experiment with the best result is shown in Fig. 7.

The input controllable modeling parameters were the number of employees in different departments of the enterprise. Controllable parameters of the experiments have been changed as follows: the changes committee - from 1 to 2 employees, the logistics department - from 4 to 5 employees, the department of technologists - from 4 to 5 employees, the department for resolving of organizational incidents - from 2 to 3 employees.

As the output information of modeling, the cost of payment of the idle time for employees (it is necessary to minimize) and the percentage of closed incidents (it is necessary to maximize) have been considered.

The basic experiment is based on the following input information: 1 employee of the changes committee, 5 employees of the logistics department, 5 employees of the department of technologists, 3 employees of the department for resolving of organizational incidents. As a result of a series of experiments, an experiment has been chosen with the best result, for which the cost of payment of the idle time for employees of four departments for two months was 11% less than the cost of payment of the idle time for employees for the basic experiment.

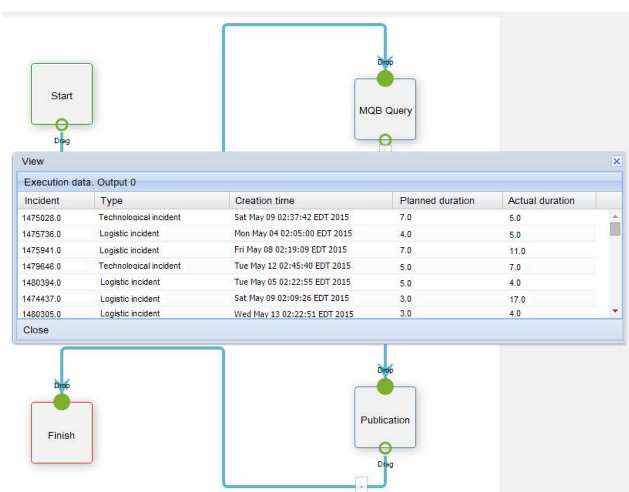

Fig. 6. The DP module view with an example of statistical data analyzed.

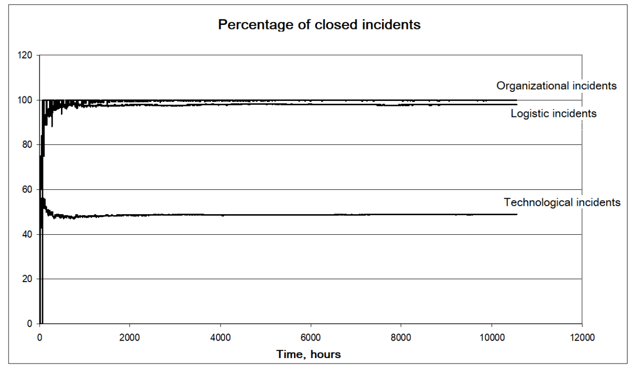

Fig. 7. The percentage of closed incidents for the experiment with the best result.

For the selected experiment with the best values of the output parameters, the following percentages of closed incidents have been obtained according to the types of incidents (Fig. 7): TI - 48.76%, LI - 97.95%, OI - 100%.

A low percentage of closed technological incidents is associated with a long resolution time for incidents of this type. Often technological incidents are associated with imperfect manufacturing technology. Changing the existing manufacturing technology is a lengthy process that can take from one week to several months.

The experiment with the best result is characterized by the following values of the controlled parameters: 4 specialists-technologists, 5 specialists-logists, 2 people from the change committee and 2 specialists of the department for resolving of organizational incidents.

V. Conclusion and Future Work

The architecture of the metallurgical enterprise information system has been considered. This system is intended to monitoring, tracking, production data collecting and analyzing, processes modeling and developing control actions in order to improve the quality of manufactured products. Storage and data collection in the MEI system are based on solutions in the field of Big Data and industrial automation. The MEI system maintains a multi-user mode and access to the models of production processes and conducting experiments via the Internet.

A hybrid decision-making method based on a simulation-genetic algorithm implemented in the modeling subsystem of the MEI system is described. The method allows carrying out optimization of technological, logistic, and organizational processes.

The method has been tested for solving the problem of optimizing the number of enterprise employees. In the MEI system, the simulation model has been developed to implement the measures taken to prevent three types of incidents: technological, logistic and organizational. During the experiments with the model, statistical data have been used on the timing of incidents emerging and time spent on implementing measures to prevent the recurrence of incidents. The statistics have been transferred to the model using the module of the query builder and the module of the data preparation of the MEI system. As a result of the application of the hybrid decision-making method, a solution has been found that permit to reduce the cost of payment of the idle time for employees by 11 percent, while maintaining a high percentage of closed logistic and organizational incidents and an acceptable percentage of closed technological incidents.

The purpose of future work is to expand the MRCP model of the modeling subsystem of the MEI system with numerical methods for solving problems in the context of uncertainty of input information (forecasting problems of the system behavior).

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