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Research Article

Intelligent Decision Support System Based on Multi-Agent Interaction Models by The Example of The Oil and Gas Industry

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Abstract: This study develops an intelligent decision support tool for managing complex production systems using the example of a field development system. The problem solved in the study lies in the limitations of existing tools for generating optimal and realistic scenarios for managing production systems due to the lack of consideration of local knowledge and target functions of individual production sites. The relevance of the work lies in the need to improve the quality of management decisions in complex production systems through decision support systems that consider the multi-agent nature of the interaction of system elements, considering the multiplicity of target functions and incomplete awareness of individual agents. The result of the work is the developed multi-agent field development system, consisting of an environment presented as a set of computational models and intelligent agents that control production elements at different levels of the hierarchy. A hierarchical MAS with region–field–bush–crew agents was built using BDI and integrated with a Python-based simulation model. The effectiveness of the developed solution is verified by comparing the predicted oil flow rates for alternative optimization algorithms. Optimization of the distribution of teams across the region's fields and the schedules of GTO and drilling using the MAS has increased the region's production rate by 4.5%, ensured the feasibility of field plans, and reduced the costs of well logging and drilling. The testing results demonstrate the effectiveness of using multi-agent systems to generate field development scenarios.

Keywords: Complex technical and socio-economic systems; Intelligent decision support system; Multi-agent interaction; Oil and gas industry; Simulation modeling

1. Introduction

Currently, the control of the Geological and Technological Operations (GTO) schedule relies primarily on manual expertise. Suboptimal crew allocation can lead to production losses of up to 20%. As part of addressing the problem that constraints of local subsystems were not previously considered (Pospelov, Burlutskaya, et al., 2023; Kuo et al., 2022), the use of intelligent agents to manage local field systems has been proposed (Sharko, Burlutskaya, Zubkova, et al., 2025; Sharko, Burlutskaya, Gintciak, et al., 2025; Liu et al., 2024). A multi-agent approach is used to solve problems such as refined oil dispatch optimization, crude oil procurement management, coordinated control of multiple fracturing trucks , and pump scheduling. Tools for optimizing GTO schedules using a multi-agent approach are less common. Furthermore, existing solutions are often based on machine learning methods and fail to account for the system's physical properties, an omission noted by oilfield experts as significant. Current GTO scheduling optimization systems do not account for the decentralized goals and constraints of agents in real-time field scheduling.

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Within the framework of this work, it is proposed to expand the scientific base related to the application of a multi-agent approach to support decision-making, in particular for managing complex organizational systems and solving the problem of the limitations of existing tools for generating optimal and realistic scenarios for managing production systems due to the lack of consideration of local knowledge and target functions of individual production sites (Lakemond et al., 2021; Lang and Zhao, 2016). To solve this problem, a multi-agent field development system consisting of an environment represented as a set of computational models and intelligent agents that control production elements at different levels of the hierarchy is being developed. During the work, intelligent agents, their interaction types, and their design tools are described. The effectiveness of the developed solution is verified by comparing the predicted oil flow rates for alternative optimization algorithms.

This research aims to ensure continuous improvement and optimization of production processes through the introduction and use of intelligent multi-agent systems, which is part of a more general scientific problem of making informed decisions in managing complex technical and socio-economic systems. The urgency of solving this problem stems from the need to improve the quality of solutions in the management of production systems to ensure the realization of innovative technological potential.

2. Methods

2.1 The field development system

In the context of the study, the field development system refers to a set of technical and social elements that interact within the framework of organizational, economic, and production processes to achieve common goals related to maximizing the effectiveness of field development. Thus, the field development system belongs to the class of organizational systems, since organizational systems, by definition, 1) represent an internally ordered system in which more or less differentiated and autonomous parts of the whole interact in a coordinated manner, 2) represent a set of processes or actions leading to the formation and improvement of relationships between parts of the whole, and 3) they are an association of people, jointly implementing a certain program or goal and acting on the basis of certain procedures and rules (mechanisms) (Novikov, 2013). If we consider organizational systems from the point of view of the first two definitions, then interdisciplinary systems can also be classified as socio-technical or organizational-technical systems, the elements of which are both social and technical agents—people and technical subsystems (equipment, software, networks, and so on). According to the definition of a system of technological processes, the field development system refers to organizational systems of an interdisciplinary nature. Interdisciplinary systems have the following specific features:

- The limited rationality of the system elements, demonstrated in the process of implementing its own functions and interacting with other system elements;

- Cooperative and competitive interaction of system elements;

- A distributed system for processing system data and making decisions.

Regarding the field development system:

- The limited rationality of individual system elements is associated with the multiplicity of objective functions of each agent, including both the goals of the entire system and the agent's local goals, which may contradict each other. In addition, the limited awareness of individual agents about each other's parameters and strategies.

- Cooperative and competitive behavior is manifested in the process of forming a production schedule, particularly in the allocation of resources, which is also caused by a multiplicity of local goals.

- A distributed data processing and decision-making system is associated with agents' relative autonomy, expressed in the independent implementation of local processes.

Thus, a field development system consisting of social agents who carry out strategic and operational management (employees, heads of production sites, directors, and so on) of production processes, interacting with the material and technical base, individual elements of which can also be represented as separate agents (for example, agent-resource) according to their properties, will belong to the class of complex systems because (Perko et al., 2022; Novikov, 2013):

1. It contains a set of different levels of subsystems and elements;
2. A multitude of local goals corresponding to individual agents characterize it (Z. Yu et al., 2021);
3. It has a complex hierarchical structure, at least in terms of social agent organizational structure.
4. Internal uncertainty related to the characteristics of social agents
5. It is characterized by the dynamic nature of the indicators, which also depend on the system's equilibrium conditions and the target functions' parameters.

The presence of many relatively autonomous agents implementing their own program of activity and having their own goals means that the field development system is actually multi-agent (V. Yu et al., 2022). Real multi-agency, combined with a distributed information processing and decision-making system, means the transition to a decentralized system. Taking multiagency into account when managing decentralized systems reduces the risk of unstable solutions arising from a conflict between the global and local goals of the system, but complicates decision-making processes due to the exponential growth of possible management scenarios. Therefore, developing a mathematical decision support tool for managing production systems that considers the features of interdisciplinary complex organizational systems is an urgent task.

In this case, it is important to note that organizational and technical (or sociotechnical systems) systems differ from socio-economic systems in that social agents are considered separate agents for whom not only their own goals are defined but also unique strategies that take into account the limited rationality manifested in information processing and decision-making. Solutions (Pospelov, Vatamaniuk, et al., 2023). Thus, neither algorithms based on emergent artificial intelligence (swarms of particles, bee colonies, and a network of needs and opportunities) can be successfully used to model complex systems, including multi-agent ones, nor the basic paradigms of simulation modeling, in particular, system dynamics used in demographic models and in modeling the spread of diseases, meet the requirements of production process systems, since they consider social agents as a set with common properties, albeit capable of self-organization and evolution, but still as a set of rational agents.

The multitude of autonomous unique social and technical agents interacting at different levels of the hierarchy necessitates a detailed description of the interaction of individual agents, which limits the choice of system modeling tools. Modeling a system as a set of interconnected and interacting intelligent agents is implemented only using MACs.

2.2 Intelligent Agents

An agent is an entity capable of perceiving and interacting with the environment, taking certain actions to achieve set goals (Wooldridge, 2009). For example, in robotics, agents perceive the environment using sensors, and software agents perceive it through communication protocols (Z. Yu et al., 2021). This definition is general, and in the context of the study of multi-agent systems, two more specific definitions are needed: a software agent and an intelligent agent (Oroojlooy and Hajinezhad, 2019).

A software agent is an autonomous software object capable of achieving its goals in uncertain conditions, analyzing various solutions, and coordinating its actions with other agents (Wooldridge, 2009). Unlike a regular software object, an agent has autonomy, which allows it to respond independently to requests from other agents or the user. He can accept or reject an incoming request based on many conditions, such as agreements with other agents, the state of the environment, and risks. A regular program object is called upon request to perform specific tasks.

The software agent has the following properties (Chernyshev, 2023; White, 2015; Wooldridge, 2009):

- Purposefulness: The agent has his/her own set of goals, which he/she strives to achieve (Gorodetsky et al., 2019);
- Autonomy: the agent can control his actions and internal state and strive to achieve goals.
- Proactivity: the agent can take the initiative to achieve his/her goals;
- Reactivity: the agent can perceive the external environment and react to changes, adapting his/her behavior strategies to achieve goals (White, 2015).
- Social behavior: The agent can interact with other agents of the environment to achieve common goals and coordinate or change decisions (White, 2015).

Thus, an agent is more than a set of algorithms. This includes sets of behavior scenarios, strategic and operational planning of actions, and analysis of results. This entire set of characteristics forms the agent's "Personality" (White, 2015).

In the literature, the concepts of "software agent" and "intelligent agent" are often equated as objects with a single set of properties. However, to avoid terminology specific to engineering and robotics, we define the properties of an intelligent agent separately (Shen et al., 2022). It is assumed that software objects can also be considered intelligent agents, but with their inherent application specifics.

Intelligent agents are understood as agents with their own evolving set of knowledge, behavioral strategies, and goals, capable of perceiving and responding to the environment, as well as creating new or improved scenarios based on knowledge about other agents' domain and behavior (Chernyshev, 2023; Gorodetsky et al., 2019).

Let us highlight the additional properties of intelligent agents:

- Information and motor mobility: the agent can actively move and purposefully search for and find information, energy, and objects necessary for a cooperative solution to a common task.
- adaptability: the agent can automatically adapt to uncertain conditions in a dynamic environment;
- Communication skills: The agent can interpret and form his/her own messages. Communication skills are based on a discourse model and certain procedures that allow you to interpret and evaluate incoming messages and form your own.
- Reflexivity: the agent is capable of reflecting. A reflecting agent can analyze its own actions and those of other agents and then make predictions about the possible development of the system in the future based on the findings (Shvetcov et al., 2022).

2.3 Architecture of the intelligent agents

The BDI and SOAR models are the most popular models. The BDI model is based on the principles of ”folk psychology” (Caillou et al., 2017; Chen et al., 2007). It is intuitive and the most common in commercial projects, as evidenced by the variety of BDI-based tools. Agents implemented using the BDI model are described in terms of beliefs, desires, and intentions. Unlike BDI, SOAR is based on the basic principles of classical AI (Chen et al., 2007). Since, within the task framework, individual intelligent agents will mean separate production units with the corresponding characteristics of social agents, the BDI model is assumed to be the closest to social agents in terms of design logic. Another reason for using BDI is its scalability. Not only have many software tools been created based on BDI but also many architectures, such as PRS, dMARS, and COZY. Each architecture represents a more complex model of an intelligent agent that expands cognitive abilities and communication strategies. Accordingly, as part of the continuation of the study, if necessary, the development of intelligent agents can be achieved without fundamentally changing the architectural solution.

3. Results and Discussion

The field development system can be represented as a set of intelligent agents and their interaction environment (Sharko, Burlutskaya, Zubkova, et al., 2025). In this case, the multi-agent system environment will mean a set of computing modules that implement calculations related to the main production and support activities, in particular: modules for calculating oil and gas flow, including after geological and technical measures (GTM) and drilling, as well as modules for calculating operating and capital costs and other economic indicators (Oroojlooy and Hajinezhad, 2019).

In the context of this study, intelligent agents are understood as autonomous software objects capable of achieving their goals in conditions of uncertainty, analyzing various solutions, and coordinating their actions with other agents (Ahmadi et al., 2022; Li et al., 2021). Then, individual production sites can be considered as intelligent agents, particularly the level of the region, the level of the field, and the level of the bush (Bolsunovskaya et al., 2023; Fedyaevskaya et al., 2023). Local target values (production plan) are defined for each production site. Another agent required for accounting is the crew, which is the main resource for operations.

Agents: Region, field, and bush are agents of the same type. Their architecture and logic of interaction are similar: obtaining a production plan, allocating resources, and communicating with an agent of their own level to exchange resources. The task of the crew is to minimize logistical costs by ensuring that the flow rate is maintained or increased. The introduction of crews as intelligent agents allows us to consider the real limitations of the system, considering incoming information about the state of the infrastructure and the parameters of operations, depending on the actual parameters of the geophysical tablet wells (Ferrigno et al., 2024; Bolsunovskaya et al., 2023).

The internal architecture of intelligent agents in accordance with BDI is defined as a set of beliefs, desires, and actions (Table 1) (Sharko, Burlutskaya, Zubkova, et al., 2025; Caillou et al., 2017). Table 2 lists the utility functions of the agents. The BDI architecture was used to build the agents. The reasoning cycle of the agent is presented in Algorithm 1.

The system’s plans are built upon the actions listed in Table 1, which are instantiated with specific execution conditions and associated desires. Plans can be presented in multiple forms. The plan formation methodology also depends on the selected approach to decentralized optimization, which merits a dedicated study. CAPEX- and OPEX-based metrics employed by the data-providing company were applied when calculating costs.

A secure agent coordination protocol based on Jason Speech Acts (Seidita et al., 2022) was developed to address the problem of asynchronous agent communication. The details of the design and software implementation of this protocol are the subject of another study. Intelligent agents have their own knowledge of the system, considering the appropriate level of detail

Table 1 Intelligent agent architecture of the field development system

Agent	Belief	Desire	Actions
Region	Available resources: the number of crews of each type; the number of fields; historical production and cost data.	Maximizing the debit $QR(t) \to max$ QR – the region's oil production.	Distribute crews of each type between fields and calculate the expected oil production rate and production costs.
Field	Available resources: the number of crews of each type, production plan, drilling and GTO schedule, number and parameters of bushes; projected production volume under the baseline scenario; projected production volume during resource exchange; altruism coefficient.	Maximizing the total debit, meeting/exceeding the plan $\alpha \times QR(t) + (1-\alpha) \times QM_i(t) \to max$ $QM_i(t) \geq Qplan_i$ α – the coefficient of altruism, QM_i – oil production rate of the i-th field.	Distribute crews of each type among the bushes; receive/transfer crews to other fields; calculate the expected oil production rate and production costs.
Bush	Drilling schedule and GTM; projected production volume under the baseline scenario; projected production volume during resource exchange; bush parameters; list of wells; altruism coefficient.	Maximizing total flow rate $\alpha \times QM_i(t) + (1-\alpha) \times QB_j(t) \to max$ QB_j – oil flow rate of the j-th bush.	Receive/transfer crews to other bushes; calculate expected oil production rate and production costs.
Crew	Time and financial costs for moving equipment; bush coordinates; operation duration; basic drilling schedule and GTM; projected costs and production under the baseline scenario; projected costs and production during the exchange of operations.	Maximizing the total flow rate and minimizing the moving equipment cost $QM_i(t) \to max$ $\alpha \times Tmove(t)$ $+(1-\alpha) \times Tmove_k(t) \to min$ $Tmove$ – is the total time to move equipment for a given type of resource, $Tmove_k$ –s the time to move the kth crews.	Receive/transfer operations to other teams; create an address schedule of operations.

hierarchy. A top-down scheme is used to calculate the control scenarios (Figure 1).

Table 2 Utility functions of the field development system's intelligent agents

Agent	Utility function
Region	$U_R(t) = \frac{QR(t)}{\max_t QR(t)}, \quad QR(t) = \sum_{i=1}^{N_{\text{Fields}}} QM_i(t)$ N_{Fields} – the number of fields in the region.
Field	$U_F(t) = \alpha_f \times \frac{QR(t)}{\max_t QR(t)} + (1-\alpha_f) \times \frac{QM_i(t)}{\max_t QM_i(t)}$ $QM_i(t) \geq Qplan_i, \quad QM_i(t) = \sum_{j=1}^{N_{\text{i Bush}}} QB_j(t)$ $N_{\text{i Bush}}$ – the number of bushes in field i.
Bush	$U_B(t) = \alpha_B \times \frac{QM_i(t)}{\max_t QM_i(t)} + (1-\alpha_B) \times \frac{QB_j(t)}{\max_t QB_j(t)}$ $QB_j(t) = \sum_{h=1}^{N_{\text{j Well}}} QB_h(t)$ N_{Well} – the number of wells in bush j. The well's future production rate $QB_h(t)$ is calculated based on the Arps decline curve: $QB_h(t) = QB_h(0) * (1 + b * D_h * t)^{-1/b}$, $QB_h(t)$ – calculated oil flow rate $QB_h(0)$ – initial oil flow rate. Set for each well. b – reduction factor D_h – the reduction factor at the beginning of the period. Specified for each well. t – the period for which the simulation is conducted.
Crew	$U_C(t) = \alpha_c \times \frac{Tmove(t)}{\max_t Tmove(t)} + (1-\alpha_c) \times \frac{Tmove_k(t)}{\max_t Tmove_k(t)}$ $Tmove(t) = \sum_{k=1}^{N_{\text{i Crew}}} Tmove_k(t)$ $N_{\text{i Crew}}$ – the number of crews in field i subject to $QM_i(t) \geq QM_i(t-1)$

Algorithm 1 BDI agent reasoning cycle (Wooldridge, 2009)

```
while true do
  B = brf(B, perception()); // gathering new information from the environment
  D = options(B,I); // updating the belief base based on the new perceptions
  I = filter(B,D,I); // selection from potential desires and current intentions the new, relevant set of intentions
  π = plan (B,I,A); // searches for a plan (sequence of actions) in a library to achieve current intentions with given beliefs. A is the set of primitive actions available to the agent
  while π ≠ ∅ and ¬succeeded(I, B) and ¬impossible(I, B) do // the cycle continues until the set of actions in the plan is not empty and the intention is not realized
    act(head(π)); // execution of the current plan action
    π = tail(π); // updating the plan: leaving only uncompleted actions
    B = brf(B, perception()); // gathering new information from the environment
    if reconsider(I,B) then // if the plan needs to be reconsidered
      D = options(B,I); // updating the belief base based on the new perceptions
      I = filter(BDI); // selection of the new, relevant set of intention from potential desires and current intentions
    if ¬ sound(π,I,B) then // if the current plan is not relevant given the updated desires and beliefs, then
      π = plan (B,I,A); // searches for plan (sequence of actions) in a library to achieve current intentions with given beliefs. A is the set of primitive actions available to the agent
```

After allocating resources from the Region, Field-level agents generate possible scenarios based on target functions, system knowledge, and available resources. The resulting scenarios are sent down to the bush level for clarification. Bushes generate their own scenarios based on detailed system data and target functions. Intelligent Bush-level agents communicate with each other for a possible resource exchange to possibly increase the efficiency of mining. The resulting schedule is returned to the field level, where intelligent agents compare the obtained data using the planned values and their own target function. They also communicate with each other to redistribute resources to increase production values. The received schedule is then refined by the teams and returned to the field (Figure 1).

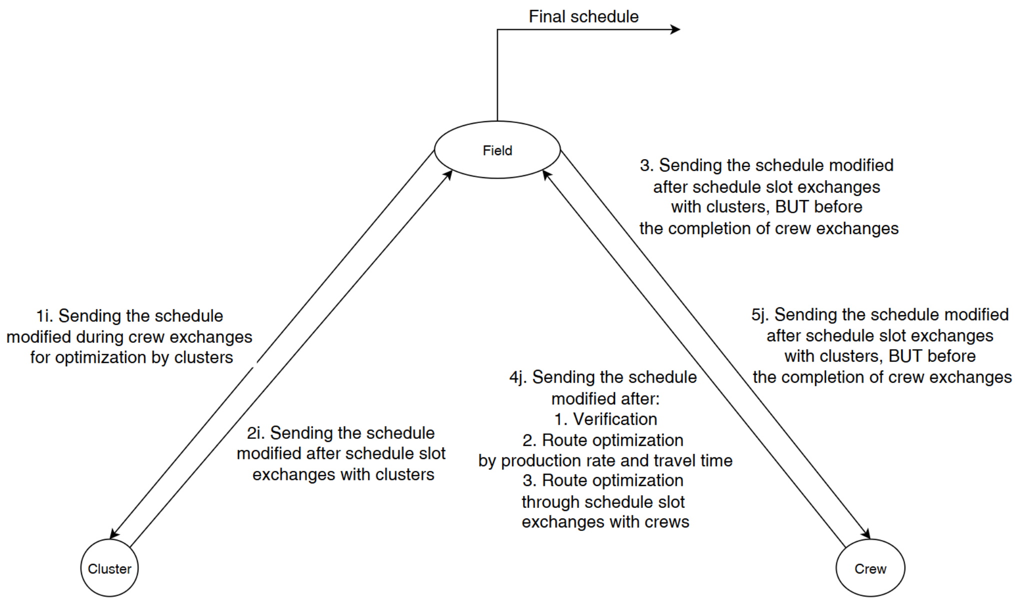

Figure 1 Schematic of the schedule refinement scheme

All scenario calculations are based on a simulation model of the production and economic processes of the field development system, which in the context of this system is an environment (Ferrigno et al., 2024; Bolsunovskaya et al., 2023). The combination of intelligent agents and the environment is a multi-agent model (Oroojlooy and Hajinezhad, 2019). The developed multi-agent model is implemented in Python. Figure 2 shows the structure of the multi-agent model.

Depending on agents' beliefs, desires, and intentions, they are determined in connection with individual modules of the simulation model of the environment, which in the context of modeling multi-agent systems plays the role of an environment. The basic modules are as follows: the module for statistical calculation of the forecast of oil flow, the module for calculating additional production from GTO, the module for calculating drilling, and the module for calculating costs (Reddicharla and Mayada, 2024; Saboo and Shekhawat, 2024).

As part of the testing of the developed tool, alternative optimization tools were used: genetic algorithms, Bayesian optimization, particle swarm optimization algorithm, and simulated annealing algorithm. These optimization algorithms were integrated with a simulation model of the oil production process (multi-agent model environment).

The approbation was carried out on synthetic data that were close to the real data.

Data parameters for testing: Average operating well stock:

- 348 wells;
- Region: 4 fields and 24 bushes
- Resources: 12 drilling teams and 12 GTO teams
- The average flow rate for new wells: $\sim$ 200 tons of oil per day.
- Modeling horizon: 1 year.

The data used were obtained from an expert in the oil and gas field as part of the project, performed by the team of the Laboratory of Digital modeling of Industrial systems Peter the Great St. Petersburg Polytechnic University in developing decision support systems for Gazprom Neft. The proposed solution was also tested on other datasets. The examination of test results at different regional scales and ablation study will be presented in future works. An example of sensitivity analysis, along with an ablation study on the impact of the altruism coefficient, is provided (Sharko, Burlutskaya, Gintciak, et al., 2025) and will be supplemented with more advanced statistical analysis methods in future publications. Table 3 presents the results of the testing.

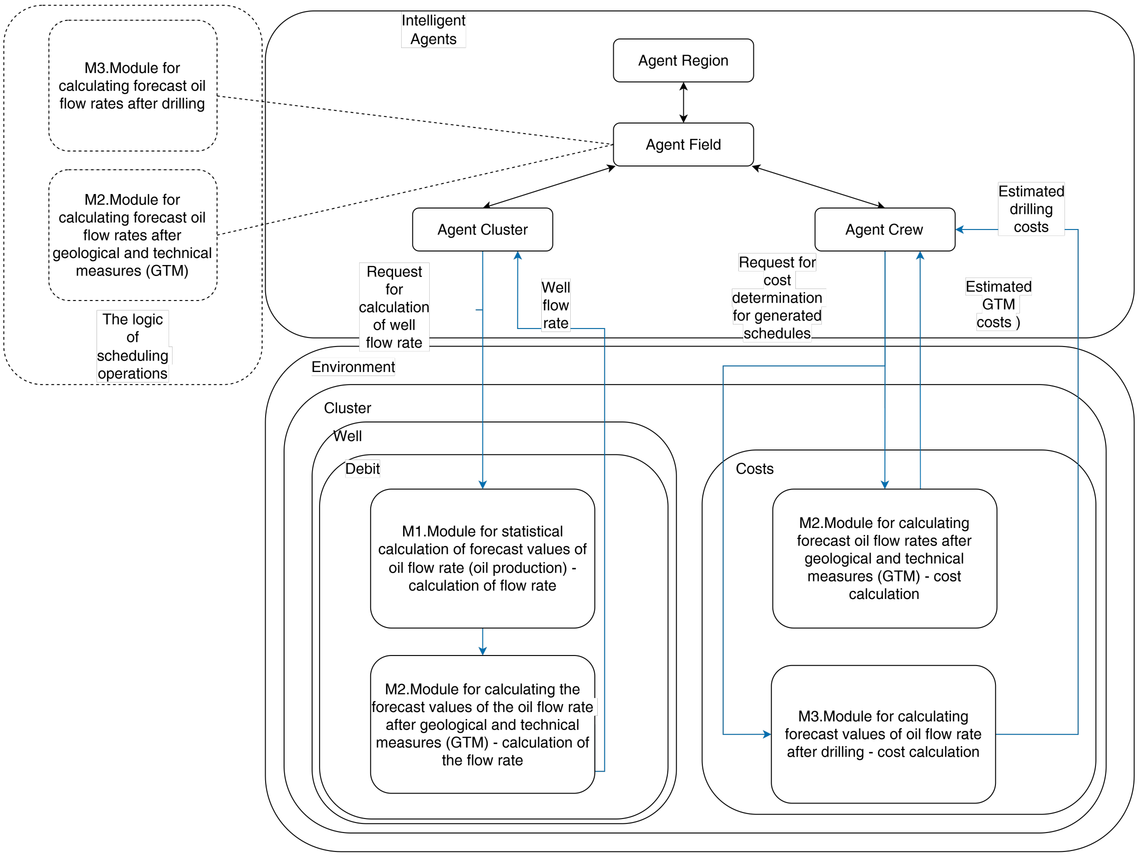

Figure 2 Interaction scheme between agents and the environment

Regional production rates increased by 4-4.5% due to the identification and implementation of a more efficient GTO schedule. MAS application not only boosted regional production but also ensured the feasibility of field development plans. The optimization of crew routes made it possible to reduce the costs of implementing GTO schedules without compromising the production rate. Time-series plots of the testing results are presented in Figure 3.

Table 3 Experimental results

Model	Increase in the debit
Genetic algorithms	0,03-0,05%
Bayesian optimization	0,07-0,09%
Swarm Optimization Algorithm	2,6-2,8%
Simulated annealing algorithm	1,9-2,1%
MAS	4-4,5%

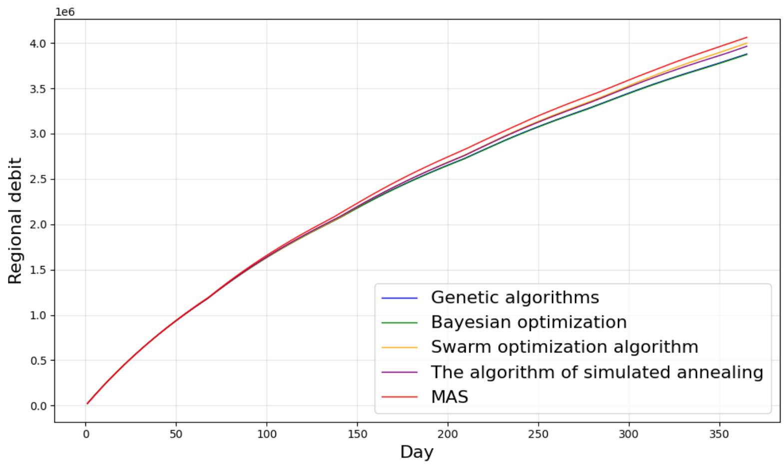

Figure 3 Time-series plots of the testing results

Figure 4 shows the mean runtime for the genetic algorithms, Bayesian optimization, swarm optimization algorithm, the algorithm of simulated annealing, and MAS. Thus, the results of the testing demonstrated the effectiveness of using intelligent agents to generate optimal scenarios for field development compared with other optimization algorithms. In the next stages of the study, strategies for intelligent agents and their communication tools will be developed to ensure that the model is close to the real field development system. A prototype of a multi-agent field development system using the JACOMO framework, which assumes formalized approaches to the description of multi-agent systems, including for the implementation of autonomous reactive intelligent agents, is also planned (Boissier et al., 2020; Boissier et al., 2013).

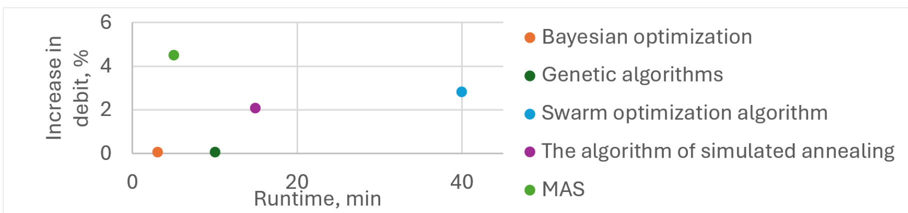

Figure 4 Runtime of the tested algorithms

4. Conclusions

Within the framework of this work, the field development system is considered a complex organizational system of an interdisciplinary nature with its corresponding features, in particular, the multi-agent nature of the interaction of elements, the multiplicity of target functions, distributed data centers, and decision-making. The result of the work is the developed multi-agent field development system, consisting of an environment presented as a set of computational models and intelligent agents that control production elements at different levels of the hierarchy. The solution has increased the production rate of the region by 4.5%. The developed solution has been tested on synthetic data from one region, which is close to the real data. This study used only synthetic data. Future research will include real-field validation, integration with reservoir simulators, and enhancement of the limited agent adaptation rules. The reinforcement learning-integrated agents will also be addressed. The results of the testing demonstrated the effectiveness of using MAS to solve the problem of generating scenarios for field development, showing an increase in flow rate compared to other optimization algorithms.

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Author Contributions

Conceptualization, A.M. Gintciak; methodology, Z. V. Burlutskaya; software, P. A. Zakharov; formal analysis, P. A. Sharko.

Conflict of Interest

The authors declare no conflicts of interest.

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