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Agent-Based Modeling for Decision Making Support: Case of Transport Logistics in Oil Company

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Abstract

At present the use of modern modeling methods and tools is an essential component of management information systems for a company to succeed in rapidly changing environment. It is important that simulation is considered today as obligatory stage of decision making in oil companies, which use modern information technologies actively. The paper is focused on the description and comparative analysis of system dynamics and agent-based modeling, used for intelligent decision support systems development in transport logistics. The main goal of this research is evaluation of the multi-agent systems role for decision making processes and management information systems development and creating the model of logistics processes (the process of oil products loading and unloading). It also considers the main determinations and notions of the intellectual agent modelling methodology, gives the types of modeling categorization. The work is based on generalization of theoretical researches in this area along with the international practices and domestic experience.

Keywords: Agent modeling; transport logistics; oil industry

1. Introduction

When decision making on the strategic level of management, intellectual modeling tools should ensure mutual understanding at all organizational levels and bridge the gap between strategic vision and its implementation. One of the solutions is multi-agent systems (MAS) that have been developing rapidly in the last decade. Major advantages of the multi-agent approach relate to the economic mechanisms of self-organization and evolution that become powerful efficiency drivers and ensure enterprise's stable development and prosperity. Based on the multi-agent approach, a brand-new intellectual data analysis can be created, open and flexibly adaptive to solve problems, and can be deeply integrated in the decision support systems. Modern business simulation tools use special software, programming languages and systems to develop models demonstrating structure of business processes, relations between people and areas for optimization in the organizational structure as a whole.

The study of problems that occur in the development of the theory and practice of logistics is carried out taking into account the application of a systematic approach and modern technologies, such as simulation. Along with others, such a logistics subsystem as transport logistics is especially important. The functionality of transport logistics is actively used in various sectors of the economy. For example, vertically integrated oil companies create complex supply chains. Methods and means of transport logistics are used to deliver oil from the field to refineries, then for loading, and subsequently for transportation and discharge of various oil products to numerous consumers in Russia Federation and abroad.

The purpose of this work is a comparative analysis of such approaches in simulation as agent modeling and system dynamics, as applied to logistics processes (the processes of oil products loading and unloading). To achieve this goal, it is necessary to develop principles for constructing a model for the process of unloading and loading oil products in AnyLogic software.

Modern research claims that decision makers operate in a complex and rapidly changing environment, which is characterized by the fact that:

- It is necessary to make several decisions to achieve the goal, each of which is considered in the context of other decisions.
- Decisions are not independent; each subsequent decision is limited by the consequences of previous decisions and in turn imposes restrictions on the following decisions;
- The decision-making environment changes on its own, as well as a result of decisions;
- Decisions are made in real time.

Methodology of the research is based on system approach, comparative analysis, and methods and procedures of modeling.

2. Theoretical Fundamental and Brief Literature Review

The foundations of decision-making research in a dynamic environment were laid by J. Forrester (Forrester, 1961). Further, D. Pospelov (Pospelov, 1998), D. Sterman (Stermam, 2000), A. Law and W. Kelton (Law and Kelton, 2000), M. Wooldridge (Wooldridge, 2002), M. Pidd (Pidd, 2004), S. Albright, C. Zappe, W. Winston (Albright, Zappe, and Winston, 2011) made their contribution to this area. In the late 1970s and early 1980s. many studies in the field of decision making have been carried out on the basis of experiments in the framework of static systems. However, over time, the conclusions of such studies were criticized and the need arose for conducting experiments in the field of decision-making in dynamic systems. Studies appeared in which subjects had to make decisions in experimental systems that included feedback, time lag effects, and nonlinear behavior. This has become possible thanks to the use of computer simulation models.

Currently, the so-called "complexity economy" is gaining ground, which refutes the thesis about the desire to maximize utility when deciding by a person as an economic agent. The concept of economics as a complex adaptive system creates the need for a search and implementation of a new methodology that allows modeling processes. The behavior of the system is formed from the relationships of many agents, each of which has certain behavioral features.

The major approaches (methods) in simulation modeling are: System Dynamics (SD), Discrete Event (DE) and Agent Based (AB). SD and DE are traditional; AB is relatively new. There is also Dynamic Systems (DS), but as a rule it used to model and design "physical" systems (Borshchev and Filippov, 2004, 2006; Karpov, 2005; Serova, 2012a, 2012b; Krichevsky and Serova, 2016; Elberg and Tsygankov, 2017). According to Serova (2013) Multi-agent systems or agent-oriented programming can be considering as a step forward from the object-oriented programming (OOP) and integrate the latest advances of artificial intelligence, parallel computing, and telecommunications. Unlike common objects in OOP, intelligent agents are autonomous objects. This means that agent behavior is dictated by its goals, and it has knowledge how to achieve them. Agents cannot be called subprograms (or methods in OOP), for they have their own states and continuously work on achieving their goals—virtually like co-programs that can pass control to one another at any time. Thus, they can only be offered new tasks, though they have the right to accept or decline the offer depending on whether it meets their goals and interests. To ensure their autonomy, agents can react to events, make and reconsider decisions, and interact with other agents. As a rule, software implementation of a traditional system is centralized, has a hierarchical structure and executes determined algorithms. In opposite, multi-agent system is a self-organizing network of agents (software objects) that work continuously and simultaneously on establishing and reconsidering links. This system is decentralized; every agent is autonomous and strives to achieve its own goals.

Agent technologies are offering various types of agents, models of their behavior and characteristics, ranges of architectures and libraries of components.

Multi-agent systems as systems of distributed artificial intelligence have the following benefit (Serova, 2013):

- They speed up task fulfillment by parallelism and save the volume of data transmitted by passing high level partial solutions to other agents.
- They are flexible by using agents of various capacity to carry out a task dynamically in cooperation.
- They are reliable by passing functions from agents unable to carry out a task to other ones.

Agents should have the following characteristics:

- The agent is identifiable, i.e. possesses a set of characteristic characteristics and principles that determine his behavior and decision-making process; autonomous and can make decisions taking into account interaction with other agents, while acting independently.
- The agent has a specific goal that affects his behavior.
- Self-learning agent.

Every MAS consists of the following components (Serova, 2013):

- Set of organizational units with a subset of agents and objects;
- Set of tasks;
- Environment, i.e. a space where agents and objects exist;
- Set of relations between agents;
- Set of agent actions (e.g., operations on objects).

Another approach to modeling is system dynamics.

System dynamics is a methodology for studying and modeling systems that are characterized by feedback cycles in complex mutual causal relationships of their parameters. This modeling approach was developed by J. Forrester in the 1950s (Forrester, 1961). Processes that occur in the real world in system dynamics are characterized by the terms of stocks, flows between these stocks and information that determines the value of these flows. System dynamics abstracts from individual objects and events and involves an "aggregate" approach to processes. In system dynamics, modeling is a set of interacting positive and negative feedbacks and delays, and the structure of the system determines its behavior. After the model is built, it is possible to apply a simulation of numerical indicators, which in the form of a graph or table will represent the behavior of the system.

The main advantages of agent modeling compared to system dynamics are:

- Modeling the behavior of each of the agents.
- The possibility of adaptation.
- The presence of a mechanism for the formation of goals and a mechanism for interaction (communication and cooperation) of agents.

The main disadvantage of agent modeling compared to system dynamics is that it is often difficult to develop a detailed agent model that takes into account all the cause and effect relationships that affect the agent's decision.

Below a comparative table (Table 1) of two approaches to simulation is shown brief but thorough description of the literature on the topic of the paper as well as recent research projects and their outcomes.

Currently, there are a large number of software in which it is possible to conduct simulation. One of these programs is the AnyLogic. AnyLogic is a tool that covers the main areas of modeling: system dynamics, agent modeling, etc.

The basic concept of AnyLogic is that the model is described by a set of interacting and simultaneously functioning activities, where the active object has its own functioning and interaction with the environment.

Table 1. Comparative characteristics of approaches to simulation (Katalevsky, 2015)

Parameter	System dynamics	Agent modelling
Basic model element	Feedback loop	Agent
Analysis area	System structure	Agent behavior rules
Simulation level	Macro level	Micro level
Time	Continuous	Discrete
The core of modelling	Mathematics	Logic

AnyLogic graphical modeling environment is capable of supporting the following processes:

- Design.
- Development.
- Documentation of the model.
- Performance of computer experiments with the model.

3. Modeling of Loading and Unloading Oil Product

Due to the fact that the behavior of each of the participants in the processes of loading and unloading operations with petroleum products is unique, agent modeling in AnyLogic was chosen for the purpose of building the model and conducting a series of experiments.

There are several main stages to create a model (Table 2).

Table 2. The main modeling stages

№	Stage	Result
1.	Analysis of the system	Understanding the functioning of the system, its structure, the processes taking place in it.
2.	Formulation of the purpose of modeling the system	Compiling a list of tasks that need to be solved with the help of a future model, including a list of input and output parameters of the model, initial data and criteria for completing the future study.
3.	Development of the conceptual structure of the model	The structure of the model and its essential processes, a list of assumptions, a description of the control logic for subsystems.
4.	Implementation of the model in a modeling environment	Implemented subsystems with characteristic behavior, their

		parameters and variables, implemented logic and communications of the subsystems.
5.	Implementation of the animation representation of the model	Animation representation of the model.
6.	Verification of the correct implementation of the model	Verification of the correct display of the processes of the real system of the model for further analysis.
7.	Calibration of the model	Fixing parameter values, coefficients of equations and distributions of random variables, reflecting those situations for the analysis of which the model will be used.
8.	Planning and conducting a computer experiment	Simulation results - graphs, tables, solving tasks.

Examples of a sketch of agent-based simulation of a filling station with four columns that refuel vehicles with three types of fuel are shown in Figure 1 and Figure 2.

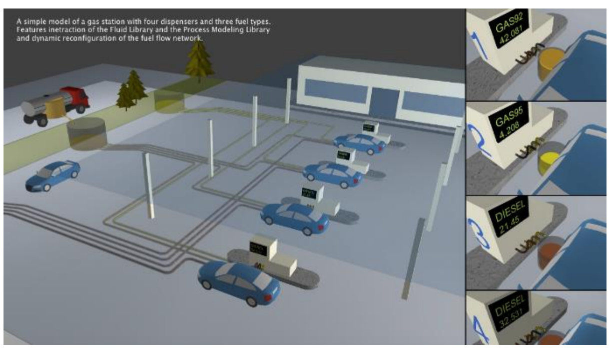

Figure 1. A visual image of the work of filling stations (with AnyLogic software)

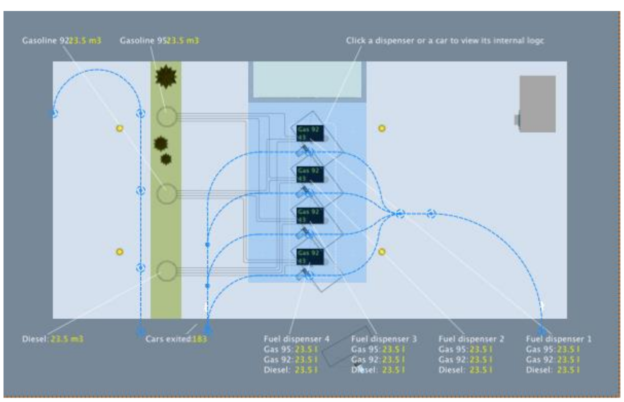

Figure 2. The architecture of the simulation model of the filling station (AnyLogic software)

Agents in the above model are:

1. Cars that come for refueling;
2. Fuel trucks that come to drain the oil product;
3. Columns that load oil to cars.

Initiatives of Russian oil companies in the sphere of corporate social responsibility include the sale of fuels that have a less negative impact on the environment. Modern gas stations refuel vehicles, including liquefied petroleum gas (propane, butane and mixtures thereof), which are used as an alternative fuel for refueling cars. The use of motor gas fuel is currently very important, because every year the domestic fleet, consisting of more than 34 million units of vehicles, emits 14 million tons of harmful substances together with exhaust gases. And this makes 40% of the total industrial emissions into the atmosphere.

In this regard, an LPG tank (Liquefied petroleum gas) was added to the existing model, that is a tank that receives liquefied petroleum gas, which is subsequently sent to the columns as an additional fourth type of fuel (to the existing RON-92, RON-95, Diesel) (Figure 3).

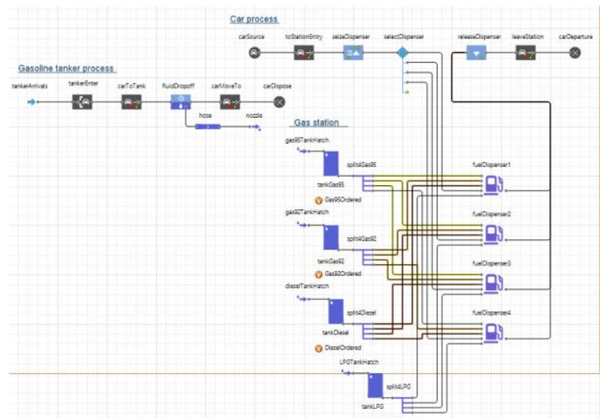

Figure 3. Flowchart (AnyLogic software)

The production chain originates from reservoirs filled with fuel trucks with specific fuel products. These tanks are filled when the content level drops to the minimum mark (object "tankerArrivals"). Having connected the drain device to the receiving tank with the appropriate type of fuel, the fuel truck drains oil products ("fluidDropoff") into the tank. Subsequently, petroleum products enter the columns during the refueling of cars. The column operation scheme is shown in Figure 4.

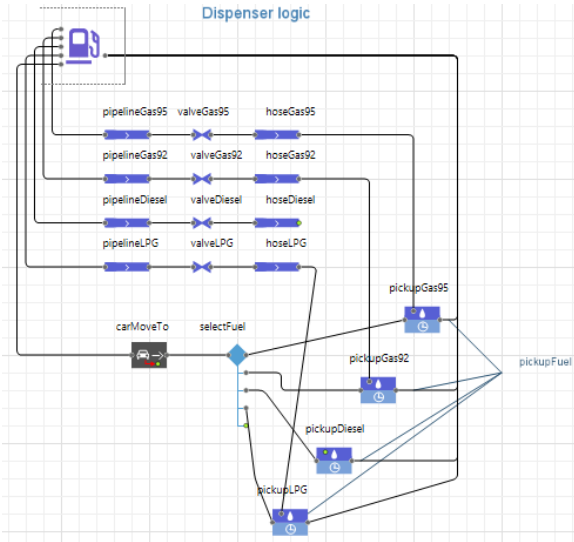

Figure 4. Detail flowchart (column) ("fuelDispenser")

When refueling, the driver drives into the gas station site, drives up to one of the columns ("seizeDispencer"), selects the type of fuel ("selectDispenser"), refuel the car and leaves the site. The object "pickup [Fuel]" object at the moment of filling a full tank automatically stops the fuel filling procedure in a car.

4. Results and Discussion

The model consists from the next agents:

— Tanks («tankGas95», «tankGas92, «tankDiesel»).
— Fuel dispenser.
— Gasoline tanker.
— Consumer (cars arriving at a gas station).

At the 8th stage (Table 2) of modeling (planning and conducting the experiments) - series of the experiments on the filling station agent-based model were carried out to confirm that the model is working correctly.

1. Tank volume variation experiments. Agent: Tanks («tankGas95», «tankGas92, «tankDiesel»):

a) In the case of an increase in the volume of tanks from 30 m³ to 500 m³, and in the case of an increase in the initial volume of filling the tanks to 400 m³, the fuel truck does not arrive at the gas station for a much longer time in comparison with the initially set values.
b) In the case of a decrease in the volume of tanks from 30 m³ to 4 m³, and in the case of a decrease in the initial volume of filling the tanks to 0 m³, a queue of cars is formed due to the lack of fuel at the gas station: in other words, there is a deficit of fuel at the gas station (Figure 5).

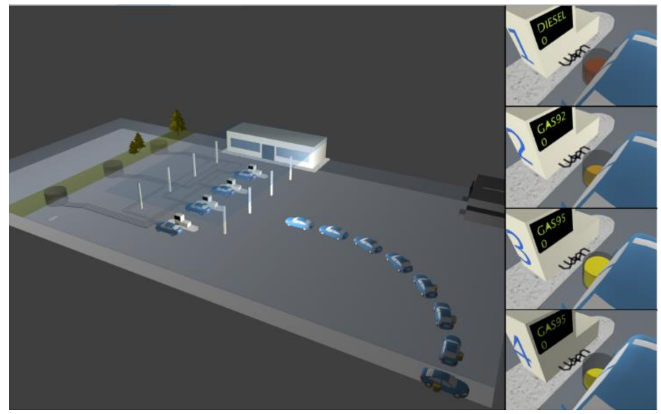

Figure 5. Tank volume variation experiment

2. Experiments with varying throughput of fuel supply pipeline, as well as fueling nozzle. Agent: Fuel dispenser.

If the throughput of the fuel supply pipe and the fueling nozzle decrease to 0, an error occurs so that the model is not working: indeed, why do we need an open idle gas station?

3. Experiments to change the rate of fuel discharge into tank. Agent: Gasoline tanker.

In the case of increasing rate of fuel discharge into the tank from 25 l/s to 150 l/s, it is obvious that tank is filling faster: this significantly reduces the probability of a deficit at the gas station.

4. Experiment to change tank capacity. Agent: Consumer (cars arriving at a gas station).

Experiments included increasing of initially partly filled tank to the level of tank's capacity.

The main results of the agent based model experiments are presented in Table 3.

Table 3. The main results of the experiments.

№	Experiment	Result
1	Increasing the volume of tanks from 30 m³ to 500 m³, an increasing the initial volume of filling the tanks to 400 m³.	The fuel truck does not arrive at the gas station for a much longer time in comparison with the initially set values.
2	Decreasing the volume of tanks from 30 m³ to 4 m³, a decreasing the initial volume of filling the tanks to 0 m³.	There is a deficit of fuel at the gas station.
3	Increasing the rate of fuel discharge into the tank from 25 l/s to 150 l/s.	The probability of a deficit at the gas station significantly reduces.

5. Conclusions

Multi-agent systems as systems of distributed artificial intelligence are concept that starts an era of network organizations with intellectual robots' collective interaction by offering to switch from powerful centralized systems to fully decentralized ones, with hierarchical structure replaced with network organization, rigid bureaucratic "from top to bottom" management (based on bosses' commands for subordinates) with negotiations, and planning with flexible agreements. As a result, production volumes, profitability, competitiveness and mobility are growing. Major advantages of the multi-agent approach relate to the economic mechanisms of self-organization and evolution that become powerful efficiency drivers and ensure enterprise's stable development and prosperity. Based on the multi-agent approach, a brand-new intellectual data analysis can be created, open and flexibly adaptive to solve problems, and can be deeply integrated in intelligent decision support systems. Thus, at present, for the purpose of modeling processes of oil products loading and unloading, such types of simulation as agent-based modeling and system dynamics can be used. Agent modeling involves the development of a behavior model for each of the agents. System dynamics, on the other hand, abstracts from individual objects and events and suggests an "aggregate" approach to processes. As an example of the software used for logistics tasks simulation, AnyLogic is presented in this paper.

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