Development of Logistical Model Based on Integration of Ontology, Multi-Agent approach and Simulation

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***Abstract*—The paper focuses on development of logistical model based on multi-agent model of a resource conversion process. The model is used for planning and dispatching of gas stations network. We compare existing approaches to multi-agent planning, including requirements and capabilities nets, multi-agent resource conversion process model, active and passive convertors model, agent-based simulation modeling, and their software implementations (Magenta, BPsim, Onto Modeler, AnyLogic). The most perspective approaches are implemented in Magenta and BPsim systems. However multi-agent approach based on distributed calculations has one disadvantage, which is frequent plan modification, resulting in certain instability of the model. To avoid this effect, we use situation filtration and diagnosis block. In order to take delays into consideration and analyze the bottlenecks in logistical chain, we use simulation modeling. We compare existing knowledge representation models, identify the benefits, and develop a methodology that considers all advantages.**

Keywords-logistics; decision support; simulation; expert system; frame; UML

I. INTRODUCTION

The following components are considered during system analysis of logistical, production, business systems, and business processes: mission, vision, strategy, processes [1]. Development of applied decision support systems based on hybrid (dynamic and intelligent) models requires the following functions [1]:

- Design of conceptual model of the problem domain,
- Problem domain knowledge definition and knowledge-based output,
- Definition of dynamic resource conversion processes,
- Development of hierarchical process model,
- Availability of situation and command definition languages (to define control model),
- Design of multi-agent models (availability of coalitions of intelligent agents). Models of intelligent agents correspond to the models of decision-making people,
- Integration of conceptual, simulation modeling, expert systems, and situational management,
- Integration with tools for Computer-Aided Software Engineering (CASE-tools).

Multi-agent systems engineering approaches can be distinguished into two types:

- Based on object-oriented methods and technologies and
- Application of traditional knowledge engineering methods.

An actual task is development of dynamic situations modeling system, based on object-oriented technologies.

Planning is one of applied directions of multi-agent systems. "An agent is an encapsulated computer system that is situated in some environment and that is capable of flexible, autonomous action in that environment in order to meet its design objectives" [2-3].

An example of multi-agent system applications to operation planning of a flexible industrial system is discussed by Jennings [2]. We can name the following advantages of multi-agent planning systems:

1. Formalization of decision making nodes (situation processing scenarios) in form of the agents, which relates to knowledge formalization,
2. Planner is embedded in between certain elements of a multi-agent system by means of interaction (negotiations) of these elements. Thus, it may modify the plan in case of delays or unexpected situations,
3. Network of interconnected agents coordinates its activity independently.

Additional advantage of multi-agent planning consists in availability of automatic notifications of process actors about events and changes at control object, which makes control transparent. Therefore, problem domain knowledge data is formalized during development and deployment of a multi-agent system, and the decision making process is automated. This all facilitates decision making activity.

Among the most considerable results, one may note the development and practical application of the Requirements and Capabilities (RC-) networks apparatus [4-5]. This approach adheres to the “classical” interpretation of a multi-agent system and is oriented to problem solving in computer networks.

Apparatus of RC-networks has been developed by Vittich and Skobelev [4] and implemented within Magenta technology [5]. It has been applied in a family of applied intelligent planning systems for the following objects [5]:

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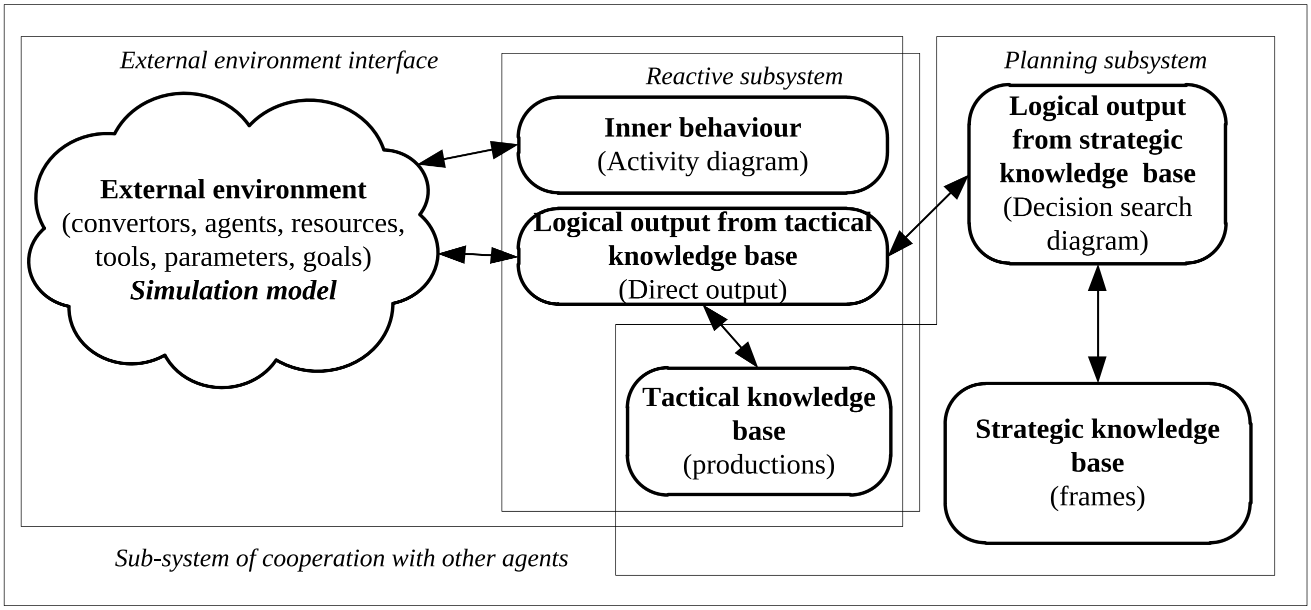

Figure 1. Multi-agent resource conversion process model structure

- An enterprise, controlling ocean tanker fleet,
- Cargo transportation company,
- Project managing company.

Multi-agent approach also found its use in simulation modeling. Thereby, the simulation modeling system AnyLogic supports modeling of reactive agents [6]. AnyLogic uses state chart extensions of Unified Modeling Language for. Real-Time (UML-RT) for agent behavior formalization. An example of multi-agent system implementation within the dynamic expert system G2 [7] is presented in [8]. G2 makes use of the built-in simulation modeling sub-system ReThink [7].

The agent concept is re-considered within the framework of simulation modeling. Here, its communication features at the network protocols level, as well as capabilities of moving on the network, are becoming less important. At the same time, its intelligence and sociality are increasing. By intelligence we mean consideration of large volumes of data and knowledge and complexity of logical output machine implementation, at least for G2 and BPsim systems. Sociality includes modeling of social behavior, internal beliefs, desires, and agent goals.

II. Simulation Modeling, Knowledge Representation and Design of Decision Support Systems

Range of simulation modeling systems application substantially broadened during last decades. First, simulation modeling systems and software-based simulation models are built into enterprise control loops, integrated with sensors, controllers, corporate information systems via data exchange interfaces, thus, receiving data on current state of the managed object. Second, most simulation modeling systems allow modification/refresh of initial data and adapt decision on the basis of current situation, during experiment execution. Third, most applied decision support systems, that are based on simulation modeling sub-system or simulation model, use heuristic-based sub-systems of decision optimization and improvement for formalization of decision making people knowledge and control algorithms.

Projects in the areas of hybrid decision support systems deployment for logistical, industrial management, and construction are described in [9-11]. Such systems integrate simulation model with heuristic or optimization blocks. Therefore, we are dealing with open integrated modules/systems for simulation modeling. Expert system elements, including a knowledge base and logical output machines, and ontologies are actively used in decision support systems as well.

Despite active application of conceptual modeling tools based on Unified Modeling Language (UML) in the area of information systems development, application of such tools in simulation modeling engineering is limited [12]. An advantage of conceptual and simulation modeling integration approach is the capability of rapid transition from conceptual models to the models of engineering and application (program implementation) [12]. To define a transition from conceptual models to simulation models one may use ontologies or knowledge representation models. Ontology development experience for logistical projects and supply chains is presented in [13]. RC-networks [4-5] use ontologies for formalization of decision making points in distributed networks of control object (logistical chain). The following agents are available in the cargo transportation project: truck, technical examination, order, gas station, driver.

Multi-agent resource conversion process model has been implemented in BPsim software suite [10-11]. Multi-agent resource conversion process model has been implemented as a result of integration of simulation, multi-agent and expert modeling [1, 20]. Multi-agent resource conversion process model structure is presented in Figure 1.

III. ANALYSIS OF EXISTING KNOWLEDGE REPRESENTATION MODELS

Comparison of typical knowledge representation models for the problem of knowledge extraction for the problem domain of logistics, business, Multi-agent Resource Conversion Processes (MRCP), and further application in software simulation models is presented in Table 1.

Comparison revealed that the most effective approach is a combination of production-based and frame-based approaches for knowledge formalization in the logistical problem domain. A disadvantage of frame-based approach is the complexity of logical output machine.

For system analysis, the UML class diagram may be used as a basis for the definition of frame-concepts structure. Further definition of conceptual graphs (semantics) and filling with data form the knowledge base. Decision search diagrams (extended UML sequence diagrams) are used for implementation of logical output machine visual builder. Sequence diagram graphically define sequence of method calls between classes while solving a specific problem (scenario). Such approach allows to visual definite the solution [14].

Depending on modeling aspects, various concepts of the problem domain use different elements of the resource conversion process model. Base classes (concepts) of the problem domain of simulation modeling of logistical and business processes include the following.

- *Business process* together with its temporal and cost features, as well as properties of inputs, outputs, and tools of multi-agent resource conversion process operations (ultimate units of a business process),
- *Locations* (inhabited and non-inhabited), containing geo-information – in multi-agent resource conversion processes may be represented with corresponding transacts,
- *Transportation vehicles* – in multi-agent resource conversion processes may be represented with corresponding transacts or tools,
- *Personnel* – in MRCP represented with tools or corresponding transacts,
- *Decision making people* – in MRCP represented with agents; heuristics are formalized in form of agent rules,
- *Road network* and transportation routes – in MRCP represented by transaction processing routes between operations, defining transitions on logical chain,
- *Resources and cargo* (resource and cargo storage), used in business processes – in MRCP represented by corresponding transacts or resources,
- *Statistics* and experiment results accumulation classes are generated on the output of MRCP model.

Results of development of tools and methods of business processes modeling and software engineering for automation of the process starting with process formalization, development of dynamic models of the processes and decision making processes, running simulation experiments with the models, bottlenecks analysis, re-engineering, and optimization of the processes, until software engineering (database structure generation and software module prototypes implementation), are presented in [15]. Also, a semantic model, defining multi-agent resource conversion process, is presented in [15]. The model uses discrete event simulation modeling as a dynamic component and expert and multi-agent simulation of intelligent agents as an intelligent component. It includes the following components: *processes*, *operations*, *resources*, *control commands*, *mechanisms*, resource *sources* and *receivers*, *junctions*, *parameters*, *agents*. Information resources due to their features are defined separately. These are *Messages* and *Requests* for operation execution. Cause-and-effect relations between conversion elements and resources are defined with the *Relation* object.

A specialized problem-oriented language is used in dynamic situations modeling system BPsim.MAS [10] for definition of subject ontologies and cause-and-effect laws for definition of process dynamics. According to Guizzardi and Wagner [12], subject ontology of discrete-event simulation modeling uses a concept of “CasualLow”, which is equivalent to the “Action” concept in multi-agent resource conversion process model.

Semantic model became the basis and was extended with detailed definition of semantics from the point of view of simulation modeling and consideration of agents’ behavior. Actions may result in both parametric and structural modifications of MRCP model elements. Model is presented in Figure 2. This model is extended with elements of logistical projects ontology, presented in [13], and adapted to specific features of gas stations supply network project.

TABLE I. COMPARISON OF VARIOUS KNOWLEDGE REPRESENTATION MODELS

Requirements for the model	Productions	Semantic networks	Frames
Visibility	○	●	●
Hierarchical data definition	○	●	●
Simplicity of adding new knowledge	●	○	○
Consistency with object-oriented approach	○	○	●
Use of UML	○	○	●
Consideration for process dynamics	○	○	○

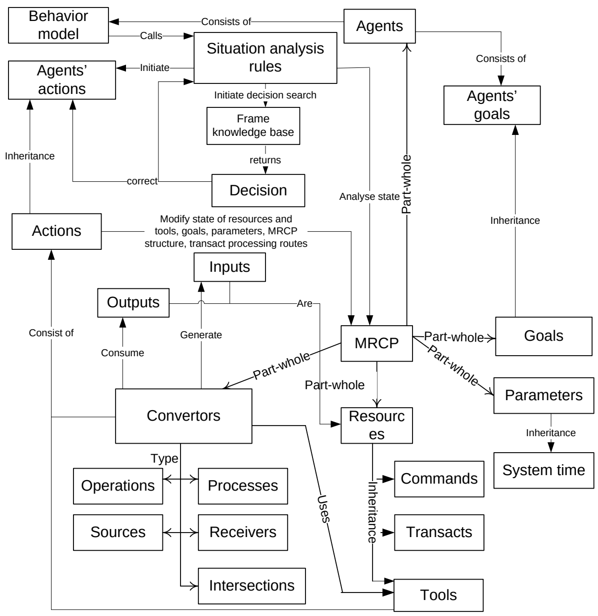

Figure 2. Semantic model of multi-agent resource conversion processes

IV. METHODOLOGY OF INFORMATION SYSTEMS ENGINEERING WITH AID OF BPSIM

The suggested methodology has the following specific features: 1. Simulation modeling for “as-to-be” model verification at re-engineering stage; 2. Capability of defining decision making people models. Software engineering process is separated into several stages. These stages are discussed further in relation to BPsim software.

First stage is research. Simulation model “as-is” is designed on this stage. Simulation experiments are carried out targeting identification of non-optimal process organization. Model results are used for design of the “as-to-be” model of the multi-agent resource conversion process, which in turn is used for software engineering. The following products from BPsim family are used on this stage: 1. Dynamic situations modeling system BPsim.MAS (“Multi-agent simulation”) is used for design of simulation model and running simulation experiments, 2. CASE tool BPsim.SD (“Software Developer”) is used for designing diagrams, defining software architecture. Note that the results of work in BPsim.MAS may be automatically (with aid of software assistant) transformed into BPsim.SD model, since operations, defined in multi-agent resource conversion process mode, are transformed into operations on Data Flow Diagrams (DFD) [12], agents – into external entities, and order of operations defines direction of data flow [15].

Second stage consists in the project study. Structural analysis results become the basis for object-oriented engineering when building information system model. An important feature of BPsim.SD is the capability to acquire use-case diagrams on the basis of the data from data flow diagrams: external entities of DFD diagrams are transformed into roles, and processes – into use-cases. Sequence of data processing method calls in multi-agent resource conversion processes problem domain in reflected on sequence diagrams. Class diagrams are defined for the conceptual model specification of the problem domain. Class properties define the features of the problem domain objects, and methods describe operations of resources seizure, release and conversion, and the code from multi-agent resource conversion process model may be transferred into method definition [15].

The third stage consists in system development, while the fourth refers to system deployment. Effectively designed elements of the hybrid model of multi-agent resource conversion processes implemented in software, may be immediately included into decision support system or the corporate information system and used in decision making process, both as a whole or separately in form of calls to software assistants. Program model may be converted into the library of executable application and be used in control system. The most complex and costly intelligent components in decision support systems development are the logical output machine simulation modeling core, multi-agent system core and agent communications. Due to that, an actual problem is development of applied decision support systems based on ready-made intelligent components.

V. ANALYSIS OF EXISTING APPROACHES

Skobelev refers to Magenta [16] technology as to the first generation of multi-agent platforms and presents results of second generation platform development. One of the features of second generation multi-agent platform is the control over all kinds of mobile resources that have built-in GPS (Global Positioning System) and/or GLONASS (Global Navigation Satellite System) sensors. Part of this platform is deployed directly on the mobile devices. Advantages of second generation platform are illustrated in [16] on the truck control project for the European transportation network, since no similar system can “consolidate cargo, adapt delivery routes, plan deliveries and assign trucks on the basis of events flow, such as new order entry or changes in resource availability”. A conceptual approach to design of a similar system is presented in [17].

One of multi-agent planning platform requirements is support of the full control cycle that consists of the following stages [16]:

1) **Reaction to event** (discrete event control). Events (orders, delays, failures, etc.) are received in real time. They need to be planned, taking into account current plans, individual preferences and limitations of resources and orders,

2) **Dynamic planning** (re-planning / dispatching),

3) **Coordination and plan revision “on the fly”.** Changes are made to resource plans without stopping and restarting the main program, by modifying the schedule “on the fly”, making use of both free windows and adaptive repositioning of previously assigned orders. When planned and actual schedules differ, automatic re-planning and user coordination are required.

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4) **Plan execution monitoring and control**
Successful deployment of planning system highly depends on user "trust" factor. Users, typically logistical specialists or dispatchers, are responsible for planning and control of transportation process. User trust may be provided by offering aids to override the system operation and make modifications accordingly. Planning problem is usually complex, since certain events, situations and parameters can be omitted during development of intelligent planning system. Thus, the following additional requirements emerge:

1) Negotiations on the plan with end users

2) Manual plan editing, including manual planning

In order to design an efficient supply chain planning system one must control of supply and individual order terms; diagnose the bottlenecks of transportation networks and logistical centers. Thus, there is a requirement for analysis and modeling of logistical systems that are based on queuing systems.

The following approaches to multi-agent system and business process models are available: 1. Multi-agent resource conversion process model [1, 20], 2. Requirements and capabilities networks (RC-nets) by Vittich, Skobelev, and Rzevski [4-5, 16], used for development of intelligent multi-agent systems in logistics, 3. Models of Active and Passive Convertors (APC) by Moskalyov and Klebanov (Onto Modeler software) [19], 4. Approach, implemented in AnyLogic software [6, 9].

The results of these approaches analysis are presented in Table 2. The requirements for logistical system may be separated into 3 groups: knowledge formalization; analysis and simulation; full control lifecycle support.

As we can see from the table, the RC-net satisfies most requirements of logistical models and supports corresponding tasks. Also the multi-agent resource conversion process model is perspective, if improved and perfected, due to detailed study of integration of conceptual, simulation, expert, multi-agent, and situation modeling.

Generally, there is the following difference between RC-networks based and multi-agent resource conversion processes apparatuses:

1. Approaches have different knowledge distribution and representation. Each agent of RC-network possesses only its own knowledge. In order to achieve the common goal of planning and control a feature of agent communication is required. Thus, the RC-network provides a decentralized control system. AnyLogic provides a set of blocks for simulation modeling of transportation systems, but lacks tools for knowledge (ontology) processing. Since all knowledge about the whole control object in multi-agent resource conversion processes and APC is stored in a common knowledge base, the multi-agent resource conversion process offers a more centralized control system. It receives information from distributed sources (fuels residues sensors, transportation vehicles monitoring systems, corporate information system).

2. Approaches differ by technical implementation**.** Last applications of RC-networks are oriented towards distributed calculations and networks. Software implementations of multi-agent resource conversion process model and APC model, as well as AnyLogic system, are all local simulation modeling systems..

3. Planning and dispatching tasks are solved with aid of RC-networks and multi-agent resource conversion process model. AnyLogic system is not oriented towards these problems, since the planning block needs to be implemented. APC approach cannot be used in planning tasks and logistical systems dispatching. Still, there are some disadvantages in the RC-networks approach [16]:

TABLE II. ANALYSIS OF APPROACHES AND DYNAMIC MODELS OF SITUATIONS

Features	MRCP	RC-net	APC	AnyLogic
1. Various resource types	●	●	●	●
2. Temporal parameters	●	●	●	●
3. Conflicts on common resources and tools	●	●	●	●
4. Discrete operations	●	●	●	●
5. Complex resources (transacts), transact queue	●	●	●	●
6. Situations analysis and decision search (heuristics block)	●	●	○	○
7. Agent communications	●*	●	○	●
8. Use of geo-data	●	●	○	●
9. Development of subject ontologies	●	●	●	○
10. Subject ontology of logistical problems	●	●	○	○
11. Software engineering (use of UML)	●	○	○	●
12. Support for distributed computing environments	○	●	○	○
13. Simulation modeling	●	○	●	●
14. Full control cycle				
14.1. Reaction to external event from the control object	●	●	○	○
14.2. Dynamic planning	●	●	○	○
14.3. Dispatching (re-planning)	●	●	○	○
14.4. Coordination and plan revision "on the fly"	●	●	○	○
14.5. Plan execution monitoring and control	●	●	○	○
14.6. Negotiations on the plan with end users	●	●	○	○
14.7. Manual plan editing	●	●	○	○

* – feature under development

a. Most scheduled trips are edited during execution (23% of all decisions are revised within the first hour after they are accepted, and only 10% of all decisions are alive for over 3 hours),
b. Generally, there are 0 to 18% of proactivity phases that improve the schedule,
c. System notifies logistical chain actors of all changes related to in, which causes certain tension.

Multi-agent resource conversion process model software implementation was further improved by agent heuristic blocks, implemented on the basis of production and frame-based expert sub-systems, and also situation diagnosis and filtration blocks, which altogether drastically solaces the disadvantages of logistical chains.

VI. Application of BPsim.MAS for Modeling of Logistical Processes

Currently, the intelligent planning system is under development. It is going to be deployed at logistical department of gas supplying company, located in Ekaterinburg, Russia, a major city in authors' area. The gas stations network of the supplier consists of 24 gas stations. Fuel to these stations is delivered by 12 fuel tankers. The total number of fuel tanks at all gas stations is 85 [10]. Interaction of intelligent system modules is presented in Figure 3.

Initially, a logistics specialist sets initial values. They include date of the plan, fuel tankers shift start time, distribution strategy for various fuel types. Initial data also includes residues at gas stations and technical condition of tanker fleet. After finishing the algorithm operation, users have an opportunity to modify the plan. Next, the plan is exported into simulation module and is corrected depending on simulation results. Simulation model also monitors residues on each gas station and fuel usage dynamics. Events, received from the control object, are processed in situation diagnosis block. Processing results determine, whether the plan needs to be modified either in part, in whole, or not at all. Sample situations include failure of the gas tanker, availability of new tanker, closure of oil farm, appearance of a new order.

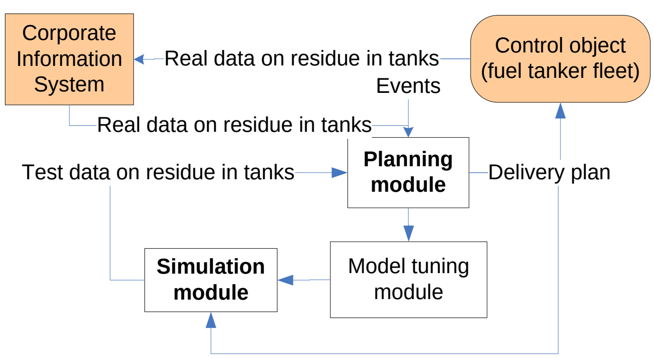

Figure 3. Interaction of planning system

VII. Conclusion and Future Work

The paper discussed development of logistical model based on multi-agent model of a resource conversion process. Also the following problems have been solved:

A semantic model of multi-agent resource conversion processes has been designed,

A methodology for design of information systems, based on the model of multi-agent resource conversion processes has been presented,

A comparison of existing multi-agent approaches of information system development for the problems of planning and logistics has been presented.

We analyzed requirements and capabilities nets, multi-agent resource conversion process model, active and passive convertors model, agent-based simulation modeling, and their software implementations (Magenta, BPsim, Onto Modeler, AnyLogic). The most perspective approaches are implemented in Magenta and BPsim systems. However multi-agent approach based on distributed calculations has one disadvantage, which is frequent plan modification, resulting in certain instability of the model. To avoid this effect, we use situation filtration and diagnosis block. In order to take delays into consideration and analyze the bottlenecks in logistical chain) we use simulation modeling.

Despite the active application of UML-based conceptual modeling tools in the area of information systems development, their application in simulation modeling engineering is limited. An advantage of conceptual and simulation modeling integration is the availability of rapid transition from conceptual models to design and application models, and software implementation. Ontologies and knowledge representation models may be used for transitions from conceptual model to simulation model. The ontologies are used in Magenta and BPsim systems.

Further research includes:

1. Estimation of proactivity phases of various event types for the suggested approach,
2. Improvement of multi-agent resource conversion process model architecture,
3. Design of full knowledge base for situations,
4. Study of separate situations effect on plan stability,
5. Deployment of decision support system.

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