# OSTIS technology overview in the context of fuzzy systems development


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***Abstract*—This article provides an overview of OSTIS technology. The prospects of using OSTIS technology in the field of data analysis and the development of fuzzy systems are considered. An approach to modeling time series based on type 2 fuzzy sets is described. An approach to constructing a fuzzy knowledge base is presented.**



***Keywords*—ostis, overwiev, type 2 fuzzy sets, fuzzy knowledge base**


## I. Introduction

The implementation and use of knowledge-based intelligent systems are relevant in all problem areas nowadays [1], [2]. A huge amount of information produces the need to develop new models, methods, and algorithms for storing, presenting, and operating with knowledge. However, a serious problem in the evolution of information technology is ensuring information compatibility and integration of various computer systems.

This problem is especially important in the domain of artificial intelligence researches in studies related to solving problems based on machine learning methods. The isolation of groups that develop various technologies in this direction determines the slow growth of the market for intelligent systems. The significant results have been obtained in various researches in the domain of artificial intelligence, but integrating these results is a difficult task.

There is a need to create a technology that would integrate various models of problem areas and various types of knowledge. The relevance of solving this problem is determined by a number of reasons [1], [2]:

1) A single technology for data and knowledge representation will allow increasing the level of learning, and the degree of diversity of knowledge. Such knowledge can be used in solving various problems without the need to develop specialized software and ensure their information compatibility.
2) Simplification of the computer systems development process. The development and continuous expansion of the set of components, solutions, and typically embedded knowledge can significantly reduce development time.
3) Simplification of the maintaining computer systems process and the compatibility of information stored in them. The form of data storage in information systems can change significantly during the life cycle. This situation produces the need to modify the software to ensure compatibility with other information systems.

These problems partially solved in the concept of open semantic technology for intelligent systems (OSTIS).

## II. Important aspects of the open semantic technology for intelligent systems

The problems of unification of the principles for constructing various components of computer systems are solved in the OSTIS project [1], [2]. The OSTIS project aims to create an open semantic technology for designing knowledge-driven systems.

Important aspects of OSTIS technology are [1], [2]:

1) Applying modern experience in the field of information technology. Language tools have been created for a unified description of the developed intelligent systems as part of the OSTIS technology.
   Each OSTIS-system uses semantic memory (sc-memory). Each action in sc-memory denotes a transformation performed by some subjects. The problem area of abstract sc-agents has been developed within the framework of OSTIS technology. A set of ontologies is used to describe sc-agents. These ontologies describe a specification of the

sc-agent concept and related to sc-agent concepts, and also includes formal tools that ensure synchronization of actions produces by sc-agents in sc-memory.

The SCP language is considered as the base language for programs that describe some activity of sc-agents with sc-memory. The SCP language is a graph procedural programming language designed to efficiently process homogeneous semantic networks with set-theoretic interpretation encoded using SC-code.

SC-code is a unified format for representing knowledge in the form of homogeneous semantic networks with a set-theoretic interpretation in OSTIS technology.

2) Separation of a unified description of the developed intelligent system and various interpretations of formal descriptions of intelligent systems.

Clear separation of the design process of a formal description of the semantic model of the developed knowledge base from the process of interpreting this model is performed in the process of developing knowledge bases using OSTIS technology.

3) Common library for a set of components, solutions, and typically embedded knowledge that will be available to all developers.

The problem arises of systematization and structuring of knowledge with the accumulation of large data volumes. Each of the concepts of the current domain has a role. This role can either be a class of the research object or a relation defined on the set of objects of study, etc.

## III. Perspectives for the development of OSTIS technology in the field of fuzziness

The previously discussed advantages of OSTIS technology can be used to develop high-level abstractions of data mining models and methods. Such high-level abstractions can form a higher level of intelligent computing machine by analogy with high-level programming languages and machine instructions. Thus, you can create sets of functions for solving problems in the field of data mining using the OSTIS technology. Libraries of these functions can significantly reduce the time to development of intelligent systems.

### *A. Dynamic data analysis based on fuzzy sets of type 2*

It will be possible to model time series with more quality if create a component for working with type 2 fuzzy sets for the OSTIS platform.

There is also a need to form type 2 fuzzy sets based on the features of the current problem area.

It is necessary to create tools for the automated building of an ontology based on the analysis of enterprise data to solve such a problem.

Let see an example of an approach to solving the problem of modeling time series using type 2 fuzzy sets.

The task of forecasting is always relevant in the context of management. Prediction is made using a variety of methods and approaches. If the deterministic model of the system is absence then such methods based on the study of the evolutionary history of processes and indicators. One of the popular tools for studying the evolutionary history of processes and indicators are time series models. Time series models have a different nature: statistical, based on neural networks, fuzzy, etc. The use of models is complicated by data characteristics. Data may require preprocessing, normalization, may have a high degree of uncertainty.

The nature of the fuzzy time series is caused by using expert evaluations. Expert evaluations have a high level of uncertainty and fuzziness. Fuzziness, unlike stochastic uncertainty, makes it difficult or impossible to use statistical methods and models. However, fuzziness can be used to make subject-oriented decisions based on approximate reasoning of an expert. The formalization of intellectual operations that simulate fuzzy human statements about the state and behavior of a complex system nowadays forms an independent area of scientific and applied research called ”fuzzy modeling” [3].

First-order sets (type 1) are usually used to build a process model. Type 1 fuzzy sets are used to represent or to create a model of domain uncertainties [4]. L. A. Zade introduced in 1975 second-order fuzzy sets (type 2) and higher-order fuzzy sets (type n) to eliminate the shortcomings of type 1 fuzzy sets [5]. The main disadvantage is the mapping of the membership function to exact real numbers. The solution to this problem can be the use of type 2 fuzzy sets, in which the boundaries of the membership regions are themselves fuzzy [4]. For each value of the $x$ variable from the universe $X$ the value itself is a function, not a value at a point. This function represents a type-2 fuzzy set, which is three-dimensional, and the third dimension itself adds a new degree of freedom for handling uncertainties.

The union, intersection, and complement operations can be over type 2 fuzzy sets. Type 2 fuzzy sets have an extended representation of uncertainties, which creates additional computational complexity.

The designation of the fuzzy type 2 membership function can graphically shown as a region called the footprint of uncertainty (see fig. 1). In contrast to using the membership function with crisp boundaries, the values of the type 2 membership function are themselves fuzzy functions.

This approach has given an advantage in bringing the fuzzy model closer to the model in linguistic form. People may have different evaluations of the same uncertainty. There was a need to exclude an unambiguous comparison of the obtained value of the degree of mem-

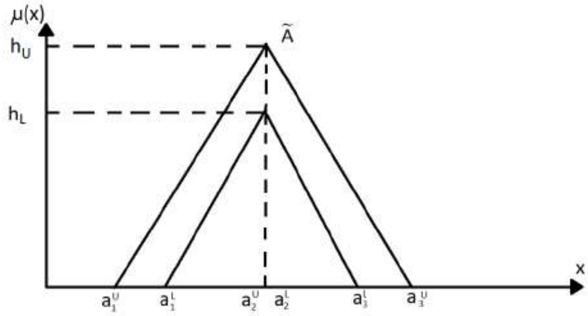


Figure 1. Example of a type 2 fuzzy sets.

bership function. Thus, the risk of error accumulation is reduced when an expert sets the membership degrees due to not including points located near the boundaries of the function and being in uncertainty.

Blurring boundaries is the first step in moving from type 1 fuzzy sets to type 2 fuzzy sets. It is required to choose the type of membership function at the second step as is done for type 1 fuzzy sets (for example, triangles).

The uncertainty present in the tasks of managing the activities of any enterprise and characterized by the statements of experts containing incomplete information, with fuzzy and unclear information about the main parameters and conditions of the analyzed problem. Thus, the solution to the control problem becomes complicated and is generated by multiple factors. The combination of these factors in practice creates a wide range of different types of uncertainty. Therefore, it becomes necessary to use methods that allow the use of blurry values of indicators.

Type 2 fuzzy sets $\tilde{A}$ in the universum $U$ can be defined using type 2 membership function. Type 2 fuzzy sets can be represented as:

$$\tilde{A} = ((x,u), \mu_{\tilde{A}}(x,u)) | \forall x \in U, \forall u \in J_x \subseteq [0,1]$$

where $x \in U$ and $u \in J_x \subseteq [0,1]$ in which $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$. The main membership function is in the range from 0 to 1, so the appearance of the fuzzy set is expressed as:

$$\tilde{A} = \int_{x \in U} \int_{u \in J_x} \mu_{\tilde{A}}(x,u)/(x,u) J_x \subseteq [0,1]$$

where the operator $\int\int$ denotes the union over all incoming $x$ and $u$.

Time series modeling needs to define interval fuzzy sets and their shape. The figure 1 shows the appearance of the sets.

Triangular fuzzy sets are defined as follows:

$$\begin{gathered}\tilde{A}_i = (\tilde{A}_i^U, \tilde{A}_i^L) = \\ = ((a_{i1}^u, a_{i2}^u, a_{i3}^u, h(\tilde{A}_i^U)), \\ (a_{i1}^l, a_{i2}^l, a_{i3}^l, h(\tilde{A}_i^l))).\end{gathered}$$

where $\tilde{A}_i^U$ and $\tilde{A}_i^L$ is a triangular type 1 fuzzy sets, $a_{i1}^u, a_{i2}^u, a_{i3}^u, a_{i1}^l, a_{i2}^l, a_{i3}^l$, is reference points of type 2 interval fuzzy set $\tilde{A}_i$, $h$ is the value of the membership function of the element $a_i$ (for the upper and lower membership functions, respectively).

An operation of combining fuzzy sets of type 2 is required when working with a rule base based on the values of a time series. The combining operation defined as follows:

$$\begin{gathered}\tilde{A}_1 \oplus \tilde{A}_2 = (\tilde{A}_1^U, \tilde{A}_1^L) \oplus (\tilde{A}_2^U, \tilde{A}_2^L) = \\ = ((a_{11}^u + a_{21}^u, a_{12}^u + a_{22}^u, a_{13}^u + a_{23}^u; \\ min(h_1(\tilde{A}_1^U), h_1(\tilde{A}_2^U)\tilde{A}_1^U)), min(h_2(\tilde{A}_1^U), h_2(\tilde{A}_2^U)), ); \\ (a_{11}^l + a_{21}^l, a_{12}^l + a_{22}^l, a_{13}^l + a_{23}^l; \\ min(h_1(\tilde{A}_1^L), h_1(\tilde{A}_2^L)), min(h_2(\tilde{A}_1^L), h_2(\tilde{A}_2^L)));\end{gathered}$$

### *B. Algorithm for smoothing and forecasting of time series*

The main principle of the proposed algorithm is closely related to the nature of the time series. Type 2 fuzzy sets are used for modeling in the process of smoothing and forecasting of time series because the time series has the interval nature. [4].

The proposed algorithm can be represented as a sequence of the following steps:

1) Determination of the universe of observations. $U = [U_{min}, U_{max}]$, where $U_{min}$ and $U_{max}$ are minimal and maximal values of a time series respectively.
2) Definition of membership functions for a time series $M = \{\mu_1, ..., \mu_l\}, l << n$, where $l$ is the number of membership functions of fuzzy sets, $n$ is the length of a time series. The number of membership functions and, accordingly, the number of fuzzy sets is chosen relatively small. The motivation for this solution is the multi-level approach to modeling a time series. It is advantageous to reduce the number of fuzzy sets at each level to decrease the dimension of the set of relations. Obliviously, this approach will decrease the quality of approximation of a time series. However, creating the set of membership functions at the second and higher levels will increase the approximation accuracy with an increase in the number of levels.
3) Definition of fuzzy sets for a series. In that case, the superscript defines the type of fuzzy sets. $A^1 = \{A_1^1, ..., A_l^1\}, A^2 = \{A_1^2, ..., A_m^2\}$, where $l$ is the number of type 1 fuzzy sets, $m$ is the number of type 2 fuzzy sets.

4) Fuzzification of a time series by type 1 sets. $\forall x_i$ $\tilde{y}_i = Fuzzy(x_i)$
5) Fuzzification a time series by type 2 sets.
6) Creation of relations. The rules for the creation of relations are represented in the form of pairs of fuzzy sets in terms of antecedents and consequents, for example: $A_1^1 A_1^2 ... \longrightarrow A_2^1 A^2 1$.
7) Doing forecasting for the first and second levels based on a set of rules. The forecast is calculated by the centroid method, first on type 1 fuzzy sets $A^1 = \{A_1^1, \ldots, A_l^1\}$, then on type 2 fuzzy sets.
8) Evaluation of forecasting errors.

### *C. Knowledge discovery*

Modern organizations have a large amount of accumulated knowledge presented in the form of various corporate knowledge bases. Thus, the development of a technological platform (TP) is necessary to solve the following tasks:

- the TP should not require additional skills and knowledge from the user;
- the TP should provide the programmer the familiar and easy to use data access mechanism;
- the TP should provide an inference mechanism to implement knowledge discovery (KD) functionality;
- the TP should provide functions to the automation of the process of obtaining essential knowledge about problem area (PrA) in the internal knowledge base (KB).

At the moment, a lot of researchers use the ontological approach for the organization of the knowledge bases of expert and intelligent systems: F. Bobillo, U. Straccia [6], [7], M. Gao, C. Liu [8], D. Bianchini [9], N. Guarino [10], G. Guizzardi [11], R.A. Falbo [12], G. Stumme [13], T.R. Gruber [14], A. Medche [15].

The inference is the process of reasoning from the premises to the conclusion. Reasoners [16] are used to implementing the function of inference and form logical consequences from many statements, facts, and axioms. Currently, the Semantic Web Rule Language (SWRL) is used to record logical rules for reasoners [17].

### *D. The model of the fuzzy domain knowledge base content with contexts support*

Contexts of the KB represent the parts of ontology in space and time. Each space context is associated with a value from 0 to 1 defining the expert level of expertise in the part of the problem area (PrA). Time contexts allow using versioning of the PrA ontology and give an opportunity to monitor the dynamics of the ontology development. The fuzzy nature of the KB appears in the process of integration of contexts of the domain ontology.

The problem of developing the model of fuzzy domain KB with support of logical rules for inference is coming up. One of the KB main objectives is providing the mechanism for adapting the TP [18], [19] to the concrete PrA with the use of methods of ontological analysis and data engineering.

Let the following definition represents the model of the KB content:

$$O = \langle T, C^{T_i}, I^{T_i}, P^{T_i}, S^{T_i}, F^{T_i}, R^{T_i} \rangle, i = \overline{1, t}, \qquad (1)$$

where $t$ is a number of the KB contexts,
$T = \{T_1, T_2, \ldots, T_t\}$ is a set of KB contexts,
$C^{T_i} = \{C_1^{T_i}, C_2^{T_i}, \ldots, C_n^{T_i}\}$ is a set of KB classes within the $i$-th context,
$I^{T_i} = \{I_1^{T_i}, I_2^{T_i}, \ldots, I_n^{T_i}\}$ is a set of KB objects within the $i$-th context,
$P^{T_i} = \{P_1^{T_i}, P_2^{T_i}, \ldots, P_n^{T_i}\}$ is a set of KB classes properties within the $i$-th context,
$S^{T_i} = \{S_1^{T_i}, S_2^{T_i}, \ldots, S_n^{T_i}\}$ is a set of KB objects states within the $i$-th context,
$F^{T_i} = \{F_1^{T_i}, F_2^{T_i}, \ldots, F_n^{T_i}\}$ is a set of the logical rules fixed in the KB within the $i$-th context, logical rules are used to implement the functions of inference by the content of KB,
$R^{T_i}$ is a set of KB relations within the $i$-th context defined as:

$$R^{T_i} = \{R_C^{T_i}, R_I^{T_i}, R_P^{T_i}, R_S^{T_i}, R_F^{T_i}\},$$

where $R_C^{T_i}$ is a set of relations defining hierarchy of KB classes within the $i$-th context,
$R_I^{T_i}$ is a set of relations defining the "class-object" KB tie within the $i$-th context,
$R_P^{T_i}$ is a set of relations defining the "class-class property" KB tie within the $i$-th context,
$R_S^{T_i}$ is a set of relations defining the "object-object state" KB tie within the $i$-th context,
$R_F^{T_i}$ is a set of relations generated on the basis of logical KB rules in the context of the $i$-th context.

Figure 2 shows an example of the translation of the OWL representation of the ontology of family relations into the entities of the KB.

As seen in figure 2:

- OWL class "Person" was translated into the KB class with the same name;
- OWL individuals "Alex", "Helen", "Kate" and "17" was translated into the KB objects with same names;
- KB objects "Alex", "Helen" and "Kate" are objects of KB class "Person";
- KB object "17" is the object of built-in KB class "Integer";
- OWL data property "hasAge" was translated into the KB property with the same name;
- OWL object properties "hasFather" and "hasSister" was translated into the KB properties with the same names;
- OWL data property assertion "Helen hasAge 17" was translated into the KB state with the same name,

the range of this state is "Helen", the domain of this state is "17";
- OWL object property assertion "Helen hasFather Alex" was translated into the KB state with the same name, the range of this state is "Helen", the domain of this state is "Alex";
- OWL object property assertion "Helen hasSister Kate" was translated into the KB state with the same name, the range of this state is "Helen", the domain of this state is "Kate".

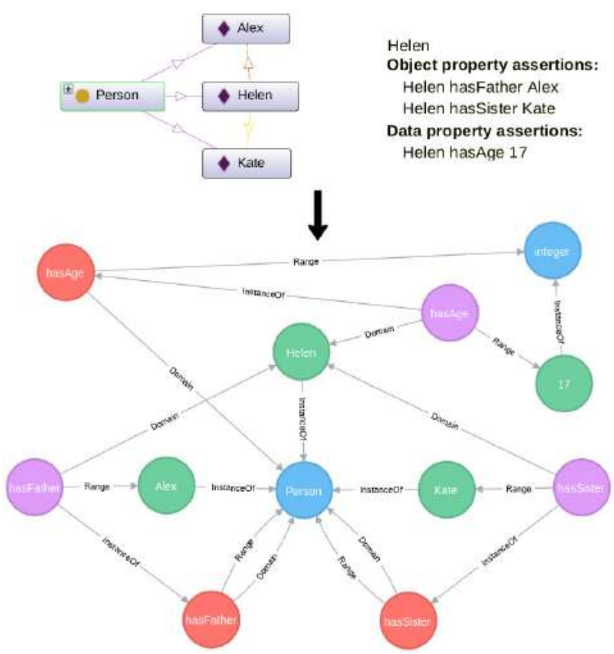


Figure 2. Example of the translation of the OWL representation of ontology of family relations into the content of the KB.

### E. Dynamical user interface

The dynamic graphical user interface (GUI) mechanism is used to simplify the work with KB of untrained users and control of user input [20], [21].

Need to map the KB entities to the GUI elements to build a GUI based on the contents of the KB. Formally, the GUI model can be represented as follows:

$$UI = \langle L, C, I, P, S \rangle, \quad (2)$$

where $L = \{L_1, L_2, \ldots, L_n\}$ is a set of graphical GUI components (for example, ListBox, TextBox, ComboBox, etc.),
$C = \{C_1, C_2, \ldots, C_n\}$ is a set of KB classes,
$I = \{I_1, I_2, \ldots, I_n\}$ is a set of KB objects,
$P = \{P_1, P_2, \ldots, P_n\}$ is a set of KB properties,
$S = \{S_1, S_2, \ldots, S_n\}$ is a set of KB states.

The following function is used to build a GUI based on the content of KB:

$$\phi(O) : \{C^O, I^O, P^O, S^O, F^O, R^O\}^{T_i} \to \\ \to \{L^{UI}, C^{UI}, I^{UI}, P^{UI}, S^{UI}\},$$

where $\{C^O, I^O, P^O, S^O, F^O, R^O\}^{T_i}$ is a set of KB entities represented by definition 1 within the $i$-th context; $\{L^{UI}, C^{UI}, I^{UI}, P^{UI}, S^{UI}\}$ is a set of GUI entities represented by the definition 2.

Thus, the contents of the KB are mapped to a set of GUI components. This mapping makes it easier to work with KB for a user who does not have skills in ontological analysis and knowledge engineering. It also allows you to monitor the logical integrity of the user input, which leads to a reduction in the number of potential input errors.

We are confident that the creation of tools for the formation of an ontology for ”simple” users will simplify and speed up the process of generating new knowledge [22].

If in the OSTIS technology will be a tool for working with ontology contents in the form of catalogs, this will speed up the process of solving the problem of integrating semantic data.

## IV. Conclusion

Thus, OSTIS technology aims to unify and standardize models, methods, and tools for developing knowledge-based intelligent systems.

OSTIS technology uses approaches that have proved their in various implemented projects aimed at solving problems of a wide range of prolem areas [23]–[25].

As for recommendations for the further development of OSTIS technology, we can distinguish:

1) It is necessary to develop tools for translating ontologies in OWL and RDF formats into the knowledge format of OSTIS technology.
2) It is necessary to develop tools to translate SWRL rules into fragments of scp-programs.
3) It is necessary to develop the centralized repository to store up-to-date documentation on OSTIS technology, covering all aspects of installing, configuring, launching, using and developing OSTIS technology.
4) It is necessary to build a container image to allow the use of the latest version of OSTIS technology.

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# Обзор технологии OSTIS в контексте разработки нечетких систем

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В данной статье представлен обзор технологии OSTIS. Рассмотрены перспективы использования технологии OSTIS в области анализа данных и разработки нечетких систем.

Описан подход к моделированию временных рядов на основе нечетких множеств типа 2. Представлен подход к построению нечеткой базы знаний.

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