Integration of Fuzzy OWL Ontologies and Fuzzy Time Series in the Determination of Faulty Technical Units

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Abstract. The method of constructing fuzzy ontologies was investigated in the framework of this work. An ontological model for assessing the state of helicopter units has been developed. The article provides a formal description of fuzzy ontologies and features of the representation of elements of fuzzy axioms in FuzzyOWL notation. According to the proposed approach, the summarizing of the state of a complex technical system is carried out by means of an inference based on a fuzzy ontology. Objects, properties and axioms of fuzzy ontology determine the parameters of the membership functions and linguistic variables of the objects of analysis in the form of time series. A software product was developed to implement the proposed approach. As part of this work, experiments were conducted to search for anomalous situations and search for possible faulty helicopter units using the developed approach to the integration of fuzzy time series and fuzzy ontology. For the first time, the results of the inference of knowledge based on the integration of fuzzy time series and fuzzy ontologies in the tasks of analyzing the diagnosis of complex technical systems were obtained. The proposed approach of hybridization of fuzzy time series and fuzzy ontologies made it possible to reliably recognize anomalous situations with a certain degree of truth, and to find possible faulty aggregates corresponding to each anomalous situation.

Keywords: Fuzzy time series · Fuzzy ontology · Fuzzy OWL · Summary

1 Introduction

The uncertainty of data and information incompleteness is an inalienable part of any complex technical system, in which the functioning quality of processes depends on a person. In the analysis, modeling, and design of such systems, a large distribution was obtained by expert systems that use experience and knowledge of the expert.

Expert assessment is the some qualitative aspect's linguistic form of the system element being evaluated or even of the system itself.

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Currently, the inference methodology of expert assessments based on the subject ontologies that play the role of a knowledge base in decision support systems (DSS) is used in various subject areas, including in the field of situational control in the energy sector [1], designing complex diagnostic systems [2], etc. Also, ontologies have been used as a knowledge base of intelligent risk prevention systems in the context of heterogeneous information for the complex technical systems critical infrastructure design phase [3].

Despite the application breadth, the classical languages of ontology and semantic networks, which are usually used to summarize and characterize the features of a subject domain, cannot be used to solve uncertainties and inaccuracies in the knowledge inherent in most real world applications in this area.

Fuzzy set theory, as well as fuzzy logic, is formalism suitable for processing incomplete knowledge, therefore ontologies based on such logic are adequate means of formalization.

One of the most effective solutions for representing a knowledge base in the context of accounting for fuzziness and uncertainty in human reasoning and evaluations in the DSS is a representation in the form of fuzzy ontologies. For example, fuzzy ontologies are used in such systems as disease diagnosis systems [4], fuzzy search engines [5], knowledge systems based on group decision making about the importance of data [6], etc. In most cases, such systems operate with facts objects or terms that are described in natural language and contain the features of the considered domain.

Fuzzy time series (FTS) is a way to obtain expert assessments that satisfy the conditions for completeness, consistency, and adequacy [7].

One of the main areas of application for FTS is process diagnostics. Diagnosis is the process by which a search for problems in the system occurs: defects, anomalies, faults, or lack thereof. When solving problems of diagnostics of complex technical systems, the state of which is determined by the data set in the form of FTS, it is advisable to apply methods for comparing the dynamics of processes with the expected or required dynamics.

Therefore an urgent task requiring a systemic solution is the interpretation of the results of the analysis in the form of expert assessments. To summarize the results obtained in the analysis of FTS, a system of rules is usually applied, which are stored in the knowledge base of the expert system. The knowledge base for solving this problem is ontologies and similar graph forms of knowledge representation and storage, which allow to take into account the semantic features of the object of the specified subject area, and not only their inference [8, 9].

Interpretation of the extracted comparisons in the form of expert assessments, the values of which are presented in the form of semantic units that correspond to certain classes of fuzzy ontology, taking into account the deviations between the current and the required FTS, can be obtained by solving the problem of integrating FTS and fuzzy ontology. Thus, the purpose of this work is the development of algorithms and models for the integration of fuzzy ontologies and FTS in the tasks of diagnosing complex technical systems.

2 Fuzzy Time Series and Fuzzy Ontology Model

The models and algorithms for analyzing and forecasting the FTS are described in detail in [10, 11]. At present, the basic notation of the fuzzy ontology representation is the FuzzyOWL standard [12–14]. Formally FuzzyOWL-ontology is:

$$I = (If, Cf, Pf, Af, Df, Qf, Lf, Modf),$$

where

- *If* is an Individual that simply represents an individual of the vocabulary;
- *Cf* is a Concept that represents a fuzzy concept of the vocabulary:

$$C_f = \left\{C_f^A, C_f^C\right\},$$

where C_f^A are Abstract Concepts, C_f^C - Concrete Concepts;

- *Pf is* Property that represents a fuzzy role:

$$P_f = \left\{P_f^A, P_f^C\right\},$$

where P_f^A are Object Properties, P_f^C are Datatype Properties;

- *Df* is Axiom that represents the axioms:

$$D_f = \left\{A_f^{ABox}, A_f^{TBox}, A_f^{RBox}\right\},$$

where A_f^{ABox} is the Abox that contains role assertions between individuals and membership assertions, A_f^{TBox} is the Tbox that contains assertions about concepts such as subsumption and equivalence, A_f^{RBox} is the RBox that contains assertions about roles and role hierarchies. Some of the axioms are subclasses of FuzzyAxiom, which indicates that the axiom is not either true or false, but that it is true to some extent.

- *Of* is Degree that represents a degree which can be added to an instance of FuzzyAxiom:

$$Of = \left\{LD_f, MD_f, ND_f, Var_f\right\},$$

where LD_f are Linguistic Degrees, MD_f are Modifier Degrees, ND_f are Numeric Degrees, Var_f are Variables.

- *Lf* is Fuzzy Logic represents different families of fuzzy operators that can be used to give different semantics to the logic.

$$L_f = \left\{ L_f^{Luk}, L_f^{Zad}, L_f^{Goed}, L_f^{\text{Prod}} \right\},$$

where L_f^{Luk} is the fuzzy operators logic of Lukasiewicz, L_f^{Zad} is the fuzzy operators logic of Zadeh, L_f^{Goed} is the fuzzy operators logic of Goedel, L_f^{Prod} is the fuzzy operators of product logic;

- *Modf* is Fuzzy Modifier that represents a fuzzy modifier, which can be used to modify the membership function of a fuzzy concept or a fuzzy role. Current subclasses are Linear Fuzzy Modifier and Triangular Fuzzy Modifier.

Table 1 shows the elements of fuzzy axioms FuzzyOWL, as well as their possible representation.

Table 1. Elements of fuzzy axioms in FuzzyOWL

№	Element	Possible values	Representation in FuzzyOWL
1	LD_f – Linguistic Degrees	«high», «above average», «low»	`<AnnotationAssertion> <AnnotationProperty IRI="#fuzzyLabel"/> <IRI>#HighLoad</IRI> <Literal datatypeIRI="&rdf;PlainLiteral">fuzzyOwl2 fuzzyType="datatype"; Datatype type="rightshoulder"; a="15.0"; b="30.0";/fuzzyOwl2</Literal> </AnnotationAssertion>`
2	MD_f – Modifier Degrees	«very», «not very»	`type="modified" modifier="very"`
3	ND_f – Numeric Degrees	$0 \leq ND \leq 1$	`Degree Value=0,6`
4	Var_f – Variables	a, b,c, k1, k2	`b="30.0";`
5	L_f – Fuzzy Logic	Zadeh, Lukasiewicz Goedel and Product	`hasSemantics="Zadeh"`
6	*Modf* – Fuzzy Modifier	Linear, Triangular	`<Datatype type="triangular" a="32.0" b="41.0" c="50.0" />`

3 Subject Area

Consider the use of the integration approach of FTS and fuzzy ontologies in solving the problem of diagnosing the state of a helicopter. Diagnostics of a helicopter consists in checking its units in order to establish their exploitation and the possibility of using the helicopter.

The result of the diagnosis will be assessment values of physical quantities key indicators. The main goal is to assess the danger of values. To solve this problem, it is necessary to construct models of the behavior of the selected nodes and make conclusions about the health of the nodes by using the models. Models are built at expert base of assessment about the conduct of a particular component.

Table 2 show the parameters of the membership functions used for construct the FTS (Table 2).

Table 2. Parameters of the membership function

Physical parameter	Range boundaries	Very little	Little	Good	Big	Very big
Exhaust gases temperature, °C	0–1000	a < 100 b = 200 c = 200,5	a = 100 b = 275 c = 350,5	a = 350 b = 560 c = 600,5	a = 600 b = 700 c = 720,5	a = 720 b = 800 c > 1000
Engine oil temperature, °C	0–150	a < 0 b = 5 c = 10,5	a = 10 b = 15 c = 20,5	a = 20 b = 30 c = 60,5	a = 80 b = 100 c = 120,5	a = 120 b = 135 c > 150
Engine oil pressure, kgf/cm^2	0–20	a < 0 b = 1 c = 2,05	a = 2,0 b = 3,5 c = 5,05	a = 5,00 b = 8 c = 10,5	a = 10 b = 12 c = 15,5	a = 15,2 b = 17,5 c > 20
Main gearbox oil temperature, °C	0–100	a < 0 b = 5 c = 10,5	a = 10 b = 15 c = 20,5	a = 20 b = 35 c = 50,5	a = 50 b = 70 c = 80,5	a = 80 b = 90 c > 100
Main gearbox oil pressure, kgf/cm^2	0–8	a < 0 b = 1 c = 2,05	a = 2,0 b = 2,5 c = 3,5	a = 3,45 b = 4 c = 4,55	a = 4,50 b = 5 c = 7,55	a = 7,5 b = 7,8 c > 8

Thus 5 fuzzy labels are defined for each physical quantity. The task of analyzing technical time series is reduced to the task of searching for anomalous situations in TS of main gearbox and engine propulsion system physical quantities indicators. The analysis is a sequence of the following steps:

1. Formation of FTS on the basis of the received information on the values of key physical quantities after the end of helicopter flight.
2. Search known abnormal situations in the resulting FTS.
3. Determination of the correct operation of the nodes. Work is incorrect if at least one abnormal situation.

The fuzzy ontology was developed for experiments. The developed FuzzyOWL ontology has a hierarchical structure and includes 55 classes, eight object properties, 40 data types.

Table 3 contains objects properties of the used in the work (OP - oil pressure, EGT - exhaust gas temperature, OT - oil temperature, PP - power plant).

Table 3. Property of objects

Property	Domain	Range
has OP main gearbox	main gearbox	OP main gearbox
has OP left engine	PP gearbox	OP PP gearbox
has OP right engine	PP gearbox	OP PP gearbox
has EGT left engine x	PP gearbox	EGT PP gearbox
has EGT right engine	PP gearbox	EGT PP gearbox
has OT main gearbox	main gearbox	OT main gearbox
has OT left engine	PP gearbox	OT PP gearbox
has OT right engine	PP gearbox	OT PP gearbox

Property declaration example for « hasOPMainGearbox»

```
<SubObjectPropertyOf>
  <ObjectProperty IRI="# hasOPMainGearbox"/>
  <ObjectProperty IRI="owl:topObjectProperty"/>
</SubObjectPropertyOf>
<ObjectPropertyDomain>
  <ObjectProperty IRI="# hasOPMainGearbox"/>
  <Class IRI="#MainGearbox"/>
</ObjectPropertyDomain>
<ObjectPropertyRange>
  <ObjectProperty IRI="# hasOPMainGearbox"/>
  <Class IRI="#OTMainGearbox"/>
</ObjectPropertyRange>
```

In addition, 40 data types were allocated: 5 fuzzy labels for 8 variants of relationships. The data type parameters correspond to the parameters of the membership function. The type of membership function in all data types was chosen triangular.

Example of declaring a data type in FuzzyOWL notation:

```
<AnnotationAssertion>
  <AnnotationProperty IRI="#fuzzyLabel"/>
  <IRI>#BigOPMainGearbox </IRI>
  <Literal datatypeIRI="&rdf;PlainLiteral">
    <fuzzyOwl2 fuzzyType="datatype">
      <Datatype type="triangular" a="4.50" b="5" c="7.5" />
    </fuzzyOwl2>
  </Literal>
</AnnotationAssertion>
```

As an object of experiments, time series for the diagnostics of helicopter units and the fuzzy ontology of the helicopter units design were investigated. In the course of

these experiments, the fuzzy time series and fuzzy ontologies integration algorithms were used.

4 FTS and Fuzzy Ontology Integration System

A software system was developed to solve the problems of forming the inference of the recommendation based on the integration of fuzzy time series and fuzzy ontologies. The software system is written in C# on the .NET 4.5 platform. The system development was carried out in the Microsoft Visual Studio 2015 environment. SQLite was used as the DBMS. The exchange protocol is a function call to the SQLite library. This method simplifies the program and shortens the response time. To store the database (definitions, tables, indexes, and the data itself), a single standard file is used on the computer on which the program runs.

The expert develops a fuzzy ontology of the domain with the help of the ontology editor Protégé. To check the adequacy and consistency of the ontology, the built-in Reasoner HermiT or FACT++ is used. The scheme of the used software package is presented in Fig. 1.

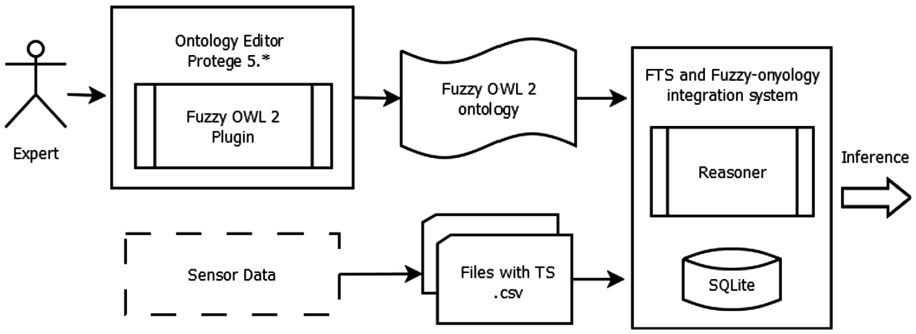

Fig. 1. FTS and fuzzy-ontology integration system.

The user has the opportunity to conduct research using the developed integration system. A prerequisite for obtaining an inference is to combine a time series with annotation properties. The result of the study is the resulting list of abnormal situations and possible faulty helicopter units.

5 Experiments

Diagnostics of a helicopter consists in checking its units in order to establish their serviceability and the possibility of operating the whole helicopter. The result of the diagnosis will be an assessment of the values of key physical quantities. The main goal is to assess the danger of values. To check the adequacy of the algorithm for integrating fuzzy time series and fuzzy ontology based on FuzzyOWL, as well as the correctness of

the software that implements this algorithm, a series of experiments were conducted in which possible problem situations were performed. As part of the experiment, the following actions were carried out:

1. The expert has developed a fuzzy ontology according to the FuzzyOWL standard. To build a fuzzy ontology, the Protégé [16] editor with the connected FuzzyOWL Plugin [17] was used.
2. FuzzyOWL fuzzy ontology data types contain parameters of membership functions.
3. FuzzyOWL fuzzy ontology data types contain a binding to a specific class of ontology (Table 4).

Table 4. Data type descriptions

Datatype	Type of membership function	Specific class	a	b	c
VeryLittleEGTLeftEngine	Triangular	PP engine	100	200	200,5
Little EGTLeftEngine	Triangular	PP engine	200	275	350,5
GoodEGTLeftEngine	Triangular	PP engine	350	560	600,5
Big EGTLeftEngine	Triangular	PP engine	600	700	720,5
VeryBigEGTLeftEngine	Triangular	PP engine	720	800	1000
VeryLittleOPMainGearbox	Triangular	Main gearbox	0	1	2,05
LittleOPMainGearbox	Triangular	Main gearbox	2,0	2,5	3,5
GoodOPMainGearbox	Triangular	Main gearbox	3,45	4	4,55
BigOPMainGearbox	Triangular	Main gearbox	4,5	5	7,55
VeryBigOPMainGearbox	Triangular	Main gearbox	7,5	7,8	8

The task of the experiments is to search for possible faulty helicopter units. The analysis represents the sequence of the following steps.:

(1) the formation of TS on the basis of the obtained information on the values of key physical quantities after running the machine;
(2) search for defective helicopter units in the received TS;
(3) determination of defective helicopter units.

A helicopter unit will be considered faulty if at least one abnormal situation is detected for a physical quantity associated with a specific ontology class corresponding to the faulty unit.

The effectiveness of the diagnostic algorithm of technical systems can be evaluated when solving the problem of modeling the behavior of helicopter units. The system should correctly identify possible faulty helicopter units. To confirm the efficiency, it is necessary to analyze the data characterizing the machines, both without defects and

with possible defects, and then analyze the information about the faulty units obtained by the system and received from an expert.

For the experiment, data were obtained on the run of the three machines, and data was generated that simulates certain abnormal situations. Description of the time series is given in Table 5.

Table 5. Description of time series

Series number	Airplane number	Period	TVG1	TVG2	Pm1	Pm2	Pmp	Tm1	Tm2	Tmp
1	210111	15.09.2050	739,59	258,85	2,3	0,8	0	58,1	59,2	29,3
2	210111	16.09.2050	757,29	256,93	2,4	0,8	0	57,1	59	29,3
3	210111	30.09.2050	503	227,78	7,4	0,8	1,8	47,5	51,3	29
4	210111	12.04.2052	536,85	520,93	7,6	6,6	4	53,9	56,5	35
5	240111	11.09.2054	176,43	178	0,8	0,8	0	42,5	46	31,3
6	240111	12.09.2054	176,57	178	0,8	0,8	0	42,5	46	31,3
7	240111	13.11.2046	483	448,85	6,4	5,6	3,4	49,5	51,9	23,5
8	240111	11.08.2047	479,13	0	6,4	5,4	3,3	51,6	55,1	29
9	250111	22.01.2046	189,72	206,22	0,8	1	1,6	52,5	55,5	24,5
10	250111	23.01.2046	193,3	209,22	0,8	1	1,6	52,5	55,5	24,5

The following designations are used: TVG1 - left engine exhaust temperature, TVG2 - right engine exhaust temperature, Pm1 - left engine oil pressure, Pm2 - right engine oil pressure, Tm1 - left engine oil temperature, Tm2 - right oil temperature engine, Pmp - oil pressure of the main gearbox, Tmp - oil temperature of the main gearbox.

Experiments were conducted with ten-time series. The results of experiments are shown in Table 6.

Table 6. Experiment results

Period	TVG1	TVG2	Pm1	Pm2	Pmp	Tm1	Tm2	Tmp	Faulty part
15.09.2050	739,59	258,85	2,3	0,8	0	58,1	59,2	29,3	#EnginePowerPlant
16.09.2050	757,29	256,93	2,4	0,8	0	57,1	59	29,3	#EnginePowerPlant
30.09.2050	503	227,78	7,4	0,8	1,8	47,5	51,3	29	#EnginePowerPlant
12.04.2052	536,85	520,93	7,6	6,6	4	53,9	56,5	35	No broken parts
11.09.2054	176,43	178	0,8	0,8	0	42,5	46	31,3	#MainGearbox
12.09.2054	176,57	178	0,8	0,8	0	42,5	46	31,3	#MainGearbox
13.11.2046	483	448,85	6,4	5,6	3,4	49,5	51,9	23,5	No broken parts
11.08.2047	479,13	0	6,4	5,4	3,3	51,6	55,1	29	#MainGearbox
22.01.2046	189,72	206,22	0,8	1	1,6	52,5	55,5	24,5	#EnginePowerPlant
23.01.2046	193,3	209,22	0,8	1	1,6	52,5	55,5	24,5	#MainGearbox

The result of the experiment is the construction of a fuzzy time series fuzzy ontology allowed us to conclude that the helicopter unit was malfunctioning when analyzing the precise values of the aggregates.

6 Conclusion

In this work, it was investigated by the method of constructing fuzzy ontologies and ontological model state helicopter units has been developed. In the process of integrating fuzzy time series and fuzzy ontology, the method integrating TS and ontology was implemented, and a software product was developed that ensures the implementation of this method.

Also, experiments were conducted to search for anomalous situations and search for possible faulty units using the developed approach to the integration of fuzzy time series and fuzzy ontology.

According to the results of the experiments, we can conclude that the proposed approach of hybridization of FTS and fuzzy ontologies allows one to reliably recognize anomalous situations with a degree of truth, and to find possible faulty units corresponding to each abnormal situation. The work is relevant, since the phenomenon of uncertainty, expressed in terms and concepts, is quite common in human knowledge.

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References

1. Massel, L.V., Vorozhtsova, T.N., Pjatkova, N.I.: Ontology engineering to support strategic decision-making in the energy sector. Ontology Designing **7**(1), 66–76 (2017). https://doi.org/10.18287/2223-9537-2017-7-1-66-76
2. Grischenko, M.A., Dorodnykh, N.O., Korshunov, S.A., Yurin, A.Y.: Ontology-based development of diagnostic intelligent systems. Ontology Designing **8**(2), 265–284 (2018). https://doi.org/10.18287/2223-9537-2018-8-2-265-284. (in Russian)
3. Kovalev, S.M., Kolodenkova, A.E.: Knowledge base design for the intelligent system for control and preventions of risk situations in the design stage of complex technical systems. Ontology Designing **7**(4), 398–409 (2017). https://doi.org/10.18287/2223-9537-2017-7-4-398-409. (in Russian)
4. Torshizi, A.D., Zarandi, M.H.F., Torshizi, G.D., Eghbali, K.: A hybrid fuzzy-ontology based intelligent system to determine level of severity and treatment recommendation for Benign Prostatic Hyperplasia. Comput. Methods Programs Biomed. **113**(1), 301–313 (2014)
5. Lai, L.F., Wu, C., Lin, P., Huang, L.: Developing a fuzzy search engine based on fuzzy ontology and semantic search. In: 2011 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2011), pp. 2684–2689 (2011)

6. Morente-Molinera, J.A., Pérez, I.J., Ureña, M.R., Herrera-Viedma, E.: Creating knowledge databases for storing and sharing people knowledge automatically using group decision making and fuzzy ontologies. Inf. Sci. **328**, 418–434 (2016)
7. Yarushkina, N.G., Afanasyeva, T.V., Perfilyeva, I.G.: Intellectual Analysis of Time Series: Textbook. UlSTU, Ulyanovsk (2010). (in Russian)
8. Natalya, F.N., Deborah, L.M.: Ontology development 101: a guide to creating your first ontology. Stanford Knowledge Systems Laboratory Technical report KSL-01-05 and Stanford Medical Informatics Technical Report SMI-2001-0880, March 2001
9. Yarushkina, N.G., Filippov, A.A., Moshkin, V.S., Filippova, L.I.: Application of the fuzzy knowledge base in the construction of expert systems. IT Ind. **6**(2), 31–36 (2018)
10. Afanaseva, T.V., Namestnikov, A.M., Perfilyeva, I.G., Romanov, A.A., Yarushkina, N.G.: Time Series Forecasting: Fuzzy Models. UlSTU, Ulyanovsk (2014). (in Russian)
11. Romanov, A.A., Egov, E.N., Moshkina, I.A., Dyakov, I.F.: Extraction and Forecasting of the International Scientific and Practical Conference "Fzz 2018", Russia, Ulyanovsk, 23–25 October 2018, pp. 50–55 (2018)
12. Bobillo, F., Straccia, U.: Fuzzy ontology representation using OWL 2. Int. J. Approximate Reasoning **52**, 1073–1094 (2011)
13. Lee, C.S., Jian, Z.W., Huang, L.K.: A fuzzy ontology. IEEE Trans. Syst. Man Cybern. Part B **5**, 859–880 (2005)
14. Straccia, U.: Towards a fuzzy description: logic for the semantic web. In: 2nd European Semantic Web Conference, pp. 167–181 (2005)
15. Yarushkina, N.G., Filippov, A.A., Moshkin, V.S.: Development of a knowledge base based on context analysis of external information resources. In: Proceedings of the International Conference Information Technology and Nanotechnology, DS-ITNT 2018. Session Data Science, Samara, Russia, 24–27 April 2018, pp. 328–337 (2018)
16. Protégé: Ontology editor. https://protege.stanford.edu
17. Fuzzy Ontology Representation using OWL 2. http://www.umbertostraccia.it/cs/software/FuzzyOWL/index.html