The building of the production capacity planning system for the aircraft factory

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***Abstract*—This article describes the basic principles of building the decision support system for the production capacity planning of large aircraft factory. The method for integration of the aircraft factory information systems with the production capacity planning system based on ontology merging is described. The process of mapping the database structure into the ontological representation is performed for each information system. An integrated data model is formed based on the ontological representations of each information system database structure. The integrated model is a mechanism for semantic integration of data sources. Also presents the method of extracting the time series from the business processes of an aircraft factory. The model of time series forecasting based on type-2 fuzzy sets in the task of production capacity planning is presented.**

***Keywords*—production capacity planning, aircraft factory, ontology merging, semantic integration, time series forecasting, type-2 fuzzy sets**

I. Introduction

The technological preparation of complex production at large enterprise requires the analysis of production capacities. The aim is to increase the efficiency of the use of material, technical and human resources [1]. The calculation of a production capacity based on a methodology approved in the industry has many disadvantages, like not enough precision because of averaging and troubles with adaptation to the concrete factory. The proposed new models and algorithms allow adapting the methodology to increase the efficiency of management at the expense of the increasing precision of forecast of production processes.

The solution of these tasks allows building a unified information environment for technological support of production. The task is to balance the production capacity of an aircraft factory. The current approach of management is based on using a common methodology for a few factories approved in the industry. Methodology contains algorithms and coefficients, accumulated from the statistic of production. The main disadvantage of this approach is a strong discrepancy between the real production indicators and the collected statistical data on the concrete factory [2].

Limitations of methodology application:

- the long extraction time of statistical coefficients from production indicators;
- the impossibility of dynamic adaptation of calculations into separate periods shorter than the forecast horizon;
- the methodology does not provide for adaptation to a specific production.

By analyzing this methodology it was found out that the coefficients (staff time, staff performance, equipment performance and depreciation of equipment) are aggregated and averaged information from the indicators of production processes. These processes are easily represented by discrete time series. Using a fuzzy approach allows creating models with more options such improving quality because of applying knowledge about time series [3], [4]. Also by analyzing production processes, it was found that this discrete interval is the one month – the minimum forecast horizon, and the time interval in which the indicators are unchanged.

It is necessary to take into account the existing information systems of the aircraft factory that automate various business processes in the process of developing a production capacity planning system. Data consistency can be achieved by integrating a production capacity planning system with existing information environment of the aircraft factory. Data integration means combining data from different data sources and providing data to users in a unified way. The main problems of data integration are [5]–[8]:

1) Heterogeneity of data models.
2) Autonomy and independence of information systems from each other.
3) Distribution – data can be located in different segments of a local enterprise network and/or on the Internet.
4) Differences in data formats.
5) Differences in values representation.
6) Loss of data actuality by one of the sources.

Thus, it becomes necessary to solve the following methodological tasks when organizing the information interaction of the production capacity planning system with the information environment of the aircraft factory [5]–[8]:

1) Creating an integrated data model. The integrated data model is the basis of a single user interface of the integration system.
2) Development of methods for building mappings between the integrated model and models of different data sources.
3) Integration of data sources metadata.
4) Removal of heterogeneity of data sources.
5) Development of mechanisms for semantic integration of data sources.

II. Integration of information systems based on an integrating data model

Linked Data methods are commonly used to solve the methodological problem of building an integrating data model of information systems. Tim Berners-Lee introduced the term Linked Data [9]:

1) Uniform resource identifiers.
2) The HTTP protocol is used for accessing the list of resources.
3) Standard Semantic Web technologies: RDF, OWL, SWRL, SPARQL.
4) Hyperlinks are used to identify web documents and domain entities.

The linked data principle uses standard tools and mechanisms to determine the semantics of relationships between entities represented by data. The OWL [10] knowledge representation language is used to describe the domain entities and the relationships between them. The OWL knowledge representation language has the following advantages [9]:

1) Allows linking the domain entities and documents.
2) Links and relationships between domain entities are typed.
3) The unique identifier of resources allows linking any domain entities by any relationships.
4) Each domain entity is part of global metadata and can be used as a starting point for viewing the entire data space.
5) Information from various sources can be combined by merging a set of entities into one semantic graph.
6) The data model structure is flexible.

Thus, the OWL knowledge representation language is used in the integrating data model as a single unifying data metamodel. The integrated data model based on OWL uses common dictionaries containing terms from various dictionaries of external data sources.

A. Ontological data model

Ontological engineering methods are used to implement the integrating data model between the data model of production capacity planning system and data models of existing at the enterprise information systems.

An ontology is a model of knowledge representation of a specific domain that contains a set of definitions of basic concepts (classes, individuals, properties, etc.) and various semantic links between them. The ontology is based on a glossary of terms that reflecting the domain concept and a set of rules (axioms). Axioms allow combining terms to build reliable statements about the state of the domain at some point in time [11].

Thus, the ontology of the integrating data model is:

$$O = \langle C, P, L, R \rangle, \tag{1}$$

where $C = \{C_1, C_2, \ldots, C_n\}$ – is a set of ontology classes;
$P = \{P_1, P_2, \ldots, P_m\}$ – is a set of properties of ontology classes;
$L = \{L_1, L_2, \ldots, L_o\}$ – is a set of ontology constraints;
R is a set of ontology relations:

$$R = \{R_C, R_P, R_L\}, \tag{2}$$

where R_C is a set of relations defining the hierarchy of ontology classes;
R_P is a set of relations defining the 'class-property' ontology ties;
R_L is a set of relations defining the 'property-constraint' ontology ties.

B. Mapping the data model to the ontological representation

At present, relational databases (RDB) are commonly used for the realization of data models of information systems. RDBs contains a description of the domain in the form of related entities (tables) [12], [13]. It is necessary to develop a method for mapping an RDB structure into an ontological representation of a data model.

The relational data model can be represented as the following expression:

$$RDM = \langle E, H, R \rangle, \tag{3}$$

where $E = \{E_1, E_2, \ldots, E_p\}$ is a set of RDB entities (tables);
$E_i = (name, Row, Col)$ is the i-th RDB entity that contains the name, set of rows and columns;
$Col_j = (name, type, constraints)$ is the j-th column of the i-th RDB entity that contains properties: the name, the type and set of constraints;
$H = \{H_1, H_2, \ldots, H_q\}$ is a hierarchy of RDB entities in the case of using the table inheritance function:

$$H_j = E_i D(x) E_k, \tag{4}$$

where E_i and E_k are RDB entities;
$D(x)$ is a 'parent-child' relation between E_i and E_k;
$R = \{R_1, R_2, \ldots, R_r\}$ is a set of RDB relations:

$$R_l = E_i \frac{F(x)}{G(x)} E_k, \tag{5}$$

where $F(x)$ is an RDB relation between E_i and E_k;
$G(x)$ is an RDB relation between E_k and E_i.

Functions $F(x)$ and $G(x)$ can take values: U is a single relation and N is multiple relations.

The following function is used to map the RDB structure (ex. 3) to the ontological representation (ex. 1):

$$F\,(RDM,O):\{E^{RDM},H^{RDM},R^{RDM}\}\rightarrow \\ \rightarrow\{C^{O},P^{O},L^{O},R^{O}\}, \qquad (6)$$

where $\{E^{RDM},H^{RDM},R^{RDM}\}$ is a set of RDB entities and relations between them (eq. 3);
$\{C^{O},P^{O},L^{O},R^{O}\}$ is a set of ontology entities (eq. 1).

The process of mapping the RDB structure into an ontological representation contains several steps:

1) *Formation of ontological representation classes.*
A set of ontological representation classes C is formed based on the set of RDB entities C $E_i \rightarrow C_i$. The number of classes of the ontological representation must be equal to the number of RDB entities.
2) *Formation of properties of ontological representation classes.*
A set of properties P of the i-th ontological representation class C_i is formed based on the set of columns Col of the i-th RDB entity E_i $Col_j \rightarrow P_j$. The number of properties of the i-th ontological representation class C_i must be equal to the number of columns of the i-th RDB entity E_i. The name of the j-th property P_j is the name of the j-th column Col_j of the RDB entity.
3) *Formation of ontological representation constraints.*
A set of constraints L of the properties of the i-th ontological representation class C_i is formed based on the set of columns Col of the i-th RDB entity E_i $Col_k \rightarrow \hat{L}$. The number of constraints of the i-th ontological representation class C_i must be equal to the number of constraints of the i-th RDB entity E_i. However, there are limitations to this approach due to the difficulty of mapping constraints if their presents as triggers or stored procedures.
4) *Forming hierarchy of ontological representation classes.*
It is necessary to form a set of ontology relationships R_C between all the child and parent classes corresponding to the hierarchy of RDB entities if table inheritance uses in RDB $H \rightarrow R_C$. The domain of the j-th ontological representation relationship R_{Cj} is indicated by the reference to the parent class C_{parent}. The range of the j-th ontological representation relationship R_{Cj} is indicated by the reference to the child (or a set) class C_{child}.
5) *Formation of relations between classes and properties of classes of ontological representation.*
A set of ontological representation relationships R_P is formed based on the set of columns Col of the i-th RDB entity E_i and the set of RDB relations R. Two types of relationships are formed for each j-th ontological representation property P_j:
   a) The relationship 'class-property'. The domain of the ontological representation relationship is indicated by the reference to the i-th class C_i to which the j-th property belongs, and the range to the j-th property reference P_j.
   b) The relationship 'property-data type class'. The domain of the k-th ontological representation relationship is indicated by the reference to the j-th property P_j. The range is indicated by the reference to the l-th class C_l corresponding to the l-th RDB entity E_l, or the reference to the m-th ontology class C_m corresponding to the data type of the j-th RDB column Col_j.
6) *Formation of relations between properties of classes and constraints of properties of classes of ontological representation.*
A set of relations R_L of ontological representation is formed based on the set of columns Col of the i-th RDB entity.The domain of the j-th ontological representation relationship R_{Lj} is indicated by the reference to the k-th property P_k. The range of the j-th ontological representation relationship R_{LJ} id indicated by the reference to the k-th constraint $Col \rightarrow R_L$.

Table 1 contains the description of the mapping of the RDB structural components with the ontological representation entities.

Table I
COMPLIANCE OF RDB COMPONENTS AND ONTOLOGY ENTITIES

RDB component	**Ontology entity**
Table E_i	Class C_i
View E_i	Class C_i
RDB Data type Col_j	Class C_i
Table hierarchy H	Relations R_C
Foreign key Col_j	Property P_j and Relations R_P
Column Col_j	Property P_j and Relations R_P
Constraint Col_j	Constraints $\hat{L}$ and Relations R_L

C. Formation of an integrating data model

It is necessary to form an integrating data model based on the ontological representations that obtained after mapping the RDB structure of each of the integrated information systems into the ontological representation. The definition of an ontological system is used as a formal representation of an integrating data model [14]:

$$\sum^{O}=\langle O^{META},O^{IS},M\rangle, \qquad (7)$$

where O^{META} is the integrating data model ontology (metaontology);
$O^{IS}=\{O_1^{IS},O_2^{IS},\ldots,O_g^{IS}\}$ is a set of ontological representations of information systems that must be integrated;
M is a model of reasoner.

The following steps are necessary to form an integrating data model based on the set of ontological representations of the information systems that must be integrated:

1) *Formation of the universal concept dictionary for the current domain.*
The process of forming an integrating data model O^{META} is based on the presence of common terminology. Ontological representations of all information systems that must be integrated O^{IS} should be built from a single concept dictionary. The concept dictionary is formed by the expert based on the analysis of the obtained ontological representations.
2) *Formation an integrating data model O^{META}.*
At this step, the set of top-level classes C^{META} are added to the integrating data model O^{META}. The set of top-level classes C^{META} describes systems that must be integrated and is used as the basis for ontology merging.
3) *Formation of class hierarchy of integrating data model O^{META}.*
At this step, the integrating data model establishes a correspondence between the class hierarchies $C^{O_i^{IS}}$ of ontological representations O^{IS} of information systems that must be integrated.
4) *Formation of class properties of the integrating data model O^{META}.*
At this step, the integrating data model establishes a correspondence between the properties $P^{O_i^{IS}}$ of ontological representations O^{IS} of information systems that must be integrated. The expert decides which class properties of ontological representations O^{IS} should be included in the integrating data model O^{META}.
5) *Formation of axioms of classes and properties, checking the integrating data model O^{META} for consistency.*
At this step, constraints $L^{O^{IS}}$ are applied to the properties $P^{O^{IS}}$ and classes $C^{O^{IS}}$ of the integrating data model O^{META} based on the constraints presents in the ontological representations O^{IS}. After that, the resulting integrating data model O^{META} should be checked for internal consistency using the reasoner M. However, the development of methods for checking the conditions of constraints is required, since the existing reasoners do not support working with such objects.

III. Types of extracted time series of factory

The task is to extract changes in the values of production processes indicators. Time series models are used for tracking these changes. The methodology for calculating of production capacity uses some coefficients, defined above. But these coefficients not always must be given by an expert or a method. Each of them can be extracted on the factory. As an example, staff time can be tracked for each factory unit; depreciation of equipment can be calculated based on summarizing volumes of completed works.

We extract the following types of time series:

- staff work time fund (fluctuating time series);
- tool work time fund (fluctuating time series);
- performance ratio (growing time series);
- area usage (growing time series);
- depreciation of equipment (growing time series).

These types of time series may be different for different factory units. For all types of processes can be identified monthly indicator values. Very important to find the following characteristics of time series: seasonality, local and global tendencies. The proposition is to use several models for smoothing, extracting and forecasting tendencies and values of the time series of production processes.

IV. Definition of type-2 fuzzy sets to use in time series models

The tasks of time series modeling are solved by a large number of methods. These methods have a different mathematical basis, are divided according to application possibilities (that is, they may have particular applicability conditions depending on the type of problem being solved and the nature of the time series), they may require constant or temporary use of the analyst directly during the modeling process. An important condition for the application of methods is the focus on obtaining short-term forecasts. It follows from the recent features of the processes for which time series models are applied.

The nature of fuzzy time series due to the use of expert estimates, the inherent uncertainty of which belongs to the class of fuzziness. Unlike stochastic uncertainty, fuzziness hinders or even excludes the use of statistical methods and models, but can be used to make subject-oriented decisions based on approximate human reasoning. The formalization of intellectual operations that simulate human fuzzy statements about the state and behavior of complex phenomena, forms today an independent area of applied research, called "fuzzy modeling" [15].

This direction includes a complex of problems, the methodology for solving which is based on the theory of fuzzy sets, fuzzy logic, fuzzy models (systems) and granular calculations. In 1975, Lotfi Zadeh presented fuzzy sets of the second order (type-2) and fuzzy sets of higher orders, to eliminate the disadvantages of type-1 fuzzy sets. These disadvantages can be attributed to the problem that membership functions are mapped to exact real numbers. This is not a serious problem for many applications, but in cases where it is known that these systems are uncertain.

The solution to the above problem can be the use of type-2 fuzzy sets, in which the boundaries of the membership areas themselves are fuzzy [16].

It can be concluded that this function represents a fuzzy set of type-2, which is three-dimensional, and the third dimension itself adds a new degree of freedom to handle uncertainties. In [16] Mendel defines and differentiates two types of uncertainties, random and linguistic. The first type is characteristic, for example, for the processing of statistical signals, and the characteristic of linguistic uncertainties is contained in systems with inaccuracies based on data determined, for example, through expert statements.

To illustrate, note the main differences between type-1 fuzzy sets and type-2 fuzzy sets. Let us turn to 1, which illustrates a simple triangular membership function.

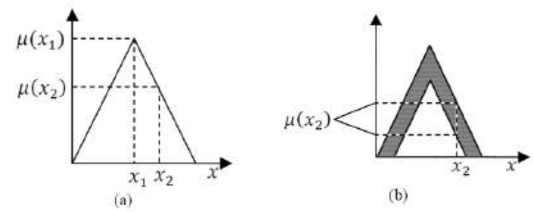

Figure 1. The type of fuzzy sets of the 1st (a) and the 2nd (b) types.

Fig. 1 (a) shows a clear assignment of the degree of membership. In this case, to any value of x there corresponds only one point value of the membership function. If you use a fuzzy membership function of the second type, you can graphically generate its designation as an area called the footprints of uncertainty (FOU). In contrast to the use of the membership function with clear boundaries, the values of the membership function of type 2 are themselves fuzzy functions.

This approach gave the advantage of approximating a fuzzy model to a verbal one. People can have different estimates of the same uncertainty. Especially it concerns estimated expressions. Therefore, it became necessary to exclude a unique comparison of the obtained value of the degree of the membership function. Thus, when an expert assigns membership degrees, the risk of error accumulation is reduced because of the non-inclusion of points located near the boundaries of the function and under doubt.

V. Time series model based on type-2 fuzzy sets

Time series modeling based on type-2 fuzzy sets allow to build the model reflecting uncertainty of the choice of values of coefficients or values of indicators determined by an expert. Choose an interval time series as type of time series for the object of modeling. For our subject area, previously selected time series of indicators are easily represented by proposed type of time series: most time series have a rare change in values. Can mark stability of intervals. For interval time series, an algorithm for constructing a model is described in [17].

The formal model of the time series:

$$TS = \{ts_i\}, i \in N, \tag{8}$$

where $ts_i = [t_i, B_{t_i}]$ is an element of the time series at the moment of time t_i and a value in the form of a type-2 fuzzy set B_{t_i}. For the entire time series, the universe of type-2 fuzzy sets is defined as $U = (B_1, ..., B_l), B_{t-i} \in U, l \in N, l$ - the number of fuzzy sets in the universe. A set B_{t_i} is a type 2 fuzzy set, therefore, a type-1 fuzzy set is assigned to it as a value. For interval time series, a prerequisite for creating type-1 sets is a part separated from the source series, limited, for example, by a time interval of 1 day, 1 month or 1 year. For the selected interval, a universe of type-1 fuzzy sets is defined.

The algorithm for constructing a model will be used the same as described in [17], except for the moment of choice of intervals: they will be determined based not on the time characteristic, but on the boundaries of the initially formed sets of type 2.

The form of fuzzy sets is proposed to use a triangular due to the small computational complexity when conducting experiments.

VI. Experiment

The experiment plan implies the construction of time series models and the assessment of their quality. For experiments, time series have been generated. The fore-

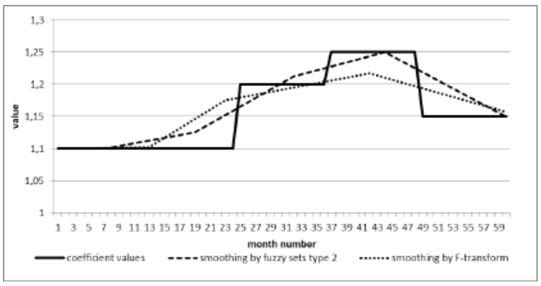

Figure 2. Smoothing the time series of the coefficient

casting process at this stage will not be carried out; therefore, an internal measure of the quality of the model will be assessed using the SMAPE criterion [18]:

$$SMAPE = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|F_t - A_t|}{(|A_t| + |F_t|)/2} \tag{9}$$

Consider the process of smoothing the coefficient. The original time series has 60 points. For comparison, the graph of Fig. 2 shows the smoothing of the time series by the F-transform method [19].

For smoothing, a set of 15 type-2 fuzzy sets and 5 sets of type-1 was selected. As can be seen from the, Fig. 2, 5 points of a smooth series were obtained. SMAPE score for both types of smoothing:

- for F-transform - 2.01%,
- for type-2 fuzzy sets - 0.65%.

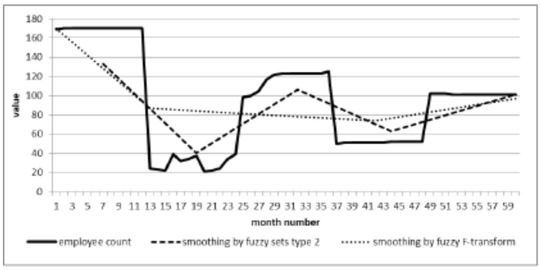

Figure 3. Smoothing the time series of employee count

Next smooth employee count time series, Fig. 3. For smoothing, a set of 15 type-2 fuzzy sets and 5 sets of type 1 was chosen. For the time series, 5 points of a smoothed series were also obtained. SMAPE score for both types of smoothing:

- for F-transform - 47.54%,
- for type-2 fuzzy sets - 13.23%.

It was also a comparison of the internal measures of the quality of the model for SMAPE with simple exponential smoothing. The estimates showed the best by 0.1% smoothing quality by the method we proposed using using type-2 fuzzy sets.

CONCLUSION

This article presents the implementation of the method of integrating the information systems of the aircraft factory with the production capacity planning system. The principles of linked data and ontological engineering allows mapping database structure of each information system that must be integrated into ontological representation. From the proposed methodology, an integrated data model is formed based on the obtained ontological representations for each information systems that must be integrated.

The analysis of existing algorithms, data and information systems has shown a strong accumulation of errors in process of production capacity planning. These principles allow improving the quality of technological preparation of complex industries. Proposed methods of prediction of time series are improve the quality of management decisions.

Successfully applied an approach based on type-2 fuzzy sets, to form a model of a time series of production processes. It should be noted that the approach based on modeling interval time series gives a positive result. This moment is fixed as a result of the smoothing procedure, when the number of selected points and their values are as close as possible to the stabilization intervals.

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ПОСТРОЕНИЕ СИСТЕМЫ БАЛАНСА ПРОИЗВОДСТВЕННЫХ МОЩНОСТЕЙ АВИАЦИОННОГО ЗАВОДА

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В данной статье описаны основные принципы построения системы поддержки принятия решений для планирования производственных мощностей крупного авиационного завода. Описан метод интеграции информационных систем авиационного завода с системой баланса производственных мощностей на основе метода слияния онтологий. Для каждой информационной системы выполняется процесс отображения структуры базы данных в онтологическое представление. Интеграционная модель данных формируется на основе онтологических представлений структуры базы данных каждой информационной системы. Интеграционная модель представляет собой механизм семантической интеграции источников данных. Также представлен метод извлечения временных рядов из бизнес-процессов авиационного завода. Предложена модель прогнозирования временных рядов в задаче планирования производственных мощностей на основании нечетких множеств типа 2.

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