Approach to Data-Driven Production Management

Anton Romanov
Department of Information Systems
Ulyanovsk State Technical University
Ulyanovsk, Russia
romanov73@gmail.com
ORCID: 0000-0001-5275-7628

Aleksey Filippov
Department of Information Systems
Ulyanovsk State Technical University
Ulyanovsk, Russia
al.filippov@ulstu.ru
ORCID: 0000-0003-0008-5035

Nadezhda Yarushkina
Department of Information Systems
Ulyanovsk State Technical University
Ulyanovsk, Russia
jng@ulstu.ru
ORCID: 0000-0002-5718-8732

***Abstract*—There are many methods and models for analyzing and managing complex systems. They differ in both the degree of complexity and the degree of detail of the described objects. Mathematical models of business processes are very hard to implement. They do not consider multiple external and internal influences on the production, which makes such models less effective.**

An alternative way to solve the production management problem is to introduce some parameterized algorithms as a simplified form of mathematical models. Such algorithms are usually expressed in the form of instructions, which are based on the analyzed statistics. The disadvantage of this approach is the significant averaging of the values of indicators and parameters of the modeled objects. Methods are formulated for a whole range of similar industries, and they are unsuitable for the specific conditions of each enterprise.

It is necessary to create data analysis methods and process models that are adaptable to specific production conditions.

Data from the information systems of various manufacturing enterprises can be analyzed to determine the states and conditions of production. The important knowledge for production management is extracted as a result of such analysis.

The article describes a hybrid approach for analyzing the dynamics of production indicators and forming linguistic recommendations to increase the efficiency and quality of decision making. Hybridization means the usage of ontological engineering methods to describe the characteristics of production in the context of production indicators represented by time series models.

***Keywords*—data-driven decision making, type-2 fuzzy sets, time series forecasting, ontology, inference**

I. Introduction

Existing formal models of production processes do not have the necessary capabilities for organizing data-driven production management for modern complex industries, taking into account the dynamics of production [1]–[3]. Aircraft manufacturing is used as an example of a manufacturing enterprise in this study.

Aircraft is a complex system with both quantitative and qualitative complexity. The quantitative complexity is determined by the quantity of the components of the aircraft. The qualitative complexity is determined by the complexity of production processes and a high degree of uncertainty caused by the integral influence of many external and internal factors.

Modern aircraft enterprises produce a line of systems and their modifications. This fact determines the dynamic nature of production processes and the need for their adaptation to the changing nature of the problem area.

The industry-accepted standards of the industrial methodology are used to represent aircraft manufacturing and capacity management. The industrial methodology is formed based on averaged indicators in the industry, which leads to the following problems [4], [5]:

1) A large number of statistical factors and assumptions are used for production control.
2) Absence of methods for an objective evaluation of the current state of production.
3) Absence of methods for identifying problems and deviations in production processes.
4) Automation of production processes does not imply an evaluation of the complex state of the enterprise leads to:
   - the complexity of forming an adaptable production model,
   - frequent changes in methods for calculating evaluation indicators,
   - the inability to identify hidden processes and subprocesses.

Capacity management is the decision-making process for the choice of equipment used, planning and management of the work schedule and working hours, materials and blanks, units, and assemblies.

The solution is based on an analysis of the data of the enterprise information systems. The dynamic state of objects is modeled by a fuzzy time series.

In this case, the task is similar to the traditional problem of situational control of some object [1] (fig. 1).

As you can see from figure 1, $(n + r)$ inputs X and W act on the controlled object. The value of the input x_i can be determined at any time, but there is no such possibility for the value of the input w_j. The controlled object has m outputs Y. It is assumed that changes in the input values of X and W affect to the output values of Y, therefore exists some implicit function $Y = f(X, W)$.

The output values of Y are usually critical in the decision-making process for controlling an object. The decision-maker (DM) needs to get certain values of the output parameters Y, while the DM cannot modify the input values of X and W.

Obtaining the necessary values of Y is possible by changing the values of U, so the function $Y = F(X, U, W)$ exists. It is necessary to find such values of U to get the output values of Y that satisfy the decision-maker with known input values of X and unknown input values of W. Thus, the function to control an object is $U = \Phi(X, Y)$.

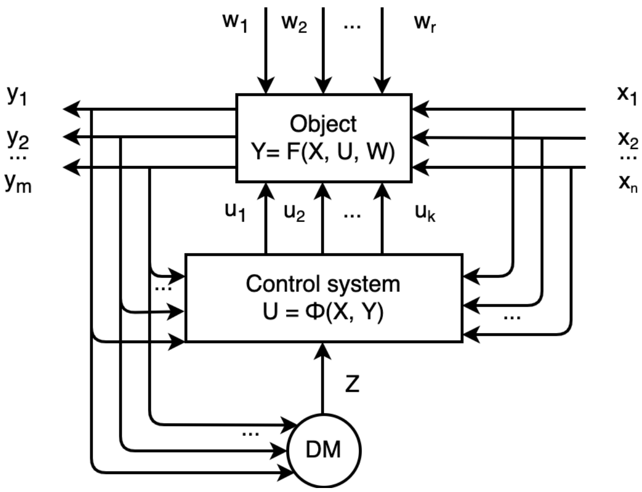

Fig. 1. An example of situational control of an object.

II. The task of data-driven production management

The main goal of the study is to reduce the degree of uncertainty in the capacity management process of complex production. Each production has various characteristics. Also, complex production is an unconventional object of management in the concept of the situational control theory [1].

The capacity management includes next steps:

- developing technical passport of the enterprise;
- calculation of capacities for each production unit and the enterprise as a whole;
- development of shortage control strategy;
- generation of a consolidated report with the forecast for the implementation of the product program;
- calculation of consolidated capacity balance.

The input parameter vector W from situational control includes such indicators as the fund of working time, equipment usage, the useful annual fund of equipment time, and others. These indicators have a great influence on the evaluation of total production productivity. The inability of the DM to set the values of these indicators severely limits the efficiency of decisions.

Thus, the following research objectives must be solved:

- data collection of production state through integration with enterprise information systems (data consolidation, ETL) [6],
- trend analysis of process performance (time-series analysis and modeling),
- developing recommendation for the DM to manufacture upgrade in terms of balancing production capacities.

Trend analysis in production processes is carried out using the proposed models and methods for analyzing time series based on type 2 fuzzy sets. The results of modeling the time series of production indicators are input data for the subsystem for generating recommendations for the modification of production. This allows to expand the output vector Y. Estimated and forecasted values of indicators and recommendations for production modification allow discarding some parameters of the vector W.

These models and the analyzed indicators will be included in the control system $U = \Phi(X, Y)$.

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

Type-2 fuzzy sets are making it possible to model uncertainty of higher degree in the process of time series modeling [7], [8]. It is suggested to use the triangular shape of fuzzy sets. The triangular shape of fuzzy sets has low computational complexity on time-series modeling.

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 fig. 2 shows the appearance of the sets.

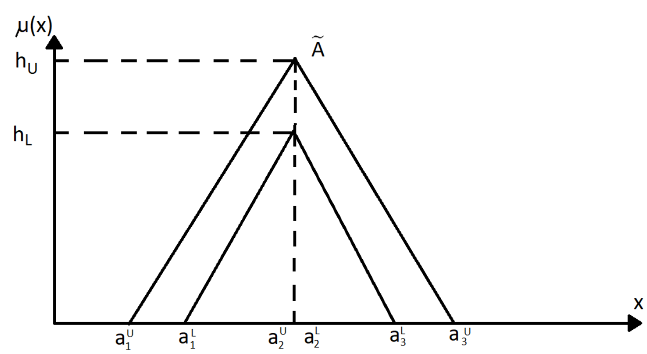

Fig. 2. The shape of the upper and lower membership functions.

Triangular fuzzy sets are defined as follows:

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

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

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

The proposed algorithm for smoothing and forecasting of time series based on type 2 fuzzy sets 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 $M = \{\mu_1, \ldots, \mu_l\}, l \ll n$, 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. To decrease the dimension of the set of relations it is necessary to reduce the number of fuzzy sets at each level. Obliviously, this approach decrease the approximation accuracy of a time series. However, creating the set of membership functions at the second and higher levels increase the approximation accuracy with an increase in the number of levels.
3) Definition of fuzzy sets for a time series. The superscript defines the type of fuzzy sets in that case. $A^1 = \{A_1^1, \ldots, A_l^1\}, A^2 = \{A_1^2, \ldots, A_m^2\}$, 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: $A_1^1 A_1^2 \ldots \longrightarrow A_2^1 A^2 1$.
7) 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) Errors evaluation.

IV. Ontology-based linguistic summarization of a time series forecast

Linguistic Summarization of the time series forecast allows the decision-maker to react to changes in the production state more operatively. The rule base in the form of the following ontology is used to get linguistic summarization of the time series forecast [10], [11]:

$$O = \langle I, E, S, A, R, F \rangle, \tag{1}$$

where $I = \{I_1, I_2, \ldots, I_n\}$ is a set of indicators that determine the state of the production capacities at some point in time;
$E = \{Bad, Good, High, Middle, Low\}$ is a set of linguistic labels for linguistic summarization of the values of production indicators;
$S = \{StateHigh, StateMiddle, StateLow\}$ is a set of textual representations of linguistic labels from the set E;
$A = \{\langle I_1, Bad\rangle, \langle I_1, Good\rangle, \langle I_2, Bad\rangle, \langle I_2, Good\rangle, \ldots, \langle I_n, Bad\rangle, \langle I_n, Good\rangle\}$ is a set of textual representations of recommendations for each production indicator that depends on various evaluation of its condition: $Good$ (within the norm) and Bad (deviation from the norm);
R is a set of ontology relationships:

$$R = \{R_E S, R_E A, R_I E\},$$

where $R_E S$ is a set of relationships between a linguistic label and its textual representation;
$R_E A$ is a set of relationships between a linguistic label and a textual representation of a recommendation;
$R_I E$ is a set of relationships between a value of production indicator and its linguistic label. This type of relationship is formed in the process of linguistic summarization of the values of production indicators using the reasoner and the set of rules in the SWRL language [12];
F is interpretation function that forms the set of relations $R_I E$ defined by the set of rules in SWRL.

The $\mathcal{ALCHF}(\mathcal{D})$ [13]–[15] extension of the descriptive logic is used for the logical presentation of the ontology O (eq. 1) for linguistic summarization of the time series forecast. With using the description logic $\mathcal{ALCHF}(\mathcal{D})$ the ontology O can be represented as:

$$O = TBox \cup ABox,$$

where $TBox$ is the terminological box;
$ABox$ is the assertional box.

The $TBox$ contains statements describing concept hierarchies and relations between them. The $ABox$ contains axioms defined as a set of individuals and relations between individuals and concepts.

A. Terminological box $TBox$

$E \sqsubseteq \top \qquad Bad \sqsubseteq E \qquad Good \sqsubseteq E$
$High \sqsubseteq E \qquad Middle \sqsubseteq E \qquad Low \sqsubseteq E$
$High \sqsubseteq \neg Low \qquad High \sqsubseteq \neg Middle$
$Middle \sqsubseteq \neg Low \qquad Bad \sqsubseteq \neg Good$
$Recommendation \sqsubseteq \top \qquad A \sqsubseteq Recommendation$
$S \sqsubseteq Recommendation$
$StateHigh \sqsubseteq S \qquad StateMiddle \sqsubseteq S$
$StateLow \sqsubseteq S$
$StateHigh \sqsubseteq \neg StateMiddle$

$$StateHigh \sqsubseteq \neg StateLow$$
$$StateLow \sqsubseteq \neg StateMiddle$$
$$I \sqsubseteq \top$$
$$I \equiv \top \sqcap \exists hasResume.A \sqcap \exists hasState.S \sqcap$$
$$\sqcap \exists hasValue.Double$$
$$Recommendation \equiv \top \sqcap \exists hasDescription.String \sqcap$$
$$\sqcap \forall hasDescription.String$$

where E is a concept representing a linguistic label of ontology;
Bad, $Good$, $High$, $Middle$, Low are concepts representing linguistic labels for linguistic summarization of values of production indicators;
I is a concept representing a production indicator;
S is a concept representing a linguistic label;
A is a concept representing ontology recommendations;
$StateHigh$, $StateMiddle$, $StateLow$ are concepts representing the state of production capacities;
$Recommendation$ is a concept representing linguistic labels and recommendations in textual form;
$\sqsubseteq$ is the concept inclusion axiom;
$hasResume$ is a role to set the correspondence between the recommendation and the production indicator;
$hasState$ is a role to set the correspondence between a linguistic label and a production indicator;
$hasValue$ is a role to set a value (in Double) of production indicator;
$hasDescription$ is a functional role to specify a textual description (in String) of a linguistic label or recommendation.

B. Assertional box $ABox$

$i_1 : I$ $\qquad$ $i_1 : High$
$s_1 : StateHigh$ $\qquad$ $a_1 : A$
$(i_1, value1 : Double) : hasValue$
$(i_1, s_1) : hasState$
$(a_1, value2 : String) : hasDescription$
$(i_1, a_1) : hasResume$

C. Linguistic summarization of production indicators

Suppose that at some enterprise two indicators of production capacities are used:

1) Power in man-hours per 1 month (EP).
2) Power in machine hours per 1 month (TP).

Production indicator values must be specified based on forecast values in the form of following $ABox$ axioms:

$EP : I$ $\qquad$ $TP : I$
$(EP, 3610) : hasValue$
$(TP, 2700) : hasValue$

The expert is forming the following set of SWRL-rules to produce a linguistic summarization for each production indicator:

```
EP(?ind) ^ hasValue(?ind, ?val)
   ^ swrlb:lessThanOrEqual(?val, 2000)
   −> Low(?ind)
EP(?ind) ^ hasValue(?ind, ?val)
   ^ swrlb:greaterThan(?val, 2000)
   ^ swrlb:lessThanOrEqual(?val, 4000)
   −> Middle(?ind)
EP(?ind) ^ hasValue(?ind, ?val)
   ^ swrlb:greaterThan(?val, 4000)
   −> High(?ind)

TP(?ind) ^ hasValue(?ind, ?val)
   ^ swrlb:lessThanOrEqual(?val, 1000)
   −> Low(?ind)
TP(?ind) ^ hasValue(?ind, ?val)
   ^ swrlb:greaterThan(?val, 1000)
   ^ swrlb:lessThanOrEqual(?val, 3000)
   −> Middle(?ind)
TP(?ind) ^ hasValue(?ind, ?val)
   ^ swrlb:greaterThan(?val, 3000)
   −> High(?ind)
```

Each production indicator is associated with a specific linguistic label after the implementation of these rules:

$EP : Middle$ $\qquad\qquad$ $TP : Middle$

A predefined set of SWRL rules is used to map a linguistic label to its textual representation:

```
Low(?ind) ^ StateLow(?state)
   −> hasState(?ind, ?state)
Middle(?ind) ^ StateMiddle(?state)
   −> hasState(?ind, ?state)
High(?ind) ^ StateHigh(?state)
   −> hasState(?ind, ?state)
```

Following axioms are added in $ABox$ after executing the set of SWRL rules presented above:

$(EP, StateMiddle) : hasState$
$(TP, StateMiddle) : hasState$

The following rule in SQWRL language [16] is used to produce the linguistic summarization of production indicators based on the content of $ABox$:

```
hasState(?ind, ?state)
   ^ hasDescription(?state, ?descr)
   −> sqwrl:select(?ind, ?descr)
```

Executing a query in the SQWRL language presented above produces the following result:

TP	The value of the production indicator is average
EP	The value of the production indicator is average

Linguistic labels are used to forming recommendations for balancing the production capacities of an enterprise.

D. Generation of linguistic recommendations for production management

The following set of SWRL rules set by the expert is used to generate recommendations for balancing the production capacities:

EP(?ep) ˆ Low(?ep) −> Bad(?ep) EP(?ep) ˆ Middle(?ep) −> Bad(?ep) EP(?ep) ˆ High(?ep) −> Good(?ep)

TP(?ep) ˆ Low(?ep) −> Bad(?ep) TP(?ep) ˆ Middle(?ep) −> Bad(?ep) TP(?ep) ˆ High(?ep) −> Good(?ep)

The SWRL rules presented above are based on linguistic labels assigned by the linguistic summarization algorithm and generate the following $ABox$ axioms:

$EP : Bad$ $\quad$ $TP : Bad$

The following SWRL rules are used to generate textual recommendations for balancing production capacities based on the attached linguistic labels of production indicators:

EP(?ep) ˆ Bad(?ep) ˆEP_Bad(?res)
−> hasResume(?ep, ?res)
EP(?ep) ˆ Good(?ep) ˆ EP_Good(?res)
−> hasResume(?ep, ?res)

TP(?tp) ˆ Bad(?tp) ˆ TP_Bad(?res)
−> hasResume(?tp, ?res)
TP(?tp) ˆ Good(?tp) ˆ TP_Good(?res)
−> hasResume(?tp, ?res)

EP(?ep) ˆ Bad(?ep) ˆ TP(?tp) ˆ Bad(?tp)
ˆ EP_TP_Bad(?res)
−> hasResume(?ep, ?res) ˆ hasResume(?tp, ?res)

EP(?ep) ˆ Good(?ep) ˆ TP(?tp) ˆ Good(?tp)
ˆ EP_TP_Good(?res)
−> hasResume(?ep, ?res) ˆ hasResume(?tp, ?res)

Recommendations for balancing production capacities (EP_Bad, EP_Good, TP_Bad, TP_Good, EP_TP_Bad, EP_TP_Good) set by the expert and contains some textual representation.

$ABox$ is contained the following axioms after the execution of SWRL rules presented above:

$(EP, \text{EP\_BAD}) : hasResume$
$(EP, \text{EP\_TP\_BAD}) : hasResume$
$(TP, \text{TP\_BAD}) : hasResume$
$(TP, \text{EP\_TP\_BAD}) : hasResume$

The following rule in SQWRL language is used to develop recommendations for balancing production capacities of enterprise based on the content of $ABox$:

hasResume(?ind, ?rule)
ˆ hasDescription(?rule, ?descr)
−> sqwrl:selectDistinct(?ind, ?rule, ?descr)

The following result will be obtained as a result of executing the SQWRL rule presented above:

EP EP_Bad ”Capacity in man−hours per 1 month is not enough to execute the production program. Additional personnel is required.”

TP TP_Bad ”Capacity in machine hours per 1 month is not enough to execute the production program. Additional equipment is required.”

EP EP_TP_Bad ”Capacity in man−hours and machine hours per 1 month is not enough to execute the production program. The following steps must be taken: buy additional equipment, hire additional personnel.”

TP EP_TP_Bad ”Capacity in man−hours and machine hours per 1 month is not enough to execute the production program. The following steps must be taken: buy additional equipment, hire additional personnel.”

Recommendations generated for different indicators (EP and TP) and received after the implementation of the same rule (recommendation EP_TP_Bad) are displayed only once. Recommendations formed by more complex (compound) rules (recommendation EP_TP_Bad) overlap recommendations of more simplistic rules (recommendations EP_Bad, TP_Bad). Thus, the user has received the following information as recommendations for balancing the production capacities of the enterprise:

Capacity in man−hours and machine hours per 1 month is not enough to execute the production program. The following steps must be taken: buy additional equipment, hire additional personnel.

V. Conclusion

Data-driven production management is a relevant area of research. The growth of data-driven production management is promoted by both the existing automation systems at enterprises and the volumes of data accumulated in such systems.

This article has proposed an approach to the analysis of the dynamics of production indicators based on time series models. Type 2 fuzzy sets are used for time series modeling. Type 2 fuzzy sets allow modeling objects with a higher degree of uncertainty.

The proposed approach allows to increase the efficiency of decision-making on production management. The proposed approach in contrast to the decision-making process based on an industrial methodology operates not with average production indicators, but with values of production indicators extracted from the information systems of an enterprise.

The proposed approach to the formation of linguistic recommendations allows decision-makers to gain a deeper understanding of the current state of production and respond to changes in production indicators more operatively. The process of forming linguistic recommendations is based on a set of fuzzy and SWRL-rules.

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