About the formation of the knowledge base for fuzzy control system of pricing in the pharmacy network

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Abstract. This article offers the approach to the formation of a knowledge base in the form of a set of fuzzy production rules. It is assumed that the parameters characterizing a complex system are divided into basic and additional, which depend on the basic ones. To describe the trends of the basic parameters, a linguistic scale is formed. Using a special clustering method, the typical states of a complex system are determined, as well as the critical values of additional parameters. Each production rule establishes a correspondence between the typical state and the critical values of additional parameters. The proposed approach was tested in the task of managing pricing in the pharmacy network by determining the optimal mark-up value for pharmaceutical products using an expert system.

1. Introduction
When developing models and methods of data analysis, the results of which should be integrated with decision support systems, the central place is occupied by the problems of developing valid methods for modeling the knowledge components defined on time series intervals.

The formulation of the problem of modeling a time series in general form consists in identifying the dependence of the corresponding indicator on time based on historical data, and it is assumed that the revealed dependence will continue for a limited period in the future. This allows us to estimate the values of this indicator, considering a given forecasting horizon. Currently, there are several main approaches to time series modeling: statistical approach [1, 2], neural network approach [3–5], fuzzy approach [5–7]. The statistical approach, which has become a classical one, is based on the restoration of dependence in the form of a statistical model, which includes systematic and random components. Here, the systematic component in the general case is a linear combination of the trend, periodic and seasonal components, as well as (if necessary) the autoregressive component. Modeling time series in the framework of the neural network approach is reduced to the problem of the best approximation of a nonlinear function of many variables, the parametric model of which is a neural network. The learning capability is one of the main advantages of neural networks, and in the process of learning a neural network can identify complex non-linear dependencies and perform a generalization. The Fuzzy Approximation Theory, according to which, we can arbitrarily accurately describe the arbitrary relationship inputs-output using conditional statements if-then followed by their formalization based on linguistic variables, is the basis of fuzzy modeling of time series.
The purpose of the paper is to present the approach for building a knowledge base of a fuzzy system for predicting the state of a complex system based on time series describing its behavior on a given time interval.

2. Materials and methods

2.1. Decomposition Tree Method

Currently, there are a significant number of clustering/classification methods for various types of information. In addition to the class of statistical methods that are well-proven and widely used in applications, other methods have appeared — they work with symbolic data [8], as well as with approximate information.

Let us consider the fuzzy classification problem in the following formulation [9]: let a finite set of objects be given, and the distance matrix between them defines an anti-reflexive and symmetric fuzzy relation, which by definition is a dissimilarity. It is required to define the transitively nearest subsets, i.e. those that fall into one class when using so-called transitive distances.

Based on the method for determining the transitively nearest subsets [9], the decomposition tree method [10] was developed as part of the author’s research. Its flow chart is presented in figure 1.

![Figure 1. Flow chart of the decomposition tree method.](image_url)

The initial information is formed in the form of a fuzzy binary relation of dissimilarity (anti-reflexive and symmetric relation) or similarity (reflexive and symmetric relation). Distance functions, resemblance functions, and similarity/dissimilarity indices can be used for this purpose. Each variant of the method is determined by the type of the relationship — similarity or dissimilarity — formed at the beginning. We note that similarity and dissimilarity relations in the general case do not have transitivity property. To ensure this property, a transitive closure operation is used, which is determined by the type of fuzzy composition. In [11, 12], the properties of \(\text{max-}T\)- and \(\text{min-}S\)-compositions and the corresponding types of transitivity are investigated. Here, \(T\) and \(S\) are the triangular norm and conorm, which model respectively the operations of intersection and operations of union of fuzzy sets. A reflexive, symmetric, and transitive relation is called a resemblance, its negation is a difference (and vice versa). The difference relation matrix is a matrix of transitive distances. According to the decomposition theorem [9], any resemblance \(\alpha\)-cuts a usual equivalence relation and, therefore, determines the partitioning of a set of objects into disjoint equivalence classes. Assigning successive values to the parameter \(\alpha\), we get the set of partitions that form the decomposition tree. In [11], the decomposition theorem was proved for the difference relation, which allows us to obtain the same equivalence classes as the additional resemblance relation. 
The main advantages of the decomposition tree method are the following:

– the possibility to work with heterogeneous information due to the fact that the similarity/dissimilarity relation formed at the initial step is based on special functions. Their domain can be arbitrary, related to the measurement scale, and the value domain can always be represented as [0, 1];

– the possibility of obtaining many different partitions, which allows us to select the most suitable partitioning option by attracting additional information about the decision-making situation or by clarifying the optimality criteria;

– the decomposition tree represents the sequential process of partitioning a given set of objects into classes, and for each object it is possible to trace its evolution from the situation when all objects fall into one class, to the situation when this object forms a unique class;

– each level can be associated with a certain classification threshold, and we can select the optimal threshold value by analyzing the resulting partitioning;

– the use of parametric fuzzy operations (triangular norms and conorms) allows us to set the method for a specific user or a specific problem.

To estimate the proximity of objects in the formation of the dissimilarity relation, we can use the standard distance functions, which are generalized by the formula

$$\rho(x^i, x^j) = \sqrt{\left(\sum_{k=1}^{n} |x^i_k - x^j_k|^p\right)},$$

where $x^i, x^j$ are vector estimates of objects and $p$ is an adjustable parameter.

### 2.2. General description of the proposed approach

Let the $n$ parameters of some complex system be observed at the moments of time $t = t_0, \ldots, T$, so that at each moment of time $t$ the state of the system is characterized by the vector $x^t = (x^t_1, \ldots, x^t_n)$. On the other hand, each parameter $P_i$ ($i = 1, n$) can be assigned the time series $X_{i,T} = \{x^i_{t_0}, \ldots, x^i_T\}$. Thus, for the interval $t_0, \ldots, T$, the behavior of the system is described by a set of $n$ time series.

We note that if we obtain a partition of the set of states $\{x^t\}_{t=1,T}$ into $m$ clusters, when similar in a certain sense state vectors are combined into one cluster, we can distinguish $m$ typical states of the system $S_j$ ($j = 1, m$), each of which can be described in terms of its parameters $P_i$ ($i = 1, n$).

Let the moment of the beginning of observation $t_0$ be equal to 0. Suppose that a piecewise linear approximation of all time series is made based on segmentation methods [7, 13–15], and all linear trends are constructed. On $[0, T]$, we define the points $\tau_i$ at which the direction of the trend changes for at least one time series. As a result, we obtain the intervals $T_i = [\tau_i, \tau_{i+1}]$ ($i = 0, N - 1$) that form a partition of the observation area $[0, T]$, and the direction of any trend does not change on each interval. We assume that the set of trends on any of the intervals $T_i$ describes a certain state of the system $S_j$ ($j = 1, m$).

Let $\alpha$ be the inclination angle of the trend. We construct the Increase-Decrease scale of a linear trend, considering the angle $\alpha$ [13]. Figure 2 shows the graphical representation of the axes of directions, which will be called the basic ones. Each ray corresponds to the axis of the base direction $D_i$. Table 1 lists the scale graduations, and the value of the inclination angle $\psi_i$ of the axis of the basic direction $D_i$ is indicated for each graduation. For each value $t$, the corresponding value $y_i$ located on the direction axis $D_i$ is determined by the formula

$$y_i = t \cdot \tan(\psi_i).$$

Let us hold the interval $T_i$ fixed. Each parameter $P_j$ ($j = 1, n$) on this interval corresponds to the linear trend $LT_j$ with the inclination angle $\psi_{LT_j}$. For the given inclination angle $\psi_{LT_j}$,
it is possible to determine the value of the membership functions $\mu_{D_1}(\psi_{LT_j}), \ldots, \mu_{D_9}(\psi_{LT_j})$ corresponding to all basic directions, where

$$\mu_{D_k}(\psi_{LT_j}) = \frac{1}{1 + \left| \frac{\psi_{LT_j} - \psi_k}{a} \right|^b},$$

where $b$ is an adjustable parameter.

Then we attribute the basic direction $D_k$ to the parameter $P_j$. This direction corresponds to the index

$$k^* = \arg \max_k \{\mu_{D_k}(\psi_{LT_j})\}.$$

Thus, each state $S_{T_i}$ of the system on the interval $T_i$ can be assigned the vector $Y_{T_i} = (y^j_{T_i})_{j=1}^n$, where $y^j_{T_i}$ is the basis direction code for the trend $LT_j$ on the interval $T_i$. This vector will be called the code vector.

![Figure 2. Axes of basic directions.](image)

The evolution of the system is described by the set of code vectors $\{Y_{T_i}\}_{i=0}^{N-1}$. Using the cluster procedure (the decomposition tree method), we obtain a partition of the set of system states into classes of states that are close in behavior. Additional information is used, or an expert is involved to select the appropriate partition.

Suppose that clusters $Cl_1, \ldots, Cl_N$ are identified based on the analysis of the behavior of the system, and each cluster corresponds to a certain behavior of parameters $P_1, \ldots, P_n$. We define a typical system state, which corresponds to the cluster $Cl_r = \{S_{t_1}, \ldots, S_{t_{nr}}\}$, where each state
Table 1. Linear trend scale.

| Code | Inclination angle | Graduations | Abbreviation |
|------|-------------------|-------------|--------------|
| 9    | $\frac{4\pi}{8} - \alpha_0$ | very quickly increases | VQI |
| 8    | $\frac{3\pi}{8}$ | quickly increases | QI |
| 7    | $\frac{\pi}{4}$ | increases | I |
| 6    | $\frac{\pi}{8}$ | slowly increases | SI |
| 5    | 0 | constant | C |
| 4    | $\frac{\pi}{8}$ | slowly decreases | SD |
| 3    | $\frac{\pi}{4}$ | decreases | D |
| 2    | $\frac{3\pi}{8}$ | quickly decreases | QD |
| 1    | $\frac{4\pi}{8} - \alpha_0$ | very quickly decreases | VQD |

$S_{ik}$ is determined by the code vector $(y_{i1}^{ik}, \ldots, y_{in}^{ik})$, as follows:

$$Type_r = \left( \text{round} \left( \frac{1}{n_r} \sum_{l=1}^{n_r} y_{i1}^{il} \right), \ldots, \text{round} \left( \frac{1}{n_r} \sum_{l=1}^{n_r} y_{in}^{il} \right) \right),$$

i.e. the typical state is determined by an averaged system behavior for each parameter in the given class.

Suppose that there is the universal set of indicators $Z = \{Z_j\}_{j=1}^M$ on which the observed parameters $P_1, \ldots, P_n$ depend, and, depending on the behavior, each parameter depends on its own set of indicators. Let the parameter $P_j$ depend on the set of indicators $Z_{ij} \subseteq Z$ on the time interval $T_i$, and this dependence, considering the type of behavior $y_j$, is described by the regression function $\varphi_{ij}(y, z_{ij})$, where $z_{ij}$ is the list of variables corresponding to the indicators from the set $Z_{ij}$. In a particular case, function $\varphi_{ij}$ can be a constant.

Let the typical state of the system be determined by the cluster $Cl_r = (S_{i1}, \ldots, S_{imr})$, where the state $S_{ik}$ corresponds to the code vector $(y_{i1}^{ik}, \ldots, y_{in}^{ik})$, $y_{ij}^{ik}$ is the code that determines the behavior of the parameter $P_j$ on the interval $T_{ik}$, and the regression function $\varphi_{ikj}(y_{ij}^{ik}, z_{ikj})$ corresponds to this behavior. We define the function for the cluster using the arithmetic mean operation in the form

$$Val_r = \left( \frac{1}{n_r} \sum_{k=1}^{n_r} \varphi_{ik1}, \ldots, \frac{1}{n_r} \sum_{k=1}^{n_r} \varphi_{ikn} \right) = (V_{r1}, \ldots, V_{rn}).$$

We note that in addition to the arithmetic mean, other averaging functions can be used, in particular, the operations of ordinal weighted aggregation, whose coefficients are found using fuzzy majority quantifiers [10].
Thus, each typical system state, which is determined by the cluster $C_l_r$, will be assigned the vector $Val_r = (V_{r1}, \ldots, V_{rn})$.

We note that each typical state of the system allows us to consider the whole set of factors acting on all considered parameters.

3. Application: pharmacy network pricing control

3.1. Problem Statement

A pharmaceutical network consisting of pharmacies located in the specific region sells a variety of pharmaceutical products. In each pharmacy, all products are divided into groups of similar, interchangeable products. Revenues of each pharmacy for a specific period are defined in the form of total profits for all groups of products. The total revenue of the pharmaceutical network is expressed in the form of total profits of all pharmacies. For simplicity we shall assume that the cost of each product is the sum of a certain base cost and a mark-up. Thus, the cost of each product can be controlled by changing the value of the mark-up, but it is important that the total profit should be no less than for a certain monitoring period, which is chosen taking into account, for example, seasonality, epidemic periods and other factors.

It is enough to consider the solution of this problem for one arbitrary group of products and then apply it to all pharmacies of the pharmaceutical network.

We assume that the mark-up value is non-negative and limited to the maximum allowable level.

3.2. Identification of typical situations and the formation of fragments of the knowledge base

Let us consider the group of products $P_1, P_2, P_3$, the dynamics of sales of which for the time interval $[0, T]$ is presented in figure 3. A change in the direction of at least one trend generates a partition of the observed time period into the intervals $T_1, \ldots, T_7$. With the help of the scale defining the basic directions, we shall compare to each interval $T_i$ a vector, the components of which determine the codes of the basic directions that most closely correspond to the trends $P_1, P_2, P_3$.

![Figure 3. Piecewise linear approximation of the products $P_1, P_2, P_3$.](image)
By state, we mean the entire set of the same-type behaviors of trends on the selected time interval. The code vectors of states are presented in table 2.

Table 2. Code vectors.

|   | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|---|-------|-------|-------|-------|-------|-------|-------|
|   | (3,8,2) | (7,7,8) | (7,7,4) | (7,3,3) | (2,3,4) | (2,6,4) | (8,6,4) |

To classify states, we shall use the decomposition tree method. The idea of the method consists in the transition from the relation of dissimilarity to the fuzzy relation of resemblance, the $\alpha$-cuts of which are ordinary relations of equivalence. By reducing the equivalence relation matrix to a block-diagonal form, it is easy to obtain equivalence classes. In our case, equivalence classes will define typical situations, in each of which certain mark-ups are applied.

We construct the matrix of relative Euclidean distances (table 3).

Table 3. Distance matrix.

|   | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|---|-------|-------|-------|-------|-------|-------|-------|
| $S_1$ | 0 | 1 | 0.63 | 0.89 | 0.75 | 0.41 | 0.79 |
| $S_2$ | 1 | 0 | 0.55 | 0.88 | 0.75 | 0.79 | 0.58 |
| $S_3$ | 0.63 | 0.55 | 0 | 0.57 | 0.88 | 0.70 | 0.19 |
| $S_4$ | 0.89 | 0.88 | 0.57 | 0 | 0.70 | 0.81 | 0.46 |
| $S_5$ | 0.75 | 0.75 | 0.88 | 0.70 | 0 | 0.41 | 0.92 |
| $S_6$ | 0.41 | 0.79 | 0.70 | 0.81 | 0.41 | 0 | 0.82 |
| $S_7$ | 0.79 | 0.58 | 0.19 | 0.46 | 0.92 | 0.82 | 0 |

We shall consider this matrix as the matrix of the fuzzy dissimilarity relation $R$, since it has anti-reflexivity and symmetry according to the properties of the distance function. In accordance with the flow chart of the decomposition tree method (figure 1), we turn to the matrix of the fuzzy similarity relation $\overline{R}$ (table 4).

Table 4. Similarity relation matrix.

|   | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|---|-------|-------|-------|-------|-------|-------|-------|
| $S_1$ | 1 | 0 | 0.37 | 0.11 | 0.25 | 0.59 | 0.21 |
| $S_2$ | 0 | 1 | 0.45 | 0.12 | 0.25 | 0.21 | 0.42 |
| $S_3$ | 0.37 | 0.45 | 1 | 0.43 | 0.12 | 0.30 | 0.81 |
| $S_4$ | 0.11 | 0.12 | 0.43 | 1 | 0.30 | 0.19 | 0.54 |
| $S_5$ | 0.25 | 0.25 | 0.12 | 0.30 | 1 | 0.59 | 0.08 |
| $S_6$ | 0.59 | 0.21 | 0.30 | 0.19 | 0.59 | 1 | 0.18 |
| $S_7$ | 0.21 | 0.42 | 0.81 | 0.54 | 0.08 | 0.18 | 1 |
Having defined the maximin transitive closure $\hat{R}$ of the relation $R$, we obtain the fuzzy resemblance relation (table 5).

| Table 5. Resemblance relation matrix. |
|---------------------------------------|
| $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|-------|-------|-------|-------|-------|-------|-------|
| $S_1$ | 1     | 0.37  | 0.37  | 0.37  | 0.59  | 0.59  | 0.37  |
| $S_2$ | 0.37  | 1     | 0.45  | 0.45  | 0.3   | 0.37  | 0.45  |
| $S_3$ | 0.37  | 0.45  | 1     | 0.54  | 0.37  | 0.37  | 0.81  |
| $S_4$ | 0.37  | 0.45  | 0.54  | 1     | 0.37  | 0.37  | 0.54  |
| $S_5$ | 0.59  | 0.3   | 0.37  | 0.37  | 1     | 0.59  | 0.37  |
| $S_6$ | 0.59  | 0.37  | 0.37  | 0.37  | 0.59  | 1     | 0.37  |
| $S_7$ | 0.37  | 0.45  | 0.81  | 0.54  | 0.37  | 0.37  | 1     |

Considering $\alpha = 0.3; 0.37; 0.45; 0.54; 0.59; 0.81; 1$, we can get all kinds of partitions. In [16], some approaches for determining the optimal partitioning are presented. In our case, we choose $\alpha = 0.59$. The corresponding $\alpha$-cut is an equivalence relation that is specified by the matrix (table 6). The matrix of this relation is presented in the following table 6.

| Table 6. Equivalence relation matrix if $\alpha = 0.59$ and its block-diagonal view. |
|---------------------------------------|
| $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|-------|-------|-------|-------|-------|-------|-------|
| $S_1$ | 1     | 0     | 0     | 1     | 1     | 0     |
| $S_2$ | 0     | 1     | 0     | 0     | 0     | 0     |
| $S_3$ | 0     | 0     | 1     | 0     | 0     | 0     |
| $S_4$ | 0     | 0     | 1     | 0     | 0     | 1     |
| $S_5$ | 1     | 0     | 0     | 0     | 1     | 1     |
| $S_6$ | 1     | 0     | 0     | 1     | 1     | 0     |
| $S_7$ | 0     | 0     | 1     | 0     | 0     | 1     |

Thus, the following clusters can be distinguished:

$$Cl_1 = \{S_1, S_5, S_6\}, \quad Cl_2 = \{S_2\}, \quad Cl_3 = \{S_3, S_7\}, \quad Cl_4 = \{S_4\}.$$  

The typical states corresponding to each cluster are presented in the table 7.

Consider the typical state $Type_1 = (2, 6, 3)$, which is determined by the cluster $Cl_1 = \{S_1, S_5, S_6\}$. We assume that for each time interval the value of the function $\varphi$ is given by the constant — by the value of the mark-up (table 8). By averaging the mark-up value, we get the recommended mark-up $\varepsilon_i$ for each product $P_i$ for the typical state $Type_1$.

Based on this information, a knowledge base fragment can be generated, which contains the following production rules

$$R: \text{if } P_i = Y_{rj} \text{ then } \varepsilon_i = V_{rj}.$$
Table 7. Description of typical situations.

| Cluster   | Code vector of the state | State description                                      |
|-----------|--------------------------|--------------------------------------------------------|
| $Cl_1 = \{S_1, S_3, S_6\}$ | $Type_1 = (2, 6, 3)$ | $Sales P_1$ quickly decrease, $sales P_2$ slowly increase, $sales P_3$ decrease. |
| $Cl_2 = \{S_2\}$ | $Type_2 = (7, 7, 8)$ | $Sales P_1$ and $P_2$ increase, $sales P_3$ quickly increase. |
| $Cl_3 = \{S_3, S_7\}$ | $Type_3 = (8, 7, 4)$ | $Sales P_1$ quickly increase, $sales P_2$ increase, $sales P_3$ slowly decrease. |
| $Cl_4 = \{S_4\}$ | $Type_4 = (7, 3, 3)$ | $Sales P_1$ increase, $sales P_2$ and $P_3$ decrease. |

Table 8. Values of the function $\varphi$ for the cluster $Cl_1$ and for the average mark-up value.

|       | $P_1$ | $P_2$ | $P_3$ |
|-------|-------|-------|-------|
| $T_1$ | 0.7   | 1.3   | 0.5   |
| $T_2$ | 0.6   | 0.8   | 0.8   |
| $T_3$ | 0.5   | 1.2   | 0.8   |
| $\varepsilon_i$ | 0.6   | 1.1   | 0.7   |

The rule base fragment corresponding to the typical situation $Type_1$ is

- $R_{11}$: if sales $P_1$ quickly decreases, then mark — up value $\varepsilon_1 = 0.6$,
- $R_{12}$: if sales $P_2$ slowly increases, then mark — up value $\varepsilon_2 = 1.1$,
- $R_{13}$: if sales $P_3$ decreases, then mark — up value $\varepsilon_3 = 0.7$.

For each typical state, a corresponding fragment of the knowledge base can be formed.

The general algorithm for forecasting mark-ups for pharmaceutical products is implemented in the form of a fuzzy system, the core of which is the developed knowledge base. The input of the fuzzy system receives specific information about the cost of products belonging to a certain group. Based on the selected distance function, the typical situation is determined, to which the source information most closely corresponds. Then, based on fuzzy inference, recommended mark-up values are formed. The fuzzy system is implemented in FuzzyClips.

In the considered example, the historical data in the form of time series allows us to indirectly consider such significant factors affecting the cost of pharmaceutical products as shelf life, seasonality, demand, novelty of the product, popularity, and others. Thus, the selection of historical data as a training set plays an essential role for the formation of a set of typical states and ultimately for obtaining a high-quality knowledge base.

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