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# Fuzzy cognitive models for socio-economic systems as applied to a management model for integrated development of rural areas

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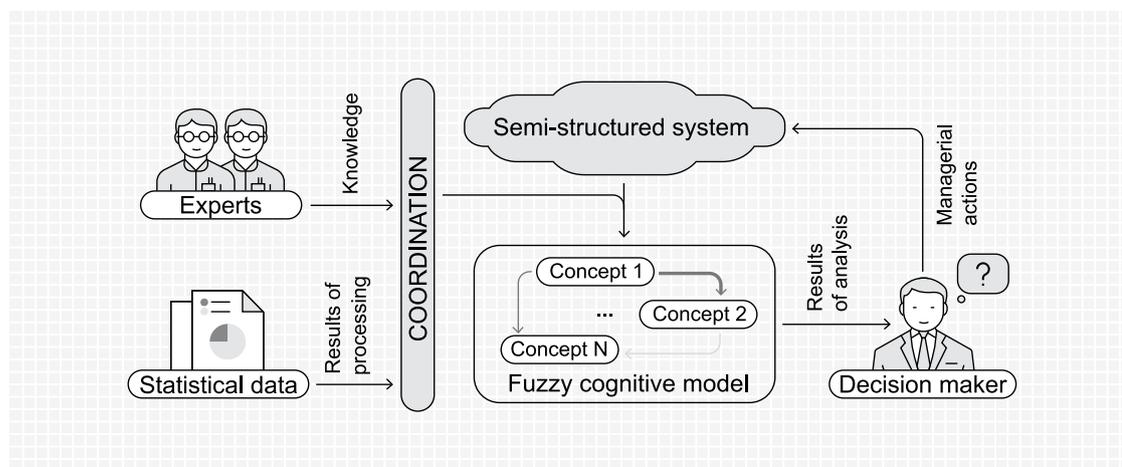
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## Abstract

The paper is devoted to fuzzy cognitive modeling, which is an effective tool for studying semi-structured socio-economic systems. The emphasis is on the process of developing (identification) fuzzy cognitive models, which are the most complex and critical stage of cognitive modeling. Existing identification methods are classified as either expert or statistical, depending on the source of information used. Typically, when constructing fuzzy cognitive models of semi-structured systems, the system under consideration possesses both quantitative (measurable) factors and factors of a relative, qualitative nature. While statistical data on the quantitative factors may be available, the only available source of information on the qualitative factors is expert knowledge.

However, each of the existing identification approaches focuses on just one source type, either expert or statistical. Thus, it is crucial to develop a more general approach to the development of fuzzy cognitive models for semi-structured systems to ensure reliable and consistent results by coordinated processing of information of both expert and statistical origins. We developed such an approach based on several identification methods with the subsequent coordination of intermediate results. To demonstrate the proposed approach, we applied it to a management problem of integrated development of rural areas. The fuzzy cognitive model we obtained can be used to predict the state of rural areas depending on initial trends and managerial actions, as well as to search and analyze effective managerial strategies for their development.

**Graphical abstract**



**Key words:** cognitive modeling; fuzzy cognitive model; identification of a cognitive model; pairwise comparison method; regression analysis; socio-economic system; integrated development of rural areas.

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**Introduction**

For socio-economic and other humanitarian systems, prediction and development of managerial strategies are complicated due to the following considerations:

- ◆ the multidimensional nature of the processes in the systems;

- ◆ the complexity of the connections between the processes, as well as their temporal variability;

- ◆ lack of quantitative information on dynamics of the processes.

This means that we can classify social, economic, and other similar systems as semi-structured. It can be complicated or even impos-

sible to study and manage such systems based on analytical models that describe correlations between the input or output parameters. However, we can use models based on expert information, experience, judgement and intuition.

Semi-structured systems are often modeled using the cognitive approach. According to this approach, managerial solutions should be based on formal models and methods which use human cognitive abilities (perception, imagination, knowledge, understanding, and explanation) [1]. The term “cognitive modeling” refers to cognitive approach-based methods of structure and target as well as imitation modeling of systems. In other words, cognitive modeling allows us to study a system’s structure and operation by analyzing its cognitive model.

Fuzzy logic is often used in cognitive modeling as a mathematical tool. There are a number of cognitive models which are based on fuzzy cognitive maps (FCM). A detailed review of these models is presented in [2]. In particular, Silov’s FCMs, which are the extensions of signed cognitive maps [4], were introduced in [3] and have proved successful in applied problems of modeling and analysis of semi-structured systems.

In this paper, we present an approach to the development of cognitive models of semi-structured systems based on expert and statistical information. We also present an application of the method to a management model for integrated development of rural areas.

### 1. Key concepts in cognitive modeling

A cognitive model is based on a formal representation of the cause and effect links between the factors that describe a system. The system is represented as a cause and effect network (cognitive map), which has the following form:

$$G = \langle E, W \rangle, \quad (1)$$

where  $E = \{e_1, e_2, \dots, e_n\}$  – a set of factors (concepts);

$W$  – a binary relation on the set  $E$ , which determines connections between its elements.

Concepts can reflect both absolute and measurable system characteristics (such as population or income), as well as relative qualitative parameters (popularity, competitiveness, etc.)

If changes in the  $e_i$  concept cause changes in the  $e_j$  concept, we say that  $e_i$  influences  $e_j$  and denote this as  $(e_i, e_j) \in W$  or  $e_i W e_j$  (hereinafter  $i, j = 1, \dots, n$ , where  $n$  is the number of concepts). An influence is called positive when an increase in the  $e_i$  state leads to an increase in the  $e_j$  state, and negative otherwise.

When we develop a fuzzy cognitive model, we assume that the intensity of mutual influence of the concepts can vary. In this case,  $W$  is determined as a fuzzy relation, and the corresponding cognitive map is called a fuzzy cognitive map (FCM).

Silov’s FCM is an example of such a model, where the  $W$  relation is given as a set of numbers  $w_{ij}$  that reflect the direction and intensity level (weight) of the influence between the concepts  $e_i$  and  $e_j$ . The following assumptions are made:

- a)  $-1 \leq w_{ij} \leq 1$ ;
- b)  $w_{ij} = 0$  if  $e_i$  does not influence  $e_j$ ;
- c)  $w_{ij} = 1$  for the maximum positive influence of  $e_i$  onto  $e_j$ ;
- d)  $w_{ij} = -1$  for the maximum negative influence of  $e_i$  onto  $e_j$ ;
- e)  $w_{ij}$  takes other permissible values for other values of the intensity.

Such an FCM can be represented as an oriented weighted graph, where vertices and edges correspond to the concepts and cause and effect relations, respectively. Weights of the edges are determined by the corresponding  $w_{ij}$  values. The  $W$  relation can be represented as a  $n \times n$  matrix (where  $n$  is the number of concepts in the FCM), which is called a cognitive

matrix and is an adjacency matrix for the cognitive graph.

The first stage in fuzzy cognitive modeling is to create an FCM for the system under consideration. This can be done by using data from experts, or by analyzing the available statistical information. The next stage is the modeling, and the problems here can fall into the following two types:

- ◆ static (structure and target) analysis, where we look for the concepts that influence the modeling the most, reveal contradictions between the goals, analyze feedback loops, etc.;
- ◆ dynamic (scenario) analysis, aimed at the prognosis of the system's state under various managerial actions, as well as at generation and selection of optimal actions that will bring the system into the desirable state (various models of impulse processes can be used to describe the system's dynamics [5]).

The results of a modeling are usually represented by tables and plots. To be understood by an expert, the results must be interpreted using natural language and understandable terminology [6].

## 2. Identification of the parameters for a fuzzy cognitive model: existing approaches

The stage where we weight the links between the concepts is called a parametric identification; this is one of the most complex and important stages in cognitive modeling. The more reliable the results of this stage are, the more reliable is the final cognitive model.

Classification of the weighting methods is presented in *Figure 1*.

Weights for an FCM are usually determined by an expert method, either direct or indirect.

In the direct methods, the weights are directly specified by an expert [7]. This is the simplest way, but the results can be unreliable and unjustified due to the human factor. Indirect methods are less subjective, and the weighting

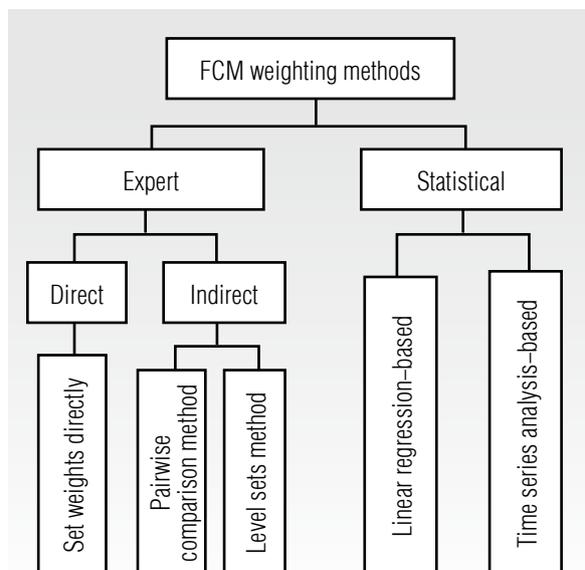


Fig. 1. Classification of the methods of FCM parametric identification

problem can be represented as a series of less complicated subtasks. Some examples are the Saaty's pairwise comparison method [8], Yager's level sets method [9], as well as authors' modifications of these methods that improve the FCM's efficacy [10, 11].

As we have mentioned above, some concepts may reflect qualitative characteristics of the system being researched. If there are statistical data on the values of these characteristics, we can use them to weight the links between the concepts. In this case, expert estimates may or may not be used. Therefore, to identify the FCM's parameters, we can additionally use statistical methods [12, 13].

Let's consider the two methods used during the experimental stage of the research.

## 3. Pairwise comparison method for weighting the links in a fuzzy cognitive model

This chapter is based on the authors' research [10]. The approach proposed there is used in the present paper as part of a more general approach for FCM development.

When experts apply the pairwise comparison method for parametric FCM identification, they consider a certain concept  $A$  pairwise with all the concepts linked to it. Concepts that influence the concept  $A$  are considered separately from the concepts that are influenced by it. Concepts whose influences have different signs are also considered separately. For each of the pairs, the concept that influences the most gets selected, and the link with this concept is assigned a bigger weight. As a result, we obtain a pairwise comparison matrix  $D$ , where every element  $d_{ij}$  reflects the ratio of the links between the concepts  $e_i$  and  $e_j$ . In this matrix  $d_{ii} = 1$  and  $d_{ij} = 1/d_{ji}$ .

To formalize  $d_{ij}$  estimations, the scales presented in Table 1 may be used (the alternative scale is introduced and justified by the authors in [10]).

Table 1.

Values for two appropriate scales

Verbal description	classical scale	alternative scale
No advantage	1	9/9
Almost no advantage	2	9/8
Slight advantage	3	9/7
Almost considerable	4	9/6
Considerable advantage	5	9/5
Almost clear advantage	6	9/4
Clear advantage	7	9/3
Almost absolute advantage	8	9/2
Absolute advantage	9	9/1

Next, the matrix  $D$  must be checked for consistency. This is done by calculating the consistency index  $CI$ , and consistency ratio  $CR$ :

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \tag{2}$$

$$CR = \frac{CI}{CIS}, \tag{3}$$

where  $CIS$  – an experimentally obtained estimation for the expected value of the consistency;

$\lambda_{\max}$  – the largest eigenvalue of the matrix  $D$ ;  
 $n$  – the dimension of the matrix  $D$ .

If  $CR$  values are greater than 0.1, the matrix  $D$  is inconsistent. In this case the model needs to be re-evaluated.

The weights vector  $W$  is calculated using the eigenvector of the matrix  $D$  at  $\lambda_{\max}$ :

$$W = \lambda_{\max} W. \tag{4}$$

Lastly, the vector  $W$  must be normalized by dividing all its elements by the maximum element and multiplying by the strength coefficient  $k \in (0, 1]$ . This coefficient is usually set by an expert and reflects the weight of the link.

#### 4. Weights of the links based on regression analysis and elasticity coefficients

In [12, 14], the authors presented a method that weighs FCM links based on statistical data. The method includes the following steps:

1. development of a linear regression model (pair or multiple) using the available statistical data;
2. estimation of the model and importance of its parameters;
3. check for multicollinearity (in case of multiple regression) and its elimination;
4. using elasticity coefficients as the base for the links' weights:

$$E_i = b_i \frac{\bar{x}_i}{\bar{y}}, \tag{5}$$

where  $b_i$  is a regression coefficient in the linear regression model,  $\bar{x}_i$  and  $\bar{y}$  are the sample means;

5. normalization of the elasticity coefficients (to obtain the links' weights in the range  $[-1, 1]$ ) using a sigmoid normalization function:

$$S(E_i) = \frac{1 - \exp(-bE_i)}{1 + \exp(-bE_i)}, \quad (6)$$

where the coefficient  $b$  is the slope of the function.

One of the ways to obtain the value of  $b$  is to set the elasticity coefficient  $E_0 > 0$  in such a way that the link's weight equals a certain value  $\alpha$ . Then the coefficient  $b$  can be obtained from the following formula:

$$b = -\frac{1}{E_0} \ln \frac{1-\alpha}{1+\alpha}, \quad (7)$$

where  $E_0$  – the elasticity coefficient;

$\alpha$  – the link's weight (both are set by an expert).

### **5. Development of fuzzy cognitive models using coherent processing of expert and statistical information**

Dealing with semi-structured systems (especially socio-economic ones), we typically have both quantitative (measurable) and relative, qualitative factors. We may have statistical data on quantitative factors, but we can only rely on expert knowledge when qualitative factors are concerned. However, every identification method available now uses a single type of information – either expert or statistical information.

Therefore, it is very important to develop a more general approach to fuzzy cognitive models of semi-structured systems which could use coherent processing of both types of information and ensure reliable and consistent results.

Such an approach may be based on combined use of available identification methods (several of which are developed by the authors) with subsequent coordination of the results. This means that to identify the links between the concepts we can use statistical methods when we have statistical data, and expert methods otherwise. For the results to be reliable and consistent, we need to coordinate the outcomes of both approaches.

Let us briefly describe some possible ways to coordinate the results of processing the expert and statistical information.

1. Statistical estimations may be used to improve and supplement the expert results. For example, for expert weighting by the pairwise comparison method, we need to set a strength coefficient for the links, and we can do this by using the available statistical estimations. This approach is preferable when statistical data are more reliable than the expert estimations.

2. As opposed to the above, expert estimations may be used to normalize statistical data, in particular, to identify a normalization function. This approach should be applied when expert estimations are highly reliable.

3. In some cases, statistical estimations may be used to coordinate separate sets of expert estimations.

4. Expert estimations may be used to coordinate statistical estimations for different parts of an FCM, as well as estimations obtained on the basis of statistical data of different types.

This approach is presented below as applied to the development of a fuzzy cognitive model for managing integrated development of rural areas.

### **6. Fuzzy cognitive model for managing integrated development of rural areas**

Rural areas as research and management subjects are highly dynamical, and the pro-

cesses in them are multidimensional. Many elements and links in this system are not fully researched and can be described only qualitatively. We also lack information on the system's behavior. The processes in the system vary over time, and they are typically nonlinear. Therefore, rural areas can be considered as semi-structured systems.

Hence, we propose to use a fuzzy cognitive model for studying the development of rural areas and finding effective managerial solutions for their sustainability.

We developed such a model using the IGLA decision support system. This system was developed by research at the "Information technology and software" department, Bryansk State Technical University [15].

The only way to obtain complete and reliable information on the structure and development of a rural socio-economic system is to use proper data collection technologies. So, we asked ten experts on rural socio-economic development to fill out a specially designed questionnaire. In addition, we researched Russian monographs on sustainable management of rural areas [16–23].

We concluded that in a cognitive model for managing integrated development of rural areas it is feasible to use eleven most important concepts. These concepts can be divided into four blocks (*Table 2*).

The next stage in the development of a cognitive model is finding links between the concepts. The experts used a cognitive map to reveal cause and effect links between the concepts and their influence type (either positive or negative).

The selected concepts are qualitative and quantitative elements of the system. Some of the quantitative elements can be described by statistical parameters, and we can estimate the strength of mutual influence by using statisti-

*Table 2.*

**Concepts in a cognitive model for managing integrated development of rural areas**

<b>Institutional block</b>
<ol style="list-style-type: none"> <li>1. Development of market infrastructure (tax, credit, budget, and innovational politics)</li> <li>2. Development of rural self-government</li> </ol>
<b>Socio-demographic block</b>
<ol style="list-style-type: none"> <li>3. Average population per year</li> <li>4. Unemployment level</li> <li>5. Development of the social sphere</li> </ol>
<b>Economic block</b>
<ol style="list-style-type: none"> <li>6. Per capita income</li> <li>7. Agricultural production</li> <li>8. Development of small and medium businesses</li> <li>9. Investments in fixed capital</li> <li>10. Economic diversification level</li> </ol>
<b>Ecological block</b>
<ol style="list-style-type: none"> <li>11. Negative influence on the environment</li> </ol>

cal methods. This can essentially increase the model's objectivity and validity.

However, the concepts from the institutional and ecological blocks cannot be quantified, hence it is impossible to use statistical methods to estimate their influence on other concepts. Therefore, the influence was determined by experts. To obtain and process the expert knowledge, we used an authors' modification of the pairwise comparison method, where an alternative scale for the preference estimation is applied [10].

The cognitive model also includes the following concepts from the socio-demographic and economic blocks: population, unemployment level, agricultural production, per cap-

ita income and investments in fixed capital. These concepts reflect the parameters that are described statistically. In this case, to reduce the influence of experts' subjectivity and to increase reliability of the results, we processed the Russian Statistics Committee's data for the years 2000–2017 using the authors' method [12]. This method is based on the pair and multiple regressions [24].

Since the cognitive model includes both cost and nonmonetized parameters, we have to exclude the influence of inflation. The following indices for the years 2000–2017 were used as the deflators:

- ◆ consumer price index for 'Per capita income';
- ◆ agricultural produce price index for the 'Agricultural production';
- ◆ annual inflation index for the 'Investments in fixed capital'.

Based on the available statistical data, we set four regression equations that allow us to estimate five links in the cognitive model:

- 1). Influence of income on the population;
- 2). Influence of the agricultural production on the unemployment rate;
- 3). Influence of the unemployment rate on the incomes of the population;
- 4). Influence of the population and investments in fixed capital on the agricultural production (multiple regression).

The regression models we developed allow us to make the following conclusions:

◆ for the first case, the correlation is very high. However, the regression coefficient and the corresponding links have opposite signs (the sign of the link was set by experts). In our opinion, this means that there are other factors that negatively influence the demographics in rural areas, such as population makeup by sex and age, the number of reproductive age women in rural areas, and negative natural and migration growth of the rural popula-

tion. These factors were not used as concepts in the model;

◆ the regression coefficient between the population and production is negligible, based on the  $t$ -statistic, and the corresponding influence is insignificant;

◆ for the remaining three links, the regression coefficients have correct signs (which coincide with the signs set by the experts), and they are significant, based on the  $t$ -statistic (influence of the production on unemployment, influence of the unemployment on income, and influence of the investments on production).

The values obtained for the regression coefficients and elasticity coefficients are presented in *Table 3*.

For the results to be consistent, we now have to coordinate the results obtained by processing statistical data and by the expert approach. To do this, let us consider how the concept "Investments in fixed capital" influences the concept "Agricultural production". Using the aforementioned method of identification of the normalization function, we calculate the value for the parameter  $b$  so the elasticity coefficient after the normalization will coincide with the experts' estimation of 0.8:

$$b = -\frac{1}{0.809} \ln \frac{1-0.8}{1+0.8} = 2.71. \quad (8)$$

Normalization of the elasticity coefficients allows us to calculate the weights of the links between the concepts. They are also presented in *Table 3*.

The final results of the parametric FCM identification are presented in *Table 4*.

The weights calculated from statistical data both supplement the experts' results and increase the objectivity and justification of the parameters in a fuzzy cognitive model.

A graphic FCM representation obtained by the visualization subsystem of the IGLA decision support system is presented in *Figure 2*.

Table 3.

**Weights of some FCM links calculated based on statistical data**

Influence	Regression coefficient	Elasticity coefficient	Weight of the link
'Agricultural production' on the 'Unemployment rate'	-0.00236	-0.306	-0.39
'Unemployment rate' on the 'Per capita income'	-1272.176	-3.378	-0.99
'Investments in fixed capital' on the 'Agricultural production'	6.975	0.809	0.8

Table 4.

**Fuzzy cognitive matrix**

Influencing concepts	Influenced concepts										
	1	2	3	4	5	6	7	8	9	10	11
<b>1</b>	0	0.434	0	0	0	0	0	0.654	0.512	0	0
<b>2</b>	0	0	0	0	0.53	0	0	0.471	0	0.417	0
<b>3</b>	0	0	0	0	0	0	0.178	0	0	0	0
<b>4</b>	0	0	0	0	-0.55	-0.99	0	0	0	0	0
<b>5</b>	0	0	0.353	0	0	0	0	0	0	0	0
<b>6</b>	0	0	0.118	0	0.353	0	0	0	0	0	0
<b>7</b>	0	0	0	-0.39	0	0	0	0	0	0	0.564
<b>8</b>	0	0	0	-0.69	0	0.527	0.8	0	0	0	0.446
<b>9</b>	0	0	0	0	0	0	0.78	0.691	0	0	0.418
<b>10</b>	0	0	0	-0.52	0.531	0	0	0.393	0	0	0
<b>11</b>	0	0	-0.6	0	0	0	0	0	0	0	0

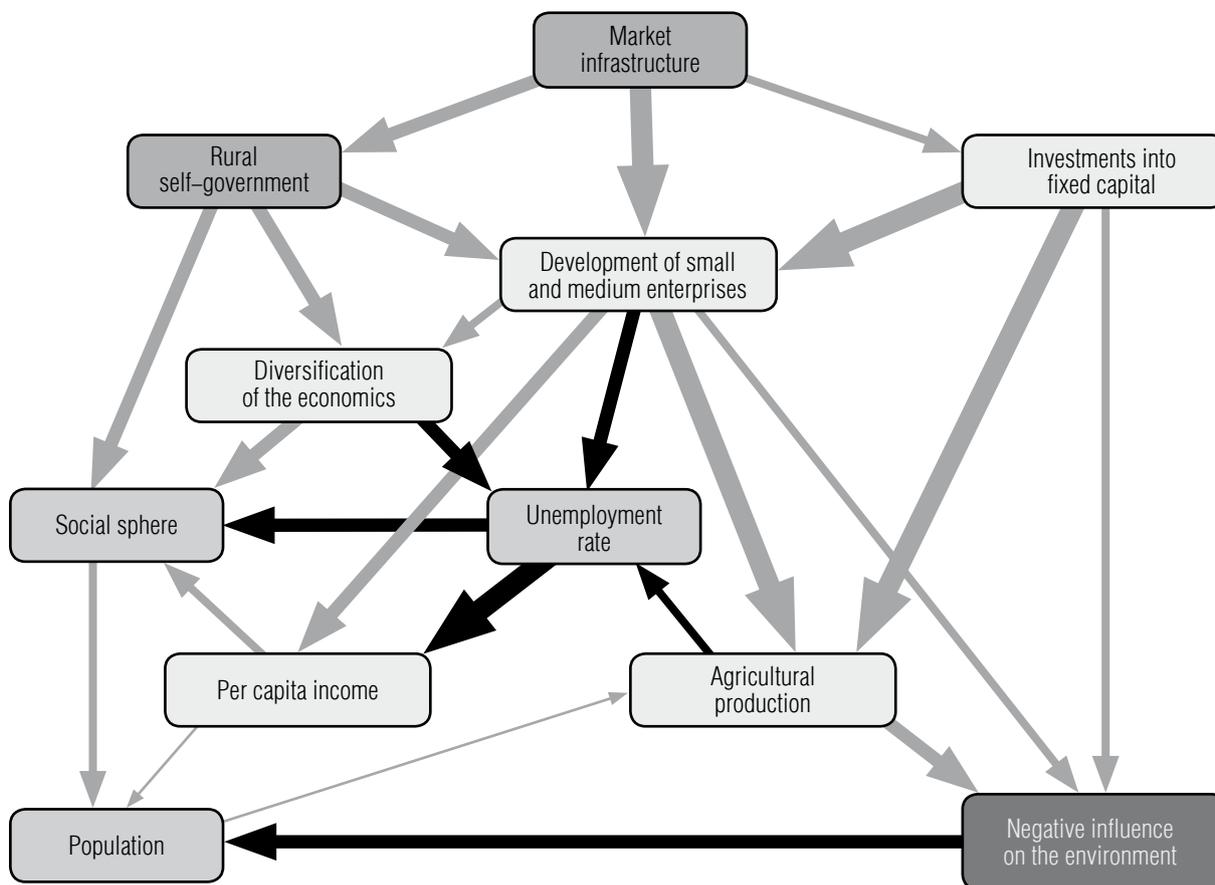


Fig. 2. Fuzzy cognitive model for rural integrated development management

Different colors correspond to different blocks (Table 2). Several other ways to visualize an FCM are described in [25].

The model we obtained may be used for the following purposes:

- ◆ to reveal the factors that influence the rural areas' development the most which must be addressed when taking managerial decisions;
- ◆ to predict the state of rural areas given initial tendencies and possible managerial decisions (or without them);
- ◆ to find effective strategies for rural areas' management that could help reach certain goals.

All these problems can be solved by structure and target and scenario analysis of the

cognitive model so developed. These stages of cognitive modeling lie outside the scope of this paper and will be addressed in future research.

### Conclusion

We present a method to develop fuzzy cognitive models for socio-economic systems containing both quantitative and relative, qualitative factors. It is assumed that statistics on the quantitative factors may be available. In this case, these factors may be processes using the authors' methods for FCM identification.

The method also utilizes an expert's knowledge (or that of a group of experts) obtained

and processed using expert methods for FCM parametric identification, such as the Saaty's pairwise comparison method or Yager's level sets method.

The final important step of the method is to coordinate the intermediate results obtained by both expert and statistical methods. This step ensures that the final results are highly reliable and consistent. This, in turn, ensures a high quality of cognitive models as well as high efficiency of the subsequent managerial decisions.

The proposed approach is applied to the problem of managing integrated development

of rural areas. The FCM obtained may be used to predict development of rural areas given different initial tendencies and managerial decisions as well as to find and analyze effective managerial strategies.

It is important that further research be devoted to structure and target, as well as scenario analysis of the model developed.

Another promising research direction is to update the approach presented to support group expertise during an FCM development. Methods that would permit us to evaluate the consistency of a group's opinions and to reach the necessary level of consistency need to be developed. ■

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