Foresight of Volga Federal District Innovation System Development using a Multi-Objective Genetic Algorithm

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Abstract. The application of simulation modeling in public administration is under study at the level of interregional interaction in specific federal districts. The main indicator for development success of a particular federal district is the natural growth of its population. For this purpose, a model of foresight of federal district innovation system development based on the use of a multi-objective genetic algorithm was proposed. Stages of this foresight included preparation of statistical data for clusters, obtaining predictive functions for clusters and Pareto frontiers of predictive functions, and planning synergy effects of clusters of regions and the entire federal district. In this case, to increase the synergy effect of a federal district, investment resources and research and development (R&D) costs were planted to be redirected to those regions where economic and financial resources are insufficient. This will eventually increase the average per capita income of the population in the regions of the federal district, which will lead to population growth in these regions. If R&D costs are redistributed, there are also information and logistics interactions that confirm the practical effectiveness of the open innovation model within the federal district. For the Volga Federal District, this foresight resulted in its total positive reserve for R&D in the amount of 8,412 million rubles. It should be forwarded to the Samara Region. Then, the synergy effect of the whole Volga Federal District will be equal to 429,344 million rubles.

Keywords: Foresight; Intercluster interaction; Multi-objective genetic algorithm; Simulation modeling

1. Introduction

Currently, fundamental research on strategic development issues is increasingly moving into the subject area of regional economics (Rodionov and Velichenkova, 2020; Rytova and Gutman, 2020). At the present time, one of the most important approaches includes the introduction of technologies for simulation modeling in business processes based on the handling of bulk data (Big Data) and its application to the analysis of regional cluster data (Kudryavtseva et al., 2020b). The creation and promotion of clusters in the Russian Federation is one of the main aims of the Russian government and is supported by two governmental programs: the program of the Ministry of Economic Development of the Russian Federation "Pilot innovative territorial clusters" and The Program of the Ministry

of Industry and Trade of the Russian Federation "Industrial clusters". Since the debate on the measurement of cluster performance is ongoing in the EU (Ketels and Protsiv, 2020), USA (Delgado et al., 2016), Russia (Stepanova, 2019), and other countries, it is essential to provide adequate approaches and tools for analysis of regional cluster development (Kudryavtseva et al., 2020a). One of the possible solutions to this problem could be the application of Genetic algorithms (Snytyuk and Suprun, 2017).

Genetic algorithm (GA) is an evolutionary search method used to solve optimization problems using mechanisms similar to biological evolution (Holland, 1992; Chen et al., 2011). The genetic algorithm itself consists of several steps: (1) preparatory step – formation of an initial population; (2) selection; (3) cross breeding; (4) mutation; and (5) solution evaluation and algorithm stopping (Morov, 2012). An important concept in GA is the fitness function, otherwise known as the evaluation function. It represents a measure of fitness for a certain individual in the population. In optimization problems, the fitness function is usually maximized and called an objective function (Rutkowska et al., 1999). Tate and Smith (1995) developed a standard GA. In this, they implemented mutation and cross breeding independently of each other, unlike most GA implementations, where mutation is used as an auxiliary procedure for individuals in the population. The algorithm used a chromosome mutation with a paired exchange (Kravets and Safronova, 2013). Many other modifications were developed for the GA, for example, greedy GA (Ahuja et al., 1995) and self-adapting algorithms with the application of heterogeneous mutations (Michalewicz, 1996), among others. Evolutionary algorithms are relatively new but are very powerful methods used to find solutions to many real search and optimization problems. Many of these problems have multiple objectives, resulting in the need for a set of optimal solutions, known as effective solutions (Nasruddin et al., 2018). The use of evolutionary algorithms is a highly effective way to find many effective solutions in a single simulation run (Kalyanmoy, 2001).

This paper suggests the application of simulation modeling at the level of interregional interaction in the Volga Federal District of Russian Federation using GA.

2. Methods

Yashin et al. (2017) suggested foresight methods based on predicting values of capitalization functions of the cluster companies and on calculating the best possible equivalent portfolio of the cluster companies using arbitrage techniques. Foresight is a set of approaches providing conditions for long-term forecasting of situations, while making strategic decisions (Martin, 1983, 1989, 2010; Tukkel et al., 2013). However, these methods are not effective enough for the foresight of development of major innovation systems, which include the federal districts of the country. In this case, it is necessary to consider various effects of intercluster interactions, which include economic, financial, informational and logistics interactions. Thus, considering the latter results, proposed a foresight model of federal district innovation system development based on the use of a multi-objective genetic algorithm (MGA). This method is principally new to the foresight of big innovational systems. The stages of this foresight are shown in Figure 1.
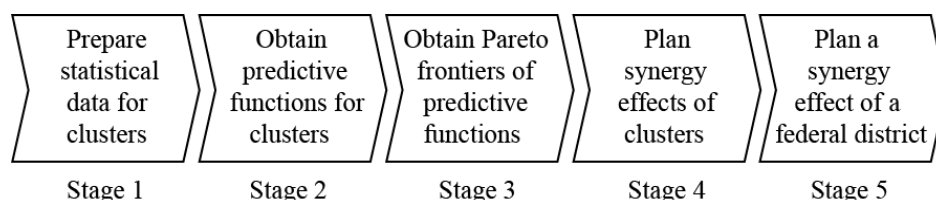
Prepare statistical data for clusters	Obtain predictive functions for clusters	Obtain Pareto frontiers of predictive functions	Plan synergy effects of clusters	Plan a synergy effect of a federal district
Stage 1	Stage 2	Stage 3	Stage 4	Stage 5

Figure 1 Stages of foresight of the federal district innovation system development

Since the paper by Yashin et al. (2019) established that the greatest influence on the natural growth of the population is exerted by the average per capita cash income of the population (per month), we primarily focused on maximizing this function (y_1) in each region of the federal district, where there are innovative and industrial clusters. The other two factors that we considered when building the model were investment in equity (y_2) and internal current expenditure on research and development (R&D) (y_3).

In this case, we embraced intercluster interactions in three previously identified areas, namely economic, financial, informational and logistics, as the identified reserve for the functions y_2 and y_3 with the view of increasing the synergy effect of the federal district planned to be redirected to those regions where there is a shortage of economic and financial resources. This will eventually increase the average per capita income of the population in these regions, which will lead to population growth. If R&D costs are redistributed in a similar manner, there are information and logistics interactions that confirm the practical effectiveness of the open innovation model within the federal district.

Turning to the essence of the proposed foresight model, we described its stages as shown in Figure 1.

Stage 1 – Prepare Statistical Data for Clusters. We already identified the three main components of the model as y_1, y_2, and y_3. However, due to the fact that this data contained annual information about 25 clusters located in the Volga Federal Region from 2009 to 2018, which is presented in money, it needs to be adjusted for inflation. Then, the real dynamics of these indicators can be seen.

Stage 2 – Obtain Predictive Functions for Clusters. It is these functions for y_1, y_2, and y_3 that were used to implement a multi-objective genetic algorithm, so it is important to build them as reliably as possible. For this purpose, we focused on the value of the determination coefficient R^2.

Stage 3 – Obtain Pareto Frontiers of Predictive Functions. For this purpose, we used a multi-objective genetic algorithm. This foresight stage is central from a technological perspective.

Let us assume that we want to maximize several objective functions simultaneously, each with a global extremum. Objective functions have their own individual extrema. However, in a multi-objective problem, any solution in the range between limiting function extrema is equally optimal. There is no single solution to this multi-objective problem. The goal of a multi-objective genetic algorithm is to find a set of solutions in a given range, ideally with a good spread. A solution set is also known as a Pareto frontier. All solutions at the Pareto frontier are optimal.

We used visualization of two graph options. The first option built a Pareto frontier (limited to any three objectives) for each generation. The second option built an interval from the global extremum of each analyzed function to the other limiting extremum of the corresponding graph function.

Stage 4 – Plan Synergy Effects of Clusters. A detailed Pareto frontier analysis for a particular region determined the optimal value of the average per capita monetary income of its population (y_1). For the obtained income, it was possible to determine the planned indicators y_2 and y_3. Then the maximum possible synergy effect for each region, where there were innovative and industrial clusters, was calculated by the formula:

$$S = y_{2,plan} - y_{2,fact} + y_{3,plan} - y_{3,fact}, \tag{1}$$

where planned values were received in accordance with the MGA, while the actual values were taken from the last analyzed year.

Stage 5 – Plan a Synergy Effect of a Federal District. If for a particular region there was an excess of the actual value over the planned one in terms of y_2 or y_3, we considered this difference as a reserve. It was redirected to those regions where there was an excess of the planned value over the actual one in terms of y_2 or y_3. This, in turn, adjusted the synergy effects of the regions that received the funds. Such mechanisms of redistribution of investment in equity and expenditures on R&D enabled the federal district to develop a partially closed innovation system with a decrease in external federal and private financing.

As a result, the method for assessment of the synergy effect was adjusted for each region receiving funds by the amount of the reserve obtained from reserve donor regions, i.e.,

$$S_{new} = y_{2.plan} - y_{2.fact} + y_{3,plan} - y_{3,fact} - \sum_{i=1}^{n} R_i , \qquad (2)$$

where R_i is the value of the reserve obtained from the i-th donor region (million rubles) and n is the number of regions in the federal district that have innovative and industrial clusters.

After that, the adjusted synergy effects of the regions were summed up, and the maximum possible synergy effect was obtained for the entire federal district:

$$S_{FD} = \sum_{i=1}^{n} S_{i,new} . \qquad (3)$$

3. Results

Let us consider the process of foresight of innovation system development using a multi-objective genetic algorithm as exemplified by the Volga Federal District (VFD) of the Russian Federation.

According to the list approved by the Government of the Russian Federation, there were 25 pilot innovative territorial clusters operating in the regions of the Russian Federation. Then, we only considered those VFD areas (regions or republics) where the clusters from this list are located (Table 1).

Table 1 Innovative territorial clusters by regions of the Volga Federal District

Regions	Innovative clusters
1) Nizhny Novgorod Region	Nizhny Novgorod industrial innovative cluster in automotive and petrochemical engineering
2) Republic of Mordovia	Energy-efficient lighting engineering and smart lights
3) Ulyanovsk Region	ULYANOVSK-AVIA Scientific and Educational Production Cluster consortium Dimitrovgrad nuclear innovation cluster
4) Samara Region	Innovative territorial aerospace cluster
5) Perm Territory	NOVY ZVEZDNY Technopolis innovative territorial cluster of rocket engine building Photonics
6) Udmurt Republic	Udmurt machine building cluster
7) Republic of Tatarstan	Kama innovative territorial production cluster
8) Republic of Bashkortostan	Petrochemical territorial cluster

Stage 1. Using the "Statistical Review" of the Federal State Statistics Service (*www.gks.ru*), we grouped the necessary data on the natural population growth (z), average per capita monetary income of the population (per month) (y_1), investment in equity (y_2), and internal current expenditures on R&D (y_3) for 10 years from 2009 to 2018. At the same time, for the sake of comparability of the data, we adjusted the indicators measured in rubles for inflation (Table 2). As a result, we obtained a data matrix for foresight of the

dimensional product 80 by 4 in 2018 prices (Table 3). This table shows data for the Nizhny Novgorod region only.

Table 2 Annual rates of inflation (%)

	2010	2011	2012	2013	2014	2015	2016	2017	2018
Ruble	8.78	6.1	6.58	6.45	11.36	12.91	5.38	2.52	4.27

Table 3 Foresight data in 2018 prices

Region	Average per capita cash income of population (per month) (RUB)	Investment in equity (million RUB)	Internal current expenditures on R&D (million RUB)	Natural growth of population (persons)
Nizhny Novgorod Region	y_1	y_2	y_3	z
2009	26,646.5	364,200.0	41,456.1	-22,094
2010	27,399.0	293,805.4	46,022.7	-22,942
2011	28,948.2	356,243.3	48,495.1	-17,869
2012	32,204.6	389,268.9	57,557.7	-13,890
2013	34,216.8	385,562.5	52,691.9	-13,457
2014	35,548.8	364,555.9	66,121.7	-12,846
2015	34,663.1	257,909.3	64,064.0	-10,714
2016	32,503.3	234,809.1	70,891.4	-11,420
2017	31,967.1	254,493.0	67,023.1	-13,556
2018	31,631.0	259,045.4	66,202.2	-15,917

Stage 2. For this purpose, we used the Internet service *WolframAlpha* (*www.wolframalpha.com*). For instance, for the Nizhny Novgorod region, we obtained three best predictive functions for y_1 using the data from Table 3. The highest determination coefficient R^2=0.988022 was attributed to the polynomial of Degree 4, so it was accepted as the best predictive function. The predictive functions for y_2 and y_3 were obtained in a similar way.
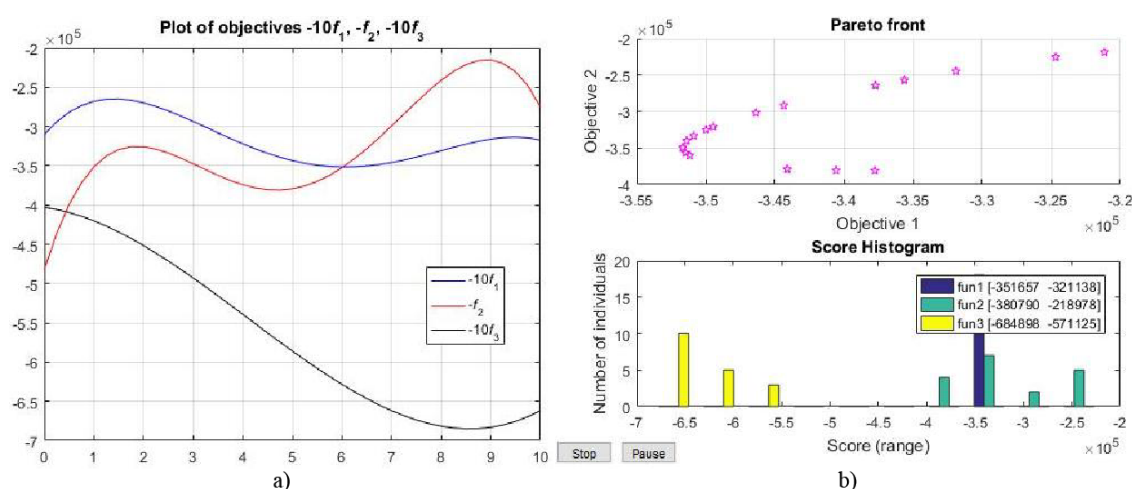

Figure 2 Graphs of functions y_1, y_2, and y_3 (a) and Pareto frontier between optimal y_1 and y_2 (b)

The predictive functions y_1, y_2, and y_3 were produced on a single graph in *Matlab* (Figure 2a). Since the *Matlab* software in which the multi-objective genetic algorithm was implemented only solves minimum problems, all three graphs were inverted. Thus, we minimized negative functions. In addition, we multiplied two of the three functions by 10 for clarity.

In light of this, Figure 2a shows that we looked for minimums for the three functions simultaneously. The Pareto frontier we needed was located between the extreme lows out of the three, i.e., approximately in the segment [4.5, 8.5] along the horizontal axis.

Stage 3. To implement the multi-objective genetic algorithm, an *M* file function was created. Then, we constructed the required Pareto frontier between the optimal y_1 and y_2 (Figure 2b). Similarly, it was possible to obtain the Pareto frontier between the optimal y_1 and y_3 (Figure 3a) and between the optimal y_2 and y_3 (Figure 3b). Additionally, Figures 2–3 show the intervals from the global extremum of each analyzed function to the other limiting extremum of the corresponding graph function. These intervals were used at the next foresight stage.
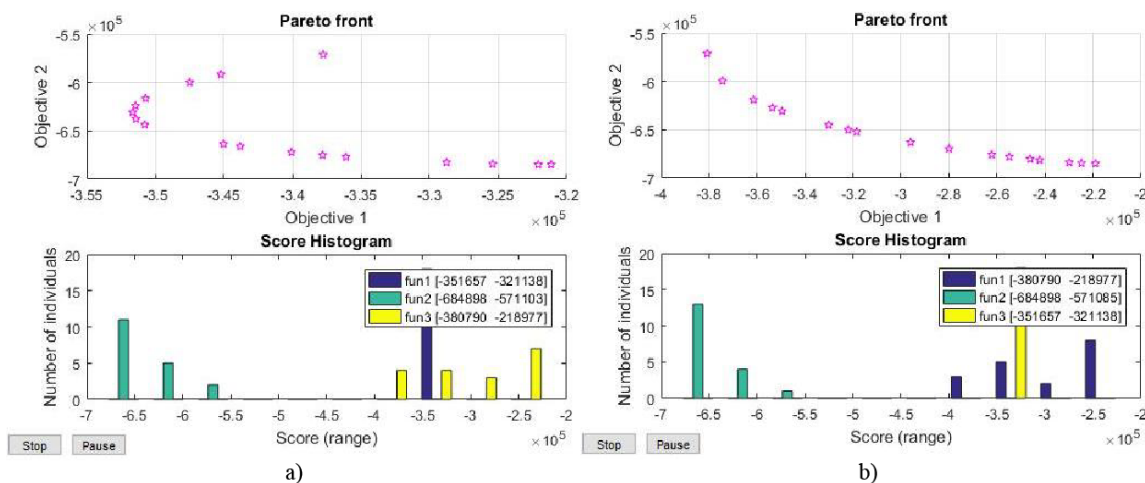

Figure 3 Pareto frontier between optimal y_1 and y_3 (a) and between optimal y_2 and y_3 (b)

As mentioned earlier, all the solutions shown at the Pareto frontier are optimal. However, we were interested in a situation where the population of the region would have the maximum average per capita income. This imposed serious adjustments to the Pareto frontier analysis process. For instance, Figure 2b shows that when moving along the optimal Pareto frontier in the direction of increasing the investment in equity (y_2), the population income first grows up, then slightly grows down. This suggests that the Nizhny Novgorod Region has an optimal amount of investment, above which the income of the population will decline, which will eventually lead to a decrease in the rate of population growth in the region.

By analyzing the Pareto frontier in Figure 3a, a similar conclusion was with respect to expenditures on R&D in the region (y_3). Moving along the Pareto frontier in the direction of increasing expenditures on R&D, the income of the population at first slightly increased, and then significantly decreased. This means that even more caution should be exercised with regard to financing R&D in the Nizhny Novgorod Region. One cannot exceed the optimal R&D shown at the Pareto frontier.

As for the graph analysis in Figure 3b, the situation here was more transparent. Investment in equity and expenditures on R&D are competing goals, which seems to be quite natural, since it is impossible to finance successfully, i.e., with good performance, the fundamental costs with a potential effect over a long period of time, i.e., R&D, and current manufacturing requirements, i.e., investment in equity, simultaneously.

Consequently, the takeaway for the Nizhny Novgorod Region at the current stage of foresight according to Figures 2–3 was that there were optimum investments in equity and R&D in this region to obtain the maximum income of the population.

The takeaways obtained in a similar way at this stage of foresight for all 8 regions of the VFD, where the presence of innovative and industrial clusters, as grouped in Table 4.

Table 4 Takeaways for 8 VFD regions based on analysis of Pareto frontiers of predictive functions

Regions	Takeaways
1) Nizhny Novgorod Region	There are optimum investment and R&D to maximize the income of the population.
2) Republic of Mordovia	Investments need to be reduced, and R&D needs to be increased to maximize the income of the population.
3) Ulyanovsk Region	The investment should be raised first, then slightly reduced. The R&D has to be reduced.
4) Samara Region	Investments need to be reduced, and R&D needs to be increased to maximize the income of the population.
5) Perm Territory	Investments should be reduced and R&D increased, then slightly reduced.
6) Udmurt Republic	Investments and R&D need to be reduced to maximize the incomes of the population.
7) Republic of Tatarstan	Investments need to be increased and R&D decreased to maximize the incomes of the population.
8) Republic of Bashkortostan	Investments need to be reduced, and R&D needs to be increased to maximize the incomes of the population.

Stage 4. We performed the calculations based on the results of the previous foresight stage in Table 5 according to formula 1.

Stage 5. The Samara Region had the largest shortage of current expenditures on R&D compared to the optimal plan. It amounted to 10,673 million rubles. It can be partially filled up at the expense of reserves for R&D in the Nizhny Novgorod and Ulyanovsk regions, the Udmurt Republic, and the republics of Tatarstan and Bashkortostan. The total amount of such reserves was 8,412 million rubles. It should be forwarded to the Samara Region. Then, its synergy effect according to formula 2 would be:

$$S_{new} = 343{,}045 - 259{,}152.3 + 24{,}419.4 - 13{,}746.4 - 8.412 = 86{,}153.7 \text{ (million rubles)}.$$

Adding up the results of the last column of Table 5, we obtained formula 3, so that the synergy effect of the whole VFD was $S_{FD} = 429{,}344$ million rubles.

Table 5 Calculation of synergy effects of clusters and the entire VFD

Average per capita cash income of population (per month) (RUB)		Investment in equity (million RUB)		Internal current expenditures on R&D (million RUB)		Synergy effect (million RUB)	
Plan	Actual	Plan	Actual	Plan	Actual	Plan	Reserve
1) Nizhny Novgorod Region							
35,165.7	31,631	350,000	259,045.4	63,000	66,202.2	87,752.4	3,202.2
2) Republic of Mordovia							
20,189.9	18,048	70,032.2	51,210.1	1,075	970.7	18,926.4	-104.3
3) Ulyanovsk Region							
26,447.4	22,846	108,000	81,105.4	9,901.5	11,291.2	25,504.9	1,389.7
4) Samara Region							
36,356.8	27,507	343,045	259,152.3	24,419.4	13,746.4	86,153.7	-10,673
5) Perm Territory							
36,845.6	28,777	244,113	238,007.9	14,100	12,754.5	7,450.6	-1,345.5
6) Udmurt Republic							
27,225.2	24,415	102,100	97,892.8	1,320.8	2,295.3	3,233.7	974.5
7) Republic of Tatarstan							
37,271.1	33,130	723,603	629,731	14,200	17,038.8	91,033.2	2,838.8
8) Republic of Bashkortostan							
33,294.9	28,645	377,164	267,868.1	10,350	10,356.8	109,289.1	6.8

4. Discussion

Based on the analysis of the Pareto frontiers of predictive functions we obtained the following insights:

1. The Nizhny Novgorod Region had a limit of optimal investments and R&D, above which it was impossible to develop the region.

2. The greatest benefit from R&D was seen for the Republic of Mordovia, Samara Region, and Republic of Bashkortostan.

3. The Republic of Tatarstan was the most investment-attractive region, provided that R&D of the other VFD regions was open.

It was also possible to partially allocate the reserve of 8,412 million rubles for R&D to the Republic of Mordovia and Perm Territory, and the rest to the Samara Region. However, the synergy effect of the entire VFD, in this case, was the same as if the total reserve was allocated for R&D in the Samara Region.

Such redistribution of resources within the VFD enabled it to reach the planned indicators of average per capita cash incomes of the population (per month), which are shown in the first column of Table 5. In turn, this will lead to the maximum values of natural population growth in the VFD regions, which can be quite easily found for each of the 8 analyzed regions in Table 1.

This paper contributed to the development of methods for assessing regional cluster performance, considering their interconnectedness and present approach that is different from expert assessment, which can be used when the information about cluster development is limited (Kudryavtseva et al., 2020a), and from classical approaches, which are based on estimation of relative concentration of the industries in the region (Delgado et al., 2014; Skhvediani et al., 2020). Application of optimization algorithms will estimate synergy effects for the regions, where clusters are located, and elaborate more scientific-based regional cluster policies.

4. Conclusion

This paper presented novel approach to the assessment of regional cluster performance using genetic algorithms. From the theoretical point of view, we presented stages of foresight, including preparation of statistical data for clusters, obtaining predictive functions for clusters and Pareto frontiers of predictive functions, and planning of synergy effects of clusters of regions and the entire federal district. From a practical point of view, this study resulted in the estimation of the reserve for R&D for the Volga Federal District based on the data of 25 clusters from 2009–2018. As a result of foresight, we estimated a total positive reserve for R&D in the amount of 8,412 million rubles, which should be forwarded to the Samara Region. Then, the synergy effect of the entire VFD would be equal to 429,344 million rubles.

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