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Model of Motivation for the Top Management of Regional Government Agencies

Egor Koshelev

Lobachevsky State University of Nizhny Novgorod, Nizhny Novgorod, Russia, ekoshelev@yandex.ru
Corresponding author: ekoshelev@yandex.ru

Abstract

The purpose of the study is to create a model of motivation for the top management of regional government agencies under which the non-material motivation of top managers will be made dependent on the achieved strategic potential of the region and their material motivation. For this purpose, it is necessary to solve a three-objective problem of global optimisation for the coefficient of natural population growth using a multi-objective genetic algorithm. Each of the three objectives – the strategic potential of the region and the material and non-material motivations of top managers – depends on three factors in the same coordinate system. The first three of the nine factors characterise the system of non-material incentives for top managers in government agencies, the next three refer to the system of their material incentives, and the last three apply to the available strategic potential of the region necessary for its further successful development. The creation of multiple effective solutions using the Pareto front is performed for two primary objectives, namely, the strategic potential of the region and material motivation of top management; then, as a consequence, a set of optimal solutions for non-material motivation is obtained. The conclusion about the actual remuneration (incentives) of the top managers at government agencies in the regions is as follows. For each of the three objectives in a particular region, the latest actual values of the nine factors under study are compared with the nearest planned (optimum) values of the Pareto front. A positive deviation from the optimum is evaluated positively, which makes it possible to additionally incentivise top managers either materially or non-materially.

Keywords: material motivation, non-material motivation, multi-objective genetic algorithm, pattern search

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Модель Мотивации Топ-Менеджмента Государственных Структур Регионов

Егор Кошелев

Нижегородский государственный университет им. Н.И. Лобачевского, Нижний Новгород, Россия
Автор, ответственный за переписку: ekoshelev@yandex.ru

Аннотация

Целью исследования является создание модели мотивации топ-менеджмента государственных структур регионов, что позволит поставить нематериальную мотивацию топ-менеджеров в зависимость от достигнутого стратегического потенциала региона и их материальной мотивации. Для этого решается трехцелевая задача глобальной оптимизации коэффициента естественного прироста населения с помощью многоцелевого генетического алгоритма. Каждая из трех целей – стратегический потенциал региона, материальная и нематериальная мотивации топ-менеджмента - зависит от трех факторов в одной системе координат. Первые три из девяти факторов характеризуют систему нематериального поощрения топ-менеджеров в государственных структурах, следующие три – систему их материального поощрения, а последние три – имеющийся стратегический потенциал региона, необходимый для его дальнейшего успешного развития. Построение множества эффективных решений с помощью Парето-фронта выполняется для двух первоочередных целей – стратегического потенциала региона и материальной мотивации топ-менеджмента, после чего уже как следствие получается множество оптимальных решений для нематериальной мотивации. Вывод о фактическом премировании (поощрении) топ-менеджеров государственных структур регионов делается следующим образом. Для каждой из трех целей в конкретном регионе сравниваются последние фактические значения исследуемых девяти факторов с ближайшими плановыми (оптимальными) значениями Парето-фронта. Положительное отклонение от оптимума оценивается позитивно, что позволяет дополнительно поощрять топ-менеджеров материально либо нематериально.

Ключевые слова: материальная мотивация, нематериальная мотивация, многоцелевой генетический алгоритм, поиск по шаблону

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1. Introduction

It is impossible to create competitive advantages in the national economy without developing and applying the necessary management methods in government agencies. Relevant strategies, such as the National Strategy for the Development of Artificial Intelligence for the Period Until 2030, are aimed at enabling the Russian Federation to achieve such innovative advantages in the global market.

Metaheuristic algorithms are an integral part of artificial intelligence technologies and allow the global optimisation of processes that have a high dimensionality. Such processes include the motivation of the top management of government agencies at both country and regional levels. However, building a rational motivation system for senior managers is a complex task, as they can be motivated both materially and non-materially. In the latter case, we primarily imply the career growth of civil servants occupying important management positions.

It is advisable to start modelling the motivation system for top managers by studying the basic principles of their motivation, which are fundamentally different from the approaches used to motivate average employees.

Khytrova et al. (2020) established that the timely identification and diagnostics of problematic situations that arise during the development and growth of organisations significantly depend on the levels of qualifications and professionalism of their managers. According to Munna (2021), moreover, a manager always has the ability to influence others, and there are three types of management skills: technical skills, interpersonal communication skills, and decision-making skills. Technical skills are ideally related to the ability to use methods and techniques to accomplish a task, and interpersonal skills focus solely on the ability to understand, communicate, and work well with individuals and groups through the development of effective relationships.

In a similar context, Dogar (2020) studied identification of the dynamics of excluding internal stakeholders from the process of making organisational strategic decisions as well as their impact on the effectiveness and sustainability of the organisation. The author proposed a mechanism to prevent such conflicts in social development organisations, in particular, and organisations in general.

The next important stage of building a rational motivation system for top management is to create the necessary models for this purpose. Thus, Kampf et al. (2017) identified significant differences between the needs of senior managers and blue-collar workers using Student's *t*-test with two samples. On the basis of the test results, the researchers concluded that in the field of motivational factors in Slovakia, it was impossible to establish a single motivational programme for the analysed groups of employees. In future, after the needs of employees are satisfied, it is possible that as requirements change, motivation may change as well.

Another successful model is the model of motivation management of executives, formed as a structural and logical scheme based on the systems approach and decomposition, which reflects the interaction of subject and object in the process of forming and implementing the system of motivation of managers at an enterprise (Popadinets et al., 2021). Using the method of linear multiple regression, a system of equations was constructed to describe the economic and mathematical model of motivation of management at oil and gas enterprises, which, after repeated experiments, provided diagnostics of indicators before, during, and after the implementation of the model of management motivation.

Motivation in the public sector deserves particularly close attention in the process of modelling top management. For example, Schwarz et al. (2020) sought to better understand leadership in the public sector by examining the relationships among accountability, compliance, political loyalty, and approaches to network management for leadership and public service motivation (PSM) and individual performance. Using a sample of 300 civil servants and their 64 managers in China, the study showed that accountability, compliance, political loyalty, and network management are highly positively related to employees' PSM levels and performance.

The subject of the current study is the construction of a motivation system for the top management of government agencies in order to align the interests of the population, the state, and its top managers. The purpose of the study is to create a model of motivating the top managers of government agencies in the regions under which the non-material motivation of such managers can be made dependent on the achieved strategic potential of the region and their material motivation.

2. Literature review

Currently, there is a cluster approach to managing the development of the country's regions, which allows the innovation component of industrial planning to be taken into account in this process. Working out a strategy for the development of regions with innovation clusters is the starting point of the research presented in this paper.

At the current stage of economic development, innovation clusters can be considered one of the main elements of the innovation system, since the strategic objective of their functioning is the development and production of innovations. Innovation potential is one element of national competitiveness, and the development of a nation's level of innovation is important for its functioning in the world economy (Andrienko, 2021).

In such a context, Zhang (2021) mainly focussed on innovative industrial clusters and the industrial cluster theory, the development areas of innovative industrial clusters, innovative enterprises, and government policies. In contrast, Ferras-Hernandez and Nylund (2018) studied when and how innovation clusters strengthen innovations at the corporate level. The authors examined the matter from different theoretical perspectives, such as neoclassical economics, evolutionary economics, behavioural economics, strategic management, and open innovations, in search of a comprehensive theoretical foundation that would explain the relationship between a specific innovation and a concentration of innovative activities. The researchers took into account five strengths that stimulate technological changes in innovation clusters: attraction, information, interaction, anticipation, and rivalry.

Héraud and Muller (2022) considered a fundamentally new problem, namely, the interaction between smart cities and innovation clusters. Their approach was strongly influenced by the philosophy of foresight and technology assessment, that is, the construction of a desired consensus future rather than a deterministic technological vision of the problem. For this purpose, the authors investigated the activities of municipal politicians or managers as well as those of people involved in technology clusters, research centres, Fab Labs, living labs, etc.

Bittencourt et al. (2018) argued that most studies on innovation capabilities analyse such capabilities at the corporate level and that little has been done to understand the interaction between inter-organisational agglomerations and the capabilities that such mechanisms preserve. Thus, acquisition capabilities, distribution capabilities, and knowledge management capabilities are the core capabilities that constitute the cluster innovation perspective.

Within the cluster approach, we apply a multi-objective genetic algorithm (MGA), which belongs to the class of metaheuristic algorithms, to model the motivation of the top management of government agencies. Hence, we explore the advantages and recent advances of the MGA in various areas of scientific knowledge.

The MGA is a direct search method for multi-objective optimisation problems. It is based on the process of the genetic algorithm (GA); the population property of genetic algorithm is well applied in MGA. Compared with the traditional multi-objective algorithm, which aims to find a single Pareto solution, the MGA seeks to determine the number of Pareto solutions.

Fita (2014) made it a research goal to find a well-defined and meaningful approximation of the solution set for linear and nonlinear three-objective optimisation problems, since it is important for a decision maker to obtain as much information as possible about the set of possible solutions. This paper uses a continuous variational GA to find an approximate near-optimal solution set. Khan and Baig (2015) presented a method based on the evolutionary algorithm to solve the multi-objective feature subset selection problem. Thus, a feature subset must be selected before creating a classifier. This proposed methodology treats feature subset selection as a multi-objective optimisation problem and utilises one of the recent MGAs.

Das et al. (2017) proposed the cluster analysis method based on the MGA to find the optimal set of overlapping clusters. The overall performance of the method was investigated on some popular sets of data and microarrays, and the optimality of the clusters was measured by certain important cluster checking indices. The experimental results showed the effectiveness of the proposed method.

Li and Jin (2018) presented research on a deadline rescheduling strategy and a new hybrid genetic algorithm (HGA) to include a new processing task. Firstly, the time interval is set according to the timing of the new task, and the optimisation of multi-objective planning is guaranteed. Then, by improving the GA and combining it with the simulated annealing algorithm, the new hybrid algorithm is presented, which implements the optimisation processing in flexible shop floor planning. The experiment showed that the algorithm improves the global optimisation capability. Finally, the modelling results showed that the algorithm can obtain a Pareto solution of higher quality under static planning and new problem insertion.

According to Thananant and Auwatanamongkol (2019), supervised clustering aims to achieve several goals, such as the compactness of clusters, homogeneity of data in clusters with respect to their class labels, and separability of clusters. With these goals in mind, the researchers proposed a new supervised clustering algorithm based on an MGA called SC-MOGA. The algorithm searches for an optimal clustering solution that simultaneously achieves the above three objectives. The experimental results showed that the proposed data sampling method not only helps to reduce the number of data instances to be clustered using SC-MOGA, but also improves the quality of the data-clustering results.

Sardaraz and Tahir (2020) presented a multi-objective scheduling algorithm to plan scientific workflows in cloud computing. The results showed that the proposed algorithm provides an improvement in execution time and reduces cost when using a load-balancing system. Wang et al. (2021) established the mathematical model of multi-objective optimisation based on a GA to design a burnable poison structure in a pressurised reactor. Then, the researchers developed an optimisation programme by combining a parallel multi-objective GA with the Monte Carlo N-Particle Transport Code as a neutronics and depletion solver.

Maghawry et al. (2021) proposed an HGA that uses a GA to perform a global search supported by a particle swarm optimisation (PSO) algorithm to perform a local search. The proposed algorithm was tested on the basis of four benchmark multi-objective optimisation functions, where the maximum balance between the exploration and search exploitation of space was achieved. The algorithm also succeeded in improving the overall performance of an HGA by limiting the average number of iterations until convergence.

Nikseresht and Raji (2021) presented a new MGA-based task mapping and scheduling (abbreviated as MOGATS) for a heterogeneous embedded system. The mapping and scheduling tasks are modelled as a GA-based optimisation approach. Thus, the authors' task scheduling tool is the first multi-objective task scheduling in the design phase of embedded systems to help designers determine which scheduling set will achieve their desired outcome.

However, the solutions of an MGA must be checked at the extreme points of the obtained Pareto front, for which the present study will use the direct search (pattern search) algorithm due to its high optimisation quality. This algorithm has several advantages, as outlined below.

Under conditions of uncertainty and turbulence, the classical and traditional approaches cannot satisfactorily find a complete solution to real optimisation problems. Therefore, new global optimisation methods are required to seriously address these problems. One of these methods consists of HGAs and pattern search, a versatile, flexible, robust, and general-purpose framework for solving complex global optimisation and search problems in real-world applications (Vasant, 2012). The performance of the pattern search algorithm was thoroughly tested by Baeyens et al. (2016) with the use of benchmark functions and compared with some well-known global optimisation algorithms. The results of their computational study showed that the algorithm combines simplicity and efficiency and is competitive with the heuristics-based strategies currently used for global optimisation.

Finally, our proposed approach to the need to verify MGA solutions using other global optimisation algorithms has also been applied by authors who used algorithms other than pattern search for this purpose. For example, Giorgio and Sangiorgio (2020) argued that a complete view of the boundary is possible by first solving single-objective problems corresponding to the extremes of the Pareto boundary and then using such solutions as elite representatives of the original solution. Their paper compared this approach to the more familiar initialisation using some classical tests with a variable number of objectives and known analytical solutions.

Yashin et al. (2020) have already solved a simpler problem of the material and non-material motivation of the top management of governing bodies of regions and districts. For this purpose, the efficiency of intercluster interaction within one federal district was assessed using a system of factors of the socio-economic development of Russian regions that directly affect the natural population growth in the regions of the district. An MGA was also used to solve the task, which allowed the Pareto front to be obtained for the two-objective function of the natural increase rate, all solutions of which are equally optimal. One can find at any point of the Pareto front the shares of material and non-material motivation of top managers.

However, the current paper studies the more complex task of the three-objective global optimisation of the motivation of the top managers at government agencies in the regions under which the non-material motivation of such managers can be made dependent on the achieved strategic potential of the region and their material motivation. In addition, the new task is solved for those regions of the whole country that have territorial innovation clusters on the list approved by the government of the Russian Federation.

3. Materials and methods

In order to model the motivation of the top management of government agencies in the regions, we define a three-objective function where the first objective is the non-material motivation of top managers, the second is their material motivation, and the third is the strategic potential of the region. Each of these goals depends on three factors x_1, x_2, x_3 in one coordinate system.

We model the motivation of the top managers of government agencies in the regions, taking into consideration external and internal relations, through an MGA in several stages (Fig. 1).

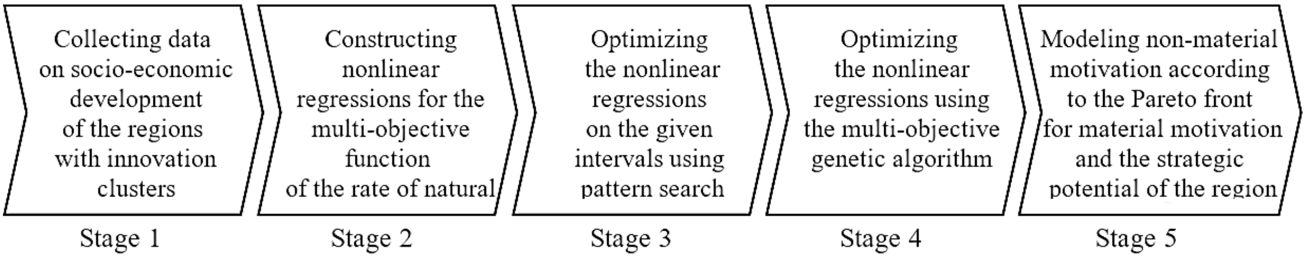

Figure 1. Stages of modelling the motivation of the top managers of government agencies in the regions

Stage 1 - collecting data on the socio-economic development of the regions with innovation clusters. Effective inter-cluster interaction within the country has economic-financial, informational, and logistic aspects. For regions with territorial innovation clusters, inter-cluster interaction refers to external relations, and for clusters within the region, it refers to internal ones. The regions' external relations with other countries should also be taken into consideration. The effectiveness of such interactions can be assessed through the system of assessment of socio-economic development of the Russian regions using the places they occupy in the Russian Federation in terms of a number of factors:

1. gross regional product (GRP) per capita (x_1);
2. investments in fixed capital per capita (x_2);
3. internal expenditure on research and development (R&D) (x_3);
4. average per capita cash income of the population (per month) (x_1);
5. total living space per capita (x_2);
6. specific weight of hard-surface roads (x_3);
7. tax revenue per capita (x_1);
8. employment-to-population ratio (x_2);
9. number of students per 10 000 population (x_3).

These factors directly affect the value of the rate of natural increase per 1000 people (y) in the regions of the country.

The first three factors characterise the system of non-material incentives for the top managers of government agencies, the next three refer to the system of their material incentives, and the last three refer to the available strategic potential of the region necessary for its further successful development. Thus, the first three factors reflect how effectively top managers solve national tasks and the next three how effectively they solve the tasks that are prioritised by the population. The priorities of the population are more important; therefore, top managers should be materially motivated to meet them effectively. We recommend motivating the realisation of national tasks non-materially.

However, as stated earlier, the non-material motivation of top managers is, first and foremost, an opportunity for their career growth. We define this opportunity depending on how successfully they accomplish the tasks prioritised by the population as well as their success in building up the strategic potential of the region. Thus, constructing a set of effective solutions with the help of the Pareto front will be performed for two priority objectives, namely, the strategic potential of the region and the material motivation of the top management, after which a set of optimal solutions for non-material motivation will be obtained as a result.

Stage 2 - constructing nonlinear regressions for the multi-objective function of the rate of natural increase. At this stage, we obtain the necessary nonlinear regressions for the strategic potential of the region and material motivation of the top management, for example, in the programme *Statistica*, which will then be used for the purpose of the global optimisation of the three-objective function of the rate of natural increase (y).

Stage 3 - optimising the nonlinear regressions on the given intervals using a pattern search. There are 85 constituent entities (regions) in Russia. Therefore, the interval on which we will optimise the three-objective function $y = f(x_1, x_2, x_3)$ will be the values (1; 85). Searching for the global largest values of each nonlinear regression using the pattern search algorithm for this purpose will allow us to check the extreme values of the Pareto front, which we will obtain later by using the MGA.

Stage 4 - optimising the nonlinear regressions using the MGA. This algorithm allows the Pareto front to be obtained for the two-objective function, all points of which are equally optimal solutions. It reflects the set of the largest y as well as the values of its factors x_1, x_2, x_3. Thus, the optimal values of the functions of strategic potential and material motivation, as well as the corresponding values of factors

x_1, x_2, x_3, can be found at any point of the Pareto front.

Stage 5 - modelling non-material motivation according to the Pareto front for material motivation and the strategic potential of the region. While conducting the two-objective optimisation, we simultaneously obtain in the *Matlab* package the value of the third function (i.e., non-material motivation) at each point corresponding to the Pareto front for the first two functions. This allows us to plan the non-financial motivation of top managers depending on how well they achieve the tasks prioritised by the population as well as the increase of the strategic potential necessary for the region's development.

The conclusion about the actual bonuses (incentives) for the top managers of government agencies in the regions is made as follows. For each of the three functions in a particular region, we compare the latest actual values of factors x_1, x_2, x_3 with the nearest planned (optimal) values. A positive deviation from the optimum is evaluated positively, which allows us to additionally incentivise top managers either materially or non-materially. A negative deviation shows that they made poor management decisions in the past, which should surely be reflected in their incentives.

4. Results

Let us consider the process of modelling the motivation of the top managers of government agencies in the regions of the country through an MGA. Thereafter, we will draw conclusions for a specific region.

According to the list approved by the government of the Russian Federation, there are 25 pilot territorial innovation clusters in Russia in the respective regions of the country. For this reason, we will study only those regions (oblasts or republics) in which the clusters from the above list are located.

Stage 1 - collecting data on the socio-economic development of the regions with innovation clusters. Using the indicators of the 'Statistical Review' published by the Federal State Statistics Service, we collect the necessary data for the decade from 2010 to 2019 for the regions under study. A 200 X 10 dimensional matrix is obtained. Table 1 reflects these data for the last year under study, 2019.

Table 1. Data for creating regression models

Region	Place occupied by the constituent entity in the Russian Federation									Rate of natural increase per 1000 people
	Non-material motivation			Material motivation			Strategic potential			
	GRP per capita	Fixed capital investment per capita	Internal R&D expenses	Average per capita cash income (per month)	Total living space per capita	Specific weight of hard-surface roads	Tax revenue per capita	Employment-to-population ratio	Number of students per 10000 population	
	x1	*x2*	*x3*	*x1*	*x2*	*x3*	*x1*	*x2*	*x3*	*y*
2019										
1. Kaluga region	27	31	20	27	10	65	25	20	59	-5.7
2. Moscow region	16	19	3	9	1	23	22	8	80	-2.5
3. Moscow	6	10	1	4	82	1	6	6	2	1.2
4. Arkhangelsk region	33	47	48	19	28	66	34	70	68	-4.4
5. Leningrad region	17	11	18	24	17	26	16	24	82	-5.3
6. Saint Petersburg	9	23	2	10	47	2	10	7	1	-0.1

7. Republic of Bashkortostan	44	50	16	32	46	10	30	67	38	-1.8
8. Republic of Mordovia	63	65	56	81	30	76	57	19	13	-5.7
9. Republic of Tatarstan	15	14	11	16	37	34	12	17	6	-0.1
10. Perm region	24	28	10	31	65	50	20	71	51	-3.0
11. Nizhny Novgorod region	34	41	4	20	33	49	31	16	29	-5.6
12. Samara region	29	42	9	35	35	82	17	21	21	-3.9
13. Ulyanovsk region	60	70	15	70	23	46	38	60	22	-5.0
14. Sverdlovsk region	22	33	5	14	45	29	32	43	26	-2.6
15. Altai Republic	76	78	40	69	63	53	68	61	47	3.5
16. Krasnoyarsk region	10	17	6	26	55	19	9	22	39	-1.7
17. Kemerovo region	47	27	45	63	57	22	54	63	65	-5.2
18. Novosibirsk region	35	45	7	33	50	44	40	33	8	-2.0
19. Tomsk region	23	43	12	41	62	52	13	39	3	-1.4
20. Khabarovsk region	20	24	38	13	67	11	28	15	12	-2.4

Stage 2 - constructing nonlinear regressions for the multi-objective function of the rate of natural increase. According to the data in Table 1, we can obtain the three most reliable multiple non-linear regressions in the *Statistica* package:

- non-material motivation (Fig. 2):

$$y = 9,96172 + 0,1769x_1 + 0,3188x_3 - 1,32628\sqrt{x_1} - 4,05206\sqrt{x_3} - 1,04676\ln x_2 + 2,72664\ln x_3,$$
$$R^2 = 0,825;$$

- material motivation (Fig. 3):

$$y = -2,77578 + 0,30824x_2 - 0,01069x_2^2 + 0,00001x_1^3 + 0,00009x_2^3 - 0,00001x_3^3 + 1,18178\ln x_1,$$
$$R^2 = 0,825;$$

- strategic potential (Fig. 4):

$$y = 15,0191 - 0,2383x_1 + 0,1342x_2 + 0,4561x_3 + 8,1069\sqrt{x_1} - 1,4168\sqrt{x_2} - 7,4633\sqrt{x_3} - 13,0338\ln x_1 + 6,8303\ln x_3,$$
$$R^2 = 0,779.$$

N=77	Regression Summary for Dependent Variable: Var10 (Regions_3.sta) R= ,92594578 R?= ,85737558 Adjusted R?= ,84515063 F(6,70)=70,133 p<0,0000 Std.Error of estimate: 1,0057					
	b*	Std.Err. of b*	b	Std.Err. of b	t(70)	p-value
Intercept			9,96172	1,784829	5,58133	0,000000
Var3	2,93552	0,692518	0,31880	0,075207	4,23890	0,000067
SQRV3	-3,63084	1,065548	-4,05206	1,189163	-3,40748	0,001090
LN-V3	1,32485	0,497763	2,72664	1,024436	2,66160	0,009638
LN-V2	-0,23202	0,079658	-1,04676	0,359385	-2,91264	0,004806
Var1	1,43075	0,542308	0,17690	0,067053	2,63825	0,010262
SQRV1	-0,94981	0,545310	-1,32628	0,761453	-1,74178	0,085939

Figure 2. Regression of non-material motivation

N=77	Regression Summary for Dependent Variable: Var10 (Regions_3.sta) R= ,90849012 R?= ,82535430 Adjusted R?= ,81038467 F(6,70)=55,135 p<0,0000 Std.Error of estimate: 1,1129					
	b*	Std.Err. of b*	b	Std.Err. of b	t(70)	p-value
Intercept			-2,77578	1,445985	-1,91965	0,058979
V4**3	0,41765	0,132844	0,00001	0,000002	3,14391	0,002446
V5**3	5,51764	1,081397	0,00009	0,000018	5,10233	0,000003
V5**2	-6,88600	1,494558	-0,01069	0,002319	-4,60739	0,000018
Var5	1,77997	0,505659	0,30824	0,087565	3,52010	0,000763
LN-V4	0,40928	0,130853	1,18178	0,377837	3,12777	0,002567
V6**3	-0,12534	0,063423	-0,00001	0,000003	-1,97632	0,052060

Figure 3. Regression of material motivation

N=77	Regression Summary for Dependent Variable: Var10 (Regions_3.sta) R= ,88245455 R?= ,77872604 Adjusted R?= ,75269381 F(8,68)=29,914 p<0,0000 Std.Error of estimate: 1,2709					
	b*	Std.Err. of b*	b	Std.Err. of b	t(68)	p-value
Intercept			15,0191	2,906653	5,16714	0,000002
Var7	-1,90463	1,940789	-0,2383	0,242775	-0,98137	0,329889
SQRV7	5,93936	3,810889	8,1069	5,201640	1,55852	0,123751
Var9	4,70427	0,887557	0,4561	0,086052	5,30024	0,000001
SQRV9	-7,87952	1,619837	-7,4633	1,534268	-4,86439	0,000007
LN-V9	3,91653	0,976773	6,8303	1,703455	4,00966	0,000154
LN-V7	-3,99155	2,031972	-13,0338	6,635115	-1,96437	0,053575
Var8	1,35475	0,775240	0,1342	0,076766	1,74752	0,085062
SQRV8	-1,32725	0,802079	-1,4168	0,856196	-1,65477	0,102581

Figure 4. Regression of strategic potential

Stage 3 - optimising the nonlinear regressions on the given intervals using a pattern search. Optimising regressions in the *Matlab* package on the interval (1; 85) using a pattern search algorithm yields the following results:

- for non-material motivation:

$$y_{max} = 14,6 \quad \text{when} \quad (x_1, x_2, x_3) = (85;1;85);$$

- for material motivation:

$$y_{max} = 12,9 \quad \text{when} \quad (x_1, x_2, x_3) = (85;85;1);$$

- for strategic potential:

$$y_{max} = 21,9 \quad \text{when} \quad (x_1, x_2, x_3) = (1;1;85).$$

Stage 4 - optimising the nonlinear regressions using the MGA. The MGA approach allows us to obtain the Pareto front in the *Matlab* package for the function of two objectives: strategic potential and material motivation (Figs. 5 and 6).

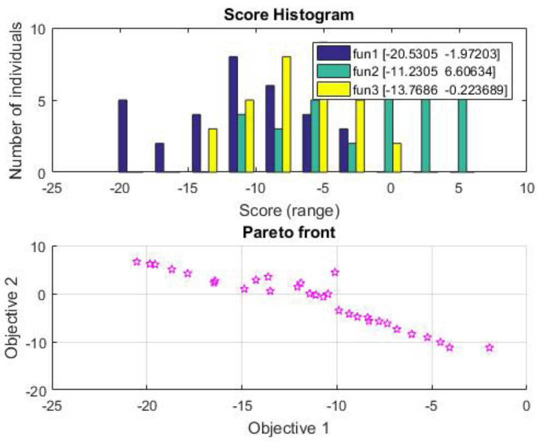

Figure 5. Pareto-front strategic potential (fun1) and material motivation (fun2)

Index	f1	f2	f3	x1	x2	x3
1	-20,531	6,606	-9,209	1,002	1,17	74,763
25	-19,844	6.157	-8,316	1,011	2,666	74,541
4	-19,563	6,057	-8,205	1,033	2,906	74,458
10	-18,69	5,024	-7,217	1,034	5,079	71,066
7	-17,855	4,194	-6,708	1,074	2,888	61,316
19	-16,472	2,267	-4,735	1,041	16,171	59,517
8	-16,414	2,642	-5,039	1,084	17,797	63,568
23	-14,877	0,974	-3,336	1,104	17,069	44,988
31	-14,261	2,833	-5,5	1,459	7,462	60,791
29	-13,621	3,479	-6,218	1,716	3,902	62,026
16	-13,509	0,537	-2,897	1,255	16,782	39,524
14	-12,078	1,401	-4,162	1,675	16,8	56,698
18	-11,91	2,198	-5,076	1,889	12,55	63,303
30	-11,436	-0,009	-1,736	1,537	24,714	25,712
13	-11,115	-0,284	-0,364	1,998	80,293	26,14
32	-10,711	-0,696	-0,224	2,15	80,993	20,844
21	-10,471	-0,074	-2,179	1,744	20,876	34,257
27	-10,103	4,409	-7,233	3,306	3,682	73,935
3	-9,901	-3,508	-13,769	83,951	1,169	80,488
2	-9,36	-4,199	-13,124	83,973	1,477	77,276
28	-8,924	-4,821	-12,709	83,651	1,269	72,825
9	-8,378	-4,946	-11,986	81,659	1,415	69,391
5	-8,315	-5,687	-12,032	83,945	1,415	67,703
24	-7,778	-5,755	-11,213	82,773	2,881	68,12
11	-7,348	-6,216	-10,699	82,868	4,594	67,809
12	-6,843	-7,403	-10,23	84,816	6,029	64,308
20	-6,061	-8,423	-9,345	84,835	10,684	61,603
22	-5,239	-9,085	-8,305	83,66	11,702	53,291
17	-4,555	-10,081	-7,217	84,293	9,74	35,426
26	-4,075	-11,194	-6,715	84,905	17,378	3,199
6	-1,974	-11,23	-6,231	85	18,994	1,352
15	-1,972	-11,23	-6,242	85	18,741	1,348

Figure 6. Coordinates of the strategic potential (f1) and material motivation (f2) Pareto front points

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Stage 5 - modelling non-material motivation according to the Pareto front for material motivation and the strategic potential of the region. Figures 5 and 6 also reflect the values of the third function (i.e., non-material motivation), which correspond to the optimal values of the functions of strategic potential and material motivation.

From the analysis of the Pareto front obtained in Figures 5 and 6, we can draw the following conclusions:

1. Maximum population growth will be observed in the case of focusing on the strategic potential. The rate of natural increase per 1000 people here is 20.5.

2. In this case, for the function of non-material motivation, the GRP per capita ($x_1 \approx 1$) and investment in fixed capital per capita ($x_2 \approx 1$) should be maximal, and internal R&D expenditure should be almost minimal ($x_3 \approx 75$). This situation is explained by the fact that investment in fixed capital and R&D expenditures are competing objectives under conditions of limited financial resources.

3. For the function of material motivation, the average per capita cash income of the population (per month) ($x_1 \approx 1$) and the total living space per capita ($x_2 \approx 1$) should be maximal, and the specific weight of hard-surface roads should be almost minimal ($x_3 \approx 75$).

4. For the function of strategic potential, tax revenues per capita ($x_1 \approx 1$) and the employment-to-population ratio ($x_2 \approx 1$) should be maximal. However, the number of students per 10 000 population is allowed to be almost minimal ($x_3 \approx 75$).

So far, preliminary conclusions have been obtained for the 20 regions under study with territorial innovation clusters. To draw conclusions for a specific region, taking the Nizhny Novgorod region as an example, let us compare the actual values in 2019 of the studied factors with the optimal values on the Pareto front (Table 2).

Table 2. Performance assessment of the Nizhny Novgorod region in 2019

Indicators	Place occupied by the constituent entity in the Russian Federation									Rate of natural increase per 1000 people
	Non-material motivation			Material motivation			Strategic potential			
	GRP per capita	Fixed capital investment per capita	Internal R&D expenses	Average per capita cash income (per month)	Total living space per capita	Specific weight of hard-surface roads	Tax revenue per capita	Employment-to-population ratio	Number of students per 10 000 population	
	x1	*x2*	*x3*	*x1*	*x2*	*x3*	*x1*	*x2*	*x3*	*y*
Actual value (2019)	34	41	4	20	33	49	31	16	29	-5.6
Closest optimum 1	2	21	34	2	21	34	2	21	34	10.5
Optimum deviation 1	-32	-20	30	-18	-12	-15	-29	5	5	-16.1
Actual value (2019)	34	41	4	20	33	49	31	16	29	-5.6
Closest optimum 2	1	17	45	1	17	45	1	17	45	14.9
Optimum deviation 2	-33	-24	41	-19	-16	-4	-30	1	16	-20.5
Actual value (2019)	34	41	4	20	33	49	31	16	29	-5.6
Closest optimum 3	85	19	1	85	19	1	85	19	1	11.2
Optimum deviation 3	51	-22	-3	65	-14	-48	54	3	-28	-16.8

As shown in Figure 6, the three closest optima of the Pareto front are located in the lines numbered

21, 23, and 6 (or 15). These are reflected in Table 2 as optima 1, 2, and 3. We consider the deviation from each optimum as the difference between the corresponding values of x_i (i = 1.3) for a particular objective function y. Thus, for the strategic potential function, the closest optimum is 1; then, the sum of deviations of the places for x_1, x_2, x_3 is 39. For the function of material motivation, the closest optimum is 2, and the sum of deviations of places will be 39. For the function of non-material motivation, the closest optimum is 3, and the sum of deviations of places will be 76. Moreover, the deviation of the coefficient of the rate of natural increase (y) is smallest in the case of orientation to optimum 1 and amounts to 16.1.

In this case, according to the results of Table 2, the number of students per 10 000 population and the employment rate roughly correspond to the planned optimal values. However, the specific weight of hard-surface roads should be increased in order for the Nizhny Novgorod region to move from 49th to 34th place; the total living space per capita should also be increased in order for it to move from 33rd to 21st place; and the average per capita cash income (per month) should be significantly increased in order for it to move from 20th to 2nd place.

At the same time, internal R&D expenditures should be reduced for it to move from 4th to 34th place, and investment in fixed capital per capita should be increased for it to move from 41st to 21st place. This is because these two objectives are competing when the budget is limited. In addition, GRP per capita needs to be significantly increased for the Nizhny Novgorod region to move from 34th to 2nd place.

5. Discussion

Comparing our results with the experiences of other researchers, we note that another successful model of managing top managers' work motivation is formalised as a structural and logical scheme based on the systems approach and decomposition and reflecting the interaction between subject and object when the motivation system is formed and introduced at an enterprise (Popadinets et al., 2021). However, our model takes into consideration different aspects of top management motivation.

Moreover, our proposed approach to the need to validate MGA solutions by using other global optimisation algorithms is applied by other authors who use algorithms other than pattern search for this purpose. For example, Giorgio and Sangiorgio (2020) argued that a complete view of the boundary is possible by first solving single-objective problems corresponding to the extremes of the Pareto boundary and later using such solutions as elite representatives of the original solution.

Finally, our results significantly improve the model presented by Yashin et al. (2020). The latter authors solved a simpler problem of the material and non-material motivation of the top management of governing structures in regions and districts. For this purpose, the efficiency of the inter-cluster interaction within one federal district was assessed using a system of factors of the socio-economic development of Russian regions that directly affect the natural population growth in the regions of the district. However, our study has carried out the more complex task of the three-objective global optimisation of the motivation of the top managers of government agencies in the regions, allowing us to make the non-material motivation of such top managers dependent on the achieved strategic potential of the region and their material motivation.

The presented approach can be useful for government agencies to develop a rational system of material and non-material motivation for their top managers.

6. Conclusion

The study results in the following key findings:

1. In order to model the motivation of the top managers of government agencies in the regions, it is advisable to solve a three-objective global optimisation problem under which the non-material motivation of such managers can be made dependent on the achieved strategic potential of the region and their material motivation.

2. Each of these objectives depends on the three factors x_1, x_2, x_3 in the same coordinate system. These factors directly affect the value of the rate of natural increase of population per 1000 people in the regions of the country.

3. The first three of the nine factors characterise the system of non-material incentives for top managers in government agencies, the next three refer to the system of their material incentives, and the last three concern the available strategic potential of the region necessary for its further successful development.

4. A set of effective solutions with the help of the Pareto front should be constructed with two primary objectives, namely, the strategic potential of the region and the material motivation of its top managers, after which a set of optimal solutions for non-material motivation will be obtained as a result.

5. The conclusion about the actual bonuses (incentives) of the top managers of government agencies in the regions is made as follows. For each of the three functions in a particular region, the latest actual values of factors x_1, x_2, x_3 are compared with the nearest planned (optimal) values. A positive deviation from the optimum is evaluated positively, which makes it possible to additionally encourage top managers either materially or non-materially. A negative deviation shows that they made poor management decisions in the past, which, of course, should be reflected in their incentives.

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About author:

Egor Koshelev, candidate of economic science, Associate Professor of the Department of Management and Public Administration, Lobachevsky State University of Nizhny Novgorod, Nizhny Novgorod, Russian Federation. ekoshelev@yandex.ru, https://orcid.org/0000-0001-5290-7913

Информация об авторе:

Егор Викторович Кошелев, кандидат экономических наук, доцент кафедры менеджмента и государственного управления, Нижегородский государственный университет им. Н.И. Лобачевского, Нижний Новгород, Российская Федерация. ekoshelev@yandex.ru, https://orcid.org/0000-0001-5290-7913