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Assessment of Material and Intangible Motivation of Top Management in Regions Using Multipurpose Genetic Algorithm

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***Abstract*—The aim of the research is to create a model of assessment of material and non-material motivations of the top managers of the regional and district management structures. To this end, the effectiveness of inter-cluster cooperation within a federal district are assessed by means of a system of socio-economic development factors in the regions of Russia that directly affect the natural population growth in the districts. The method used to solve the problem is a multi-purpose genetic algorithm, which produces a Pareto front for the dual-purpose function of natural population growth, all solutions of which are equally optimal. By choosing any point of the Pareto front, one can find in it a share of material and immaterial motivations of top-managers. They are determined by proximity to the extreme points of the Pareto front, where only one of the two regressions (motivations) is maximum.**

***Keywords*—motivation of top management, multi-purpose genetic algorithm**

I. Introduction

In the context of the introduction of simulation modeling and artificial intelligence technologies into the public administration system, it becomes important to develop and implement complex models of the evolution of regional innovation systems and innovation infrastructure.

Methods and models of motivation for top management of the governing structures of regions and districts, taking into account external and internal relations, are becoming especially relevant. The solution to this practical problem is complicated by the fact that at present the issues of the motivation of top management have not been studied in detail. On the contrary, the task of constructive motivation of top managers of private corporations studied in more detail. We can bring the results that may be useful to select some landmarks motivation of top management for the government structures.

Therefore, in the work of S.N. Yashin, E.V. Koshelev and A.V. Kuptsov [1] proposed to apply the modified actual value of economic value added instead of the usual economic value added. This allows to align the priorities of top managers and owners (shareholders) in relation to which investment project from the set of available alternatives should be implemented.

In order to solve the problem of this article, it is also necessary to harmonize the interests of top managers of government structures and the population.

In the monograph by S.N. Yashin et al. [2] presented the theory of material and non-material motivation of top managers of companies based on the standard utility functions. Also, a model has been developed for bringing non-material motivation to material motivation, considered in the context of innovation management in a firm.

We will also investigate the relationship of material and intangible motivations of top managers of government structures to develop a rational system for their promotion.

Finally, M.A. Limitovsky [3] created a model of which is determined by the proportion of top managers - an insider in the company's income and which thus outweighs the loss of alternative income (diversionist), and at the same time does not create the destructive motivation (regent). As a result, an important conclusion was obtained that a rational insider who does not bear material responsibility for the adoption of ineffective projects cannot be constructively motivated.

In contrast to the position of M.A. Limitovsky, we will not consider the system of punishments of top managers, but at the same time, we will study in more detail the system of their encouragement (bonus) from the position of material and intangible motivation, using a multipurpose genetic algorithm (MGA) for this purpose as one of the evolutionary approaches applied in simulation modeling.

Naturally there is a question, why in the present work was to study selected a multi-purpose genetic algorithm. Let us discuss this in more detail.

Recent advances in the development of information technology in dynamic environments represent an in-depth discussion of the information technology revolution in areas such as government, games, social networking, and cloud computing (M. Hosrow-Pur [4]).

Evolutionary algorithms are relatively new, but very powerful techniques used to find solutions to many real world search and optimization problems. Many of these problems have multiple objectives, which leads to the need to obtain a set of optimal solutions, known as an effective solution. It was found that the use of evolutionary algorithms is a highly efficient way to find a set of efficient solutions in one run of modeling (D. Kalianmoy [5]).

Evolutionary programming is also used as a teaching technique for a general neural network. This approach can provide faster, more effective, but safe training procedures that allow for arbitrary interconnection of neurons, with the option of processing (T. Beck, J. Vogel, Z. Mikhalevich [6], D.B. Vogel, L.J. Vogel, VV Porto [7], D.B. Vogel [8]).

Solving multipurpose problems is an evolving effort, and computer science and other related disciplines have spawned many powerful deterministic and stochastic methods for solving these large-scale optimization problems. Evolutionary algorithms are one of such general stochastic approaches, which turned out to be successful and widely applicable in solving both single-purpose and multi-purpose problems (K.A. Coello Coello, G.B. Lamont, D.A. Van Veldheissen [9]).

Multi-purpose optimization tasks associated with the solution, with not just one, but several, often conflicting criteria. Such problems can arise in virtually all areas of science, technology and business, and the need for effective and reliable solutions is increasing. The task is challenging because, instead of a single optimal solution, multi-objective optimization leads to a number of solutions with different trade-offs between criteria, also known as optimal or efficient Pareto solutions. Therefore, a decision maker (DM) is required to provide additional information about preferences and determine the most satisfactory solution. Depending on the paradigm used, such information can be entered before, during, or after the optimization process. Obviously, the research and applications in the field of multi-objective optimization require expertise in the field of optimization and decision support (J. Branke et al. [10]).

Let us consider what the main ideas of the MGA approach are.

A. Messak A. Ismail-Yahaya, and K.A. Mattson [11] proposed a normal limit (NC) method for generating a set of uniformly spaced on the boundary Pareto solutions - for multi-objective optimization problems. Since few methods offer this desirable characteristic, this method can have significant practical application in choosing the optimal solution in a multipurpose environment. The specific contribution of this work is twofold. First, it presents a new formulation method of NC, which includes a linear mapping of the critical design goals. This mapping is a desirable property, consists in the fact that the resulting performance of the method is completely independent of the scale of the design goals. That being said, scaling up problems can be enormous. Secondly, the concept of a Pareto filter is presented and its algorithm is developed. As its name implies, Pareto filter - an algorithm, which retains only the global Pareto point, given a set of points in the target area. As explained in the Pareto filter is useful when applying NC and other methods.

Optimization is one of the most important and difficult part of any engineering project. In real design, multipurpose optimization with constraints must be considered. Optimal in this case the solution is not unique, since the objectives may contradict each other. Therefore, the complex of optimal solutions that forms the Pareto boundary should be considered. There are many algorithms for generating the Pareto set. However, only few of them have the potential to provide a uniformly distributed set of solutions (T. Erfani, S.V. Utyuzhnikov [12]).

This property is especially important in a real design, since the decision-maker can typically analyze only a very limited number of solutions. The main purpose of the article T. Erfani and S.V. Utyuzhnikov [12] is to develop and provide a detailed description of the algorithm capable of generating evenly distributed set of Pareto in the general formulation. The approach is based on shortening the search area to generate the optimal Pareto solution in the selected area on the Pareto boundary. The efficiency of the algorithm is demonstrated by a series of complex test cases.

These advances have allowed to use MGA approach in various fields of knowledge.

For example, in the article K. Sim and John. Kim [13], the authors find evolutionarily stable strategy (ESS) as a solution to the problem multiob- optimization (MOP), using the co-evolutionary algorithm based on evolutionary game theory. By applying newly developed coevolutionary algorithms to multiple MOP, the authors confirmed that evolutionary game theory can be implemented by a coevolutionary algorithm, and this coevolutionary algorithm can find optimal equilibrium points as solutions for MOP. K. Sim and John. Kim also showed performance optimization joint evolutionary algorithm based on evolutionary game theory, applying this model to several MOP and comparing solutions with the decisions of the previous evolutionary optimization models.

S.M.R. Rafey, A. Amirahmadi and G. Griva [14] developed a simple but optimal PID controller for the *Boost* converter to obtain a set of best characteristics that are good transition, as well as stable response and switching stability. This is done using a multi-objective optimization approach called the Pareto Force Algorithm, which is based on the concept of Pareto optimality used in the game theory literature. In the first scenario, the converter startup mode is optimized. Installation time and excess are assumed for two target functions, while PID controller amplifications (Kp, Ki, and Kd) are constructive variables. The program generates a set of optimal amplifications called the “Pareto set” corresponding to the Pareto front, which is a set of optimal results for target functions. We can easily select any of the results based on its functions and our own engineering view. Then the maximum and minimum hard limiter band in the cycle are considered as additional variables that significantly improve response. In another design, besides the long signal triggering, the dynamic response of the converter is also optimized. Finally, the determined optimum start a new objective function, which provides stability and switching failure from the chaos and the concept is very important. Extensive simulation and some experimental results prove the superiority of the proposed design techniques to achieve a wide range of desired technical goals.

A. Bemporad and D. Munoz de la Pena [15] proposed a new scheme for predictive control model (MPC), based on multi-objective optimization. At each sample time, the MPC control action is selected from a set of optimal Pareto solutions based on a time-varying state-dependent decision criterion. Compared to standard single-purpose MPC formulations, this criterion allows several, often irreconcilable, control specifications to be taken into account, such as high bandwidth (closed-loop speed) when the state vector is far from equilibrium and low bandwidth (good noise suppression properties) near equilibrium. After reprocessing the optimization problem associated with a multiobjective MPC controller in the form of a multiparameter multiobjective linear or quadratic program, the authors showed that it is possible to compute each optimal Pareto solution as an explicit piecewise affine function of the state vector and the vector of weights that must be assigned to different goals in order to get this particular optimal Pareto solution. In addition, the authors provided conditions for choosing optimal Pareto solutions so that the MPC control loop was asymptotically stable, and showed the effectiveness of the approach in modeling examples.

J.O.H. Sandin, A.A. Alonso and J.R. Banga [16] described an efficient and reliable multicriteria optimization method that can be successfully applied to large dynamic systems, such as those that arise in modeling heat treatment of food products. In addition, their ability to improve the design and operation of these processes were highlighted in the individual case studies, which analyzed developed Pareto solutions. Finally, the authors demonstrated their advantages over other recently proposed strategies.

S.R. Mott, A.M.B. Silvana and L.R.M. Paulo [17] tested several well-known procedures for solving multiobjective optimization (MOP) problems and proposed a new modified procedure when applied to the existing Normal Boundary Intersection (NBI) and Normal Constraint (NC) methods for more than two purposes, which overcomes some of their shortcomings. For the three and four objective applications analyzed in the work, the proposed scheme represents the best performance in terms of both quality and efficiency for obtaining a set of correct Pareto points compared to the existing analyzed approaches.

F. Domingo Perez et al. [18] used the decision support system, which is based on the evolutionary multi-objective optimization for the deployment of sensors in the system localization inside buildings. Their methods aim to provide the sensor resource manager with a complete set of effective Pareto solutions to the sensor placement problem. In the analysis, the authors used five scalar performance measures as objective functions derived from the score covariance matrix, namely, tracing, determinant, maximum eigenvalue, a ratio of maximum and minimum eigenvalues, and uncertainty in this direction. The authors ran a multipurpose genetic algorithm to optimize these goals and generate Pareto fronts. The article contains a detailed explanation of each aspect of the system and the application of the proposed decision support system to an indoor infrared positioning system. The final results show various alternative accommodation in accordance with the objectives and can be seen clearly a compromise between different measures of accuracy. This approach contributes to the modern level of technology in that the authors pointed out problems of optimizing one accuracy indicator and suggested using a decision support system that provides the resource manager with a complete overview of Pareto's set of efficient solutions, taking into account several accuracy metrics. Since the manager will know all Pareto's optimal solutions before deciding on the final sensor placement scheme, this method provides more information than working with a single function weighted goals. It is also possible to use this system to optimize goals derived from rather complex functions.

In the work of H.A. Ngaena et al. [19] presented a development to incorporate multipurpose optimization algorithms into scientific workflows. The authors demonstrated the effectiveness of these capabilities by formulating a three-objective problem of aerodynamics optimization. The aim was to improve the aerodynamic features of a typical *2D* wing profile considering also a platestormy transition location for a more accurate assessment of the complete resistance. The authors used two different heuristic optimization algorithms and compared their results.

For all the attractiveness of MGA approach, we must not forget that there is often a problem of defining a multi-purpose function, which is necessary to optimize the parameters at certain intervals. In this case, A. Abakarov, Y. Sushkov and R.H. Mascheroni [20] propose to use multiple non-linear regression analysis to a set of experimental data to obtain the specific multi-purpose function. We will act in a similar way in our study.

Finally, the results obtained by MGA, must be evaluated. To do this, in our view, well suited for pattern matching method (Pattern Search). Direct search (pattern matching) - a method for solving optimization problems, does not require any information about the gradient of the objective function. Unlike more traditional optimization techniques that use information about the gradient or higher derivatives to find the optimal point, the forward search algorithm searches for many points around the current point, looking for the point where the objective function value is lower than the value at the current point. Direct search can be used to solve problems for which the target function is not differentiable or even continuous (A. R. Conn, N.I.M. Gould, F.L. Toynt [21, 22] TG Kolda, R.M. Lewis, W. Torkzon [23]).

II. MODEL DEVELOPMENT AND RESULTS

A. *Model assessment of material and non-material motivation of top management regions using MGA*

Modeling and assessment of the material and non-material motivation of the top management in the governing structures of regions and districts, taking into account external and internal relations, using the MGA approach, will be carried out in several stages (Fig. 1).

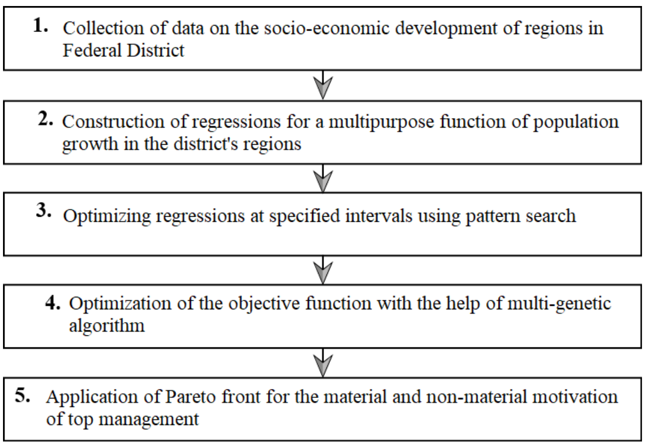

Fig. 1. Modeling and assessment of material and non-material motivation of top management

Stage 1 - the collection of data on socio-economic development of the Federal District. Effective intercluster interaction within a Federal District receives economic and financial, information and logistic nature. For regions with innovation and industrial clusters, these will be external relations, and for the region - internal. And external district communications should be considered with the rest of Russia and other countries. The effectiveness of such links allows us to determine the system for assessing the socio-economic development of the regions of Russia using the places occupied by these subjects in the Russian Federation, according to a number of factors, which we include:

1) Gross regional product (GRP) per capita (x_1);

2) Investments in fixed capital per capita (x_2);

3) Domestic expenditure on research and development (R & D) (x_3);

4) The average per capita income (per month) (x_1);

5) Living area per capita (x_2);

6) The proportion of paved roads (x_3).

These factors directly affect the natural population growth (*y*) in the Federal District.

The first three of these factors make it possible to develop a system of intangible encourage top management in government regions of the district, and the other three - the material incentive system. That is, in this way, we argue that the first three factors characterize the effectiveness of the solution of national problems, while the remaining three - the effectiveness of solving problems that are a priority for the population. Since the population priorities are more important, the effectiveness of their implementation should be motivated financially. It is then proposed to motivate the implementation of national tasks non-materially.

Thus, two goals are defined in the MGA approach, i.e., material and non-material motivation of the top management of the governing structures of regions and districts. Factors similar in their economic nature, on which natural population growth depends, will be denoted by the same variables x_i ($i = \overline{1,3}$). It allows us to create a coordinate system for the multi-purpose (dual-purpose) population growth regions of the district function (*y*).

Phase 2 - construction of a multipurpose regressions for population growth regions of the district function. At this stage, for material and non-material motivation of top management, it is possible to construct the corresponding nonlinear regressions, for example, in the *Statistica* program, which will then be used in the process of global optimization of the dual-purpose function of population growth.

Stage 3 - Optimize regressions at given intervals using pattern search. The places occupied by subjects (regions) in the Russian Federation, according to the six factors given earlier, make it possible to obtain intervals for all x_i ($i = \overline{1,3}$), on which the dual-objective function y will be optimized. Searching for its global largest values for each of the two regressions using pattern search makes it possible to check the future extreme values of the Pareto front, which will be obtained using the MGA.

Stage 4 - optimization of the objective function using a multipurpose genetic algorithm. MGA approach allows

TABLE I. DATA FOR BUILDING REGRESSION MODELS (EXAMPLE FOR 2018)

Region	Place occupied by a subject in the Russian Federation						Natural growth population (people)
	Intangible motivation			*Material motivation*			
	GRP	*Investments in the maincapital per capita*	*Internal R&D costs*	*Average money income (per month)*	*General area residential premises per capita*	*The proportion of roads with solid covering*	
	x_1	x_2	x_3	x_1	x_2	x_3	y
1. Nizhny Novgorod region	39	44	4	20	33	49	-15917
2. The Republic of Mordovia	62	60	55	80	29	76	-4094
3.Ulyanovsk region	60	58	15	70	25	44	-5413
4. Samara region	27	43	12	35	37	*82*	-9927
5.Perm region	23	35	11	34	64	50	-5224
6. Udmurt Republic	44	59	36	59	71	68	-1670
7. Republic of Tatarstan	15	13	9	18	40	34	1600
8. Republic of Bashkortostan	46	56	16	31	46	9	-3429

obtaining the Pareto-front for the dual-function, all of which equally optimal solutions. It shows the set of best y as well as the values of the factors x_i ($i=\overline{1,3}$) for all received y .

Step 5 - Pareto front for the use of financial and non-financial motivation of top management. Choosing any point of the Pareto front, you can find in it the share of material and non-material motivation of top managers. They are determined by the closeness to the extreme points of the Pareto front, in which only a maximum one of the two regressions (motivation).

The conclusion about the actual incentives (bonuses) of top managers is made as follows. For both regressions estimated planned values of natural increase *(y)* in each region, based on values x_1, x_2, x_3. Then, they are compared with actual values *y.* If the actual population growth is positive, the estimated its closeness to one or another of the planned values and accordingly selected the proportion of intangible and material incentives (bonuses).

B. Empirical results

Let us consider the process of modeling and assessing the material and non-material motivation of the top management of the governing structures of regions and districts, using the MGA approach, using the example of the Volga Federal District (VFD).

According to the list approved by the Government of the Russian Federation, there are 25 pilot innovative territorial clusters in Russia in the regions of the Russian Federation. Then we will consider only those in the PFD regions (region or country) in which there are clusters of this list.

Stage 1 - the collection of data on socio-economic development of the Federal District. Using the indicators of the "Statistical Review" of the Federal Service of State Statistics (*www.gks.ru*), we group the necessary data for analysis from 2009 to 2018 in Table 1.

Phase 2 - construction of a multipurpose regressions for population growth regions of the district function. Using Table 1 data, the Statistica program has obtained two of the most reliable models of multiple nonlinear regression:

- Intangible motivation:

$$y=-218,221-198,754x_1-877,781x_2+2\ 212,374x_3+$$
$$+12,888x_2^2-45,879x_3^2-0,001x_2^4+0,005x_3^4,\quad R^2=0,76$$

- Material motivation:

$$y=139\ 588,7+2\ 202x_2-34\ 383\sqrt{x_2}-521,1\sqrt{x_3},\quad R^2=0,66$$

Stage 3 - Optimize regressions at given intervals using pattern search. According to the Table 1, the intervals of places occupied by subjects in the Russian Federation are as follows:

$$x_1\in[1;\ 81],\ x_2\in[1;\ 74],\ x_3\in[1;\ 82].$$

Optimization of regressions in *Matlab* program at predetermined intervals by using pattern matching produces results:

- for intangible motivation:

$$y_{\max}=97\ 703\ pp\ at\ (x_1,x_2,x_3)=(1;\ 1;\ 82);$$

- for material incentives:

$$y_{\max}=106\ 887\ pp\ at\ (x_1,x_2,x_3)=(1;\ 1;\ 1).$$

Stage 4 - optimization of the objective function using a multipurpose genetic algorithm. MGA approach allows us to get in the program *Matlab* Pareto front for dual-purpose function, which is shown in Fig. 2 and 3.

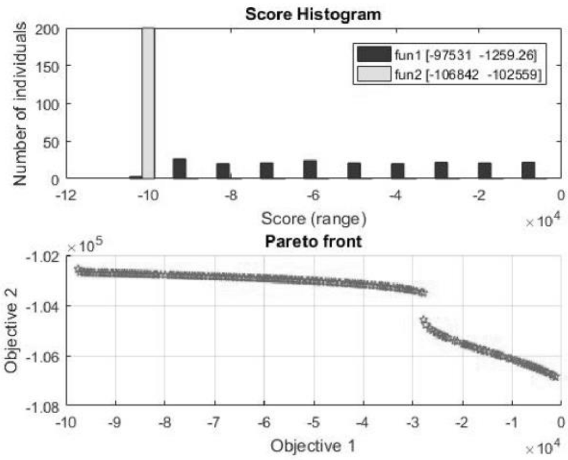

Fig. 2. Pareto front for the material (fun 1) and non-material (fun 2) motivation

Pareto front - function values and decision variables

Index	f1	f2	x1	x2	x3 ▲
1	-884,631	-106 886,6	1	1	1
2	-884,631	-106 886,6	1	1	1
9	-5 194,583	-106 482,637	1,027	1	3,133
15	-16 448,459	-105 743,429	1,058	1	10,119
10	-20 405,595	-105 482,619	1,026	1,001	13,521
13	-25 131,439	-105 071,709	1,051	1,002	19,512
14	-31 725,35	-103 330,308	1,095	1,001	60,609
18	-33 475,959	-103 300,486	1,074	1	62,064
8	-40 088,508	-103 154,033	1,167	1,001	66,189
6	-44 272,34	-103 096,418	1,054	1,001	68,159
16	-48 558,622	-103 042,443	1,121	1,001	69,908
7	-52 721,125	-102 998,532	1,056	1	71,398
19	-54 869,141	-102 966,639	1,071	1,001	72,111
12	-61 164,736	-102 915,002	1,139	1,001	74,017
5	-65 533,9	-102 872,558	1,127	1,001	75,206
4	-68 286,507	-102 858,452	1,126	1,001	75,91
3	-73 711,96	-102 819,218	1,132	1,001	77,213
17	-84 847,32	-102 750,339	1,145	1,001	79,603
21	-88 993,297	-102 734,071	1,148	1	80,414
11	-92 610,426	-102 700,475	1,206	1,001	81,094
20	-97 622,505	-102 587,594	1,376	1,007	82

Fig. 3. Coordinates of the points of the Pareto front for material (f1) and non-material (f2) motivation

Step 5 - Pareto front for the use of financial and non-financial motivation of top management. Analysis of the resulting Pareto front allows us to draw the following conclusions:

1. Maximum population growth in a separate region of PFO in case of orientation to intangible motivation of top management is obtained at the minimum internal cost of research (x_3). This suggests that they are beneficial to top managers and not the population. The population is interested in meeting basic needs in the form of cash income, housing area, and the quality of roads.

2. In the case of orientation to material motivation maximum population growth will be observed in the most residential area per capita (x_2) and the largest specific weight of paved roads! (X_3). Consequently, infrastructure is important for population growth, that is, an increase in the area of housing and the quality of roads. This is the priority objective in the bonuses of top managers of government structures.

3. Figures 2 and 3 show the possibility of a qualitative jump in population growth (function f2) in case of increases in road costs. At the same time, a separate region in such conditions can sharply move from 60th to 19th place, occupied by a constituent entity in the Russian Federation.

III. Conclusion

Let us formulate the most important conclusions:

1. It is necessary to harmonize the interests of top managers of state structures and the population. To do this, it is important to examine the relationship of material and non-material motivation of top managers to develop a rational system for their promotion.

2. Effective intercluster interaction within one federal district takes economic, financial, information and logistical character. The effectiveness of such links allows one to determine the system for assessing the socio-economic development of Russian regions using the places occupied by these subjects in the Russian Federation, for a number of factors that directly affect the natural population growth in the regions of the district. One group of factors allows developing a system of intangible encouragement of top management in the government structures of the regions of the district, and another - a system of material encouragement. That is, the first group characterizes the effectiveness of solving national problems, and the second - the effectiveness of solving problems that are a priority for the population. Since the population priorities are more important, the effectiveness of their implementation should be motivated financially. It is then proposed to motivate the implementation of national tasks non-materially.

3. A multipurpose genetic algorithm allows you to obtain a Pareto-front for a two-purpose function of natural population growth, all solutions of which are equally optimal. Choosing any point of the Pareto front, you can find in it the share of material and non-material motivation of top managers. They are determined by the closeness to the extreme points of the Pareto front, in which only a maximum one of the two regressions (motivation).

4. The conclusion about the actual encouragement (premonitions) of top managers is made as follows. For regressions of material and non-material motivation, the planned values of natural population growth in each region are estimated, based on the values of factors of socio-economic development of Russian regions. If the actual population growth is positive, the estimated its closeness to one or another of the planned values and accordingly selected the proportion of intangible and material incentives (bonuses).

The results obtained can be useful to government agencies in order to develop a rational system of material and non-material motivation of their top managers.

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