Research article

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Model of Cross-Financing for Research and Development Costs in a Federal District

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Abstract

The issue of an optimal amount of funding for research and development (R&D) costs within the Russian regions that have the appropriate scientific potential is investigated. For this purpose, a model is developed to optimise and plan the cross-financing of R&D costs in a federal district, which takes into consideration the specific technological and economic results of R&D in the regions. This model makes different R&D expenditures by type of work dependent on three planning directions of innovative development in the regions of the district: investment, production, and financial. All three processes are considered simultaneously. Investment planning is reflected by investment in fixed capital, production planning (by gross regional product), and financial planning (by indebtedness of legal entities on loans). Nonlinear regressions of R&D costs by type of work are optimised using a genetic algorithm, simulated annealing, and pattern search, which eventually allow calculation of the reserve or deficit of the corresponding R&D costs in each region of the federal district. The results of global optimisation reflect the conclusion that in conditions of saving federal budget funds, the federal district can partially finance all R&D costs in those regions that need it. Identifying such regions more reasonably requires analysing this situation in more detail, that is, in terms of various R&D costs by type of work. For the Privolzhsky Federal District, the findings indicate that the Samara region, the Republic of Bashkortostan, and the Perm region are the most in need of financing various types of R&D expenditures. However, the main donor for the costs of different types of R&D is the Nizhny Novgorod region. The findings of this model can allow considerable savings in the federal budget funds allocated for scientific and, consequently, innovative development of the regions.

Keywords: innovative development, region investment planning, production planning, financial planning, research and development costs

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Модель Перекрестного Финансирования Затрат на Научно-Исследовательские Работы в Федеральном Округе

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Аннотация

Исследуется вопрос оптимального объема финансирования затрат на научно-исследовательские работы (НИР) в пределах регионов страны, имеющих соответствующий научный потенциал. Для этого **р**азработана модель оптимизации и планирования перекрестного финансирования затрат на НИР в федеральном округе, учитывающей конкретные технологические и экономические результаты НИР регионов округа. Данная модель ставит в зависимость различные затраты на НИР по видам работ от трех направлений планирования инновационного развития регионов округа: инвестиционного, производственного, финансового. При этом все три процесса рассматриваются одновременно. Инвестиционное планирование отражают инвестиции в основной капитал, производственное планирование – валовой региональный продукт, а финансовое планирование – задолженность юридических лиц по кредитам. Нелинейные регрессии затрат на НИР по видам работ оптимизируются с помощью генетического алгоритма, имитационного отжига и поиска по шаблону, что позволяет в итоге вычислить резерв или недостаток соответствующих затрат на НИР в каждом регионе федерального округа. Результаты глобальной оптимизации позволяют сделать вывод, что в условиях экономии федеральных бюджетных средств федеральный округ может частично сам профинансировать все затраты на НИР в тех регионах, которые в этом нуждаются. Чтобы более обоснованно определить такие регионы, необходимо анализировать эту ситуацию подробнее, т. е. в разрезе различных затрат на НИР по видам работ. Для Приволжского федерального округа (ПФО) получено, что наиболее нуждающимися в финансировании различных видов затрат на НИР оказываются Самарская область, республика Башкортостан и Пермский край. Но при этом основным донором затрат на различные виды НИР является Нижегородская область. Это позволило бы существенно сэкономить федеральные бюджетные средства, выделяемые на научное и, как следствие, инновационное развитие регионов страны.

Ключевые слова: инновационное развитие, регион, инвестиционное планирование, производственное планирование, финансовое планирование, затраты на научно-исследовательские работы

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1. Introduction

Currently, the cost of research and development (R&D) is an important component of Russian state budget expenditures. The financing of R&D allows the state to solve the problems of global technological challenges, including the problems of implementing the import substitution policy. However, the issues of the optimal amount of funding for R&D expenditures within the country and its regions, which have the appropriate scientific potential, have not been completely resolved. By scientific potential, we refer to both research institutes and universities, and scientists working in these institutes. It seems impossible to solve such problems in isolation from the specific technological and economic results of regional R&D. Planning of these results, as well as the resources necessary to achieve them, is an urgent task to optimise the costs of R&D. In this regard, we distinguish three types of planning: investment, production, and financial. We consider all three processes simultaneously. This will allow us to cover a wide range of tasks to optimise R&D costs in the regions and contribute to their innovative development.

Similar optimisation issues have been studied in detail by many scientists in relation to the business development planning of companies. For example, Kruschwitz and Lorenz (2019) studied the processes of simultaneous investment and financial planning, as well as simultaneous investment and production planning. Limitovskiy (2019) supplemented their results by taking into consideration the systemic financial effects of investment programmes. By such effects, the author referred to cross-financing, cross-subsidization, cross-holding, and cross-hedging. Despite the usefulness of these studies, there is still a need to create programmes of innovative development for manufacturing companies and industrial regions. In this regard, Fabiana et al. (2016) studied how the technological innovation process occurs in small and medium technology companies located in Paraíba Valley Metropolitan Region and Northern Coast, Brazil. The study revealed that the development of innovations depends on the type of economic activity that the company develops and the interactions it undertakes with the internal and external environments. Vasconcellos et al. (2016) argued that the resources invested in research do not guarantee immediate practical application. With the aim of developing and presenting a methodology for evaluating a research portfolio and selecting the best research investment, the author showed that risk and return criteria should be used to manage R&D portfolios when selecting projects.

To this end, the present study explores the issue of the optimal amount of funding for R&D costs within the regions of the country that have the appropriate scientific potential.

2. Literature review

Although the abovementioned findings are of real practical interest for implementing the successful development of commercial firms, we aim to leverage them to optimise and plan national and regional R&D expenditures. Other useful results from various researchers in this field include those of Xu (2018), who found that regional investment in R&D in the area of human resources has a positive effect on the efficiency of the internal R&D of an enterprise. The scientist formulated three policy recommendations: increasing regional investment in R&D, expanding, and consolidating the enterprise as the basis of R&D status, and increasing regional investment in R&D in human resources. Chen et al. (2019) found that the production elasticity of R&D capital in China was much higher than that of R&D personnel, suggesting that R&D capital is the main driver of the research results. The elasticity of substitution between R&D capital and personnel has changed from replacement to additional since 2014. To ensure sustainable growth in research results, the contribution of R&D with positive output elasticity should be increased, or the contribution of R&D with negative output elasticity should be decreased with the necessary compromises made according to the ratio of substitution between the two R&D inputs.

Dobrzanski and Bobowski (2020) determined whether funds spent on R&D are used in the countries of the Association of Southeast Asian Nations (ASEAN). Fifteen countries were examined over the period of 2000-2016. R&D spending efficiency was measured using a non-parametric data envelopment analysis (DEA) methodology, which measures input–output efficiency. Hong Kong and the Philippines were found to be the best performing countries in R&D when analysed using the constant returns to scale approach. However, Hong Kong, Indonesia, Singapore, and the Philippines are the most efficient ASEAN countries under the variable returns to scale approach. The study also confirmed that increasing spending on innovation leads to disproportionate effects. Dehmer et al. (2019), relying on recent developments in spending on science in countries such as China, Korea, India, and Brazil, have found that global scientific activity is undergoing major shifts. Using the evolving pattern of past R&D expenditures for forward-looking projections and in the absence of notable changes in science policy and spending priorities, the authors predicted the continuation of a major shift in R&D geography towards Asian countries and an ongoing large and, in many respects, growing gap between the scientific haves and have-nots in the world.

Kiselakova et al. (2018) examined the relationship between R&D expenditures and the development of global competitiveness in Slovakia, as well as in member states of the European Union from Central and Eastern Europe (CEE EU (11)). To assess the competitiveness of the CEE EU (11) countries, the researchers used the Global Competitiveness Index processed by the World Economic Forum and found that an increase in R&D spending can contribute significantly to the level of competitiveness of CEE EU (11) countries. All the analyses confirmed the importance of focusing on increasing R&D expenditure, especially in the higher education sector, as it has a significant impact on improving the global competitiveness of the CEE EU (11) countries in the case of a number of Global Competitiveness Index sub-indices.

In this regard, the issue of national and regional R&D expenses is especially important. According to Feoktistova (2014), when planning R&D and its financing, the project approach should be used by selecting the expected results from implementing a research project as one of the key criteria and selecting the results already achieved by the research project by its would-be executor as the key criterion. Gaponenko (2018) considered situations in which it is potentially possible to reduce the actual costs of performing R&D: (1) performing R&D similar to work previously performed by the same contractor—a scientific organisation or a researcher; (2) performing R&D similar to work previously performed by other contractors—scientific organisations; (3) performing (possibly simultaneous) of similar R&D for different customers; (4) using previously obtained research results or previously assembled installations in new research, if the subjects of old and new research are not analogous to each other; and (5) including in the terms of reference of tasks that do not correspond to the goal of R&D, the results of which can be used, for example, in another R&D or a publication, a patent.

Nevertheless, in our opinion, these studies did not sufficiently elaborate on the problem of selecting reasonable quantitative benchmarks for planning the R&D expenditures of the regions. The issue of planning the redistribution of R&D expenditures among regions also remains open. On the contrary, in the work by Yashin et al. (2020), a foresight of the evolution of the innovation system in a federal district based on the use of a multipurpose genetic algorithm revealed that to increase the synergy effect of the federal district, it is planned to redirect investment resources and R&D costs to those regions where resources are scarce. This will eventually increase the average per-capita income in the regions of the federal district, which will lead to population growth. This highlights the necessity of solving the problem of optimising regional R&D expenditures and, above all, selecting the most rational methods for this purpose. Thus, Ildırar et al. (2016) provided new estimates of the impact of R&D expenditures on economic growth. They found that there are different types of R&D expenditures, each of which has a different significance for economic growth. The authors found that all R&D expenditures have a positive and significant impact on economic growth in individual OECD countries, but their importance varies. Therefore, policymakers should develop policies to stimulate R&D based on the characteristics of these countries. Accordingly, countries should allocate more resources to different types of R&D expenditures to achieve sustainable growth rates.

Salimi and Rezaei (2018) pointed out that assigning the same level of importance to different R&D indicators, which is a common approach in existing studies, may oversimplify the R&D measurement process and lead to misinterpretations of effectiveness and, consequently, incorrectly chosen R&D strategies. Their findings showed that assigning different weights to different R&D indicators (as opposed to simple averages) leads to different rankings of firms and allows R&D managers to formulate more effective strategies to improve their firm's R&D effectiveness by applying knowledge of the importance of various R&D indicators. Bina et al. (2015) proposed comprehensive criteria for selecting R&D and innovation projects under conditions of uncertainty and taking into consideration the real constraints applicable to the Brazilian electricity sector using a combination of integer programming formulations and a method based on the PROMETHEE method. The authors identified the best results of the proposed application in solving the regulatory problems of the electricity sector, which emphasises the compliance of companies with R&D and innovation expenditure commitments. Thus, although selecting R&D and innovation projects is not a typical example of optimisation, under certain regional, sectoral, or organisational constraints, it may be the best solution.

Huang et al. (2020), taking into consideration the paradox of the spillover effect of R&D spared from the global supply chain, used a computational general equilibrium model with the GTAP v10 database to analyse the impact of Japanese public investment in R&D on key sectors of the global supply chain—chemical and pharmaceutical, electronic equipment, machinery, and transportation equipment—to assess its output, foreign trade, and welfare. Performance parameters initiated by public investments in R&D are calibrated from the SciREX Policymaking Intelligence Assistance System - Economic Simulator (SPIAS-e). The simulation results showed a significant increase in Japanese production and exports of chemical and pharmaceutical, electronic equipment, and transportation equipment. The study provides a comprehensive global analysis of manufacturing networks and an analysis to assess the spillover effects of R&D investments.

Sadollah et al. (2020) set the main goal of optimisation as improving overall sustainability, including environmental, social, economic, and energy resource sustainability, through the implementation of corresponding target functions. Since energy optimisation is one of the main objectives of sustainable development, it is studied from an energy perspective. Further, the concept, definitions, and elements of sustainability and optimisation were presented, and metaheuristic optimisation algorithms used in recently published papers related to sustainability and sustainable development were reviewed. Hyk (2021) determined the optimal cost structure for innovation and its impact on sales revenues, with a focus on the use of elements of economic and mathematical modelling. The scientific novelty of the work lies in the development of a model that substantiates the relationship between the studied indicators of costs for innovation, enables predicting the amount of revenue from sales, and ensures the achievement of its optimal value. The author also assessed the impact of the economy of innovation on the environment, which results in preserving the potential of natural resources to achieve sustainable economic development.

In the present study, we apply metaheuristic algorithms to optimise R&D costs in the regions of the federal district. This will further allow for planning the cross-financing of R&D within a single district. Of the available metaheuristic algorithms, we use the following three, which have significant advantages: (1) a genetic (evolutionary) algorithm (GA) is a highly effective way to find multiple efficient solutions in a single simulation run (Kalyanmoy, 2001); (2) simulated annealing (SA) makes it possible to avoid "trapping" in the local extrema of the function being optimised and to continue the search for a global extremum (Lopatin, 2005). Compared to GA, adaptive simulated annealing (ASA) does not yield to genetic algorithms in most problems and wins in many (Ingber and Rosen, 1992); and (3) pattern search (PS), a direct search method, can be used to solve problems for which the target function is not differentiable or even continuous (Conn et al., 1991; Conn et al., 1997; Kolda et al., 2006).

1. Materials and methods

Using the above metaheuristic algorithms, we created a model to optimise and plan the cross-financing of R&D costs in a federal district (Fig. 1). The model includes five stages, as shown in Fig. 1.

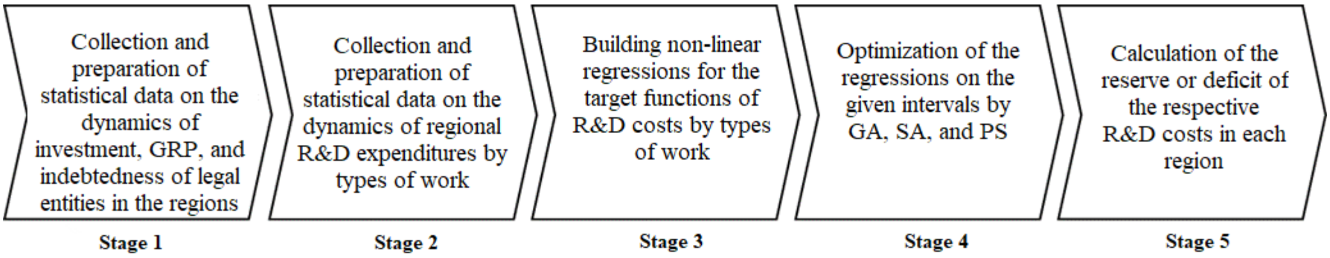

Fig. 1. A model for optimising and planning the cross-financing of R&D costs in a federal district

Stage 1 – Collect and prepare statistical data on the dynamics of investment, GRP, and indebtedness of legal entities in the regions. At this stage, we collect and adjust for inflation data on the dynamics of investment in fixed capital (x1), gross regional product (GRP) (x2), and the debt of legal entities on loans (x3) of the regions of the federal district over a long period spanning 10 years. These data are available on the website of the Federal State Statistics Service[1]. Here, parameter x1 characterises investment planning, x2 refers to production planning, and x3 captures the financial planning of the district.

Stage 2 – Collect and prepare statistical data on the dynamics of regional R&D expenditures by type of work. Here, we collect and adjust for inflation statistical information on the internal current expenditures on R&D in total (y), as well as by types of work, which are divided into fundamental research (y1), applied research (y2), and developments (y3). These data are collected for the same period of time as in the previous stage.

Stage 3 – Build non-linear regressions for the target functions of R&D costs by type of work. We use multiple non-linear regressions of R&D costs of the form $y = f\left(x_1, x_2, x_3\right)$, which more realistically reflects economic processes in comparison with linear ones. These are constructed using the Statistica software.

Stage 4 – Optimise the regressions on the given intervals by GA, SA, and PS. We perform global optimisation of the regression target functions in MATLAB using the three metaheuristic algorithms: GA, SA, and PS. To refine the results of the GA and SA methods, we supplement the optimisation results of the target functions with the hybrid functions of pattern search and the interior-point method (Babynin and Zhadan, 2008). That is, the GA or SA algorithms are applied first, and then their results are used as a starting point for the subsequent optimisation of the target function. This allowed for obtaining better solutions in each specific case of optimisation of the corresponding R&D costs.

In each particular case, we search for the global maximum of R&D costs in the federal district; that is, we calculate how much funds can be allocated to R&D maximally and on what values of parameters x1, x2, and x3 this maximum depends. We then optimise the obtained regressions for each type of R&D on the segments of parameters x1, x2, and x3, which are typical for each region of the federal district under study.

Stage 5 - Calculate the reserve or deficit of the respective R&D costs in each region. At this stage, we compare the obtained optimum R&D expenditures for each region of the district with its actual maximum value for the period under study and calculate the reserve or deficit of the respective R&D expenditures in each region as a difference between the actual and optimum values. This enables planning the possibilities of cross-financing R&D within the same district in more detail, that is, by region.

3. Results

In what follows, we demonstrate how this model works using the example of the Privolzhsky Federal District (PFD), considering only those regions (regions or republics) in which pilot innovation territorial clusters from the list approved by the government of the Russian Federation are located. These are the industrial regions where PFD's main R&D is carried out.

[1] Federal State Statistics Service. URL: https://www.gks.ru

Stage 1 – Collect and prepare statistical data on the dynamics of investment, GRP, and indebtedness of legal entities in the regions. At this stage, the necessary initial data were collected from the website of the Federal State Statistics Service2 and adjusted for inflation. They are presented in the 2020 prices in columns $x1$, $x2$, and $x3$ of Table 1. Since the above website contains data on domestic current expenditures on R&D only for 2010 and the period 2015–2020, we took the data on investment in fixed capital, GRP, and indebtedness of legal entities on loans for the same years.

Table 1. Initial data on the Privolzhsky Federal District in 2020 prices (million rubles)

Year	Investments in fixed capital	Gross regional product	Indebtedness of legal entities on loans	Internal current costs of R&D by type of work			
				Total	Fundamental research	Applied research	Developments
	x_1	x_2	x_3	y	y_1	y_2	y_3
1. Nizhny Novgorod Region							
2010	354041	1203299	335116	49755.1	2257.5	7763.1	39734.3
2015	286275	1345281	438699	69259.4	2328.5	6359.8	60571.1
2016	268126	1341478	392014	76640.5	2197.6	7618.6	**66824.4**
2017	276481	1422534	356981	72458.5	2283.8	7463.4	62711.2
2018	280429	1478448	361167	71571	2399.5	9863.7	59307.8
2019	309749	1462590	385278	**80671.8**	4970.6	**9972.7**	65728.4
2020	383102	1474561	361554	68750.3	**5220.1**	8560.3	54969.9
2. Republic of Mordovia							
2010	75165	**194177**	80800	884	156.1	267.3	460.6
2015	64242	219641	114539	996.8	147.6	293.9	555.3
2016	60822	233116	97935	896.2	141.2	173.2	581.9
2017	65984	242754	112000	885.7	126.5	212.9	546.4
2018	56551	245720	98970	1049.4	168.1	470	411.4
2019	54751	240875	102512	1009.9	125.3	438	446.6
2020	**48969**	238909	88007	1081.5	107.1	433.5	540.9
3. Ulyanovsk Region							
2010	88464	328536	75419	9242.4	175.8	1451.9	7614.6
2015	96771	370808	96010	9672	228	5190	4254.2
2016	81562	375920	99058	9114.9	262.8	4511.5	4340.6
2017	94796	375951	**71717**	12565.8	230.2	2038.7	10296.8
2018	89649	376064	84054	12206.9	302.8	1267.4	10636.7
2019	75555	339226	78955	9659.3	218.5	1791.1	7649.6
2020	61181	312577	85313	10288.1	265.6	2607.6	7414.9
4. Samara Region							
2010	284644	1282274	390241	22679.8	665.6	1249.4	20764.6
2015	368865	1540461	423126	19921.2	681.9	1616.6	17622.8
2016	296748	1468075	449779	13454.2	641.7	1220.8	11591.5
2017	292574	1520781	453792	15631.9	844.7	1282.3	13504.9
2018	286479	1633018	398565	14861.2	649	1197.6	13014.5
2019	301737	1632825	319233	19929.2	614.4	1020.9	18294
2020	202462	1648019	298558	15492.5	761	713.0	14018.6
5. Perm Territory							
2010	257417	1148574	276981	12308.4	2383.9	1325.1	8599.4
2015	275493	1295517	312592	14528.9	982.9	1873.9	11671.9
2016	276655	1266576	221842	14107	1027.2	1568.8	11511
2017	276337	1343064	215175	15007.6	843.4	1745.3	12418.8
2018	263369	1425398	243162	13788.9	1032.6	1428.7	11327.6
2019	305392	1456557	274316	15591	1090.2	1716.1	12784.6

[2] Federal State Statistics Service. URL: https://www.gks.ru

2020	290460	1467320	306550	15636.3	1148.2	1797.1	12691
6. Udmurt Republic							
2010	94280	506122	121689	821.4	451.2	85.2	285
2015	99676	630842	114739	1297.2	380.9	163.9	752.4
2016	100692	614648	119263	1263	337.2	155.7	770.1
2017	94358	622590	89959	1986	237.5	458.6	1289.9
2018	104844	682300	89920	2481.4	657.3	233.1	1591.1
2019	105451	668360	110349	2332.8	731.4	126.8	1474.5
2020	107187	675545	85536	1846.9	811.5	123.1	912.2
7. Republic of Tatarstan							
2010	606333	1846263	540376	11366.2	1526.8	1864.5	7974.9
2015	**751565**	2274027	660546	13926.5	2495.5	1772.2	9658.8
2016	735575	2234011	**710836**	13841.8	2196.6	1856.1	9789.2
2017	718755	2412123	699269	17574.2	2626.4	2249.4	12698.4
2018	680801	**2669465**	594273	18420.6	2422.4	2444.6	13553.6
2019	672302	2522721	496504	16617.8	2611.1	2232	11774.7
2020	655319	2549636	414215	16878.6	2896.6	2557.3	11424.7
8. Republic of Bashkortostan							
2010	283173	1772189	213167	7236.3	1806	1958.3	3472
2015	386986	1603409	371940	9869.2	1420.5	996	7452.7
2016	410388	1546257	334792	9960.4	1193.1	2229.1	6538.3
2017	314046	1589666	328141	9739.9	1161.9	2568.5	6009.5
2018	289657	1809428	327419	11196.7	1408.7	2582.6	7205.5
2019	337919	1746876	328865	10490.5	1361	2644.6	6484.9
2020	326850	1754979	323670	10527.2	1417.7	2483.4	6626.1

We forecast the missing data on investment in fixed capital and GRP in 2020 prices, using the period from 2009–2018 and the Wolfram Alpha search service3. The results of the forecast are shown in Table 1 in italics.

Stage 2 – Collect and prepare statistical data on the dynamics of regional R&D expenditures by type of work. At this stage, we collected and adjusted for inflation statistical information on the internal current costs of R&D in total, as well as by type of work: fundamental research, applied research, and developments. These data were collected for the same period as in the previous stage. They are presented in the 2020 prices in columns y, y_1, y_2, and y_3 of Table 1.

Stage 3 – Build non-linear regressions for the target functions of R&D costs by type of work. According to the data in Table 1, the following most accurate non-linear regressions were obtained in *Statistica*:

- regression for all R&D costs (Fig. 2)

$y = 82426.01 + 0.06x_2 - 8303.97 \ln x_3$, $R^2 = 0.948$, adjusted $R^2 = 0.938$;

- regression for fundamental research (Fig. 3)

$y_1 = 1782 - \frac{57170107}{x_1} - \frac{73870171}{x_3}$, $R^2 = 0.484$, adjusted $R^2 = 0.444$;

- regression for applied research (Fig. 4)

$y_2 = -58921.7 + 3523.1 \ln x_1 + 1925.2 \ln x_3$, $R^2 = 0.244$, adjusted $R^2 = 0.185$;

- regression for developments

$y_3 = -315317.4 - 0,02542966x_2 - 0.6432493x_3 - \frac{950912100}{x_1} + 981.9057\sqrt{x_3} + \frac{9314139000}{x_3}$, $R^2 = 0.447$, adjusted $R^2 = 0.392$.

[3] Wolfram Alpha search service. URL: www.wolframalpha.com

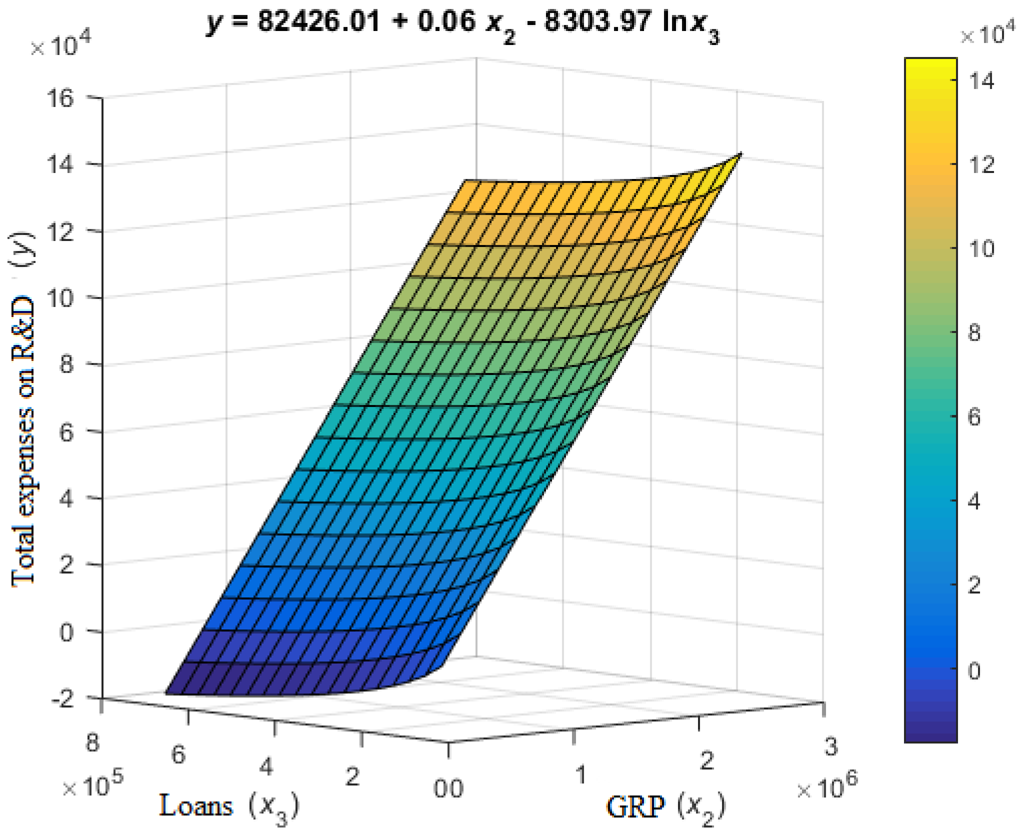

Fig. 2. Regression plot for all R&D costs

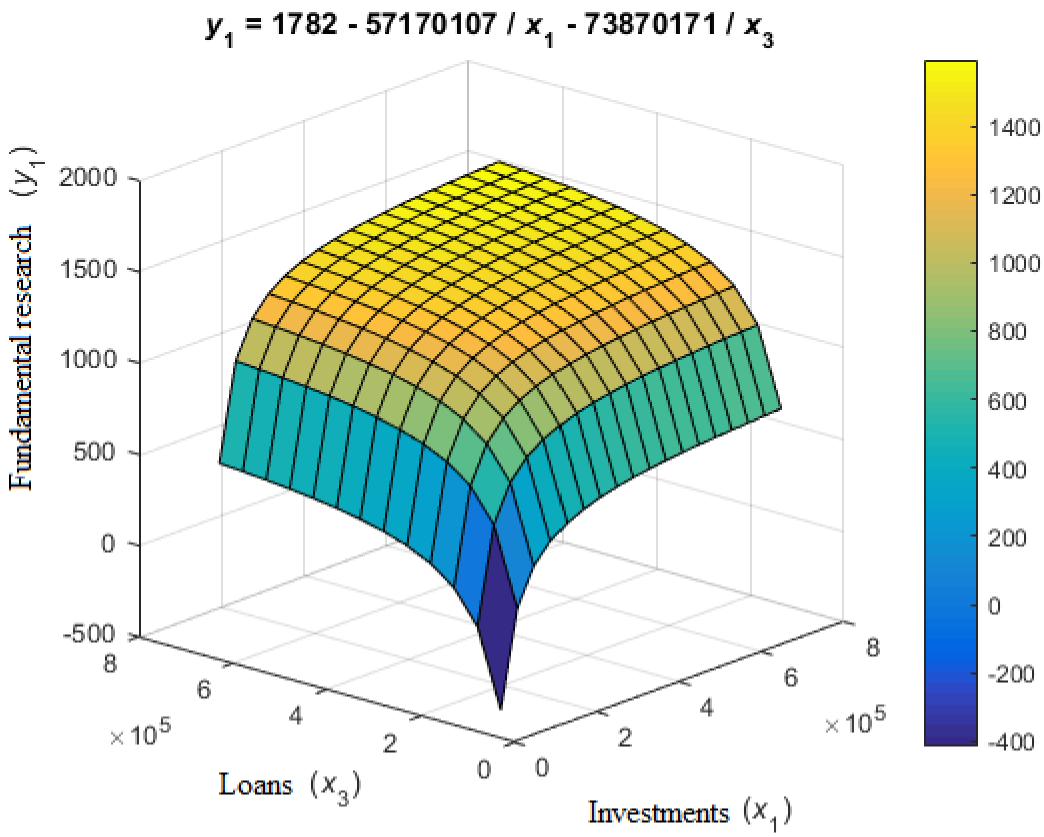

Fig. 3. Regression plot for fundamental research

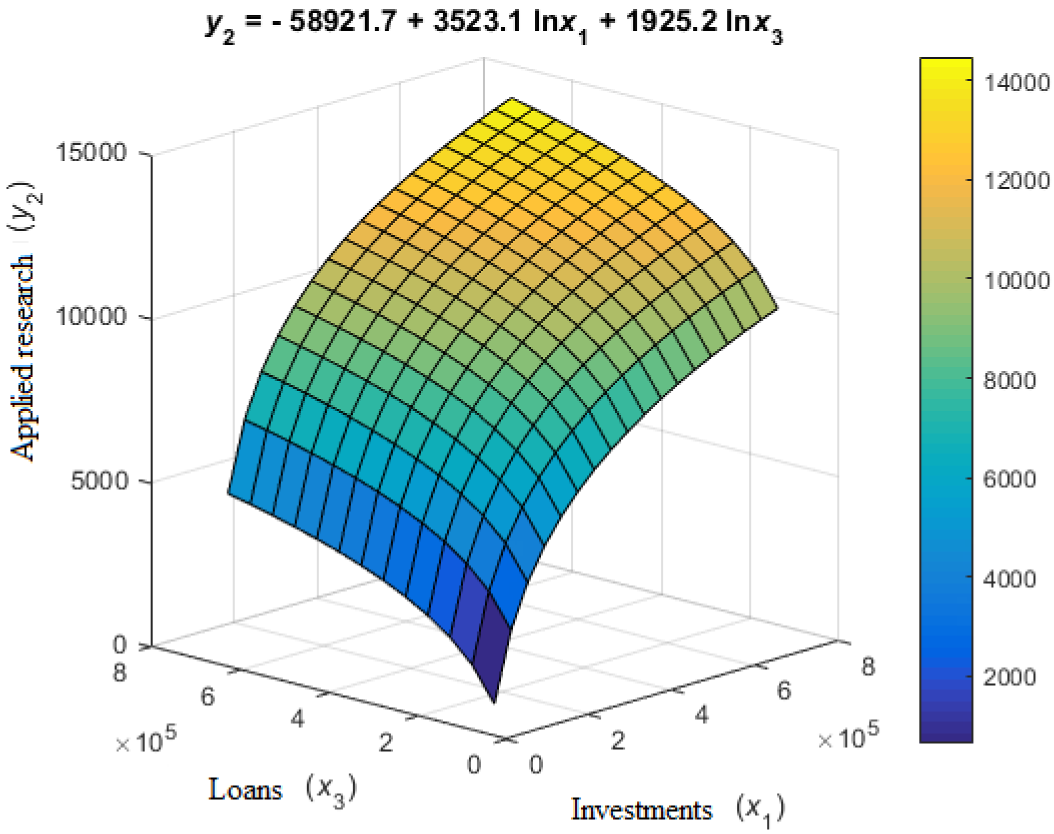

Fig. 4. Regression plot for applied research

Stage 4 – Optimize the regressions on the given intervals by GA, SA, and PS. The global optimisation of the target regression functions was performed using MATLAB. GA, SA, and PS were used for this purpose. To refine the results of the GA and SA methods, the optimisation results were supplemented with hybrid functions of the pattern search and interior-point method (fmincon). All target functions were investigated on the segments of actual values of parameters x1, x2, and x3 for the period under study, according to the data in Table 1, marked in bold type.

As an example, for all the costs of R&D in PFD, the optimisation results are given in Table 2. As shown in the table, the most reliable result is obtained by PS. Adding this algorithm or the interior-point method (fmincon) as a hybrid function for GA or SA also allowed achieving a high-quality solution to the optimisation problem.

Table 2. Results of the global optimisation of the regression for all R&D costs for PFD (million rubles)

Algorithm	Investments in fixed capital	Gross regional product	Indebtedness of legal entities on loans	Total expenses on R&D	Maximum actual value
	x_1	x_2	x_3	y	y
GA	-	2 655 302	84 056	147 583.4	80 671.8
GA + fmincon	-	2 669 465	71 717	149 751.5	
GA + PS	-	2 669 465	71 717	149 751.5	
SA	-	1 474 311	381 367	64 166.1	
SA + fmincon	-	2 669 465	71 717	149 751.5	
SA + PS	-	2 669 465	71 717	149 751.5	
PS	-	2 669 465	71 717	149 751.5	

Table 2 also shows that the maximum actual value of all R&D costs is significantly lower than the maximum possible total costs of R&D with the respective values of GRP and indebtedness of legal entities on loans. This indicates that there are real possibilities for financing R&D in a larger volume. This issue, however, requires a more detailed solution. Thus, we conducted the same global optimisation of all types of R&D costs for each PFD region separately, applying the same metaheuristic algorithms. The previous target regression functions were investigated for each region on its segments of actual values of parameters x1, x2, and x3 for the period under study, according to the data in Table 1. The results of global optimisation are shown in Tables 3-6.

Table 3. Results of the global optimisation of the regression for all R&D costs by the regions of PFD (million rubles)

Region	Investments in fixed capital	Gross regional product	Indebtedness of legal entities on loans	Total expenses on R&D	Maximum actual value	Reserve (+) or deficit (-) of expenses
	x_1	x_2	x_3	y	y	Δy
1. Nizhny Novgorod	-	1 478 448	335 116	65 487.9	80 671.8	15 183.9
2. Mordovia	-	245 720	80 800	3 336.6	1 049.4	- 2 287.2
3. Ulyanovsk	-	376 064	71 717	12 147.5	12 565.8	418.3
4. Samara	-	1 648 019	298 558	76 621.3	22 679.8	- 53 941.5
5. Perm	-	1 467 320	215 175	68 499	15 636.3	- 52 862.7
6. Udmurtia	-	682 300	85 536	29 058.4	2 481.4	- 26 577
7. Tatarstan	-	2 669 465	414 215	135 189.2	18 420.6	-116 768.6
8. Bashkortostan	-	1 809 428	213 167	89 103.4	11 196.7	- 77 906.7

Table 4. Results of the global optimisation of the regression for fundamental research by the regions of PFD (million rubles)

Region	Investments in fixed capital	Gross regional product	Indebtedness of legal entities on loans	Fundamental research	Maximum actual value	Reserve (+) or deficit (-) of expenses
	x_1	x_2	x_3	y_1	y_1	Δy_1
1. Nizhny Novgorod	383 102	-	438 699	1 464.4	5 220.1	3 755.7
2. Mordovia	75 165	-	114 539	376.5	168.1	- 208.4
3. Ulyanovsk	96 771	-	99 058	445.5	302.8	- 142.7
4. Samara	368 865	-	453 792	1 464.2	844.7	- 619.5
5. Perm	305 392	-	312 592	1 358.5	2 383.9	1 025.4
6. Udmurtia	107 187	-	121 689	641.6	811.5	169.9
7. Tatarstan	751 565	-	710 836	1 602	2 896.6	1 294.6
8. Bashkortostan	410 388	-	371 940	1 444.1	1 806	361.9

Table 5. Results of the global optimisation of the regression for applied research by the regions of PFD (million rubles)

Region	Investments in fixed capital	Gross regional product	Indebtedness of legal entities on loans	Applied research	Maximum actual value	Reserve (+) or deficit (-) of expenses
	x_1	x_2	x_3	y_2	y_2	Δy_2
1. Nizhny Novgorod	383,102	-	438,699	11,382.8	9,972.7	-1,410.1
2. Mordovia	75,165	-	114,539	3,059.7	470	-2,589.7
3. Ulyanovsk	96,771	-	99,058	3,670.3	5,190	1,519.7
4. Samara	368,865	-	453,792	11,314.5	1,616.6	-9,697.9
5. Perm	305,392	-	312,592	9,931.7	1,873.9	-8,057.8
6. Udmurtia	107,187	-	121,689	4,426.6	458.6	-3,968
7. Tatarstan	751,565	-	710,836	14,686.1	2,557.3	-12,128.8
8. Bashkortostan	410,388	-	371,940	11,307.4	2,644.6	-8,662.8

Table 6. Results of the global optimisation of the regression for developments by the regions of PFD (million rubles)

Region	Investments in fixed capital	Gross regional product	Indebtedness of legal entities on loans	Developments	Maximum actual value	Reserve (+) or deficit (-) of expenses
	x_1	x_2	x_3	y_3	y_3	Δy_3
1. Nizhny Novgorod	383,102	1,203,299	438,699	40,998.4	66,824.4	25,826
2. Mordovia	75,165	194,177	80,800	9,503.2	581.9	-8,921.3
3. Ulyanovsk	96,771	312,577	71,717	13,603.7	10,636.7	-2,967
4. Samara	368,865	1,282,274	453,792	39,572.4	18,294	-21,278.4
5. Perm	305,392	1,148,574	312,592	30,065.7	12,784.6	-17,281.1
6. Udmurtia	107,187	506,122	121,689	3,732.2	1,591.1	-2,141.1
7. Tatarstan	751,565	1,846,263	526,041	27,961.4	13,553.6	-14,407.8
8. Bashkortostan	410,388	1,546,257	371,940	27,670.3	7,452.7	-20,217.6

Stage 5 – Calculate the reserve or deficit of the respective R&D costs in each region. The last columns of Tables 3–6 present the results of calculating the reserve or deficit of the respective R&D costs in each region as the difference between the actual and the optimal values. This allowed for planning the possibilities of R&D cross-financing within one district. For example, in Table 3, in the Nizhny Novgorod and Ulyanovsk regions, the actual maximum total R&D costs exceed the optimal costs. This leads to the tentative conclusion that in the conditions of saving federal budget funds, PFD can partially finance all R&D costs in those regions that need it. According to the data in the last column of Table 3 regarding the lack of total R&D costs, we can include the Republic of Mordovia, the Samara region, the Perm region, the Udmurt Republic, and the Republics of Tatarstan and Bashkortostan in such regions. Moreover, according to Table 3, the region in need is the Republic of Tatarstan.

To better identify these regions, the outcome was analysed in more detail—in terms of the various costs of R&D by type of work. The results in Tables 4–6, for example, show that the Republic of Tatarstan, on the contrary, had some reserve in the expenditures on fundamental research, which could be redirected to other regions of PFD. Further, for Tatarstan, the shortage of expenditures on applied research (Table 5) and developments (Table 6) in total was significantly lower than the shortage of all R&D expenditures, as reflected in Table 3. By contrast, according to Tables 4–6, the Samara region, the Republic of Bashkortostan, and the Perm region were the most in need of financing various types of R&D costs. However, the main donor of the reserve of costs for various types of R&D remained the Nizhny Novgorod region, if we again consider the internal cross-financing of R&D costs within the limits of PFD. This would allow significant savings in the federal budget funds allocated for scientific and, consequently, innovative development in the country's regions.

4. Discussion

The present results correlate with the conclusions obtained by Yashin et al. (2020). Namely, for the Samara region, the model revealed the greatest deficit in current R&D expenditures compared to the optimal plan, which amounted to 10,673 million rubles. The region can be partially compensated for at the expense of R&D reserves of the Nizhny Novgorod and Ulyanovsk regions, the Udmurt Republic, and the Republics of Tatarstan and Bashkortostan. In total, such a reserve amounts to 8,412 million rubles, which should be allocated to the Samara region. The synergy effect of such an reallocation would be 86,153.7 million rubles. The reserve of 8,412 million rubles can also be partially allocated to R&D in the Republic of Mordovia and the Perm region, and the remainder should be transferred to the Samara region. However, the synergy effect of the entire PFD in this case will be the same as in the case if the entire reserve is allocated to R&D in the Samara region.

Comparing the obtained results with the experience of other researchers, it can be noted that in planning R&D and its financing, Feoktistova (2014) highlighted the use of the project approach, the choice of the expected results of a research project as one of the key criteria, and the choice of the results already achieved by a research project by its potential performer as the key criterion. Gaponenko (2018) also considered situations in which it is potentially possible to reduce the actual costs of performing R&D: (1) performing R&D similar to work previously performed by the same contractor—a scientific organisation or a researcher; (2) performing R&D similar to work previously performed by other contractors—scientific organisations; (3) performing (possibly simultaneous) similar R&D for different customers; (4) using previously obtained research results or previously assembled installations in new research terms if the subjects of old and new research are not analogous to each other; and (5) including in the terms of reference tasks that do not correspond to the goal of R&D, the results of which can be used, for example, in another R&D or a publication, a patent.

We propose justified quantitative guidelines for planning the costs of R&D in an industrial region based on global optimisation of the indicated costs. The described approach can contribute to better decision making by state structures and their experts with regard to planning the innovative development of industrial regions of the country.

5. Conclusion

The following points highlight the most important findings of the study:

1. Currently, the issues of the optimal financing of R&D expenditures within the country and its regions, which have the appropriate scientific potential, have not yet been completely solved. It seems impossible to solve such problems in isolation from the specific technological and economic results of regional R&D. Planning of these results, as well as the resources required for their achievement, is an urgent task to optimise R&D expenditures. In this regard, we distinguished three types of planning: investment, production, and financial. We considered all three processes simultaneously. This allows for covering a wide range of tasks to optimise R&D costs in the regions and contribute to their innovative development.

2. The results of global optimisation allow us to draw the conclusion that in the conditions of saving the federal budget funds, the federal district authorities can partially finance all R&D costs in those regions that need it. To identify such regions more reasonably, it is necessary to analyse this situation in more detail—in terms of various R&D costs by type of work.

3. For PFD, the Samara region, the Republic of Bashkortostan, and the Perm region are the most in need of financing various types of R&D expenditures. However, the main donor of the reserve of expenditures on various types of R&D is the Nizhny Novgorod region. This is the essence of the internal cross-financing of R&D costs within PFD. It would allow significant savings in the federal budget funds allocated for scientific and, consequently, innovative development of the country's regions.

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