Forecast of the Impact of Human Resources on the Effectiveness of the Petrochemical Cyber-Physical Cluster of the Samara Region

Natalya Baykina, Pavel Golovanov, Mikhail Livshits, and Elena Tuponosova

Abstract The chapter analyzes the impact of the training system in the field of cyber-physical production processes for the oil industry of the Samara region. Mathematical models in the form of the production function are Cobb–Douglas linking the efficiency of the petrochemical cluster of indicators of activities supporting the University in the Samara region. On the obtained mathematical models the forecast for oil production and refining volumes is shown, depending on the training of qualified specialists in the university taking into account the regular nature of economic conditions. Based on the DEA (Data envelopment Analysis) methodology, in the period under review, the comparative performance indicators of the oil industry in the Samara region as a cyber-physical production system are evaluated.

Keywords Petrochemical cluster · Oil production · Cyber-physical production system · The cobb–douglas production function · Mathematical model · Data envelopment analysis (DEA) · Comparative efficiency

1 Introduction

A significant share of the budget of the Samara region is provided by the work of the petrochemical cluster, which includes enterprises for the oil extraction and refining, as well as scientific organizations and educational institutions that supply the industry with personnel. The depth increase of oil refining characterizing the effectiveness of the oil industry is demanded strong and powerful cyber-physical industrial complex of scientific and technical potential and various specialists who support the digitalization of the industry. The personnel needs of industry are provided by specialists in many profiles: geologists, operational staff, workers in pipeline transport and oil and chemical processing enterprises, mechanics and electricians, as well as the staff

N. Baykina · P. Golovanov · M. Livshits (✉) · E. Tuponosova
Samara State Technical University, 244 Molodogvardeyskaya, St. Samara 443100, Russia
e-mail: usat@samgtu.ru

A. G. Kravets et al. (eds.), *Society 5.0: Cyberspace for Advanced Human-Centered Society*, Studies in Systems, Decision and Control 333,
https://doi.org/10.1007/978-3-030-63563-3_10

of the necessary infrastructure support: mathematicians, IT specialists, economists, etc.

The preparation of qualified specialists for such a complex, interconnected cyber-physical infrastructure requires a long time—student training at the university with an established educational process continues for at least 4–5 years. This fact does not allow to experiment for effective management for personnel policy of the industry. Assessing the relationship between the indicators of training specialists at a university and the efficiency of oil production is an urgent task, both for the development of a university and the effectiveness of digitalization of the industry as a whole. An effective tool for analyzing this relationship in the context of cyber-physical production is mathematical modeling.

It is necessary to mention that the problem of such mathematical models for crisis periods (e.g. war periods, epidemic, etc.) has not been solved yet. But for regular periods, rather well-known approaches for mathematical modeling is existed [1–5]. The relevance of forecasts of these models does not decrease moreover it is even increased during the crisis period due to several reasons.

The forecast of these models allow evaluating the loss rate not relatively retrospective industry performance but relatively predicted achievable in the absence of crisis phenomena. Besides, chaotic economic processes become regular after the crisis. And this process management requires prediction by mathematical modeling showing long-term fundamental patterns.

2 Mathematical Modeling

The method of constructing mathematical models in the form of an inhomogeneous production function (PF) of Cobb–Douglas is widely used in modern literature; it is used to describe processes and objects of various fields: social, economic, and production. PFs allow one to take into account several influencing factors and evaluate their contribution to the overall effect. For example, in the article [6], a mathematical model was constructed of the relationship and mutual influence of economic growth and innovative technologies of firms operating in monopolistic and oligopolistic markets.

The group of authors in the article [7] built a food industry growth model based on the modified Cobb–Douglas production function, taking into account the innovative factor, and received a typology of Russian regions according to the level of development of light and processing industries.

In the article [8], the dynamics of changes in the volume of production in the mining industry for the period from 2005 to 2015 are considered and a model is constructed in the form of the production function of Cobb Douglas using the example of mining in Russia. The author considered the output volume (billion rubles) as the output characteristic of the model, and the fixed capital (billion rubles) and the number of staff (people) as inputs.

In the article [9], models are presented for assessing the operational efficiency of distribution electric networks using the DEA method and based on the least-squares method with the Cobb Douglas production function. A comparison is made between the estimation methods and a conclusion is made that the model in the form of a Cobb—Douglas PF is less preferable from the point of view of evaluating efficiency points.

The author in the article [10] gives a mathematical model of GDP based on the Cobb—Douglas PF models. Agriculture, industry, and services. The conclusion is drawn about the influence of the final price of the goods on the prices of factors of production.

In [11], the author considers the issue of the Cobb–Douglas PF and offers a methodology for analysis in accordance with the elasticity of output associated with factors of production.

To describe regular development production systems, the method of constructing mathematical models in the form of an inhomogeneous production function (CF) of Cobb–Douglas (1) [12] is widely used:

$$Y(t) = A \cdot K(t)^{\alpha} \cdot L(t)^{\beta} \cdot e^{\lambda t}, \tag{1}$$

where Y is the release of the final product; $K(t)$—capital resources, $L(t)$—labor resources, α, β—characteristic of resource use efficiency—elasticity indicator, A—scaling transformation coefficient, λ—factor of influence of scientific and technological progress (STP), α—factor elasticity for factor K, β—for factor L. Cobb–Douglas model supposes to the exponential growth of the product at constant labor and capital costs as a result of scientific and technological progress (STP), the degenerate variant excluding the "no STP" option is easily obtained by and $\lambda = 0$ [12, 13].

On this basis, we will build mathematical models that link the effectiveness of the cyber-physical petrochemical complex with indicators characterizing the effectiveness of training specialists at the Samara Technical University (Samara State Technical University), a reference university in the Samara Region, which trains specialists for the oil industry in all of the above areas. For the output parameters of the model, we take quantitative indicators characterizing the productivity of the oil industry in the Samara Region: oil production—Y_1, the amount of oil received for refining—Y_2 and the number of processed products: gasoline, diesel fuel, heating oil—Y_3.

As input characteristics $K(t)$ $L(t)$ formula (1) we will take indicative indicators of the basic higher education institution of the Samara region: graduation of students of Samara State Technical University—S_i, people (characterizes the performance of the university); the total number of scientific publications—P_i, pcs.; performance of scientific and technical works (R&D) on grants—G_i, units; and the generation of intellectual property—I_i, units (characterize the level of practical significance of scientific work). Given these input factors, the model (1) of the inhomogeneous Cobb–Douglas PF with allowance for the NTP is written in the form (2).

$$Y(t) = A \cdot S(t)^{\chi} \cdot P(t)^{\kappa} \cdot G(t)^{\phi} \cdot I(t)^{\rho} \cdot e^{\mu t}, \tag{2}$$

Table 1 Factor elasticity

Factor elasticity	Input resource
χ	For the factor S_i, graduation of students of Samara State Technical University
κ	For the factor P_i, total number of scientific publications
φ	For the factor G_i, grant research
ρ	For the factor I_i, intellectual property generation
μ	For the influence factor of scientific and technological progress (NTP)

The identification of model parameters is carried out using the least-squares method (LSM) [13, 14]. We will evaluate the quality of modeling by the determination coefficient (R^2) and the criterion of F-statistics, and the predicted properties of the model by the Darbin-Watson criterion (DW). We will carry out the smoothing of the initial data based on the moving average method, providing averaging of the effect of random outliers of statistical information [15].

The sensitivity of model solutions (2) to the corresponding input resources is characterized by sensitivity coefficients, factorial elasticity, which is presented in Table 1.

We develop mathematical models in the form of an inhomogeneous Cobb–Douglas PF taking into account scientific and technological progress (2).

In these models, as an output parameter Y, we will consider the performance indicators or the oil industry that are most dependent on human resources.

oil production, $Y = Y_1$

$$Y_1(t) = A_1 \cdot S(t)^{\chi_1} \cdot P(t)^{\kappa_1} \cdot G(t)^{\phi_1} \cdot I(t)^{\rho_1} \cdot e^{\mu_1 t} \tag{3}$$

by the amount of oil received for processing, $Y = Y_2$

$$Y_2(t) = A_2 \cdot S(t)^{\chi_2} \cdot P(t)^{\kappa_2} \cdot G(t)^{\phi_2} \cdot I(t)^{\rho_2} \cdot e^{\mu_2 t} \tag{4}$$

by the number of processed products: gasoline, diesel fuel, and heating oil, $Y = Y_3$

$$Y_3(t) = A_3 \cdot S(t)^{\chi_3} \cdot P(t)^{\kappa_3} \cdot G(t)^{\phi_3} \cdot I(t)^{\rho_3} \cdot e^{\mu_3 t} \tag{5}$$

3 The Result of Modeling

For identification, we will use statistical data on the oil complex of the Samara region [16–18]. Table 2 shows the coefficients of mathematical models (3), (4), (5) obtained with the help of method LSM separately for smoothed and unstated statistical information.

Table 2 Characteristics of mathematical models (3–5)

	$Y_1(t)$		$Y_2(t)$		$Y_3(t)$	
	Oil production		Amount of oil received for processing		Amount of processed products	
Elasticity	Unstated	Smoothed	Unstated	Smoothed	Unstated	Smoothed
χ	0.0245	0.8098	0.1537	0.4567	0.1325	1.0605
κ	0.0494	0.0650	0.0155	0.0323	0.0196	0.1046
ϕ	0.0109	0.0808	−0.0236	−0.0239	−0.0222	−0.0489
ρ	0.0836	−0.4503	0.0380	−0.1531	0.0545	0.5506
μ	0.01341	0.06705	0.00106	0.02139	−0.01480	0.04674
Simulation quality						
DW	1.1461	2.0982	1.8553	3.0115	1.5339	2.9943
Ra	0.4270	−0.0491	0.0723	−0.5058	0.2331	−0.4971
R^2	0.8494	0.9698	0.9358	0.9893	0.7822	0.9769
F	5.6395	32.0996	14.5714	92.2261	3.5904	42.3796

Figures 1 and 2 show the results of modeling for oil production from the unstated and smoothed initial data of the inhomogeneous Cobb–Douglas PF taking into account the scientific and technical progress (3) from 2008 to 2018.

Factor elasticities are the components of the logarithm gradient of the corresponding industry indicator (3)–(5) in the region of the input coordinates $S(t)$, $P(t)$, $G(t)$ and $I(t)$ that is why it allows estimating the sensitivity of this parameter. The greatest factor elasticity model (3), constructed based on non-smoothed initial statistical data has the generation of intellectual property objects

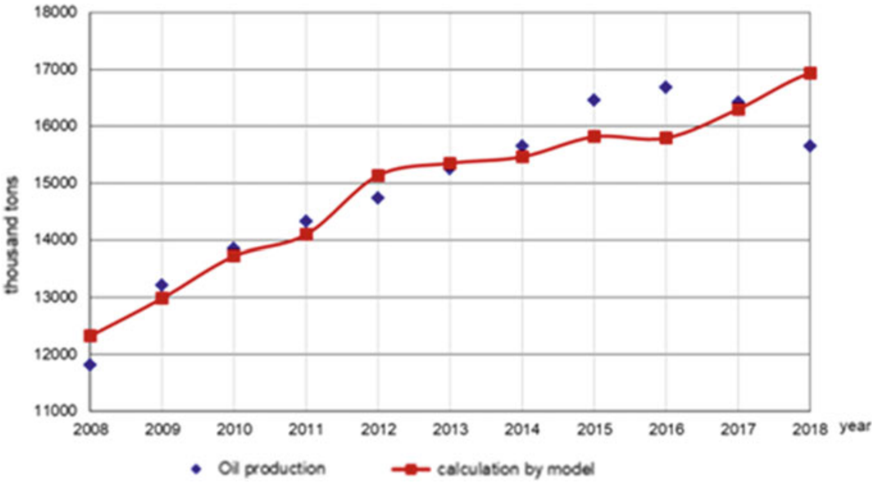

Fig. 1 Calculation of oil production (Y_1) by the model (3)

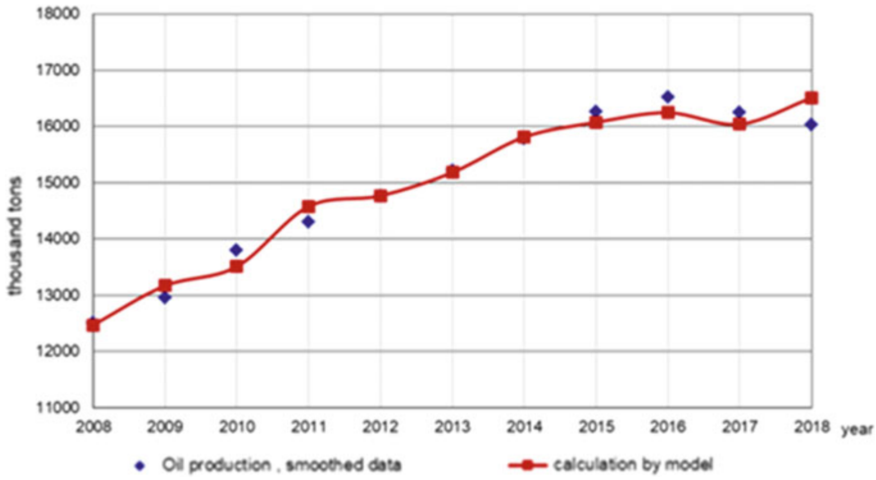

Fig. 2 Calculation of oil production (Y_1) by the model (3)—smoothed data

I_i. When smoothing data, the greatest influence for oil production Y_1 is made by the implementation of research on grants (factor G). When smoothing data, the quality of this model improves—the coefficient of determination R^2 increases by 14% to almost one. This indicates a trend of a significant influence of the scientific work of university graduates on the effectiveness of their work in the oil industry.

Similarly, the modeling results and model parameters for the amount of oil received for refining (Y_2) are presented in Figs. 3 and 4.

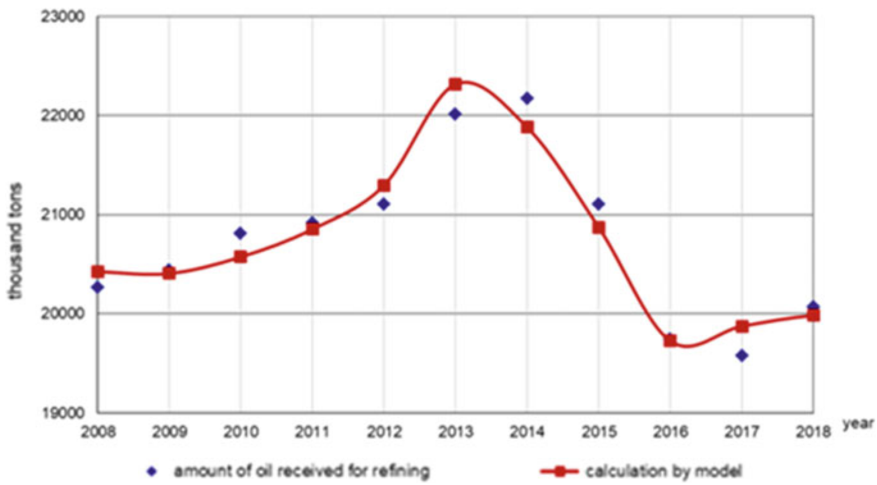

Fig. 3 Calculation amount of oil received for refining (Y_2) by the model (4)

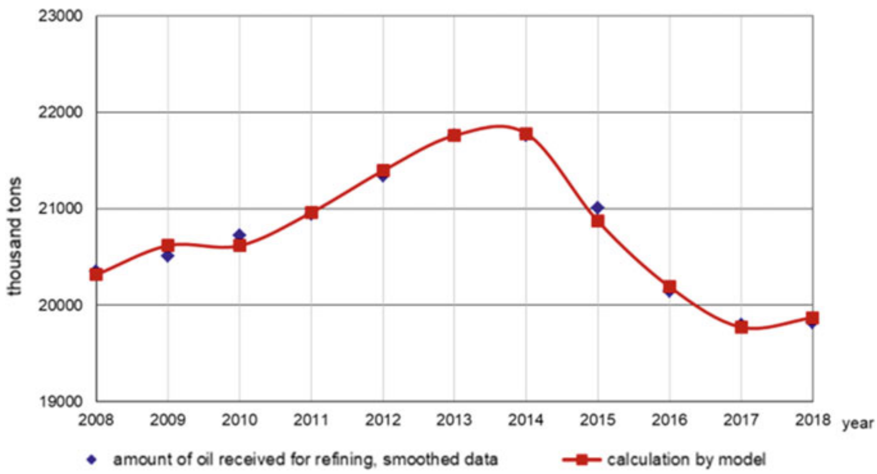

Fig. 4 Calculation amount of oil received for refining (Y_2) by the model (4)—smoothed data

The greatest factor elasticity in the model (4), taking into account scientific and technological progress, has the generation of intellectual property objects I_i, which reflects its greatest influence on the amount of oil received for refining, and when smoothing the initial data, the total number of scientific publications has the greatest impact P_i. The models are distinguished by their good approximative and prognostic properties. The value R^2 is more than 0.9, and the Darbin–Watson criterion DW in the model constructed from the smoothed data increases by 62% compared to the model constructed from the unsmoothed data and reaches a value of 3.

The result for the production of petroleum products in the Samara region (5) based on uncoated and smoothed source data is presented in Figs. 5 and 6.

When modeling the number of oil products produced, the factor generation, as in the case of the model (4), has the highest factors of the generation of intellectual property objects I_i and performing research on grants G_i. The processing of gasoline, diesel fuel, and heating oil is a complex technological process, where the scientific base of young industry experts is very important, which is largely characterized by joint research developments of teachers and university students. When smoothing the initial data, the modeling error decreases and the determination coefficient (R^2) increases by 25%.

All the obtained models are characterized by good convergence with statistical data, but at the same time, the factor elasticity χ of the number of graduates of SSTU students S_i is either the smallest or negative. This can be explained by the inefficiency of the extensive approach to training for such a high-tech and knowledge-intensive industry as the oil industry.

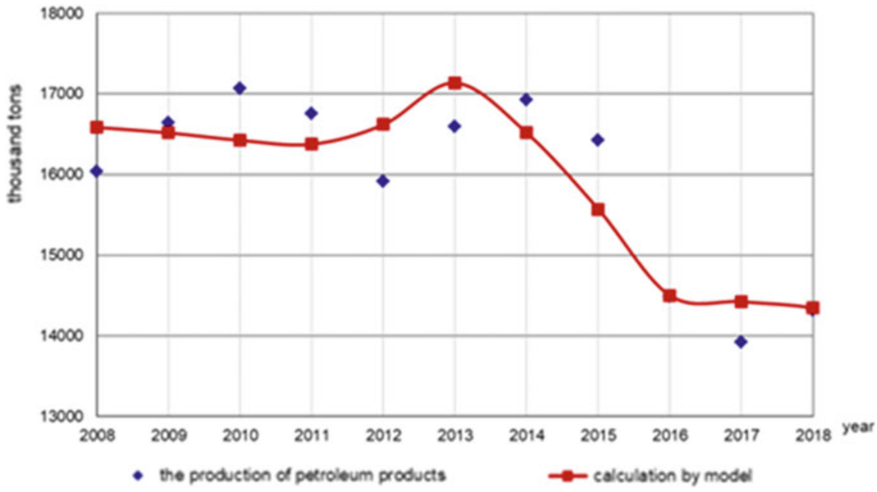

Fig. 5 Calculation processed products (Y_3) by the model (5)

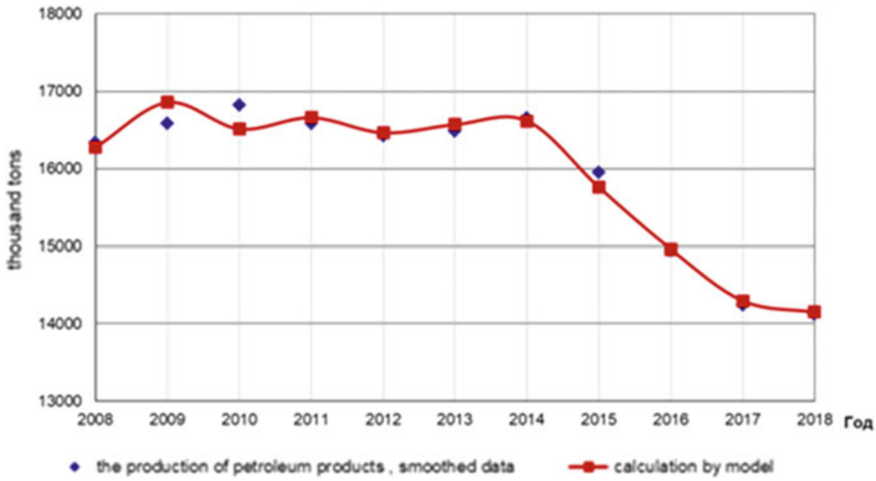

Fig. 6 Calculation processed products (Y_3) by the model (5)—smoothed data

4 Forecasting

We check the predicted properties of the Cobb–Douglas PF models taking into account the scientific and technical progress for 2008–2018 and construct forecast until 2022. Provided regular crisis-free development the student graduation S_i for the next 4 years is easily predicted. We extrapolate the data on the generation of intellectual property objects I_i by a quadratic polynomial, research on grants G_i by

Table 3 Forecast of university resources for 2019–2022

Year	Input data			
	S, people	*P*, pieces	*G*, units	*I*, units
2019	5272	4899	50	52
2020	4731	5081	51	60
2021	4235	4764	52	71
2022	3856	4987	52	87

a cubic polynomial, and the total number of scientific publications P_i in the forecast will be assumed to correspond to the roadmap of the reference university [19, 20] (Table 3).

The forecast will be built on models based on unstated source data. Figure 7 shows the forecast values obtained by the model (3) of oil production (Y_1), Fig. 8 - the amount of oil received (Y_2) for refining (4), and Fig. 9—the production of petroleum products (Y_3) (5).

From the forecast (Fig. 7) according to the initial data (graduation of specialists and scientific work at Samara State Technical University), it can be seen that in the case of regular crisis-free development oil production would be increased during the study period.

According to the model (4), the forecast for the amount of oil received for refining, presented in Fig. 8, shows that in 2019 there will be no changes in oil refining, and in the future, an increase would be expected.

Regarding the forecast of the amount of produced gasoline, diesel fuel, and heating oil (Fig. 9), in 2019 there is a slight decrease in the volume of processed products,

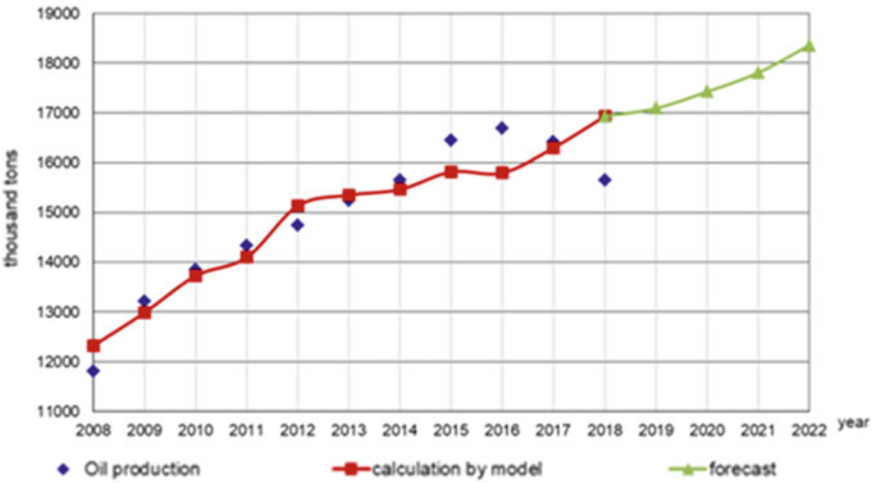

Fig. 7 Forecast of oil production (Y_1) by the model (3) until 2022

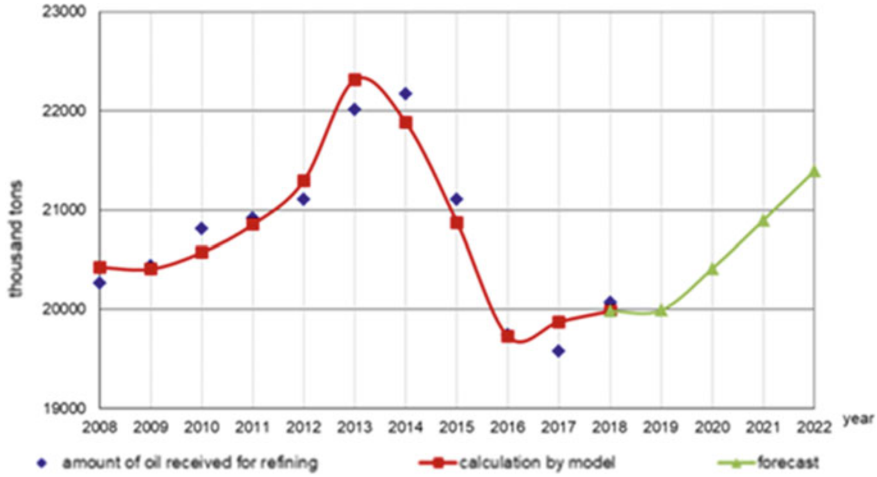

Fig. 8 Forecast of the amount of oil received for refining (Y_2) by the model (4) until 2022

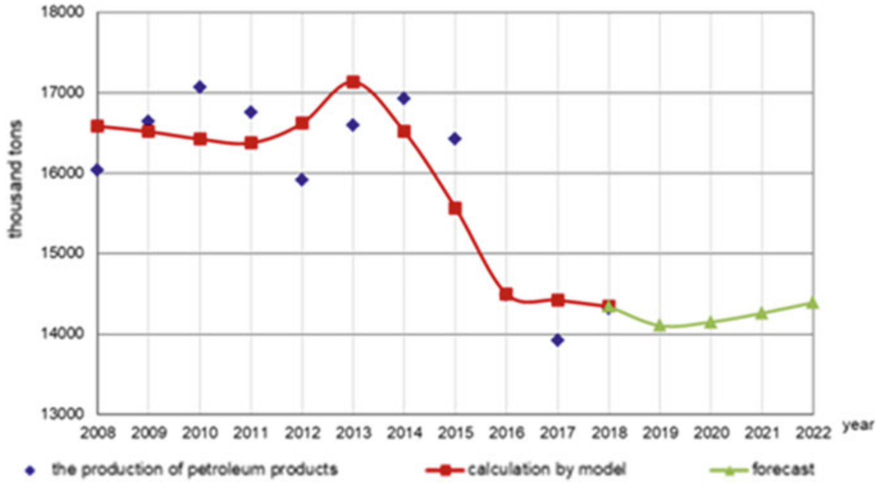

Fig. 9 Forecast of processed products (Y_3) by the model (5) until 2022

and then in case of regular crisis-free development, there would be a slight increase, which in 2022 would ensure a return to the level of 2018. It should be noted that the personnel influence on the operation of the oil complex is very important but not absolute for the high performance of output production indicators. For example, as practice shows, if the state of financial support, equipment, and arrangement of fisheries are predictable, then external factors make significant adjustments, and they can not always be taken into account.

5 Comparative Assessment of the Effectiveness

For a comparative assessment of the effectiveness in the considered period time of staffing the oil cluster of the Samara region for all three indicators Y_1, Y_2, Y_3, we use the methodology of multi-criteria evaluation of comparative efficiency—Data Envelopment Analysis (DEA) [21].

The structure of the comprehensive performance indicator DEA will form as follows:

$$f_i = \max \frac{u_1 \cdot Y_1 + u_2 \cdot Y_2 + u_3 \cdot Y_3}{v_1 \cdot S_i + v_2 \cdot P_i + v_3 \cdot G_i + v_4 \cdot I_i}, \quad (6)$$

where $u_1, \ u_2, \ \ u_3$ are the positive weighting coefficients characterizing the relative contribution of each of the output factors Y_i to the total efficiency coefficient f, and accordingly, $v_1, \ v_2, \ v_3, \ v_4$ the weighting coefficients of the input quantities to be determined during the DEA procedure.

Figure 10 shows the comparative performance indicators of the oil industry in the Samara region.

In 2008 and 2013, the comparative effectiveness of staffing in the industry was maximum and equal to 1. From 2013 to 2018, there has been a decline in production efficiency and a decrease in relative efficiency to a minimum level—$f_{\min} = 0.54$. Then the growth is possible in the absence of crisis to 0,71 by 2022. The results presented in Fig. 10 confirm the conclusions of the simulation by formulas (3)–(5), shown in Figs. 3–9.

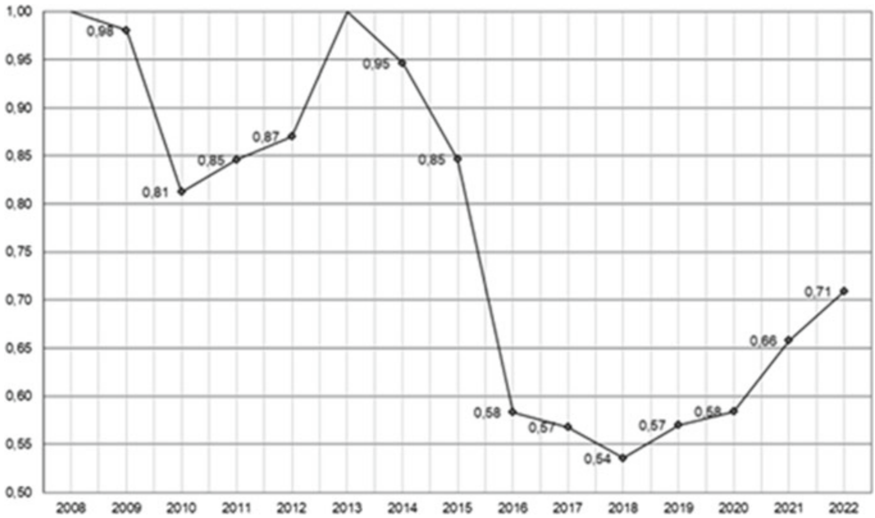

Fig. 10 Indicators of the comparative efficiency of the oil industry from 2008 to 2022

6 Conclusion

Mathematical modeling, forecasting, and comparative assessment of the effectiveness allow making the following conclusion: the practical scientific work skills together with the University scientists acquired by young specialists during their study provide high efficiency of staff replenishment contribute most to the development of the oil industry.

The obtained models allow us to forecast the absence of crisis production development and outline measures for the development of the industry, university, and forms of their interaction. Confirmation of the forecast for 2019 should be expected with the publication of statistical reports in 2020.

It should be noted that the chapter analyzes the influence of exclusively the training and graduation of specialists of SSTU on the effectiveness of the regional oil cluster and establishes a significant effect on the production of this factor. In this case, one should take into account the influence of numerous other factors, in particular, the equipment of deposits, the economic, social, and political conditions, etc.

It is necessary to highlight that maintaining the high relevance of forecasting on mathematical models in the conditions of the absence of crisis development in crisis periods. These forecasts determine long-term prospects; reflect the fundamental tendencies which are very important while industry staffing. In the long run, staffing will determine the productivity, competitiveness, and financial performance of the oil cluster.

Acknowledgements The reported study was funded by the Russian Foundation for Basic Research (RFBR), according to research project No. 20-08-00240.

References

1. Klopchenko, V.: Elements of theory of prediction in education, No.4 (93), pp. 235–241. Published by: Technological university of the Federal state educational institution of higher professional education “Southern Federal University” in Taganrog (2009)
2. Golovanov, P., Livshits, M., Tuponosova, E.: Mathematical model of issuing specialists by university. Mathem Methods Tech Tech MMTT J **2**, 114–119. Yu.A. Gagarin Saratov State Technical University, Saratov (2018).
3. Bondyreva, I.: Interaction of universities and enterprises in training personnel for innovative development. Theor. Econ. Mag. **3**, 19–25 (2011)
4. Evelev, A., Livshits, M., Tuponosova, E., Frank, E., Tsapenko, M.: Mathematical modeling process of training specialists in the engineering industry at a technical university. In: IOP CONFERENCE SERIES: materials science and engineering. «13th international conference on mechanical engineering, automation and control systems, meacs 2018». Novosibirsk, 12–14 December’s 2018 г. Institute of Physics Publishing. p. 012026. (2019)
5. Golovanov, P., Livshits, M., Tuponosova, E.: Analysis of impact made by the flagship university on the efficiency of petrochemical complex. In: Studies in systems, decision and control, vol. 260, pp. 289–300. Springer International Publishing (2020)

6. Kislickij M.M., Chumachev A.A., Gan E.P.: Evaluation of the company's performance based on the analysis of the relationship and mutual influence of economic growth and innovative technologies. In: Agri-food policy of Russia, № 8 (20), pp. 43–49. Ural research Institute of economic and food security (2013) (In Russian)
7. Glinskij, V.V., Serga, L.K., Samotoj, Simonov, N.V., Yu, E.: Development of the food and processing industry as a condition for improving Russia's national security. Vestnik NSUEM, № 3, 221–234. Publishing house of the Siberian branch of the Russian Academy of Sciences, Novosibirsk (2017) (In Russian)
8. Titkova, I.K.: Analysis of the current state of mining in Russia using the Cobb-Douglas production function. In: Collection of student scientific papers based on the materials of the XV all-Russian student scientific conference with international participation. Edited by L. A. Dremova. pp. 372–374 (2017)
9. Marcelo Azevedo Costa: Ana Lúcia Miranda Lopes, Giordano Bruno Braz de Pinho Matosc: Statistical evaluation of Data Envelopment Analysis versus COLS Cobb-Douglas benchmarking models for the 2011 Brazilian tariff revision. Socio-Econ. Plann. Sci. **49**, 47–60 (2015). https://doi.org/10.1016/j.seps.2014.11.001
10. Muro, K.: A note on the three-sector Cobb-Douglas GDP function. Econ. Model. **31**, 18–21 (2013). https://doi.org/10.1016/j.econmod.2012.11.008
11. Pavelescu, F.M.: Methodological considerations regarding the estimated returns to scale in case of Cobb-Douglas production function. Procedia Economics and Finance. **8**, 535–542 (2014). https://doi.org/10.1016/S2212-5671(14)00125-7
12. Klejner, G.: Production functions: theory, methods, application, 239 p. Finance and statistics, Moscow (1986)
13. Diligensky, N., Tsapenko, M., Gavrilova, A.: Mathematical models of management of production and economic systems: textbook allowance, 112 p. Samar. state tech. un-t—Samara (2005)
14. Gavrilova, A., Golovanov, P., Diligensky, N., Tuponosova, E.: Designing models and building a short-term perspective forecast of graduation. Bull. Samara State Tech. Univ. Ser. Eng. Sci. **2**, 21–29 (2011)
15. Ayvazyan, S., Mkhitaryan, V.: Applied statistics and fundamentals of econometrics, 1022 p. M: Unity (1998)
16. Samara Annual Statistical Report, 155 p. Stat.sb\Samarastat (2017) (In Russian)
17. Samara Annual Statistical Report. Enterprises and organizations. https://samarastat.gks.ru/wps/wcm/connect/rosstat_ts/samarastat/ru/statistics/organizations/ (2018) (In Russian)
18. Federal State Statistics Service Regions of Russia. The main characteristics of the constituent entities of the Russian Federation—2018 Volga Federal District. Samara Region. https://www.gks.ru/bgd/regl/b18_14s/Main.htm
19. Samara State Technical University. Normative documents. Roadmap of the development program. https://su.samgtu.ru/files
20. Samara State Technical University. Mission of the reference university. https://su.samgtu.ru
21. Diligensky, N., Gavrilova, A., Tsapenko, M.: Construction and identification of mathematical models of production systems: Textbook, 126 p. Samara: LLC "Etching" (2005)