

Problems of Management of Technological Systems Under Uncertainty: Models and Algorithms

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Annotation. It is known that the importance of model management is very high in the management of a technological system under conditions of uncertainty. Model management provides an opportunity to qualitatively manage the system based on quantitative criteria. The article investigates the mechanism of improving the quality of technological system management decisions under conditions of uncertainty. Based on the parametric improvement of control and forecast models, it is proposed to use a new methodical approach to increase the accuracy of the description of the technological object and control system. The effectiveness of adjusting the control object of the system to optimality in improving the quality of management decisions of a technological system of a complex nature under conditions of uncertainty is substantiated. A prototype model of the management object was selected as a research experiment, and the qualitative changes of management based on quantitative changes were considered as the most important criterion according to this model. Improvement of the model theoretically led to the solution of the problem of mathematical programming, expanded the possibilities of practical application. Algorithms of using the mathematical programming method were developed in the improvement of the prototype model. The essence of the parametric improvement of the object model in the qualitative management of an uncertain system with a control object is revealed on the basis of the law of quantitative changes leading to qualitative changes. A new approach to improving the mechanism for increasing the quality of decision-making in the optimal management of uncertain systems is proposed.

Keywords. Fuzzy system, control object, model, mathematical programming, prototype model, weight function, parametric improvement, decision making, decision quality, control quality

1. Introduction

One of the most complex aspects in the management of technological systems is optimal decision-making under conditions of uncertainty. The main focus here is that the system cannot be configured using time or other specific parameters. Today, it is noted that there is no clear solution to this situation in many sources. One of the main reasons for this is the explanation "is influenced by many indicators" [1]. In general,

there are several reasons for this. The management of technological systems under conditions of uncertainty can present a variety of challenges. Some of the problems that may arise include:

Lack of information: When faced with uncertainty, decision-makers may not have all the information they need to make informed decisions. This can lead to a lack of confidence in the decisions being made, and may result in poor outcomes;

Difficulty in predicting outcomes: Uncertainty makes it difficult to predict the outcomes of different courses of action. This can make it challenging to develop effective strategies for managing technological systems;

Increased risk: Uncertainty can increase the level of risk associated with technological systems. This is because decision-makers may be forced to make decisions based on incomplete or inaccurate information, which can lead to unexpected consequences;

Resistance to change: Technological systems are often complex and interconnected, which can make it difficult to implement changes quickly or effectively. In conditions of uncertainty, stakeholders may be resistant to changes, which can further complicate the management of technological systems;

Resource constraints: Uncertainty can lead to resource constraints, as decision-makers may be unsure about the level of resources needed to manage technological systems effectively. This can make it difficult to allocate resources appropriately, leading to inefficiencies and wasted resources.

Overall, the management of technological systems under conditions of uncertainty requires careful planning, effective communication, and a willingness to adapt to changing circumstances. Decision-makers must be able to gather and analyze information, anticipate potential outcomes, and develop strategies that can mitigate risk and improve system performance. For this, the need to develop a model that accurately and fully describes the system, as well as algorithms for its use, becomes relevant.

2. Materials and method

There are several ways to make control decisions for technological systems under uncertainty. These are:

1. Modeling method. Based on the systematic analysis of the abstract nature of the system by quantitative sets, the relationships between its elements are studied. The main point here is the reliability and accuracy of the connections. As a result, it is possible to carry out an experiment on the system as desired. There are other features of this method, which are described by "Riccardo Novo et al (2022)" [2], "Behrang Shirizadeh et al (2022)" [3], "Ryan Hanna et al. (2022)" [4] provides extensive information. The main problem is the model and the development of the algorithm for its use.

2. Method of experiment. This method is characterized by collecting experimental results according to the system input-output principle and limiting them to their systematic analysis. The importance and shortcomings of this method are presented

in the works of "Alessio Ishizaka et al (2017)" [5], "Robin Wensley (1994)" [6]. The main problem is observed in the limitation and economic contour of the process of experimentation.

3. Optimization method. This method is based on the resource potential of the system, certain limitation criteria are established and a decision is made based on these criteria. The method is widely used in practice. About the importance and shortcomings of the method "Bin Liu et al. (2022)" [7], "Kai Wang et al. (2022)" [8], "Hussein Mohammed Ridha, (2021)" [9]. In our case, it was found appropriate to use methods such as systematic analysis, mathematical-statistical analysis, along with the modeling method. Therefore, the prototype model and the principle of its improvement were used during the research.

3. Results

A prototype model and an original model are two different types of models used in various fields such as product development, engineering, and software development. A prototype model is an initial version of a product or a design that is developed to test and validate its features, functions, and usability. It is usually a basic or incomplete version of the final product that is used to gather feedback, identify flaws and make improvements before the final product is developed. Prototype models are typically used in product design, software development, and engineering to refine and optimize the design and functionality of a product.

On the other hand, an original model is a finished and fully functional version of a product or design that is ready for release to the market or for use by customers. It is the final product that has undergone various stages of development, testing, and refinement, and is intended to meet the needs and requirements of the end-users. Original models are typically used in manufacturing, software production, and other fields where a final product is being created.

In summary, the main difference between a prototype model and an original model is that a prototype is an initial version of a product that is used to test and refine its design and functionality, while an original model is a final and fully functional version of a product that is ready for use by customers [10]. Therefore, it will not always be possible to develop a real model of the system. Below we consider the construction of a prototype and a real model for a parametrically defined system, and the source of the difference between them, as well as the levels of decision-making accuracy using them. In the system under consideration, $h(t)$, $q(t)$ – main influencers – input parameters, $v(t)$ – external influence, $p(t)$ – weight function for the object, $s(t)$ – for the system be the output parameter.

The weighting function depends on the main influencers and external influence according to the area of detection. Then it can be determined multiplicatively as follows:

$$p(h, q, v) = f_1(h(t), q(t), v(t)) \cdot f_2(h(t)) \cdot f_3(q(t)) \cdot f_4(v(t)) \cdot e^{\varphi(t)-1} \quad (1)$$

Here: $\varphi(t)$ – is the degree of deviation of the system during time t , and the fulfillment of the condition $0 \leq \varphi \leq 1$ represents one of the necessary conditions for the physical realization of the system.

For clarity, we write the following expression of (1):

$$p(t) = l_0 \cdot h(t)^{A_1} \cdot q(t)^{A_2} \cdot v(t)^{A_3} \cdot e^{\tau t - 1} \quad (2)$$

Here, A is a model parameter.

Suppose that model (2) is a prototype model with a level that can be used to control the system. In that case, if the original type of (2) can be determined, it becomes possible to optimize management decisions.

Based on the results of the experiment, the following model was developed:

$$p(t) = 0,04895 \cdot h_0(t)^{0,11531} \cdot q_0(t)^{0,8846} \cdot v_0(t)^{-0,008139}, \sigma = 1,2 \%, se = 0,009 \quad (3)$$

Here, $h_0(t)$ is the material consumption at the separator inlet, $\text{sm}^3 / \text{second}$, $q_0(t)$ is the temperature of the material at the separator inlet, $^{\circ}\text{C}$, $v_0(t)$ is the measured noise intensity affecting the object, σ is the average approximation error of the model, and the acceptance limit is up to 8%; se is the standard error of the model. Also, 92% of the variance of the values in the object output comes from the weight function (3).

According to model (3), the response of the weight function takes different degrees of change for different parameters. In particular, a 0.115 percent increase response to a unit percentage change in material consumption at the separator inlet, a 0.88 percent increase response in the corresponding unit of material temperature at the separator inlet, and a 0.008 percent increase in the measured noise intensity affecting the object there is a reduction reaction.

We will also consider the model of connection of the output of the system object to the system reaction:

$$\ln(S(t)) = 1,651201 + 1,335073 \cdot p(t), \sigma = 1,03 \%, se = 0,012 \quad (4)$$

Here $S(t)$ is the concentration of the substance at the output of the system, in percent. At the same time, it should be said that model (4) is built based on the results of model (3) with system reaction. On the contrary, the connection between the actual values of the object and the output of the system will be as follows (this model is built for pre-known values for testing):

$$\ln(S(t)) = 1,652282 + 1,329012 \cdot p(t), \sigma = 0,17 \%, se = 0,003 \quad (5)$$

According to (4) and (5), this linear connection with the output parameter of the object justifies the importance of the accuracy (quality) of constructing the weight function. This indicates the need to search for opportunities to improve the model (4) when making decisions to increase the accuracy of system management. In this case, we suggest using a mathematical programming tool. According to it, we put forward the following hypothesis, that is, (4) it is possible to increase the parametric accuracy of the model without changing its structure. Then, logically, the following expression follows:

$$p(t) = 0,04895 \cdot h_0(t)^{0,11531+B_1} \cdot q_0(t)^{0,8846+B_2} \cdot v_0(t)^{-0,008139+B_3} \quad (6)$$

It is not difficult to see why the structure is not taken into account here, (4) is related

to the level of model adequacy. As a result of creating and solving the appropriate programming problem, the calculation of the parameters of the model (6) satisfying the minimum requirement of the square of the residuals is presented in the following table (Table 1).

Table 1.

A solution to a computational mathematical programming problem for parametric optimization of a weight function¹

Improvement parameters		
B_1	B_2	B_3
0,00139998	0,00041586	-0,00091357
The difference in the sum of the squares of the residuals		0,000124954

The obtained results show that the improved model is high in terms of quality and significance. Of course, the optimality criterion [11, 20], modeling rules [12], and other aspects are fully satisfied here. Thus, accuracy limits become important when making complex technological system management decisions. In modern sources, the practice of using regression equations to determine the weight function for the control object in the technological system can be found in many sources [13, 25, 27]. The main reason for this is that the object has many parameters and these parameters are not mutually scalable. Classical models usually do not exist for unscaled parameters [14, 19, 26].

One of the requirements for system modeling (which is also present in the modeling phase) is the availability of a model calculation algorithm [15, 18]. In fact, it is possible to observe many cases of using methods of solving complex calculated models, which were not accepted in practice before [16]. This process is related to the evolution of computer technology development.

Thus, under conditions of uncertainty, the algorithm of the method of controlling the system based on improvement using the object prototype model can be given as follows.

Step 1. Determining the degree of correlation between the weight function values and the system response;

Step 2. Development of this connection model;

Step 3. Adding a parametric addition to the weight function and constructing a mathematical programming problem for this addition;

Step 4. Selection of approximation criterion by absolute difference, residual square, approximation error;

Step 5. Solving the issue of programming and determining additional values;

¹ Calculated by the authors

Step 6. Test the result. Evaluation of model error and quality change in management

4. Discussion

The obtained results allow parametric improvement of the adequately calculated model. Compared to the approximation of the prototype model, the approximation of the improved model decreased by 0.7% (Figure 1).

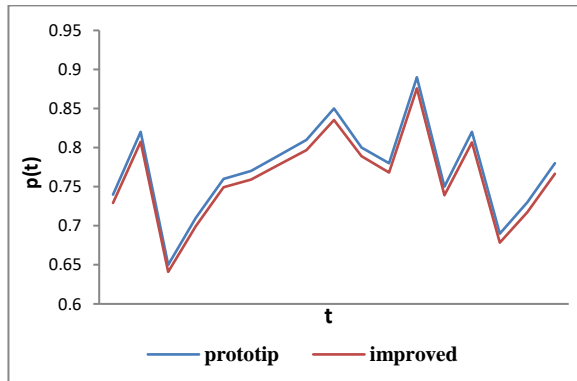


Figure 1. Approximate difference (by prototype and improved model)

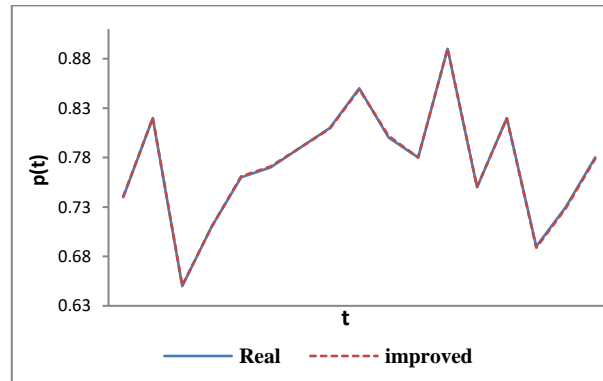


Figure 2. Approximate difference (according to the original and improved model)

If analyzed in both cases, it is possible to witness a significant increase in accuracy (Figure 2). The result increases the prediction accuracy (taking into account the confidence interval) by 3.7%. It is known that one of the difficult requirements of forecasting is that the confidence interval has a small length [17]. Below, we evaluate the quality of decision-making for forecasting the degree of change of the object in the optimized version of the weight function. For this purpose, we use improved shares for all criteria parameters [18]. In that case, the following results are obtained:

$$\% = \sqrt[3]{\omega_1 \cdot \omega_2 \cdot \omega_3} = 38,16 \quad (7)$$

Here ω_1 is the ratio of standard errors, ω_2 is the ratio of absolute-relative errors, ω_3 – is the degree of reduction of the confidence interval, % - is the degree of expansion of the decision-making quality.

The calculation results show that a small positive change of all the optimal adjusted quantities (parametric improvement) can provide a large increase in the quality of decision-making.

Based on the above, that is, the 38 percent efficiency of decision-making with the help of increasing the accuracy of object forecasting, we evaluate the impact on the level of its management based on the system reaction. For this, we pay attention to the differences in the system reaction calculated according to the prototype and improved versions of the weight function in the appropriate control cycle (Fig. 3).

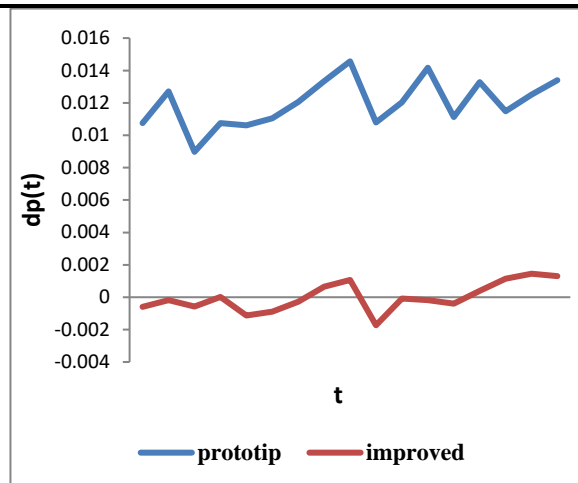


Figure 3. The output difference in the control system

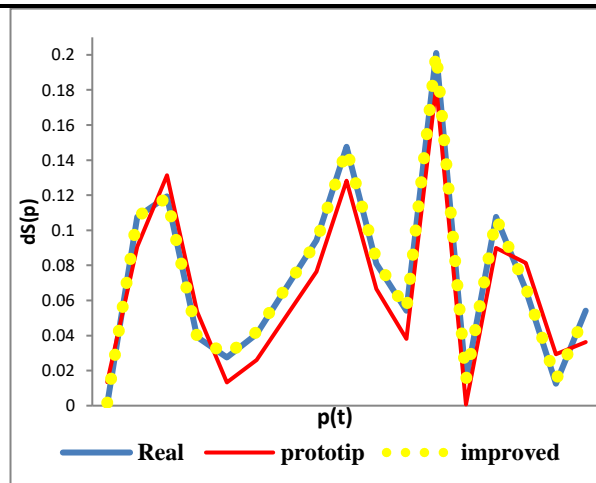


Figure 4. Differences in system description according to object models

According to it, the residual calculations according to the improved model belong to the $(-0.002; 0.002)$ interval (length equal to 0.004), and the residual calculations according to the prototype model $(0.008; 0.015)$ belong to the interval (length equal to 0.023). The difference is decreasing on average by 0.012 units. The degree of change of the absolute difference of the system reaction depending on the output of the object according to the real, prototype and improved model is given in Fig. 4. It is not difficult to see that the actual and improved model calculation results overlap.

5. Conclusions

The following conclusions can be drawn based on the research results and considerations:

1. In a control system under conditions of uncertainty, with a high degree of dependence of object output and system reaction, parametric improvement of its analytical model has a great impact on the quality of optimal control of the system;
2. If the parametrically determined weight function of the object satisfies the adequacy conditions, it will be possible to optimize it only parametrically. Structural refinement can limit the participation of structural variables in the weight function. As a result, the opportunity to fully study the object is limited;
3. Expanding the information source of the structural variable in the management system, the small level of efficiency obtained as a result of optimization of the valuation mechanism, creates an opportunity to sufficiently increase the level of management decision-making;
4. Management of a technological object and a technological system under conditions of uncertainty under the influence of random and disturbance, taking into account the

formation based on the quantitative description of each object of influence, there is always a need to improve the models of system reconfiguration;

5. In the optimal management of the technological system under conditions of uncertainty, the intensity of noise and external disturbance can always be estimated for the objective system. This is achieved by determining the residual value from the actual body of the object weight function.

References

- [1] Jo'rayev, Farrukh Do'stmirzayevich and Ochilov, Murodjon Ashurqulovich (2023) "ALGORITHMS FOR MULTI-FACTORY POLYNOMIAL MODELING OF TECHNOLOGICAL PROCESSES," Chemical Technology, Control and Management: Vol. 2023: Iss. 1, Article 8.
- [2] Novo, R., et al. (2022). Planning the decarbonisation of energy systems: The importance of applying time series clustering to long-term models Energy Conversion and Management: X 15 100274
- [3] Behrang Shirizadeh et al. (2022). The importance of renewable gas in achieving carbon-neutrality: Insights from an energy system optimization model. Energy, Volume 255, 15 September 2022, 124503
- [4] Hanna R., et al. (2022). Designing resilient decentralized energy systems: The importance of modeling extreme events and long-duration power outages. iScience 25, 103630
- [5] Ishizaka, A., et al. (2017). Are multi-criteria decision-making tools useful? An experimental comparative study of three methods. European Journal of Operational Research Volume 264, Issue 2, 16 January 2018, Pages 462-471
- [6] Wensley R., (1994). Making better decisions: The challenge of marketing strategy techniques: A comment on "effects of portfolio planning methods on decision making: Experimental results" by Armstrong and Brodie. International Journal of Research in Marketing Volume 11, Issue 1, January 1994, Pages 85-90
- [7] Bin Liu et al. (2022). Intelligent decision-making method of TBM operating parameters based on multiple constraints and objective optimization. Journal Pre-proof. - <https://doi.org/10.1016/j.jrmge.2023.02.014>.
- [8] Wang, K. , et al. (2022). An integrated collaborative decision-making method for optimizing energy consumption of sail-assisted ships towards low-carbon shipping. Ocean Engineering Volume 266, Part 2, 15, 112810
- [9] Hussein Mohammed Ridha et al. (2021). Multi-objective optimization and multi-criteria decision-making methods for optimal design of standalone photovoltaic system: A comprehensive review. Renewable and Sustainable Energy Reviews Volume 135, 110202
- [10] Ochilov, M. A., Juraev, F. D., Maxmatqulov, G. X., & Rahimov, A. M. (2020). Analysis of important factors in checking the optimality of an indeterminate adjuster in a closed system. Journal of Critical Review, 7(15), 1679-1684.

- [11] Rakhimov, A. N., & Jo'rayev, F. D. (2022). A Systematic Approach To The Methodology Of Agricultural Development And The Strategy Of Econometric Modeling. *Resmilitaris*, 12(4), 2164-2174. - <https://resmilitaris.net/menu-script/index.php/resmilitaris/article/view/2060>
- [12] Prus, Y. (2018). Statisticheskoye modelirovaniye i texnologii iskusstvennogo intellekta v otsenke i upravlenii parametrami yedinogo kreativnogo polya komand: opit kolichestvennogo analiza. *Sotsiologiya i upravleniye*. - Т. 4. № 3. - 85-96.
- [13] Malinetskogo, G. G. (2019). Robototexnika, prognoz, programmirovaniye: sbornik. - Izd.stereotip. - М. - 2019 . - 206 s.
- [14] Жураев, Ф. Д. (2021). Econometric modeling of the development and management of agricultural production based on cluster analysis (on the example of the Kashkadarya region). *Экономика и предпринимательство*, (ISSN 1999-2300), 15(8), 133.
- [15] Mukhitdinov, K. S., & Juraev, F. D. Methods of Macroeconomic Modeling. *International Journal of Trend in Scientific Research and Development (IJTSRD)*, e-ISSN, 2456-6470
- [16] Islamnur, I., Murodjon, O., Sherobod, K., & Dilshod, E. (2021, April). Mathematical account of an independent adjuster operator in accordance with unlimited logical principles of automatic pressure control system in the oven working zone. In *Archive of Conferences* (Vol. 20, No. 1, pp. 85-89).
<https://conferencepublication.com/index.php/aoc/article/view/1005>
- [17] Jo'rayev, F. D., & Aralov, G. M. (2023). Qishloq xo'jaligi mahsulotlari ishlab chiqarish jarayonini ekonometrik modellashtirish zaruriyatining asosiy jihatlari. *Educational research in universal sciences*, 2(2), 36-43. - <https://zenodo.org/record/7702123#.ZCF0VHZBxPY>
- [18] An enhanced gradient based optimizer for parameter estimation of various solar photovoltaic models/ Premkumar, M., et al (2022). /*Energy Reports* 8. -p- 15249–15285
- [19] Parameters extraction of three-diode photovoltaic model using computation and .../ Hasanien, M.H., et al. (2020). *Energy* 195, 117040.
<http://dx.doi.org/10.1016/j.energy.2020.117040>
- [20] A new explicit doublediode modeling method based on Lambert W-function for photovoltaic arrays / Lun, S. et al. *Sol. Energy* 116. (2015)
- [21] Sine-cosine algorithm for parameters' estimation in solar cells using datasheet information./Montoya, O.D., et al. (2020).
- [22] Mallayev A., Sevinov J., Xusanov S., & Boborayimov O. (2022, June). Algorithms for the synthesis of gradient controllers in a nonlinear control system //AIP Conference Proceedings. – AIP Publishing LLC, Vol. 2467, No. 1, p. 030003.
- [23] Marine predators algorithm for parameters identification of triple-diode photovoltaic models/ Soliman, M.A., et al (2020). *IEEE Access* 8, 155832.

- [24] Mallaev A. R., Sharipov G.K., Sodikov A.R., Zhovliev S.M. Mathematical modeling of dynamics formation of hydrates at pipeline natural gas transport //International Journal For Innovative Engineering and Management Research. – 2021. – p. 31-35.
- [25] Heterogeneous differential evolution algorithm for parameter estimation of solar photovoltaic models/ Wang, D., et al. (2022). Energy Rep. 8, 4724–4746.
- [26] Jo'rayev, Farrukh Do'stmirzayevich and Ochilov, Murodjon Ashurqulovich (2023) "ALGORITHMS FOR MULTI-FACTORY POLYNOMIAL MODELING OF TECHNOLOGICAL PROCESSES," Chemical Technology, Control and Management: Vol. 2023: Iss. 1, Article 8.
- [27] Маллаев, А.Р., & Жураев, Ф. Д. (2017). Операционная теория исчисления по преобразованию Лапласа. Научное знание современности, (7), 5-16.
- [28] Electronic source: <https://cyberleninka.ru/article/n/ishlo-h-zhalik-ma-sulotlari-ishlab-chi-arishni-is-a-muddatli-proгноzlashtirish>