

*Research Article*

Organizational Systems Control Model with Bounded Rationality of the Control Subjects

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Abstract: This article proposes a model for evaluating bounded rationality in real production and socio-economic systems. The proposed model is relevant for a wide range of different production and socio-economic systems. By applying such a model, researchers and practitioners can reduce the negative impact of bounded rationality on the adequacy of decision support systems, which will solve the problem underlying the research. In the framework of the study, the control object is represented by a set of attributes that together form the phase space of the control object states (each attribute is one dimension of this space). The practical application of the proposed model can be found in the field of forecasting the range of consequences of control decisions in innovative projects. The use of the model may improve the accuracy of forecasting in decision support models, which may increase the efficiency of control processes in such systems. Obviously, the presented solution will mathematically expand the range of possible outcomes in the implementation of predictive planning, which means reducing the number of cases of erroneous forecasting and difficulty reading the forecasting results. Practitioners can use it to gain a more adequate understanding of the possible consequences of their decisions. In addition, the model requires a certain level of formalization of control objects, which contributes to the systematization and concretization of information about enterprises.

Keywords: Bounded rationality; Control sciences; Operational research; Organizational systems

1. Introduction

The study of bounded rationality in an application to operations research is now an urgent topic (Novikov, 2022). The reason for this is clear: with the increasing complexity of production and market relations, the requirements for the adequacy of decision support models are increasing. As a result, the old algorithms and models are no longer effective enough, and they need to be refined. One of the possible clarifications is to take into account the bounded rationality of human behavior, which seriously affects the quality of decision-making (Abas et al., 2023; Lomakin et al., 2023; Sabara et al., 2022; Song et al., 2021).

Bounded rationality is a natural property of human behavior (Thorstad, 2024). The reasons for bounded rationality are information incompleteness, inattention (insufficient focus on non-key aspects of the system), inconsistency of actions between agents, and a number of others. In any case, bounded rationality can be considered a constant companion of decision-making processes in systems with social components, i.e. socio-economic and sociotechnical systems. The persistence of limitations in people’s rational behavior was also pointed out by Simon and Thaler (Girolotta & Petralia, 2024; Thaler, 2000).

In the context of operations research, bounded rationality has so far found little use, however, interest from various research groups in it remains (Albats et al., 2022; Andronchev et al.,

2024; Baranovskiy & Romanova, 2023; Cheong, 2024; Collins & Shenhav, 2022; Novikov, 2022; Petracca, 2021; Sharma et al., 2022; Wajanawichakon et al., 2025). The reasons for the low applicability of the concept of bounded rationality in operations research should be explained in more detail. The researcher also acting under the bounded rationality conditions, therefore most modern methods of modeling bounded rationality become inaccessible, such as providing the agent with a bounded set of input data, assigning the agent a probabilistic choice from several sets of information, assuming probabilities of agent error, the “threshold of indifference” for indicators, the transition to a learning agent (Akbulut et al., 2024; Eigner & Händler, 2024; Ghasemieh et al., 2013; Li et al., 2022; Liu & Zhou, 2016; Masters & Sardina, 2021; Wang et al., 2022; Yun et al., 2022). The low applicability of the concept of bounded rationality in operations research, therefore, can be explained both by the specifics of subjectivity of human thinking and by the specifics of operations research tasks. In this regard, it becomes relevant to find a way to adequately represent bounded rationality in situations where it is not possible for a researcher to view the system from above.

Existing models of accounting for bounded rationality in operations research tasks are usually concentrated in the field of game theory (Novikov, 2022; Upravitelev, 2017). This is a useful tool, but its applicability is limited by acts of strategic interaction between several control subjects. The development of ways to account for bounded rationality that are not tied to such conditions can seriously strengthen the instrumental base of operations research. Thus, this study partially addresses the problem related to both the small number of methods for accounting for bounded rationality in operations research and the specifics of most of them.

This article proposes a model for evaluating bounded rationality in real production and socio-economic systems. Basically, this model is mathematical, in addition to its computational core, the article offers practical recommendations for its application. This model is new. It combines various aspects of bounded rationality highlighted by various researchers. By applying such a model, researchers and practitioners can reduce the negative impact of bounded rationality on the adequacy of decision support systems, which will solve the problem underlying the research.

The proposed model is relevant for a wide range of different production and socio-economic systems. Practitioners can use it to gain a more adequate understanding of the possible consequences of their decisions. In addition, the model requires a certain level of formalization of control objects, which contributes to the systematization and concretization of information about enterprises.

2. Methods

In the framework of the study, the control object is represented by a set of attributes that together form the phase space of the control object states (each attribute is one dimension of this space). There are generally no requirements for attributes: they can be measured on any scale, calculated by objective measuring instruments, or evaluated by experts.

The concepts of the objective functions of agents – subjects of control, the states of the object of control and the transitions between these states are also important in the framework of the study.

The presented methods provide a tool base for identifying the management model of any objects, which expands the possibilities of taking into account bounded rationality in operations research, as well as increases the descriptive abilities of management models.

2.1 Existing research

The concept of bounded rationality was first proposed by the American economist and psychologist Herbert Simon (Upravitelev, 2017). There are indications that Simon has been working towards formalizing the phenomenon of bounded rationality since 1955, but traditionally the starting point is considered to be 1957, when Simon published a paper called “Human Models”,

where he identified and described the factor of bounded rationality in economics (Babaei et al., 2025; Tabilo Alvarez & Ramírez-Correa, 2023). In modern scientific discourse, the concept is taken into account in a large number of multidisciplinary studies on various topics (Du et al., 2025; Zhang et al., 2022; Zhang et al., 2023).

The concept of bounded rationality in Simon's first sentence is based on the following basic principles (Upravitelev, 2017):

1. Decisions made in economics can only be bounded to rational ones, since agents (decision makers) do not have sufficient cognitive resources to process the available information in its entirety and calculate all options (the problem of information incompleteness);
2. Business subjects of the economy do not seek to maximize profits, but to achieve some solution that will provide an acceptable, but not necessarily maximum result (the problem of the level of indifference);
3. Since agents have to focus on many factors to make a decision, attention is reduced to individual problems (the problem of defocusing); some agent solutions are formulaic or intuitive, while others use special methods (the problem of decision inertia).

Simon contrasted his concept with the neoclassical model of economic decision-making, in which a person is presented as an absolutely rational agent (Upravitelev, 2017). Up to a certain point, this approach was relevant in economics and clearly reflected the economic behavior of agents, allowing companies to prepare for rational actions by competitors and consumers as the most likely expected actions. However, with the saturation of markets, the emergence of a large number of competitors, and the increasing complexity of decision-making (due to the large number of alternatives and the complexity of market relations), this idea has ceased to be relevant and required correction – bounded rationality is designed to bridge the gap between reality and models of economic behavior by describing cognitive limitations that make decisions made in the market far from rationally sound (Matiashvili, 2015).

At the same time, despite the widespread use of the concept of bounded rationality in economic research, in recent years it has become increasingly widespread in control and decision-making tasks in organizational systems. For example, a 2015 study presents the concept of using bounded rationality in the context of organizational change control (Puranam et al., 2015). The article examines the foundations and key characteristics of the concept of “bounded rationality” from the point of view of the possibilities of using this concept to identify organizational problems, design and implement control decisions related to organizational change processes. The author defines the cognitive and practical control potentials of the concept for an adequate interpretation of the possibilities and limitations in the control of modernization projects. And another study examines the issues of taking into account bounded rationality in organizational design (Diks & Dindo, 2008). That article discusses the problem of designing organizational control structures in difficult modern conditions. A hypothesis is put forward about the need to take into account behavioral theory and the theory of bounded rationality in design. The authors pose the problems of building organizational structures that require further research: defining a set of rational (“economic”) and irrational (“behavioral”) factors and assessing the impact of these factors on organizational design.

Modern research also suggests several relatively simple ways to model the behavior of bounded rational agents (Ghasemieh et al., 2013): provide the agent with a bounded set of input data (classical bounded rationality), set the agent a probabilistic choice from several sets of information (of which only one will be true), and allow the agent to make mistakes (the agent acts according to the optimal option with some probability, usually close to 1 – a possible, albeit not very accurate solution to the problem of information incompleteness) (Liu & Zhou, 2016), introduce a “threshold of indifference” for indicators (some suboptimal value, starting from which any value will be considered optimal by the agent – that is, a de facto direct solution to the problem of the level of indifference) (Masters & Sardina, 2021), go to the learning

agent (Novikov, 2022; Sieg, 2001). For the most part, all these methods are focused on bounded rational agents, and for irrationally motivated agents or completely irrational agents, more sophisticated goal recognition methods are offered (Kuznetsov, 2019). At the same time, all these methods are also mainly used in the comparative assessment of rational and bounded rational behavior of agents, when it is possible, for example, to isolate from the total amount of information that part that can be provided incompletely to a rational agent (Diks & Dindo, 2008). Thus, predictive accounting of bounded rationality by these methods is impossible.

The key and still unresolved problem of taking bounded rationality into account in the modeling of organizational systems is the problem of predictive accounting of the influence of the bounded rationality factor on managerial decision-making. In other words, it is impossible to predict how bounded rationality will affect the adoption of a specific control decision. The accuracy of forecasting in existing models that take into account bounded rationality is mainly achieved due to the mass nature of bounded rational decision-making procedures, which is unattainable in solving particular control tasks.

Another problem of scientific discourse in terms of bounded rationality in general is the lack of consistency and chaotic presentation of materials on the issue of bounded rationality. There are a large number of extensions, additions, and clarifications of Simon's original concept, but they are not structured, their application is not regulated, and often remains at the discretion of the researcher.

This problem stems from the key difficulty of bounded rationality research, related to the inability to fully rationally evaluate bounded rationality (except for purely research purposes).

In the context of innovative projects as organizational systems, this problem is even more significant, since innovative projects, according to a generally accepted characteristic, are characterized by a high level of uncertainty and risk.

Thus, it can be concluded that over the past 70 years since the introduction of the concept of bounded rationality, the issue of bounded rationality in the consumer economy has been studied quite well. A large number of effective methods of accounting for the bounded rationality of consumers have been proposed, work in this area is underway and published in peer-reviewed publications. At the same time, by the beginning of the 21st century, there was a need to extend the consideration of the cognitive characteristics of decision makers beyond the systems of economic relations, in the field of modeling organizational systems. This issue remains relevant even now, which will be shown in the next section of this paper.

2.2 Goal functions

The goal function is a vector in the n -dimensional phase state space of the control object. Maximized attributes are included in the unit vector as components of the vector that are co-directional with increasing attribute values, while minimized attributes are counter-directional. Attributes that are irrelevant to the agent's objective function do not give components to the vector (the vector projected onto the corresponding axis is 0). Attributes for which the agent prefers striving for a certain value are included in the objective function as components that depend on the distance to the corresponding value. The weighting coefficients for optimization criteria set the multipliers of the vector components. Thus, for each control subject, there is an objective function in the n -dimensional phase state space of the control subject such that:

$$f_S = (p_1 \cdot (a_1 \cdot d_1) \quad p_2 \cdot (a_2 \cdot d_2) \quad \dots \quad p_n \cdot (a_n \cdot d_n))^T \quad (1)$$

where p_i – weighting coefficient for the i -th attribute of the control object; a_i – value of the ratio of the objective function to the i -th attribute of the control object (1 – if the attribute is maximized or tends to a specific value; 0 – if the attribute is indifferent; –1 – if the attribute is minimized); d_i – normalized distance to the optimal value of the i -th attribute of the control object (1, if the attribute is maximized/minimized without a specific target value).

The target functions may be in different relationships depending on the objectives of the control subjects.

2.3 Statuses

The status of the control object is understood as a set of attribute values for this control object. At the same time, due to the presence of bounded rationality in the accounting model, each control object has several states at each time. The following types of control object states are distinguished:

1. The real status is a set of values (all) inherent in the control object attributes describing this object. In the general case, it is considered present, but not observed – extraction of the real state of an object from data about it is impossible due to the bounded rationality of any observer.
2. The target status is a set of values desired by the subject of control of all attributes describing the object of control. It does not exist in reality – one can perceive it as a fundamentally unattainable state. It is unambiguously linked to the subject of control.
3. Perceived status – a set of values perceived by the subject of control attributes describing the control object. In conditions of bounded rationality, the perceived state deviates from the real state. In the absence of bounded rationality, the perceived state coincides with the real state.

The real and perceived state are especially important in the context of the proposed model. Subsequently, it is these two states of each control object that will be used to model decision-making processes. The states of control objects are a way of formalizing control objects. Such formalization is necessary for applying the mathematical methods presented as the results of this study to various kinds of controlled systems.

3. Results and Discussion

3.1 General modeling algorithm

The general algorithm for using the decision-making model implies a set of calculations based on the presented mathematical patterns and informal procedures. Figure 1 shows a graphical view of the described algorithm.

Decision-making using the proposed model is divided into two stages: preliminary preparation and the actual decision-making process. As part of the preliminary stage, it is assumed that the control object will be formalized with a set of attributes (in accordance with the above). The inverse function of bounded rationality is applied as part of the decision-making process. About it, as well as about the direct function of bounded rationality – further.

The stages of strategy formation and strategy selection are not strictly formalized – it is assumed that both game-theoretical implementation of these stages is possible (which is beyond the boundaries of the material in this article) and informal strategizing. It is definitely necessary to evaluate the predicted state of the control object in terms of a set of attributes corresponding to the predicted change following the implementation of each strategy.

3.2 Direct Bounded Rationality function

The direct function of bounded rationality (hereinafter referred to as the direct BR-function) implies a direct transformation from the real state of the control object to the state perceived by the control subject.

The direct BR-function value is calculated in pairs for each control subject, each control subject, and each attribute of the control subject. The numerous parameters of the direct BR-function are described below.

For both measured and expertly evaluated objects, the degree of influence of bounded rationality is influenced by α , the sufficiency of the measurement/evaluation accuracy of the attribute A_1 :

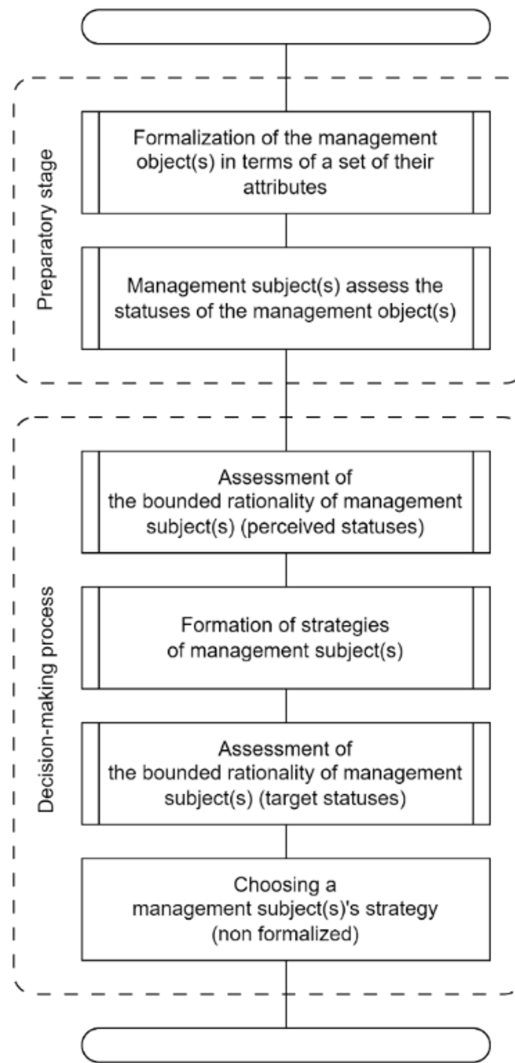


Figure 1 Algorithm of decision-making model in organisational systems with bounded rationality of control subjects

$$\alpha_{A_1} = \begin{cases} 0, & \text{if } m \leq d \\ \frac{m}{d}, & \text{if } m > d \end{cases} \quad (2)$$

where m is the accuracy of the attribute measurement scale (half the division price) / accuracy of the estimate, and d is the measurement accuracy / evaluation accuracy required for decision-making.

For decision-making by expert groups (as a single control subject), the Kendall concordance coefficient W is additionally calculated:

$$W = \frac{12D}{m^2(n^3 - n)} \quad (3)$$

where D is the sum of the squares of the ranks; $n > 0$ is the number of experts; $m > 0$ is the number of analyzed features. At the same time:

$$D = \sum_{i=1}^n r_{ij}^2 - \frac{(\sum_{i=1}^n r_{ij})^2}{n} \quad (4)$$

where r_{ij} – the rank of the i -th indicator assigned by the j -th expert, $n > 0$ is the number of experts.

One of the main factors of bounded rationality in the model is the availability of empirical experience, which, on the one hand, provides a relevant basis for decision-making by control subjects, and on the other hand, has a negative impact on the accuracy of decision-making due to the inertia of thinking. The coefficient of empirical experience of a control subject is measured by the formula:

$$E = \begin{cases} \frac{\sum_{k=1}^m w_k n_k}{\sum_{k=1}^m n_k}, & \text{if } \sum_{k=1}^m n_k > 0 \\ 0, & \text{if } \sum_{k=1}^m n_k = 0 \end{cases} \quad (5)$$

where $m > 0$ – the number of ranks of similarity of previously completed projects/works (for example: identical, slightly different, significantly different, completely different – 4 ranks); $w_k \in [0, 1]$ – the weight of one project of the k -th rank (for example: identical works have a weight of 1; slightly different – 0.75; significantly different – 0.25; completely different – 0.05); n_k – number of projects/works of k -rank.

In cases of group communications in organizational systems with distributed decision-making centers (when there are several control subjects at one facility), it is proposed to calculate the coefficient of communication between control subjects:

$$\Psi = \frac{\sum_{i=1}^p (1 - c_i) \times n_i}{n} \quad (6)$$

where c_i – the fact of communication in the i -th subgroup of subjects of control: 1 – communication in any form; 0 – any communication was absent; $n_i > 0$ – the number of subjects in the i -th subgroup; $n = \sum_{i=1}^p n_i$ – total number of control subjects.

At its core, the direct BR-function is a probabilistic function based on the accuracy of perception of the attribute value ρ (in general, we consider this to be a random variable distributed normally):

$$\rho_{(A_1, S_1)}(x, \mu_\rho, \sigma_\rho) = \frac{e^{-\frac{1}{2} \left(\frac{x - \mu_\rho}{\sigma_\rho} \right)^2}}{\sigma_\rho \sqrt{2\pi}} \quad (7)$$

where μ_ρ – mathematical expectation of the perception of an attribute (does not coincide with the true value of the attribute in the general case – to work with unmeasured values, a typical deviation for the subject should be taken), σ_ρ – the standard deviation of attribute perception.

An additional clarification is the degree of inattention of the subject of control when perceiving the attribute value (another factor in the manifestation of bounded rationality):

$$\varepsilon_{(A_1, S_1)} = |\sin(f_{S_1} \wedge a_1)| \quad (8)$$

that is, the sine of the angle between the vector of the objective function of the subject and the unit vector aligned with the axis of the corresponding attribute in the phase state space of the control object, taken modulo.

It is allowed to use the historical deviation of the subject from the correct perception of the attribute value in the calculation:

$$\delta_{(A_1, S_1)} = \sqrt{\frac{\sum_{i=1}^n (A_{1i} - A_1 S_{1i})^2}{n}} \quad (9)$$

where A_{1i} – the actual value of the attribute at the iteration of consideration i , $A_1 S_{1i}$ – the perceived value of the attribute at the review iteration i , n is the number of review iterations.

The historical variation of the subject around the expected perception of the attribute value is also used:

$$\omega_{(A_1, S_1)} = \sqrt{\frac{\sum_{i=1}^n (\overline{A_1 S_1} - A_1 S_{1i})^2}{n}} \quad (10)$$

where $\overline{A_1 S_1}$ – the external perceived value of the attribute, $A_1 S_{1i}$ – the perceived value of the attribute at the review iteration i , n is the number of review iterations. At the same time:

$$\overline{A_1 S_1} = \frac{\sum_{i=1}^n A_1 S_{1i}}{n} \quad (11)$$

The general design of the direct BR-function has the form:

$$BR(x, A_1, O_1, S_1) = \rho_{(A_1, S_1)} \left(x, A_1 + \delta_{(A_1, S_1)}, \omega_{(A_1, S_1)} \cdot (1 + \varepsilon_{(A_1, S_1)}) \cdot (1 + \alpha_{A_1}) \cdot k_{BR} \right) \quad (12)$$

where k_{BR} – the coefficient of bounded rationality of the subject of control (Equation 13); x – the perceived value of the attribute.

$$k_{BR} = 1 - \frac{\beta_1 \times (1 - \Psi) + \beta_2 \times O(W) + \beta_3 \times O(E)}{\sum_{i=1}^3 \beta_i} \quad (13)$$

where $\beta_1 \dots \beta_3$ – weight factors, $O(W)$ and $O(E)$ – optimality functions of concordance and empirical experience, calculated from expertly determined dependencies, Ψ – coefficient of communication between control subjects (Equation 6).

At the same time, individual components of the function can be discarded in special cases of decision-making, for example, in the case of individual (not group) decision-making, or if there is only one control subject in the system.

The mechanism of action of the direct BR-function in the simplest example with a two-dimensional phase space is shown in Figure 2.

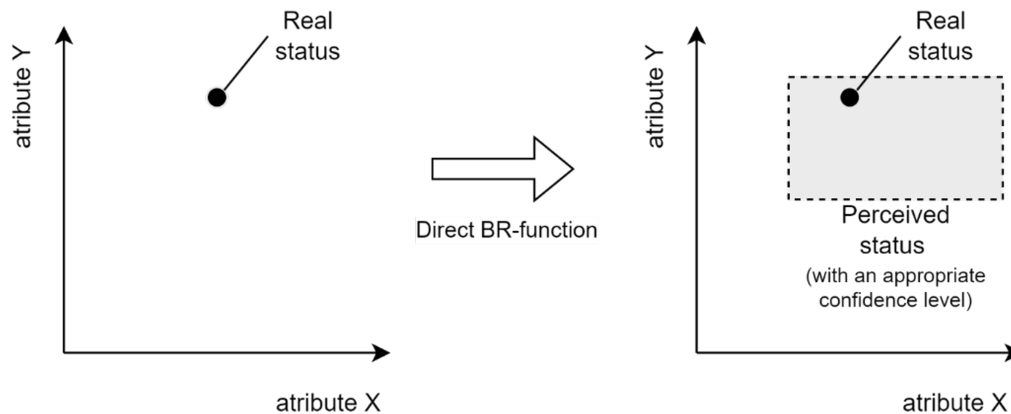


Figure 2 Direct Bounded Rationality function visualization

3.3 Reverse Bounded Rationality function

The inverse function of bounded rationality (hereinafter referred to as the reverse BR-function) implies, on the contrary, the transformation of a perceived state into a real one. The basis of the mathematical model of decision-making is based on the calculation of the reverse BR-function.

The reverse BR-function value is calculated in threes for each control subject, each control subject, and each attribute of the control subject.

The logical basis of the reverse BR-function: the application of Bayes' theorem. Here, event B is the localization of a bounded rational perception of the position of the attribute of the control object, hypothesis A is the hypothetical location of the objective value of the attribute of the control object. Thus, it is possible to calculate the probability of finding the objective value of an attribute with a known value of a bounded rational perception of an attribute as the product of the a priori probability of finding the objective value of an attribute at an assumed point and the probability of obtaining the corresponding value of a bounded rational perception from this point (the direct BR-function value) divided by the probability of a bounded rational perception (by default, one).

$$\overline{BR}(x, A_1, O_1, S_1) = P(A | B) = \frac{P(B | A) P(A)}{P(B)} = \frac{BR(x, A_1, O_1, S_1) \cdot p(x_O)}{p'(x)} \quad (14)$$

where $p(x_O) = \frac{x_O}{d}$ (that is, the fraction occupied by the value or range in question, in the range of possible attribute values), $p'(x)$ – the probability of finding the attribute value at the appropriate point, taking into account bounded rationality (1, but may vary if the subject of management defines his opinion as, for example, a range of attribute values).

Thus, the inverse BR-function differs for discrete and continuous attributes. For discrete attributes, it has the form:

$$\overline{BR}(x, A_1, O_1, S_1)_D = \frac{P(B | A) P(A)}{P(B)} = \frac{BR(x, A_1, O_1, S_1)}{p'(x) \cdot n} \quad (15)$$

where n is the number of values that the attribute can take.

And for continuous:

$$\overline{BR}(x, A_1, O_1, S_1)_C = \frac{P(B | A) P(A)}{P(B)} = \frac{\int_{x_1}^{x_2} BR(x, A_1, O_1, S_1) dx \cdot (x_2 - x_1)}{p'(x) \cdot d} \quad (16)$$

where d – total length of the segment (set of segments) of acceptable attribute values; $[x_1, x_2]$ – is the segment under study.

The mechanism of action of the reverse BR-function in the simplest example with a two-dimensional phase space is shown in Figure 3.

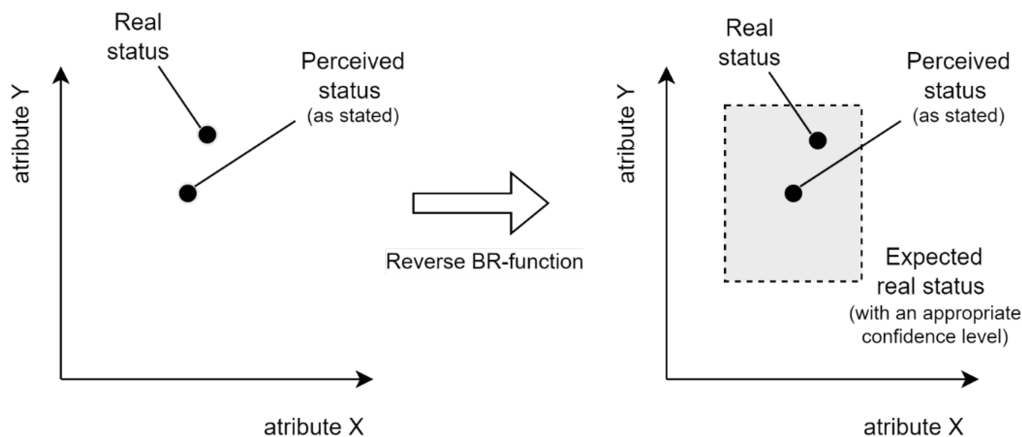


Figure 3 Reverse Bounded Rationality function visualization

We will separately explain the method of entering the confidence level into the model. Since the basis for the BR-function (Equation 14) is the normal distribution function (Equation 7), the confidence level is entered as the proportion of possible values of the function taken into account in the calculation (for example, a confidence level of 99.73% gives an occurrence in the form of a 3σ neighborhood of the mathematical expectation).

A visualization of this position is shown in Figure 4. Figure 4 shows a normal distribution visualizing the direct BR-function (Equation 14). Two possible confidence levels are set for it – confidence level 1 (which includes about 67% of the possible values of the function) and confidence level 2 (which includes about 99% of the possible values of the function). For these two cases, the values of the attribute variations in the two-dimensional phase space will have the form shown to the right of the graph. A lower confidence level more accurately localizes the state of the object in the phase space, but it is more likely not to include the actual state of the object. At the same time, the maximum (100%) confidence level mathematically covers the entire phase space – it is guaranteed to include the real state, although this will not be applicable in practice.

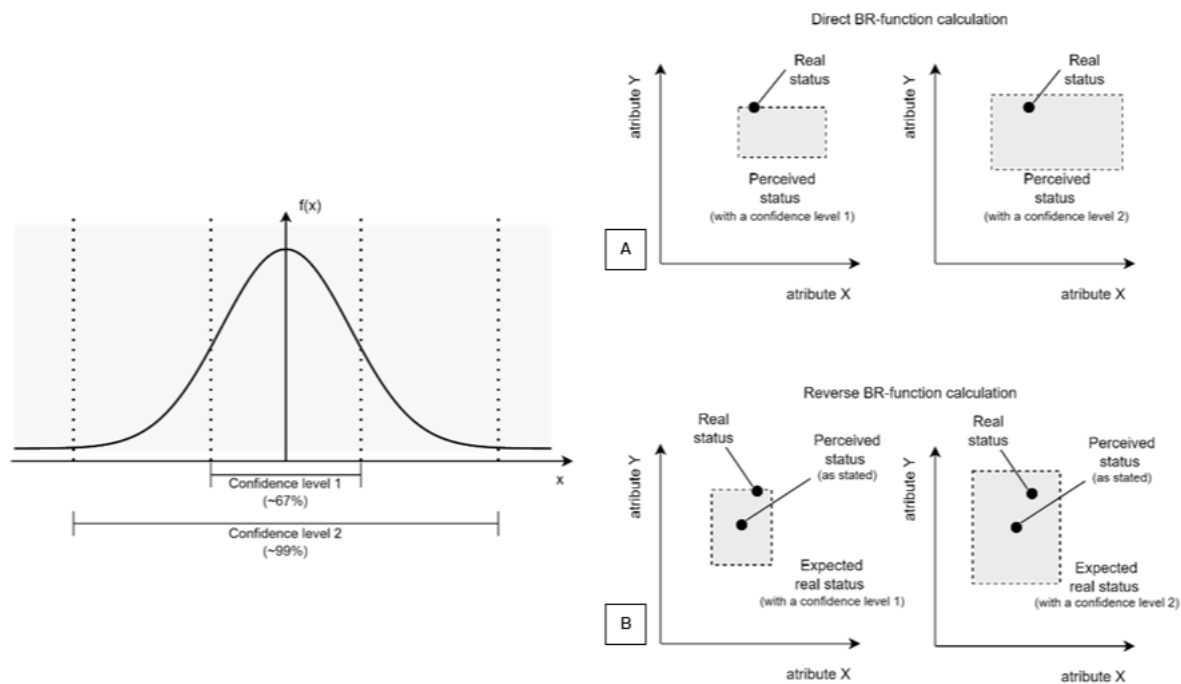


Figure 4 Visualization of the influence of the confidence level on the values of: A – direct BR-function; B – reverse BR-function

An additional significant advantage of using the model is to increase the descriptive ability of organizational system models. The model implies the representation of the management object as a system of attributes, as well as the collection of retrospective information on the assessment of the conditions of the control objects. Therefore, the collection of such information will be necessary for the application of the model. Correct assessments based on current, retrospective, and expert information will increase the transparency of the organizational system, make it more observable, and can thus enhance the descriptive power of control models.

3.4 Contribution beyond prior approaches

Comments should be made regarding the positioning of the proposed model in the system of existing methods of accounting for bounded rationality. Based on the analysis of discourse, three key groups of existing approaches to accounting for bounded rationality can be identified: game-theoretic approaches, behavioral heuristics, and models of bounded rationality of single agents. The proposed model can be attributed to the third type, but differs from its characteristic representatives in some key features.

Table 1 presents a comparative analysis of the proposed model and some representatives of the groups indicated above. The approaches are compared according to the criteria of the number of factors of limited rationality being considered, the predictive power of the method, the

breadth of the scope, the possibility of taking into account uncertainty and implicit information, and the rigor of mathematical formalization.

Table 1 Contribution beyond prior approaches

Criterion	Proposed model	Game-theoretic approaches (Ghasemieh et al., 2013; Novikov, 2022)	ap- Behavioral heuristics (Dhami & Sunstein, 2022)	Single-agent bounded rationality models (Diks & Dindo, 2008; Liu & Zhou, 2016; Masters & Sardina, 2021)
Treatment of bounded rationality	Multi-factor formalization (perception error, attention, experience, communication)	Mostly one-factor formalization (payoff perturbations, incomplete information, etc.)	Captured via heuristics and biases (multi-factor analysis, non-formalized)	One-factor or multi-factor constraints (limited information, probabilistic choice)
Predictive capability	Possible (via reverse BR-function and Bayesian inference)	Limited (mainly equilibrium analysis)	Weak (descriptive rather than predictive)	Limited (often simulation-based, not predictive for specific cases)
Applicability scope	General organizational and socio-economic systems	Multi-agent strategic settings	General organizational and socio-economic systems	Individual decision-making contexts
Handling hidden states and uncertainty	Real and perceived state separation	Incomplete information games	Limited	Limited
Formal mathematical structure	Vector space, probabilistic transformations, Bayesian inversion	Equilibria, optimization	Semi-formal	Different, mostly based on imitation of limited awareness, threshold of indifference and other bounded rationality indicators

Thus, it can be concluded that the key advantages of the proposed model are the formalization of the multifactorial nature of bounded rationality while maintaining the breadth of the field of application and relatively strict mathematical formalization. At the same time, the proposed method is not without drawbacks associated with high data collection requirements and a high level of abstraction compared to, for example, game-theoretic methods that accurately describe situations of strategic interactions.

The presented model can be used in a wide range of systems. It inherits the factors of bounded rationality proposed by other researchers, combining them into a conditionally universal methodology. The advantages of the proposed model are scalability (due to the introduction of additional BR-function factors that can be proposed by individual researchers), a high degree of versatility (unlike game-theoretic methods that are applicable only in the framework of game strategic interactions), and the complex nature of taking into account the factors of bounded rationality proposed by previous researches.

The practical application of the proposed model can be found in the field of forecasting the range of consequences of control decisions in innovative projects. The use of the model may improve the accuracy of forecasting in decision support models, which may increase the efficiency of control processes in such systems. The presented solution will mathematically expand the range of possible outcomes in the implementation of predictive planning, which means the possibility of a more accurate assessment of uncertainty by decision makers; and increasing the complexity of considering alternatives. The novelty of the proposed result is provided by formalizing multifactor bounded rationality while maintaining broad scope and mathematical rigor.

4. Conclusions

As a result of the work, a method of predictive accounting of bounded rationality is proposed, which assumes consideration of such factors as the subjective characteristics of the decision-maker affecting the correctness of communication decisions, hidden (from the agents of the system) causal relationships in the object of control. The results of the work will be used for practical application in the form of specialized tools within decision support systems in organizational systems with distributed decision-making centers. The limitation of the proposed concept is primarily the basis of the approach based on heuristics. Further research should be devoted to the verification and testing of the method on real objects, including other organizational systems with distributed decision-making centers.

Acknowledgements

The research is funded by the Russian Science Foundation, project No. 25-21-00322, <https://rscf.ru/en/project/25-21-00322/>

Conflict of Interest

The authors declare no conflicts of interest.

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