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Multiparametric Optimization of Complex System Management Scenarios Based on Simulation Models

Kapiton N. Pospelov[1], Zhanna V. Burlutskaya[1*], Aleksei M. Gintciak[1], Konstantin D. Troshchenko[1]

[1]*Peter the Great St. Petersburg Polytechnic University, 29 Polytechnicheskaya st., St. Petersburg, 195251, Russia*

Abstract. This work is devoted to the development of a multiparametric optimization module for a digital management decision support tool based on simulation models. It is noted that the optimization of simulation models of complex socioeconomic and sociotechnical systems involves the generation of multiple scenarios of system development, their calculation, and further comparison, which imposes additional requirements on the optimization algorithms used. Moreover, complex socioeconomic and sociotechnical systems are characterized by a multiplicity of goals, which leads to multiparametric optimization. The result of the work is the algorithm for solving the problem of optimization of multiparametric scenario calculations using the example of a two-parameter optimization problem. The scope of the calculation optimization problem is to form the optimal set of scenarios that will ensure satisfactory computing time and, at the same time, give a representative scenario calculation result. Thus, the contribution of the current research is to formalize the processes of optimizing the parameters of simulation models of complex systems. In the course of the study, existing approaches to process optimization are considered. Based on the analysis of existing approaches to the formation of an optimal set of scenarios, ways to improve the algorithm type using approaches to scenario reduction or the introduction of genetic algorithms for the formation of an optimal set of scenarios are proposed. This work is carried out within a project to develop a digital tool to support managerial decision-making in sociotechnical and socioeconomic systems.

Keywords: Multiparametric optimization; Scenario calculation; Simulation modelling; Stochastic programming

1. Introduction

Digital decision support tools provide an analytical framework for informed managerial decision-making in sociotechnical and socioeconomic systems based on relevant and holistic data. This case refers to complex systems that provide both technical data processing (integrity checking, outlier processing, etc.) and mathematical modeling considering a variety of computational experiments. Such scenario calculations are applicable to a wide range of stochastic programming problems. Computational experiments with simulation models of sociotechnical and socioeconomic systems are carried out at every stage of the study, from the study of models to their optimization

*Corresponding author's email: zhanna.burlutskaya@spbpu.com, Tel.: +7 (812) 980-11-31
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(Setyaningrum *et al.*, 2022; Rosyidi, Fatmawati, and Jauhari, 2016). Optimization of models of complex systems is often associated with the generation of multiple scenarios of system behavior and their further comparison (Berawi *et al.*, 2018). In turn, this leads to an increase in the load on the computing power of software tools that control the model and its results.

Moreover, complex socioeconomic and sociotechnical systems are characterized by a multiplicity of local goals associated with individual structural elements (Rodionov *et al.*, 2022; Simsek *et al.*, 2016). This means that the optimization of such systems comes down to the task of multiparametric optimization, which also leads to additional computational experiments to find the global optimum of the system.

Therefore, researchers may encounter a nonlinear increase in the time of computational operations with an increase in the number of scenarios, which is particularly common for multiparametric calculations. Moreover, with the increase in the number of scenarios, the complexity of processing the results for the end user also increases (Seeve *et al.*, 2022). Methods of reducing the number of scenarios (scenario reduction) are usually applied to address such problems. This approach category is used to manage the required amount of computational time. However, it is believed that any of them also inevitably leads to a less accurate representation of the uncertainty described by a set of scenarios. There may be other approaches; in particular, this paper will consider an approach to the formation of an optimal set of scenarios based on a genetic algorithm.

With the apparent obviousness of the described problem and the urgency of the need for its solution, the methods of scenario reduction are still described quite rarely (Kammammettu and Li, 2023; Peredo and Herrero, 2022; Dvorkin *et al.*, 2014). Interestingly, researchers often do not focus on optimization opportunities to reduce the load on computing power while noting the dependence of multi-criteria optimization on the computing capabilities of computers.

The purpose of the present paper is to describe a prototype of a scenario calculation optimization algorithm for a two-parameter optimization problem with the prospect of extending the algorithm to the entire class of multiparameter optimization problems. The paper provides a description of the common optimization algorithms for a multiparametric scenario calculation performed during simulation experiments. The methods of forming an optimal set of scenarios are also described. The result of the work is a prototype of a scenario calculation optimizer as a module for a digital tool to support managerial decision-making in sociotechnical and socioeconomic systems. Thus, the contribution of the current research is to formalize the processes of optimizing the parameters of simulation models of complex systems, as well as to develop a prototype of a flexible and scalable tool for optimizing complex system management scenarios based on simulation models, which is able to reduce the number of calculations without reducing the accuracy of the results. This work is carried out within a project to develop a digital tool to support managerial decision-making in sociotechnical and socioeconomic systems.

2. Methods

The analysis of existing theoretical and practical research in the domain of production process optimization is indisputably crucial in the initial phase of the study. However, the specifics of the study require a clear statement of the task upon which the selection of pertinent sources will depend.

2.1. Description of a typical optimization problem of multiparametric scenario calculation in stochastic programming

A typical problem solved using the proposed methods is a multiparametric optimization with a set of scenarios, usually represented by a set of values of n variables, which can be either discrete or continuous.

In this case, it is possible to represent a set of scenarios as a bounded set for discrete parameters, the number of elements of which is S.

$$S = \prod_{i=1}^{n} k_i \tag{1}$$

In the formula (1) k_i is the number of acceptable (considered) values of the i-th parameter from the set of discrete values that the parameter can accept.

For the case with at least one continuous variable in the number of scenario calculation parameters, it is obvious that $S \to \infty$.

In the scenarios under consideration, the optimization task involves narrowing down the initial set S to a set So. The objective is to ensure that the number of elements in this set does not exceed the threshold needed for a computationally efficient process, while keeping the computational error, associated with a reduction in the accuracy of calculations, below a specified level. Formally, the task at hand can be expressed as a mathematical transformation of equation (2).

$$o: S \to S_o \tag{2}$$

The task core challenge is the impossibility of accurately determining the representativeness criteria of a set of scenarios: if the computational time is predictable at a sufficient confidence level (i.e. an upper bound for the number of scenarios in the optimal set can be determined with some accuracy), then the degree of representativeness cannot be accurately estimated (which leads to uncertainty of the lower bound for the number of scenarios in the optimal set).

The hypothesis of the present study is the possibility of implementing such a transformation with a significant reduction in computational time for an optimal set of scenarios and maintaining a level of representativeness comparable to the original set of scenarios in the case of a general multiparametric optimization problem in stochastic programming.

2.2. Methods of forming an optimal set of scenarios. General information and algorithms

As part of the study, an analysis of existing theoretical and practical research in the field of multiparametric optimization of forming an optimal set of scenarios was carried out. The analysis is based on articles from the Scopus database of scientific publications over the past 5 years. The following keywords were used during the selection of sources: optimization algorithm; multiparametric optimization; scenario calculation; simulation modeling; stochastic programming.

The stochastic optimization method utilizes randomness in the search for an optimum. Thus, when simulating the system's probabilistic features to model uncertainty, random distributions are included as input data (Zakaria *et al.*, 2020; Wang, Liu, and Kirschen, 2017). Owing to the increasing number of scenarios, the scenario reduction technique is employed, enabling control of the computational burden by selecting representative scenarios for subsequent optimization. Nonetheless, this method has drawbacks, including the fact that the user must determine the number of representative scenarios as a parameter (Wang, Liu, and Kirschen, 2017).

Due to the complexity of multi-criteria optimization of production processes, the use of artificial intelligence methods has surged in popularity over the last few years (Sibalija, 2018). Metaheuristic approaches to optimization stand out for their higher computational accuracy and the capability to search for both local and global optima, setting them apart from traditional mathematical approaches.

The simulated annealing algorithm is utilized for optimizing production process parameters and serves as an illustration of Monte Carlo methods employed to study numerical processes. The method belongs to the group of metaheuristic search methods and is considered part of artificial intelligence. The algorithm starts by selecting an initial point at random whilst at high temperature. If the new point's objective function exceeds the current one, another point is selected. When the temperature reaches its minimum, the chances of selecting the worst points become negligible, indicating that the algorithm converges to the optimal solution (Sibalija, 2018).

Two metaheuristic methods based on natural or animal behavior, namely genetic algorithms (GA) and the particle swarm method (PSO), are explored in this section. This approach also utilizes optimization methods such as ant colony optimization (ACO) and artificial bee colony (ABC).

Evolutionary algorithms for multi-criteria optimization based on decomposition simplify a multi-criteria problem by breaking it down into a set of single-criteria optimization tasks through the combination of criteria in various ways. This approach divides the initial criteria into subsets using scalarization with uniformly dispersed direction vectors before jointly optimizing these subsets (Wu *et al.*, 2022; Hong *et al.*, 2019). It facilitates the inclusion of nonlinearity, variable mixing, and other factors (Cai, Qu, and Cheng, 2018). There are additional algorithms that combine criteria, utilize indicators, and focus on the dominance ratio. Genetic algorithms are a type of heuristic method for finding the extremum. This approach implies the random generation of a set of solutions and their evolution, promoting the survival of those solutions most likely to produce an optimal result after a certain number of iterations.

In the presence of numerous variations in the system state, conventional scenario-based optimization methods may prove less effective in achieving optimal result accuracy while also demanding substantial computational time and power resources. Conversely, an alternative approach that does not provide guaranteed accuracy but instead yields optimal or near-optimal results in practice may offer a more efficient solution. The algorithm's fundamental principle entails creating a random initial "population" of scenarios and subsequently selecting the "fittest" of them through evolutionary means. "Fitness" is determined by a corresponding function specifically set for solving the problem at hand. After a sufficient number of iterations of such selection, it is possible to attain an optimal "population".

Genetic algorithms are a commonly employed tool in tackling various specific problems, such as those found in administration and management. Nevertheless, the majority of issues resolved by means of such methods are characterized by a deterministic environment, where probabilistic traits (which inevitably exist in these situations, at the very least as the probability of "mutation" or "crossover" for a "population" of scenarios) possess the only and most precise value. At the same time, in certain instances of employing this approach, events are considered probabilistic, like the influence of the fitness function's value on an individual's 'probability' of survival (for instance, when chosen from a uniform distribution in the selection function). This contrasts with their survival in a deterministic sense. Consequently, the use of genetic algorithms represents a promising approach in dealing with probabilistic environments. Such algorithms enable the rapid selection of quasi-optimal scenarios. The potential consideration of probabilities, which are not usually excluded from the toolkit of genetic algorithms, indicates the applicability of such methods for addressing the problem at hand. A large number of diverse applications of genetic algorithms provide further justification for employing this approach.

The particle swarm optimization method is a heuristic technique for global optimization. It relies on simulating the motion of numerous particles (a swarm) in a multidimensional space to achieve the optimal position. A noteworthy characteristic of this approach is its lack of reliance on gradients, which positions it as a dependable stochastic optimization algorithm from the lower sensitivity perspective. For combinatorial and nonlinear optimization, a hybrid approach is employed, combining the sequential use of algorithms for simulated annealing and swarming particles. This approach aims to enhance the efficiency of optimization by locating the position of the swarm of particles and their best social behavior. The method of simulated annealing is used to determine the optimal global position. The hybrid algorithm enables the solution performance to be independent of the starting point selected and offers improved stability and rapidity in locating the global optimum point (Javidrad *et al.*, 2017).

The utilization of artificial neural networks in conjunction with simulated annealing algorithms and the particle swarm method in time series forecasting models yields the best results for optimizing process parameters. Also, it is advisable to combine annealing simulation methods and genetic algorithms to enhance optimization efficiency.

In multi-criteria optimization, the Pareto optimal solution method is a principal approach that employs scalarization techniques to obtain optimal results. The optimal value in multi-criteria optimization is achieved when one objective function cannot increase without decreasing the other objective function. This condition is called Pareto optimality (Gunantara, 2018).

When the priority of criteria is not specified, the global criterion method is used. It enables uniform priority across all functions by identifying the optimal vector that minimizes a global criterion. The weighted sum method is also employed to tackle multi-criteria optimization tasks by merging varied criteria into a unified goal. Nevertheless, the method's drawback is the challenge presented in selecting task-specific weights.

3. Results and Discussion

Each of the approaches can be applied to optimize probabilistic events and, therefore, presumably adapted to optimize simulation models. However, considering the complex structure of socioeconomic and sociotechnical systems, as well as their variability, it is imperative to opt for the most versatile solution. This solution will not necessitate integration into the model's structure but will permit external circuit control. Thus, optimization will not depend on the structure of the model but will work with a set of behavior scenarios instead. Scenario reduction and genetic algorithms were selected out of all the options examined. The selected options are essentially counterparts to simpler (scenario reduction) and more sophisticated (genetic algorithms) approaches. So, consider general algorithms.

Figure 1 demonstrates a general scenario reduction algorithm based on information from sources (Kammammettu and Li, 2023; Peredo and Herrero, 2022; Dvorkin *et al.*, 2014). Scenario reduction, as outlined by Tarasov (2016), encompasses techniques aimed at filtering out potentially unrepresentative elements from the initial set of scenarios to form an optimal one. The simplest method for scenario reduction is random sampling.

Genetic algorithms are opposed to the above scenario reduction algorithm (Alam *et al.*, 2020). Figure 2 shows the general algorithm for searching the optimal set of scenarios based on information from sources.

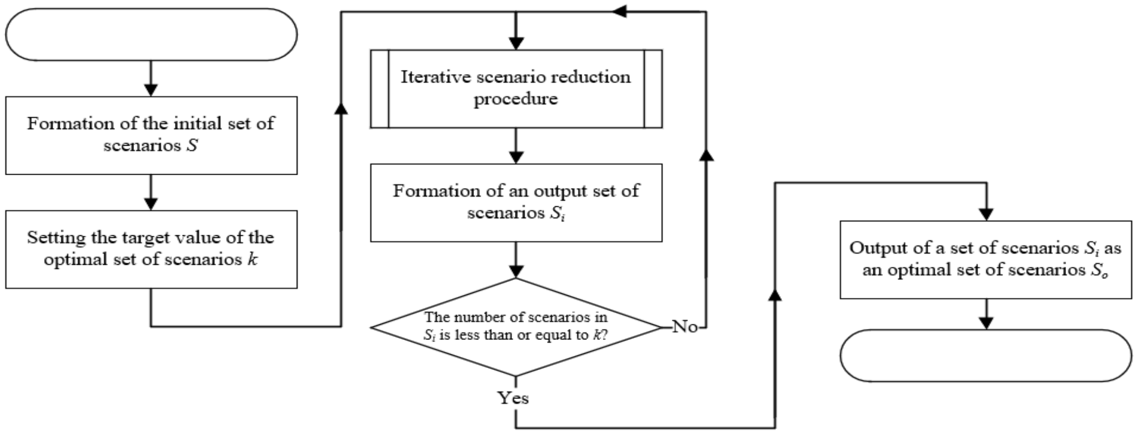

Figure 1 Scenario reduction algorithm general layout

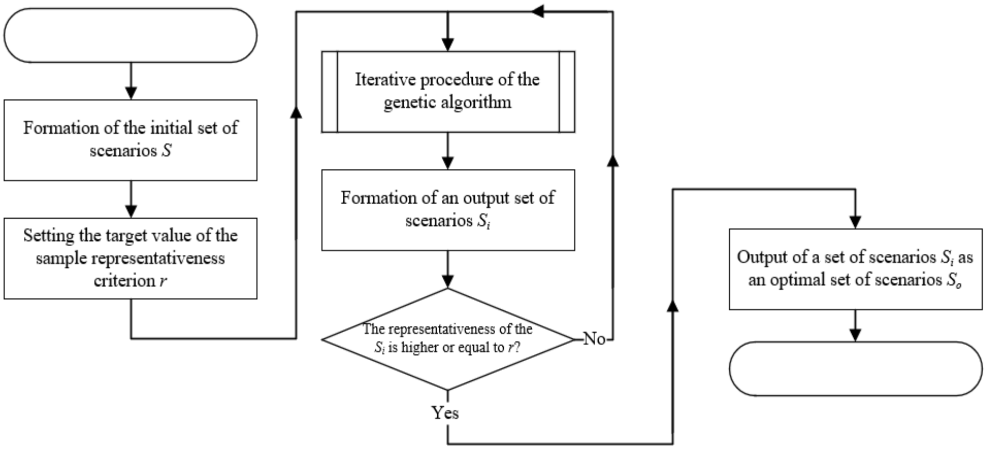

Figure 2 Search for the optimal set of scenarios via a genetic algorithm general layout

The algorithms considered are almost identical, even though the proposed methods are based on completely different prerequisites. Thus, scenario reduction is based on the formation of a large set of scenarios for input and the establishment of a criterion for the number of scenarios (Oliveira, Carravilla, and Oliveira, 2022; Heitsch and Römisch, 2007), and genetic algorithms assume the ability to set the initial set of scenarios in the volume corresponding to the volume of the optimal set of scenarios (i.e., the volume search problem needs to be solved). Scenario reduction assumes a quantitative criterion as a criterion for terminating iterations, while a genetic algorithm assumes an abstract representativeness criterion, the calculation methods of which are the subject of a separate study. Despite the obvious advantages of integrating the considered methods, it is important to understand that none of them guarantees finding the absolute optimum. It's time to move on to the formalization of optimizing the parameters of simulation models of complex systems.

The developed prototype solves the problem of two-parameter optimization by a set of interrelated input parameters. Regarding the problem, it should be noted that the input parameters have different types: integers and fractional numbers from continuous ranges or finite discrete sets. This remark allows us to declare the applicability of the prototype on the entire class of similar tasks without reference to the input data type. The problem optimality criterion includes two output parameters. Due to the requirements for consistent optimization, the solution must be a Pareto front. The algorithm of the prototype is iterative and connected with a software module that executes scenario calculation. Figure 3 shows the algorithm's general layout.

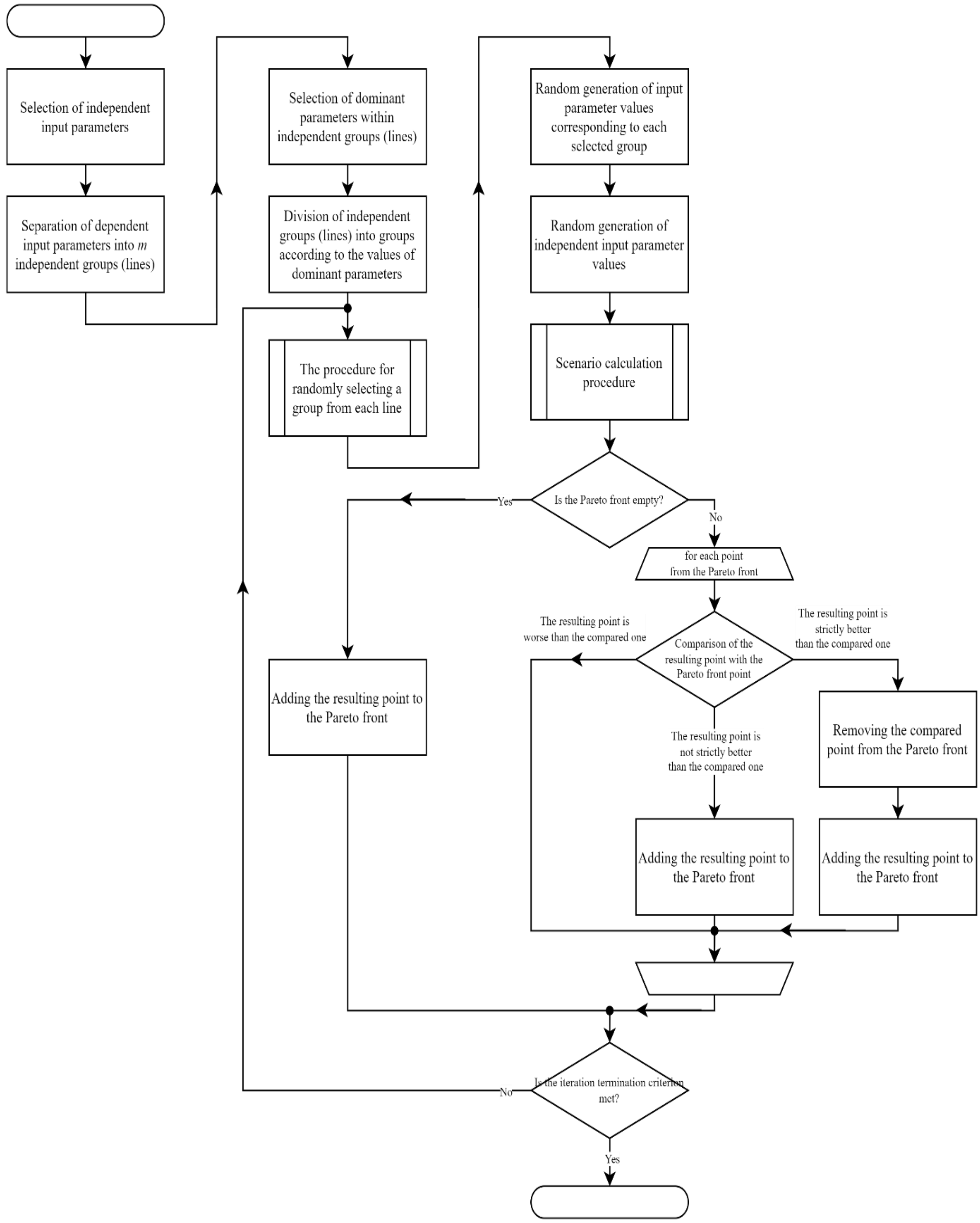

Figure 3 Scenario calculation optimizer algorithm

In conditionally independent groups, dominant parameters are specifically identified. The values of these parameters influence the potential sets of values for the remaining parameters within the group.

At the end of data preparation, groups of conditionally independent parameters are divided into subgroups according to the possible values (or ranges of values for continuous parameters) of the dominant parameters: each subgroup must differ from all others by at least one value of at least one dependent on the dominant parameter. We call sets of subgroups formed from one group a line.

At the stage of scenario generation, one subgroup is randomly selected from each line, and parameter values (both dominant and dependent on them) that satisfy the conditions of the subgroup are randomly set. Expert assignment of weights to certain subgroups in the lines is allowed to increase the probability of empirically choosing more common values of the dominant parameters. Likewise, the values of independent parameters are randomly set. The result is a set of parameters for scenario calculation.

Then, the algorithm accesses the scenario calculation program. At the output, the obtained value is checked in accordance with the Pareto criterion. The iterative comparison procedure includes an evaluation of the resulting point at this iteration from each of the points of the Pareto front formed based on the results of past iterations. If the values of at least one of the objective functions deteriorate, the resulting point is excluded from consideration. When improving the values of one of the objective functions and preserving the value of the other objective function, the resulting point is added to the Pareto front. When the values of both objective functions are improved, the resulting point is added to the Pareto front, and the point compared with it is excluded from the Pareto front. If the Pareto front is empty (first iteration), the resulting point is added to the Pareto front. Iterations continue until the specified value of the iteration termination criterion is reached. Within the prototype, such a criterion is the number of iterations.

4. Discussion

The problem raised in this study, namely the consideration of uncertainty in multiparametric optimization problems, has been widely presented in scientific publications of the last ten years (Pappas *et al.*, 2021). So, researchers take into account uncertainty by modeling the parameters themselves. That is, integer variables are treated as uncertain parameters, and the problem is solved through polynomial functions (Charitopoulos, Papageorgiou, and Dua, 2018). Thus, the problem of accounting for uncertainty is reduced to the problem of linear programming, which is generally characteristic of many other studies (Pappas *et al.*, 2021). An alternative to linear programming is the approach of describing the problem and solving it through partial differential equations (Petsagkourakis and Theodoropoulos, 2018). Each of the solutions has its own capabilities and disadvantages, but they are all characterized by the strict mathematical formalization of systems limited in complexity, as well as the impact on the characteristics of the system parameters, i.e., the introduction of uncertainty deep inside the model. We propose to solve the problem of uncertainty in the system through external control of the simulation model of the system. This approach makes it possible to separate optimization and simulation of the system, which simplifies overloaded complex models of systems and logically separates two interrelated but very different tasks: system simulation and system optimization.

Comparing the algorithm we have developed with other similar studies, it is worth noting that we do not focus on the cause-effect relationships between the parameters (Seeve *et al.*, 2022). On the one hand, this feature makes it possible to achieve the universality of the algorithm, but on the other hand, it potentially reduces its accuracy for more deterministic systems (Seeve *et al.*, 2022). This issue requires further investigation.

The proposed algorithm can be improved in accordance with the principles proposed in the Methods section. At this point, the algorithm implements a random selection of scenarios based on dependent datasets, which, as expected, gives a more representative set of scenarios than a simple random sample of scenarios. However, even such an approach cannot fully satisfy the need for the formation of a representative set of scenarios while reducing the calculation time.

Ways to improve the algorithm consist of integrating elements of scenario reduction and/or genetic procedures into it, aimed together at forming an optimal scenario with a higher probability than the existing method based on randomness. At this stage of the study, an assumption is made about the prospects of using genetic algorithms not due to their dominance over other methods but because of their popularity among researchers and successful application in a greater number of cases. However, at the next stage of the study, it is necessary to conduct a full-fledged in-depth analysis of evolutionary algorithms, as well as a series of experiments on real data. It is important to note that even though the described algorithm is implemented in software and tested on synthetic data, its applicability to real data has yet to be verified, which is the main task in the framework of the continuation of the project.

5. Conclusions

The result of the work is the developed prototype of a scenario calculation optimization algorithm for the problem of two-parameter optimization as a module for a digital tool to support managerial decision-making in sociotechnical and socioeconomic systems. In the case of the study, the problem of optimizing a set of scenarios is formalized, general ideas are formed about two opposed problem-solving methods (scenario reduction and genetic search for the optimal set), an algorithm for addressing the general problem of multiparametric optimization is proposed (providing the example of two-parameter optimization). The ways of improving the algorithm prototype using approaches to scenario reduction or implementing evolutionary algorithms for the optimal set of scenario formation are considered. In the next stage of the study, a comprehensive in-depth analysis of evolutionary algorithms is planned, along with a series of experiments on real data. This is necessary as the current results are confined to theoretical prerequisites. Thus, the contribution of the current research is to formalize the processes of optimizing the parameters of simulation models of complex systems. The research is carried out within a project to develop a digital tool to support managerial decision-making in sociotechnical and socioeconomic systems.

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