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OPTIMIZATION OF INTEGRATED ENERGY SYSTEM RESILIENCE

Bychkov I., Feoktistov A., Voskoboinikov M., Edelev A., Beresneva N., Edeleva O. **Optimization of Integrated Energy System Resilience.**

Abstract. Currently, the development of approaches that enhance the resilience of integrated energy systems is a highly relevant research direction. Such approaches are based on the structural and parametric optimization of integrated energy systems. Typically, these approaches are closely tied to a specific spatio-temporal scope and a particular optimization method. The application of developed approaches at other scopes often leads to a significant increase in computation time and a possible reduction of solution accuracy. This problem is due to the complexity of energy system optimization models and the differences between them. To solve this problem, we have developed a methodology for selecting the most suitable methods for the design of system resilience at a given spatio-temporal scope. The proposed methodology is based on testing methods within a specialized testbed and a multi-criteria analysis of test results. The indicators for evaluating the methods include both summary metrics of resilience and efficiency parameters of computational resources. The benefits of the proposed methodology are illustrated for the resilient design with respect to national and local integrated energy systems. Several dozen methods from the well-known Parallel Global Multiobjective Optimizer library were efficiently tested in up to 10 hours. The analysis of the testing results was performed with different multi-criteria algorithms regarding the prioritization of the indicators.

Keywords: integrated energy systems, resilience enhancement, synthesis, structural and parametric optimization methods, multi-criteria analysis, testbed.

1. Introduction. Over the past two decades, problems caused by a series of extreme weather events, such as Superstorm Sandy (2012) and Hurricane Maria (2017), have highlighted the need for fundamental design and efficient operation of modern power systems. After extreme power failure events, the cost of restoring the power system becomes prohibitively high. This has a direct impact on the economic and social well-being of many countries. For example, in February 2021, three severe winter storms hit Texas, causing widespread failures in the power generation, transmission, and distribution subsystems [1]. The power outages led directly and indirectly to the deaths of approximately 200 people [2].

Recent research on blackouts has predominantly focused on integrated energy systems (IES) reliability [3]. Most of the world's reliable energy systems meet the so-called $n-1$ supply security criterion, which postulates that in the event of a system component failure, the power supply can be restored to consumers without load shedding. However, reliability-based IES designs fail to account for high-impact, low-probability (HILP) disruptions because the reliability concept is concerned with normal operating conditions or controllable fault conditions. Designing a resilient IES is a challenging due to higher computational complexity.

In this paper, we propose a methodology for selecting optimization methods to solve the resilient IES design problem. Within the methodology, we test software developed to solve this problem to select the best optimization method for a particular class of IES models. The method selection is based on a multi-criteria analysis of two sets of indicators: resilience indicators, which are the summary metrics, and efficiency indicators for the use of computational resources. The proposed methodology is applicable to the design of IESs with different spatio-temporal scopes and the simultaneous modeling of different categories of disturbances

2. Related works

2.1. Energy system resilience. The resilience of an IES is defined as the ability of a system to anticipate, absorb, and mitigate the effects of the disturbances and recover from them rapidly. Under extreme conditions, the behavior of IES is described by resilience curves, each of which is a graph of the dependence of the system performance p on time t [4]. There are several ways to represent the resilience curves, such as the resilience triangle, resilience trapezoid, and multiphase resilience trapezoid [5].

The conceptual resilience trapezoid is shown in Fig. 1. From t_0 to t_1, the system is in a stable initial state characterized by the performance level p_2. When a disturbance occurs at t_1, the system attempts to resist the degradation process by absorbing and counteracting the disturbance. The disturbance causes the system performance to drop to p_0 at t_2 . Between t_2 to t_3 the system mitigates to the consequences. From t_3, the system aims to restore its functionality in the shortest possible time. The recovery process culminates at t_4, with the system reaching a new stable state. The system then gradually increases its functionality at T to one of the levels p_1 - p_3.

Performance metrics mainly illustrate technological or territorial IES characteristics. In contrast, summary metrics [4] characterize different states of the system performance, as shown in Fig. 1. These states include planning (state 1), resistance (state 2), mitigation (state 3), and recovery (state 4). The planning, resistance, and mitigation states can be collectively referred to as adaptation. Issues related to the selection of the appropriate performance measures, summary metrics, and their standardization are discussed in detail in [4, 5].

The primary objective of IES resilience research is to identify a strategy for optimal disturbance resistance and rapid recovery. The strategy is a set of partially ordered activities that facilitate both adaptation and recovery.

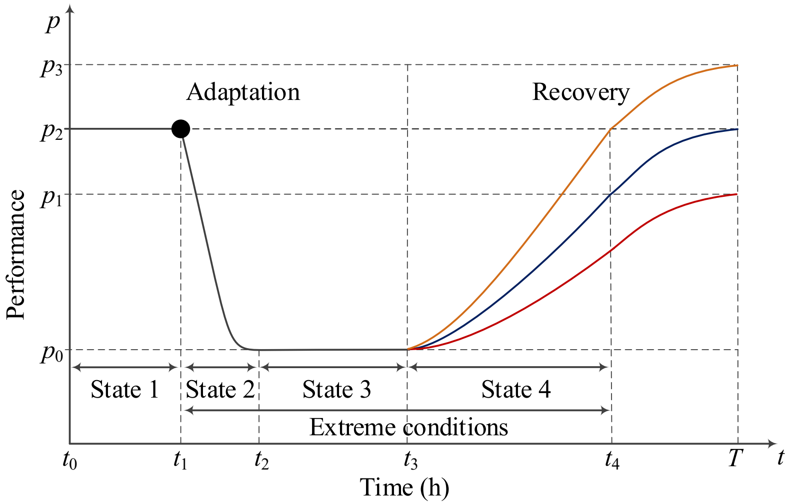

Fig. 1. The conceptual resilience curve

In the existing, most approaches to enhance the resilience of IESs focus on only one of two key areas: the adaptation to disturbances, which are typically limited to a specific category, such as natural disasters, and the subsequent recovery of the system. The advantages of considering both key areas in an integrated manner are the balanced allocation of resources to enhance resilience and the significant reduction in performance losses during extreme conditions. The main drawback of that is increased computational complexity..

2.2. Energy system synthesis problem. In this paper, we consider the enhancement of IES resilience in the context of the problem of structural and parametric optimization of energy systems, which we refer to as energy system design (synthesis). Parametric optimization enables the selection of optimal parameters for the operation of energy equipment [6]. The objective of structural and parametric optimization is to select the most appropriate types of energy equipment and locations for their installation. In general, it is formulated on the basis of parametric optimization [7]. Therefore, from a mathematical and computational point of view, structural and parametric optimization is a more complex problem than parametric optimization.

The long-term reason for the resilient IES synthesis is a growing interest of consumers in exploring cleaner and more sustainable options for energy generation. This is driven by the increasing global demand for electricity and thermal energy, as well as the exhausted supplies of fossil fuels and their harmful effects on the environment.

The short-term reasons include modern consumption concepts such as demand-side management. It is commonly understood as controlled load shedding which is not designed for permanent demand reduction or the temporal shifting of energy demand within a predefined time window. Two main types of demand-side management response measures can be defined, namely curtailment and load shifting. Curtailment focuses on the reduction of load peaks. Load shifting leads to an advanced or postponed load catch-up during another point in time, e.g., when sufficient amounts of energy from other sources become available. Both measures make energy demand more flexible. The short-term factors are influenced not only by the consumer behavior but also by resilient dispatch strategies to combine distributed energy with traditional energy systems, cooperate with the operation of various forms of energy, and give play to the advantages and potential of different energy sources.

The traditional approach to IES synthesis entails the manual creation of numerous system configurations that are significantly different from each other. The primary disadvantage of this methodology is the high degree of subjectivity inherent in the decision-making process, which depends on the expertise and experience of the IES configuration designer.

The two-level nature of the synthesis problem provides the basis for two-level methodologies to address large-scale problems [8]. High-level methods coordinate equipment investment, placement, and sizing decisions, while low-level methods focus on making decisions about equipment unit operation. High-level optimization decisions must be made simultaneously with low-level ones. Thus, the computational complexity increases according to the level of the methodology.

At least two methodologies have been identified in the literature that leverage the characteristics of the automated IES synthesis problem. The superstructure-based synthesis consists of the following main sequential steps [9]:

– development of a superstructure containing all feasible alternative energy process structures;

– conversion of the superstructure into a mathematical programming program;

– computation of an optimal system configuration using the program.

At the same time, superstructure-free synthesis does not use the combinatorial search space to obtain alternative energy process structures. This methodology then dynamically generates these structures and subsequently evaluates them using an ESOM [10, 11].

Finally, in contrast to the traditional approach, both types of automated synthesis can result in a variety of IES configurations, which is a significant advantage for decision support. Decision makers typically prefer to obtain a number of promising IES configurations of high quality, which can then be evaluated in light of additional information that may emerge in practice. Consequently, an optimal but single IES configuration is often inadequate.

2.3. IES modelling complexity. The acquisition of the requisite set of IES configurations within an acceptable period of time represents a compromise between the computational costs, accuracy of computation, and the practical significance of the resulting data. In the existing literature, the following factors, which define the complexity of ESOMs, are highlighted:

– time-series aggregation (TSA) [12];
– spatial resolution [13];
– level of system behavior detailing;
– mathematical complexity.

Among these complexity factors, TSA level selection represents a crucial modeling decision. Equipment selection and sizing depend on performance within time series accurately representing expected operating conditions. These time series must include “typical periods” or “representative periods” that represent the most typical operating profiles. For a reliable and resilient IES design, the time series must include “extreme periods” that represent the most critical operating conditions, as the energy system supply inability often occurs under extreme conditions. The extreme periods reflect abnormal profiles that are maximally distant from the representative profiles and/or with close-to-peak or close-to-minimum values of selected facilities such as energy demand or production. In addition, it is important to define the minimum number of time periods, as this reduces the computational complexity of the IES synthesis at the TSA level [12].

The mathematical complexity is significantly influenced by the system detail factor. Mixed Integer Linear Programming (MILP) has been identified as the most suitable approach for IES design in terms of accuracy and runtime. However, Linear Programming (LP) and Non-Linear Programming (NLP) are also commonly employed in IES design. A prevalent approach for converting an NLP program into a MILP program is to apply the piecewise linearization procedure to non-linear curves.

The mathematical complexity factor plays a key role in determining the optimization methods to be used at each stage of the IES synthesis problem. The methods can be classified into two different categories: meta-heuristic and rigorous. In general, meta-heuristic methods are effective in obtaining optimal solutions in a relatively short time. However, these methods lack the ability to guarantee optimality due to the inconsistent and mathematically unproven nature of their convergence. Rigorous methods, on the other hand, are capable of finding exact solutions for a wide range of objective functions. However, they suffer from two major drawbacks: a high computational cost and potentially long computation time.

At the low level of the IES synthesis problem, rigorous optimization methods such as LP, MILP, NLP, or Mixed Integer Non-Linear Program (MINLP) are typically used to make decisions about equipment operation. Meta-heuristic methods are extensively used to make decisions about the selection, placement, and sizing of IES equipment, i.e. at the high level of the IES synthesis problem.

Table 1 shows the state of the art in IES structural and parametric optimization. The known approaches are grouped according to the following aspects: flexibility, reliability, and resilience [14]. The following parameters are used as evaluation criteria in Table 1:

– IES synthesis methodology c_1 (Traditional approach / Superstructure-based approach / Superstructure-free approach);

– ESOM geographical scope c_2 (National level / Regional level / Local level);

– TSA c_3 (Representative period / Extreme period);

– supply security criterion c_4 ($n-1$ / $n-k$);

– optimization method type c_5 for the first stages of the IES synthesis problem (Meta-heuristic / LP / MILP / NLP / MINLP);

– optimization method type c_6 for the second stages of the IES synthesis problem (Meta-heuristic / LP / MILP / NLP / MINLP);

– level of system behavior detailing c_7 (nonlinear investment curves / system dynamic).

In Table 1, the sign ‘+’ means that there is support for a particular aspect within the approach. The '-' sign indicates the absence of support. If the information on an aspect is not clear, “N/A” is indicated. If the IES synthesis problem includes only one stage of its solution, “No stage” is indicated for the criteria c_6.

As shown in Table 1, the searches conducted were based on the conventional structural and parametric optimization of IESs, with the objective of enhancing flexibility, and exclusively considering representative periods. The exclusion of extreme periods from these searches can lead to the development of unreliable IESs.

Table 1. Approaches

Source	c_1	c_2	c_3	c_4	c_5	c_6	c_7
	Flexibility						
[10]	-/-/+	+/-/-	+/-	N/A	+/-/-/-/-	-/-/-/-/+	-/+
[11]	-/-/+	+/-/-	+/-	N/A	+/-/-/-/-	-/-/-/-/+	-/+
[13]	+/-/-	+/+/+	+/-	N/A	-/-/+/-/-	No stage	-/+
[15]	-/+/-	+/-/-	+/-	N/A	-/-/-/-/+	No stage	-/+
[16]	+/-/-	+/-/-	+/-	N/A	-/-/+/-/-	No stage	-/+
[17]	-/+/-	+/+/+	+/-	N/A	-/-/+/-/-	-/-/+/-/-	+/+
[18]	-/+/-	+/-/-	+/-	N/A	+/-/-/-/-	-/-/-/-/+	+/+
[19]	-/+/-	+/-/-	+/-	N/A	+/-/-/-/-	-/-/+/-/-	+/+
[20]	+/-/-	+/-/-	+/-	N/A	-/-/-/-/+	No stage	-/-
[21]	+/-/-	+/+/+	+/-	N/A	-/+/-/-/-	No stage	-/-
	Reliability						
[14]	-/+/-	+/+/+	-/+	+/-	-/-/+/-/-	-/-/+/-/-	-/-
[22]	+/-/-	-/+/-	+/-	N/A	-/-/+/-/-	-/-/+/-/-	+/+
[23]	-/+/-	+/+/+	+/-	N/A	-/-/+/-/-	-/-/+/-/-	+/+
[24]	+/-/-	-/+/+	+/+	N/A	-/+/-/-/-	No stage	-/-
	Resilience						
[25]	-/+/-	+/+/-	+/+	N/A	+/-/-/-/-	-/-/+/-/-	-/+
[26]	-/+/-	+/+/+	+/-	-/+	-/-/+/-/-	-/-/+/-/-	-/-
[27]	-/+/-	+/-/-	+/-	-/+	-/-/-/-/+	No stage	-/+
Our study	-/+/-	+/+/+	+/+	-/+	+/-/-/-/-	-/-/+/-/-	+/+

In identifying the reliable IESs, the supply security criterion $n-1$ can be employed as an additional criterion. Extending the range of its values up to $n-k$ allows the design of resilient IESs. Thus, disturbance modeling, which simulates extreme periods and/or the failure of up to k IES elements according to the supply security criterion $n-k$, should be added to the structural and parametric optimization to enhance the system's resilience.

2.4. PaGMO library. A number of strategies have been developed to balance the spatial, temporal, technological, and economic resolution of the input data with the available computational resources in order to facilitate problem-solving within an acceptable time and with minimal loss of accuracy of the ESOMs. These strategies can be classified as either model-based or solver-based [28].

Evolutionary optimization methods are typically solver-based techniques. As an illustration, we will examine the Parallel Global Multiobjective Optimizer (PaGMO) library [29]. PaGMO is based on the asynchronous generalized islanding paradigm, which is expressed by the implementation of different data migration policies between individual threads. PaGMO includes an extensive set of optimization methods. Some of these methods are related to global optimization and use local optimization techniques. The aforementioned capabilities of PaGMO allow the creation of algorithms that use one or two optimization methods in each stream. The main advantage of PaGMO is that it provides a consolidated interface for interacting with metaheuristic methods and optimization packages, including Ipopt and NLopt. Once this interface has been implemented, no further code modifications are required to replace optimization methods and add new ones that are not included in the library.

2.5. Summary. The IES synthesis methodologies described in Table 1 result in a variety of promising system configurations that improve the flexibility, reliability, or resilience aspect of a typical ESOM. A typical ESOM represents a class of IES with a given geographical scope, level of TSA, and detail of system behavior. In Table 1, most methodologies focus on the issues of TSA, spatial aggregation, and system behavior detail. In contrast, the goal of our work (the last row in Table 1) is to select and parameterize an optimization method that is capable of finding a set of resilient system configurations for any typical ESOM. All of the IES resilience enhancement methodologies described in Table 1 evaluate the efficiency of the selected equipment under a defined set of disturbance scenarios. This allows direct optimization methods to improve the resilience of the system under study.

Our approach, unlike others [25 – 27], can handle scenarios that mix extreme periods and failures according to the supply security criterion $n-k$. At the same time, this advantage can lead to increased computational cost and, most importantly, to the challenging problem of completing the IES synthesis process within an acceptable time. From the theoretical perspective represented in [30, 31], this problem can be solved by achieving a compromise between the typical ESOM hierarchy, optimization methods, and the cost determined by the available computational resources (Fig. 2).

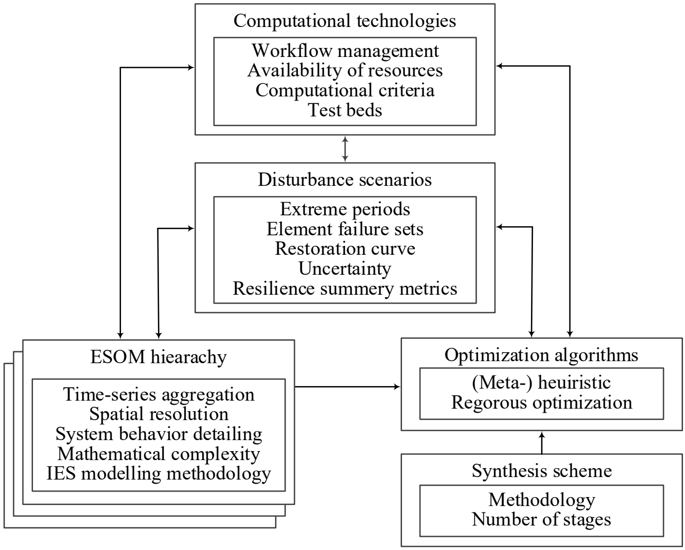

Fig. 2. Achieving a compromise between a typical ESOM hierarchy, optimization methods, computational resources, and disturbance scenarios

3. Methodology for selecting optimization methods. The IES resilience enhancement problem involves determining the most efficient combination of activities for system adaptation and recovery under worst-case disturbance scenario:

$$\underset{j=1,n_w}{\underline{min}}\,\underset{i=1,n_v}{\underline{max}}\,\underset{x\in y(v_i,w_j)}{min} f\left(x, v_i, w_j\right), \tag{1}$$

$$f(x,v,w) = \sum_{t=1}^{t_m}[(cx_t^v + bs_t^v) + a(y_t - y_t^v) + hw], \tag{2}$$

$$s_{t-1}^v + A^v x_t^v + Uq_t^v - y_t^v - s_t^v \geq 0, \tag{3}$$

$$x_t^v \leq d_t^v, \tag{4}$$

$$y_t^v \leq y_t \tag{5}$$

$$q_t^v \leq wq_t, \tag{6}$$

$$s_t^v \leq z_t^v, \tag{7}$$

$$z_0^v = s_0, \tag{8}$$

where v_i is a disturbance, n_v is a number of disturbances, w_j is a binary vector which nonzero component values activate an activity combination, n_w is a number of activity combinations,

– t_m is the number of modelling time periods,
– x_t^v is the decision vector, the elements of which characterize the operating parameters for the technological equipment of the IES,
– y_t^v is the decision vector, whose elements characterize the consumption of energy resources,
– q_t^v is the decision vector describing the usage intensity of the activities,
– s_t^v is the decision vector, whose components characterize the volumes of the fuel stocks,
– A^v is the matrix describing the production and transmission of energy resources under the impact of v,
– d_t^v is the vector defining the technically possible limits of the IES equipment,
– y_t is the vector, which elements show the demand for energy resources,
– U is the matrix reflecting the localization of the implementation of the activities,
– q_t is the vector specifying the usage intensity limits of activities,
– z_t^v is the vector that defines the energy storage capacity,
– c is the vector, which elements determine the unit cost for each technological equipment type-size,
– b is the vector of unit costs for the energy storage operation,
– a is the vector of specific damages resulting from the shortage of certain energy resources,
– h is the vector specifying the unit cost of the preparation and implementation of activities.

The objective function (2) has three criteria. The first criterion reflects the cost associated with the IES operation. The second criterion includes metrics that estimate the cumulative energy resources shortage over t_m time periods. The third criterion characterizes the costs of preparation and implementation activities.

The effects of the disturbance v are realized by the matrix A^v and vectors d_t^v, z_t^v in equations (3), (4), and (7) respectively. Their elements characterize the deformation of different IES components due to the disturbance impact at the time t.

The level of necessary supply to consumers with certain energy resources is given by equation (3). The technical constraints of the activities are defined by (4).

The fuel volumes in stocks at time t are limited by their available capacities according to inequality (7). Equation (8) assumes that in the v at the initial time period $t=t_0$ all storages have an energy stock described by the vector s_0.

Problem (1)-(8) describes the IES resilience optimization scheme (Fig. 3).

The supply security criterion n-k defines the activity efficiency to enhance the IES resilience at the national level. In relevant disturbance scenarios, up to k elements from the list of the most important ones can be shut down simultaneously. The activity efficiency for the local-level IESs is determined for disturbances whose scenarios are modeled by 1 or more extreme periods.

The scheme of the resilient IES design solving (1) consists of three levels, as illustrated in Fig. 3.

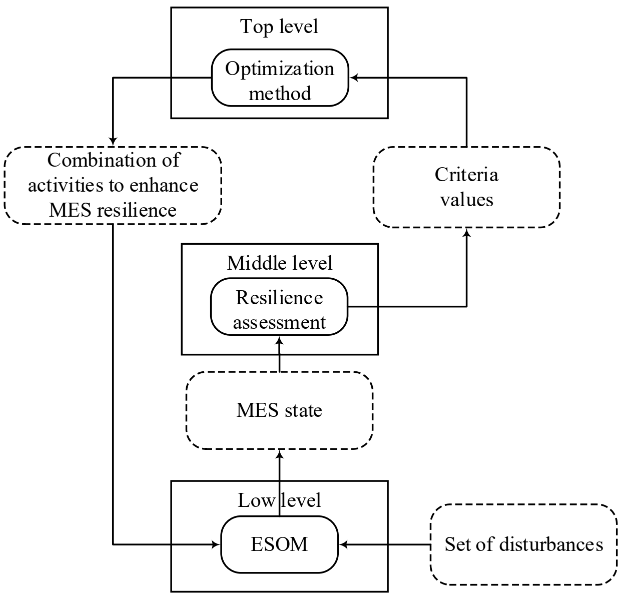

Fig. 3. Resilient IES design scheme

At the top level, the equipment types, sizes, and locations described by the vector w_j are selected with a predefined optimization method. The selected activities are then transferred to the lower levels. Subsequently, the operation of the selected equipment is evaluated under a defined set of disturbances.

The results of this evaluation are then passed to the intermediate level. At this level, the values of the resilience indicators that constitute the function f are calculated. The values are then returned to the top level, where they influence the next cycle of equipment selection. Evaluating the resilience of intermediate IES configurations, not just the resulting ones, facilitates the optimization process to improve system resilience.

In general, the high computational complexity of the scheme in Fig. 3 is determined by the complexity of the ESOM, the efficiency analysis of w_j, and the optimization method that is used at the top level. The correct choice of an optimization method has a significant impact on the ability to solve problem (1) in a reasonable time and on the accuracy of the solutions obtained. The vast majority of works on energy system synthesis do not consider the selection of an optimization method.

A comprehensive methodology for selecting optimization methods allows us to evaluate in practice the computational complexity of optimization methods from libraries such as PaGMO. We use a testbed to implement the scheme in Fig. 2 with optimization methods for testing and perform a multi-criteria analysis of the test results to rank the methods. In addition, the multi-criteria analysis is supported by expert analysis.

The methodology reflects the main stages of the qualimetry of models and polymodel complexes [30], which are preparing IES data for testing, defining evaluation indicators, performing optimization tests, and multi-criteria ranking methods.

3.1. IES data for testing. Before forming the set of disturbances for the resilient IES design, a preliminary vulnerability analysis should be performed to identify extreme periods and the most vulnerable elements of a studied IES.

The IES data for testing optimization methods differ from the original data in that the former simplifies the aspects not covered by the tests. For example, a set of realistic disturbance scenarios in the test variant can be replaced by a single disturbance that is practically unrealizable but guarantees the worst consequences for the basic configuration of the IES. This simplification speeds up the computational experiments.

3.2. Evaluation indicators. The list of the possible resilience indicators (Table 2) includes topological, functional, and economic summary metrics. The topological and functional indicators evaluate the efficiency of the activities.

The economic indicators characterize the cost of the activity combination. Topological indicators are effective in evaluating structural changes due to the failure of existing power facilities or the appearance of new facilities in the IES.

Functional indicators evaluate changes in the IES performance and characterize the energy flow distributions at the level of energy resource consumers. Economic indicators also depend on the IES performance and characterize cost changes that occur during the system recovery process.

Table 2. Resilience indicators

Indicator	Evaluation method	Evaluation aspects
IES performance	Integral evaluation of shortages in the analyzed time interval	Consumer categories and territorial affiliation
IES recovery	Comparison of the IES performance at the recovery stage	Consumer categories, territorial affiliation, and types of events
IES topological efficiency	Comparison of topological characteristics of the original and transformed IES configurations	Types (nodes and arcs) and connectivity of network elements
Damages due to disturbance impact	Integral damage evaluation on the analyzed time interval	Consumer categories and territorial affiliation
Costs of activities implementation	Integral cost evaluation in the analyzed time interval	Consumer categories, territorial affiliation, and types of events

The efficiency indicators for the use of computational resources characterize the time and computational cost of solving the IES resilience enhancement problem using different optimization methods (Table 3). The indicators values are stored in the testbed computation database.

Table 3. Efficiency indicators for the use of computational resources

Indicator	Units	Data source
Method execution time	Sec.	OProfile (a system-wide statistical profiling tool for Linux)
Average size of RAM used	MB	top (a task manager for Unix-like operating systems)
Average processor load	Percentages	top (a task manager for Unix-like operating systems)

3.3. Optimization tests. Our approach to the testing optimization methods involves creating a specialized computing environment. Compared to similar approaches, it has the following major advantages:

– use of testbed technologies with full support for High-Performance Computing (HPC);

– platform and language independence by isolating energy system frameworks in containers;

– development of the scientific workflow to execute the energy system frameworks;

– use of software module profilers to obtain the necessary hardware-dependent data for evaluating the computational complexity in ESOMs;

– support for several different algorithms for multi-criteria selection of the best optimization methods.

The advantage of our approach to constructing and using testbeds lies in unifying the development of both workflows and testbeds for testing these workflows. This allows us to significantly reduce the effort required to create a testbed and increase the efficiency of testing.

In our research, a testbed for service-oriented applications is implemented using the Framework for Development and Execution of Scientific WorkFlows (FDE-SWFs) [32] in the form of a workflow, including services for executing application and system software. The general structure of the testbed is shown in Fig. 4.

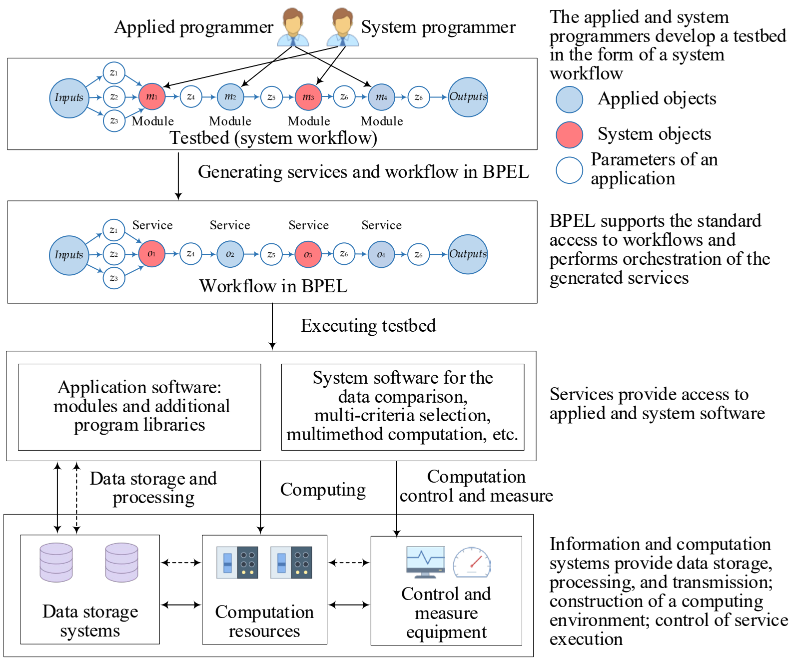

Fig. 4. Testbed structure

The testbed is created as a workflow, complemented by a set of system operations, and represented in Business Process Execution Language (BPEL). The workflow services execute tested application modules and the necessary system operations for processing and analyzing data and calculation results. The FDE-SWFs computation manager executes the workflow.

3.4. Optimization method ranks. Each of the testing n_m optimization methods results in n_i , $i+\overline{1,n_m}$ activity combinations which are evaluated with n_j indicators over n_g regions. The output of the method i evaluation for the region $g=\overline{1,n_g}$ is the matrix R_g^i of dimension $n_i \times n_j$.

Each matrix R_g^i is converted into the vector e_g^i of size n_j by the aggregation operation u :

$$e_g^i = u\left(R_g^i\right). \tag{9}$$

Depending on the chosen method selection strategy to obtain the guaranteed or potentially better result, the operation u in (2) selects either the minimum or maximum of the indicator values R_g^i or averages these values, $i+\overline{1,n_m}$. The vector e_g^i is analyzed using the multi-criteria analysis algorithm $l+\overline{1,n_a}$.

The output of the algorithm l is the rank vector $r_{g,l}^i$. These ranks allow us to evaluate the priority of each method for the region g .

4. Computational experiment. The testbed tests the application module executions for studying the IES resilience. The workflow that implements the testbed includes two application operations and seven system operations.

The applied operations generate a list of files with optimization method names and perform structural and parametric optimization using each method. The system operations are intended for data structuring and processing, as well as multi-criteria selecting the methods. The module execution is tested with different methods to solve an instance of a resilient IES synthesis problem.

The computation results of each module instance and the system metrics are combined into a parallel data list by system operations of the workflow. Each parallel data list element corresponds to a distinct result variant.

Based on this list of the indicator values, the dedicated system operation for a multi-criteria selection generates a set of methods and proposes the most effective method among them, taking into account the ranking of these indicators. The initial data and computational experiment results are stored in the database by the computation manager.

The methods of the NLopt library and the Ipopt solver package were additionally linked to the PaGMO library methods. In total, we have tested 62 methods. Most of them are evolutionary. During testing, we combined the following parameters of the methods: population size and number of generations. The values of the remaining method parameters were set by default in the PaGMO library.

The methods have been tested on a testbed in a distributed computing environment consisting of four nodes functioning under Ubuntu 22.04.1 LTS OS. Each of the nodes has the following characteristics: CPU AMD Ryzen 9 5950X, 128 GB of RAM, and 2 TB disk storage.

4.1. National IES. The typical ESOM of the national IES has the most aggregated level of spatial resolution [33]. At this level, large regions such as federal districts and separated energy facilities with the highest installed capacity are represented as nodes of energy transmission networks (Fig. 5). The smaller facilities have to be aggregated and considered by their combined average characteristics. The connections between the aggregated facilities within a node are neglected. The arcs in the energy transmission networks reflect the real connections between the most powerful objects or the connections between the different aggregated facilities. In this case study, there is only one disturbance scenario.

This scenario describes the disconnection of all consumers from the natural gas supply system network. All ruptured arcs are included in a redundant set of activities to enhance the resilience of the national IES.

In addition, new potential arcs between pairs of unconnected nodes are added to the redundant activity set. The distance between the unconnected nodes does not exceed a specified limit of 300 km. Pipe diameters are not specified. The capital cost of constructing new arcs is set equal to their length assuming that the construction investment for 1 km of all projected arcs is the same and does not depend on the terrain profile. Finally, there are over 3000 activities aimed at the national IES adaptation and recovery.

A tested method must either restore the existing gas supply network or propose a better system structure. Finally, 18 optimization methods were fully completed (Table 4) with the population size equal to 16, the number of generations equal to 1000, and the time limit for solving the IES synthesis problem equal to 10 hours.

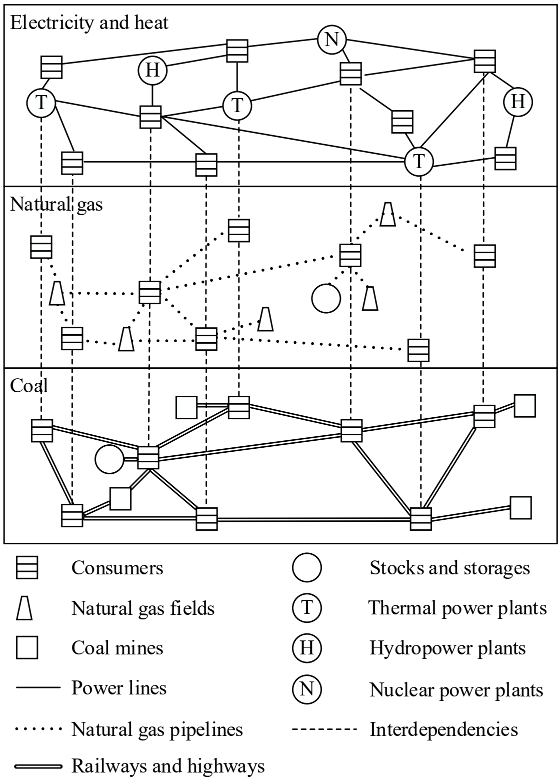

Fig. 5. The national-level IES model

The efficiency indicators for the use of computational resources are the execution time of optimization methods (Fig. 6(a)), the average amount of RAM usage (Fig. 6(b)), and the average CPU utilization (Fig. 6(c)) obtained by profiling the module execution. The metrics that measure the national IES resilience include the number of effective activities (Fig. 7(a)), the total length of new projected arcs (Fig. 7(b)), the natural gas supply metric (Fig. 7(c)), the electricity supply (Fig. 7(d)), and the heat supply (Fig. 7(e)). Fig. 7(b) also characterizes the investment value in new arcs.

Methods m3, m4, m12, m15, m17, and m18 significantly outperform other methods in execution time and average amount of RAM usage. At the same time, all methods m1-m18 show similar average processor load.

Table 4. Optimization methods for the national-level IES

Method code	Method name
m1	Particle Swarm Optimization
m2	Grey Wolf Optimizer
m3	(N+1)-ES Simple Evolutionary Algorithm
m4	Augmented Lagrangian Algorithm
m5	Non-dominated Sorting Genetic Algorithm
m6	Compass Search
m7	Simple Genetic Algorithm
m8	Particle Swarm Optimization Generational
m9	Self-adaptive DE (de_1220 aka pDE)
m10	Differential Evolution
m11	Self-adaptive DE (jDE and iDE)
m12	Multi-objective Improved Harmony Search
m13	Non-dominated Sorting PSO
m14	Compass Search
m15	Ipopt, Unconstrained Problem
m16	PRAXIS
m17	Single-objective Improved Harmony Search
m18	Ipopt, Constrained Problem

The number of activities to enhance the resilience of the national IES is sufficient to fully restore the energy supply to end-users of natural gas, heat, and electricity. Therefore, based on resilience criteria, only those methods are eligible for which the values of the indicators in Fig. 7(c), Fig. 7(d) and Fig. 7(e) have reached a value of 100%. However, in terms of potential investments (Fig. 7(b)), these methods did not perform as well as expected before the tests. It is assumed that the number of activated activities (Fig. 7(a)) would count in the hundreds. The solution to this problem may require a more precise parameterization of these methods.

Thus, based on resilience criteria, the most acceptable method for the national-level IES synthesis is m12 selected with the lexicographic multi-criteria selection algorithm. Another version of this method, namely m17, also approaches optimal performance. The lexicographic algorithm provides the ability to take into account the subject-area indicators used for prioritization into account. In terms of the efficiency indicators for the use of computational resources, the best method is m15.

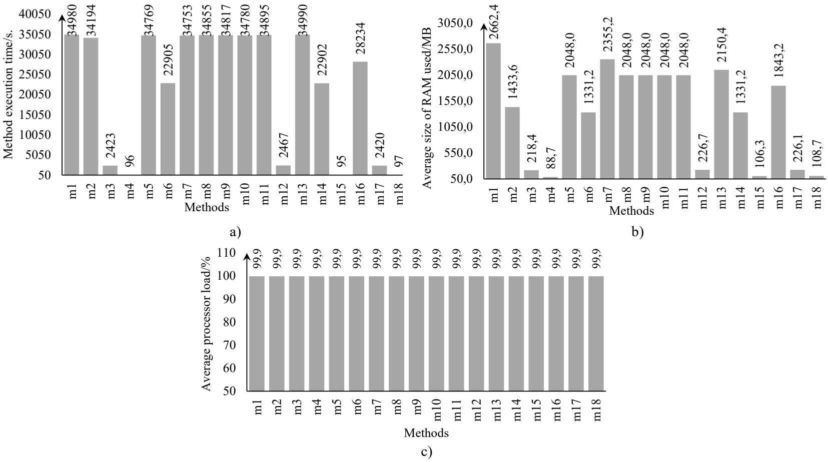

Fig. 6. Efficiency indicators for the use of computational resources: a) method execution time; b) average size of RAM used; c) average processor load

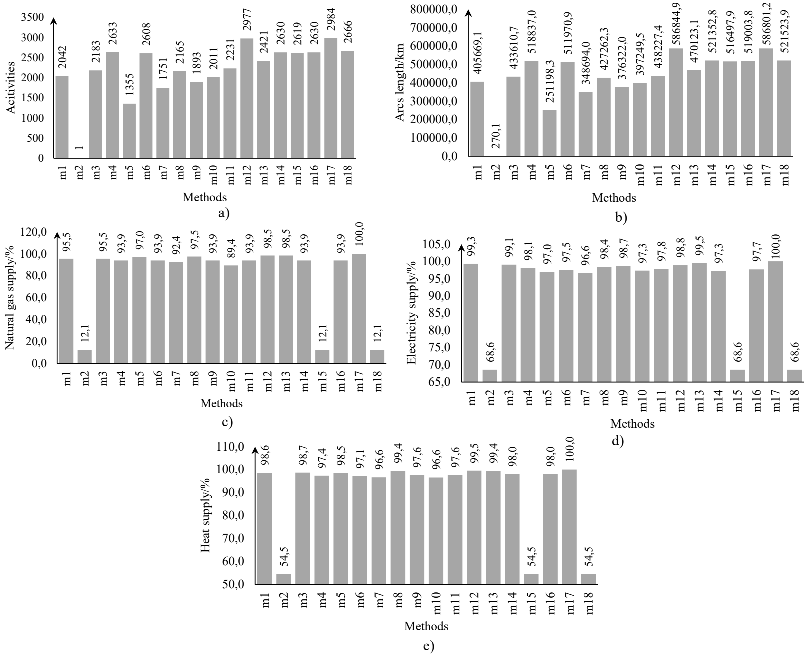

Fig. 7. Metrics that measure the national IES resilience: a) activities; b) arcs length; c) natural supply; d) electricity supply; e) heat supply

3.2. Microgrid. The typical ESOM of a microgrid is characterized by the following features [34]: a microgrid is represented as a set of interacting energy hubs; an energy hub consists of the following elements: inputs and outputs, converters, and storages; hubs are interconnected to each other by energy distribution networks; only stable states of a microgrid are modeled.

In this case, we test a microgrid represented by a modernized energy supply system for a small village (population of 6000 people) located in the Baikal natural territory. The expected heat load is equal to 23.19 gcal/h, electric load is equal to 102.91 MWh per year. This is connected with the expected population growth and the need for reconstruction of energy supply facilities. Originally, the village has one combined heat and power (CHP) installation (energy source no. 1). For the future, it is considered to increase the capacity of the source no. 1 and to reconstruct the 62 sections of the heat supply network, including the construction of new sections and a pumping station. Two fuel supply options are considered when forming alternative microgrid structures: providing natural gas supply as a part of the local gasification program; and using wood chips purchased from a wood processing plant located near the village.

Four alternative structures were considered for upgrading the energy source no. 1: natural gas-fired boiler and CHP, wood chip-fired boiler and CHP. In the case of boilers, it is assumed that the village will purchase electricity from the external grid. In the case of CHPs, the equipment type-sizes were selected taking into account the full power self-supply of the village. Any excess power is sold to the external grid. The microgrid's extreme periods during the year are modeled by increasing the specified maximum demand for electricity and heat by 10% during the fall-winter period in the test version. The tested algorithm goes to the number of activities, which is equal to 0 or 1 as a result of the solution. Then it selects an activity from a given redundant set. When the population size is 1024, the number of generations is 20 and the time limit for solving the synthesis problem of the local-level IES is 1 h, 9 optimization methods were fully completed (Table 5).

The heat and power supply indicators obtained using the methods m4-m9 do not satisfy the limitations of the microgrid model. Therefore, we consider only methods m1-m3. The efficiency indicators for the use of computational resources are the execution time of optimization methods (Fig. 8(a)), the average amount of RAM usage (Fig. 8(b)), and the average CPU utilization (Fig. 8(c)). The summary metrics measuring the local IES resilience include the number of effective activities (Fig. 9(a)), investments (Fig. 9(b)), heat supply (Fig. 9(c)), and electricity supply (Fig. 9(d)).

Table 5. Optimization methods for microgrid

Method code	Method name
m1	Grey Wolf Optimizer
m2	Non-dominated Sorting GA II
m3	Covariance Matrix Adaptation Evo. Strategy
m4	Particle Swarm Optimization
m5	Simple Genetic Algorithm
m6	Particle Swarm Optimization Generational
m7	Self-adaptive DE (de_1220 aka pDE)
m8	Exponential Evolution Strategies
m9	(N+1)-ES Simple Evolutionary Algorithm

Method m3 significantly outperforms other methods in execution time and average amount of RAM usage. At the same time, all methods m1-m3 show similar average processor load. In terms of potential investments (Fig. 9(b)), the most profitable solution is proposed by method m3. However, from a resilience point of view, the most flexible solution to meet the increased heat demand (Fig. 9(c)) is proposed by the method m2. Based on resilience indicator prioritization, method m2 emerges as optimal for local-level IES synthesis when applying the lexicographic multi-criteria selection algorithm. In terms of computational resource efficiency, the best method is m3.

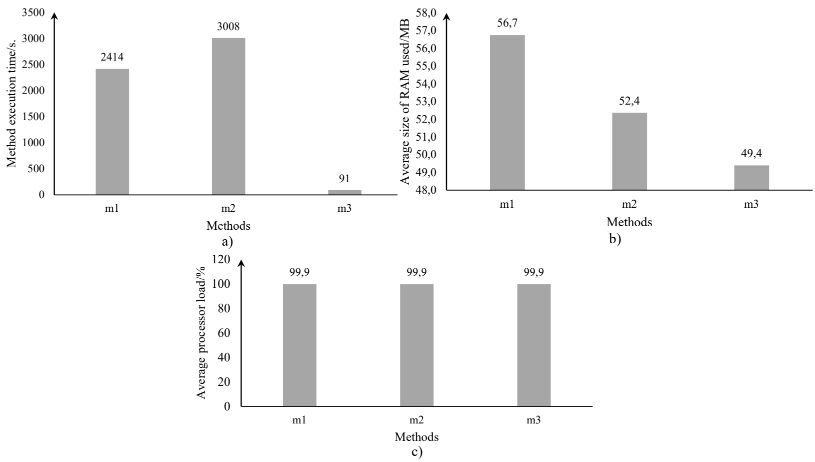

Fig. 8. Efficiency indicators for the use of computational resources: a) method execution time; b) average size of RAM usage; c) average processor load

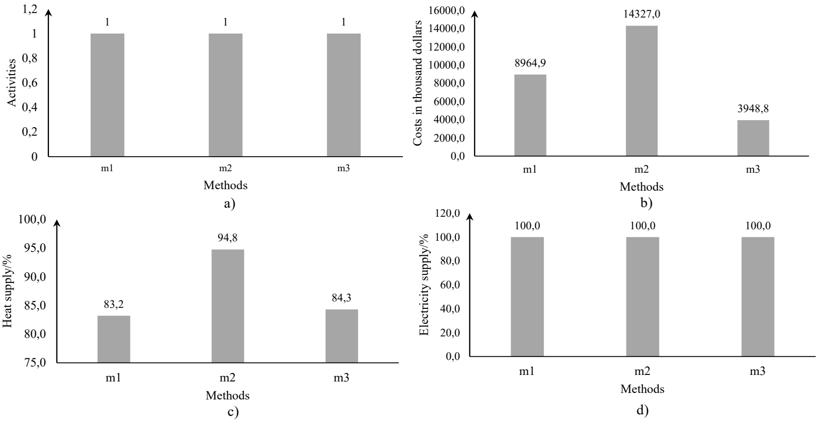

Fig. 9. Metrics that measure the local IES resilience: a) activities; b) costs of thousand dollars; c) heat supply; d) electricity supply

5. Result discussion. We tested the solver-based ESOM acceleration strategy by varying the optimization methods on the top level of the resilient IES design scheme (Fig. 2). We performed the appropriate parameterization of the methods. We used the HiGHS solver, which supports parallelization in solving MILP problems, to compute the energy flows at the lower level of the resilience optimization scheme for both IES examples. The computational results prove that the specificity of IESs of different spatio-temporal scopes determines the composition of the superstructures and affects the selection of the best methods. In the case of a country, the superstructure includes the basic IES configuration and the designed arcs of one of the sectoral energy systems. The basic configuration consists of several dozen nodes connected by backbone lines for energy transport. The designed arcs form a redundant set of activities. Their activation is independent of each other. Therefore, statement (1) contains practically no logical conditions because of the high level of factor aggregation that determines the complexity of the ESOM. However, their computational complexity is high. This is due to the large dimension of the model itself and the significant size of the redundant set of the activities (about 5000). In this respect, we have deliberately chosen a large number of generations (more than 1000). This approach reliably generated required effective activity sets through the resilience optimization scheme. In the case of the microgrid, the high computational complexity of the optimization is determined by the maximum level of data granularity. The test results allow us to draw the following conclusion. For a successful operation of the microgrid resilience optimization scheme under multiple logical conditions, and defining activity relations, it is necessary to dramatically increase the population size compared to the IES resilience optimization at the national level.

There is a wide range of optimization methods available. The selection of the most appropriate method among them is characterized by high computational complexity. This is due to the necessity of repeatedly running each method to calibrate its parameters by varying the combinations of their values. Therefore, specialists are often limited to a comparative analysis of a small number of methods (see, for example, the works [35, 36]). Generally, such limitations are due to the capabilities of the framework used to solve optimization problems and the characteristics of the available computing resources [36]. Unlike the above-mentioned works, FDE-SWFs provides the automation of the testbed creation. The testbed supports multi-method testing, parameter value generation, computational resource allocation, parallel execution, process monitoring, and data collection on IES resilience metrics and computational resource usage. Based on the results of the method runs, the testbed provides a multi-criteria selection of the best method taking into account different sets of indicators and their priorities.

6. Conclusions. We propose a new methodology for the selection of optimization methods used to solve the problem of the IES resilience enhancement at different spatio-temporal scopes. Within this approach, we have developed new models, algorithms, and application software for the IES modeling. We consider IESs as natural and technical systems, taking into account the detail of equipment and technological processes. Our developments also provide sensitivity of the modeling process to the size and degree of uncertainty of the spatio-temporal data. This methodology ensures that methods are selected at an acceptable time. The empirical study of the efficiency of the use of computational resources by optimization methods is carried out in parallel on the testbed using test datasets. The application of the methodology to the selection of optimization methods from the PaGMO library is successfully demonstrated in solving the resilience enhancement problem for two systems: the national-level IES and the microgrid supplying to the typical infrastructure object located in the Baikal natural territory.

The methodology can process numerous IES model classes. It is determined by the possible combinations of values of the factors listed in Table 1 and corresponding to the territorial and industrial levels of the Energy System Optimization Models hierarchy. These factors include ESOM geographical scope, time-series aggregation, optimization method type for the first stages of the IES synthesis problem, and level of system behavior detailing.

We hope that specialists in the field of resilient IES design will in the future consider applying the proposed methodology in practice. However, there are several limitations of this methodology for selecting optimization methods. To reduce the complexity during the optimization method testing, our methodology first simplifies the system behavior and untested disturbance aspects. The completeness of the disturbance scenarios and their number affects the complexity of the IES synthesis (Fig. 2). We also simplify the IES model classes. Since they are solved as MILP problems in the lower level of the resilient IES design scheme, all production, storage, transfer, and conversion technologies have to be linearized. This approximation is valid as these technologies exhibit predominantly linear behavior.

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ОПТИМИЗАЦИЯ ЖИВУЧЕСТИ ЭНЕРГЕТИЧЕСКИХ КОМПЛЕКСОВ

Бычков И.В., Феоктистов А.Г., Воскобойников М.Л., Еделев А.В., Береснева Н.М., Еделева О.А. **Оптимизация живучести энергетических комплексов.**

Аннотация. В настоящее время разработка подходов, повышающих живучесть энергетических комплексов, является весьма актуальным направлением исследований. Такие подходы основаны на структурной и параметрической оптимизации структуры исследуемой системы. Как правило, эти подходы тесно связаны с определенным пространственно-временным диапазоном и конкретным методом оптимизации. Применение разработанных подходов в иных диапазонах зачастую приводит к существенному увеличению времени вычислений и возможному снижению точности решения. Эта проблема обусловлена сложностью моделей оптимизации энергосистем и их различиями. Для решения этой проблемы нами разработана методология выбора наиболее подходящих методов проектирования живучих энергетических комплексов в заданном пространственно-временном диапазоне. Методология основана на методах тестирования в рамках специализированного испытательного стенда и многокритериальном анализе результатов испытаний. Критерии оценки методов включают как сводные метрики живучесть, так и параметры эффективности вычислительных ресурсов. Проиллюстрированы преимущества методологии для проектирования живучих национальных и локальных энергетических комплексов. Несколько десятков методов из известной библиотеки Parallel Global Multiobjective Optimizer были эффективно протестированы в течение 10 часов. Анализ результатов тестирования проводился с использованием различных многокритериальных алгоритмов с учетом приоритетности критериев.

Ключевые слова: энергетические комплексы, повышение живучести, синтез, методы структурно-параметрической оптимизации, многокритериальный анализ, испытательный стенд.

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