A Genetic Algorithm for Optimizing the Lifetime of Power Generation Equipment

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***Abstract* — In this study, we numerically solve an optimization problem of power generation equipment dismantling dynamics. The mathematical modeling aims to make a long-term forecast that determines the most efficient strategy for commissioning new capacities. This approach minimizes total costs, ensuring the required level of electricity demand. The mathematical formulation of the problem is represented through the Volterra integral equation of the first kind with variable limits. A key feature of the problem is determining the required parameter within the integration limits of both the functional and the constraints. The developed approach to finding an approximate solution to this problem relies on a genetic algorithm and factors in the constraints on commissioning capacity during the forecast period and on extending the equipment lifetime. The effectiveness of the proposed approach is illustrated through its comparison with the existing methods.**

***Index Terms* — Electric power system, equipment dismantling problem, Volterra integral equation of the first kind, genetic algorithm.**

I. Introduction

Mathematical modeling provides the fundamental tools for describing physical processes in energy systems. At present, the dissemination of the Smart Grid concept largely depends on the successful application of systems analysis, facilitating a qualitative transition to energy systems with intelligent infrastructure and the effective use of modern information technologies. The current scientific approach to formalizing metamodels, including both their mathematical descriptions and their “physical meanings” [p. 79, 1], should be complemented by conceptual models based on ontologies [1].

Until recently, the primary tools for systems research in the energy sector were mathematical modeling and forecasting methods, complemented by systems supporting strategic decision-making based on semantic models and visual analytics (including cognitive graphics) [3, 4]. Typically, when substantiating strategic decisions, it is necessary to formalize the integration of software tools and a hierarchical knowledge base (both as a whole and its industry components) of selected energy systems at the same level, achieving horizontal integration. This process also involves the systems at different levels, ensuring vertical integration, which includes internal connections. The emergence of high-performance computing systems and supercomputers, along with the increasing complexity of multifactor models, calls for specialized approaches capable of formalizing modeling methods to enhance their computational efficiency. One such approach is related to metamodeling. The development of metamodels is based on the ideas of machine learning [p. 49, 2], utilizing scientific knowledge about the physical laws governing the processes under study.

In the energy sector facing additional difficulties, such as the hierarchical nature of the processes being modeled, the need for real-time decision-making and data processing, and the complex nature of current problems, there is successful experience in integrating modeling and

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forecasting methods with intelligent technologies (including semantic modeling tools, agent-based computing, fuzzy logic methods, and neural networks). The methodological framework of these approaches is detailed in [5–8].

In addition to the methods listed, researchers show sustained interest in algorithms inspired by natural processes, such as genetic and swarm algorithms. These algorithms are often used in conjunction with neural networks as complementary approaches (see, for example, [9]). Genetic algorithms are employed to determine the steady-state conditions of electric networks [10], solve optimization problems [11, 12], and ensure the reliable operation of electrical systems and equipment [13].

As new technologies advance, the complexity of designing the configuration of electrical networks increases. Alternative methods for solving optimization problems to locate equipment and determine electrical parameters are discussed in [14]. An analysis of economic cost characteristics in ensuring reliability revealed the advantages of a heuristic method based on a genetic algorithm compared to an adaptive particle swarm algorithm.

Thus, genetic algorithms, which successfully adapt to various conditions and constraints, are a powerful tool for solving non-standard optimization problems in the energy sector. The purpose of this work is to analyze the effectiveness of a genetic algorithm when used to optimize the replacement of obsolete equipment in a large electric power system (EPS).

II. PROBLEM STATEMENT

Let us consider the problem of forecasting the electric power system (EPS) expansion, which involves formulating a long-term strategy for introducing capacities in a large (combined) system, given the decommissioning of obsolete equipment with a known lifetime. We will assume that all generation capacities have identical characteristics and will write an aggregated model of EPS expansion in the form of a Volterra integral equation of the first kind [15]:

$$\int_{t-c(t)}^{t} \beta(t,s)x(s)ds = p(t),\ t\in[t_0,T], \tag{1}$$

subject to

$$x(t) = x^0(t),\ t\in[t_0-c(t_0),t_0), \tag{2}$$

$$x(t)\ge 0,\ t\in[t_0,T], \tag{3}$$

where $x(t)$ is the desired total generation equipment commissioning in EPS at time t; $\beta(t,s)$ is the coefficient of intensive use at time t of a power unit commissioned previously at time s; $p(t)$ is the expert-defined future dynamics of power consumption (load); $c(t)$ is the lifetime of the oldest power unit in the EPS at time t; $x^0(t)$ is the known dynamics of equipment commissioning within the prehistory $[t_0-c(t_0),t_0)$.

Using models (1)–(3), consider the problem of selecting long-term capacity input strategies $x(t)$ that, given the decommissioning of obsolete equipment, ensure a specified demand $p(t)$, while minimizing the total costs over the forecast period for new capacity installation and operation of power generation units. The problem formulation is as follows:

Find

$$c^*(t) = arg\min_{c(t)\in C} I(x(t),c(t)), \tag{4}$$

where

$$I(x(t),c(t)) = \int_{t_0}^{T} a^{t-t_0}\left\{\int_{t-c(t)}^{t} u_1(t-s)u_2(s)x(s)ds\right\}dt + \int_{t_0}^{T} a^{t-t_0}k(t)x(t)dt, \tag{5}$$

$$C=\left\{c(t)\,\middle|\,\underline{c}\le c(t)\le\overline{c},\ c'(t)\le 1,\ t\in(t_0,T]\right\}, \tag{6}$$

under the constraints on the phase variable $x(t)$ (1)–(3). The first term in (5) corresponds to operating costs, the second represents the costs of capacity introduction for the entire forecast period. The constraint $c'(t)\le 1$, which originates from the non-decreasing nature of the function $t-c(t)$, means that the rate of aging for the oldest component cannot exceed the rate of natural aging.

The notation used is as follows: $u_1(t-s)$ is the increase coefficient at time t for the operating costs of equipment commissioned at time s; $u_2(t)$ is the specific (unit) operating costs of equipment commissioned at time t; $k(t)$ is the costs of commissioning a power unit at time t (capital costs); a^{t-t_0} is the costs discount coefficient, $0<a<1$. These functions, as well as $\overline{c}$, $\underline{c}$, $\beta(t,s)$, $p(t)$, and the power units $x^0(t)$ commissioned during the prehistory $[t_0-c(t_0),t_0)$ are considered known (defined by experts).

The assumptions made in the model calculations are as follows. The forecast period is 50 years, from 2000 to

TABLE 1. Dynamics of Equipment Commissioning Within the Prehistory, MW

Year	$x^0(t)$	Year	$x^0(t)$
1963	6 239	1982	4 093
1964	5 437	1983	5 087
1965	4 883	1984	5 515
1966	4 602	1985	8 311
1967	5 149	1986	4 083
1968	5 494	1987	6 662
1969	8 166	1988	5 787
1970	7 556	1989	1 800
1971	6 206	1990	4 000
1972	6 058	1991	2 100
1973	5 649	1992	700
1974	5 719	1993	2 700
1975	7 225	1994	2 400
1976	6 144	1995	1 000
1977	5 062	1996	1 350
1978	4 910	1997	640
1979	8 199	1998	830
1980	9 647	1999	850
1981	5 946	2000	680

2050, $([t_0, T] = [2000, 2050])$. The lifetime $c(t)$ is 38 years (the real mean equipment lifetime in the Russian power industry). Data for equipment commissioning within the prehistory are given in Table 1. Since the system characteristics remain invariable over the forecast period (the system is stationary), the function $\beta(t,s)$ depends only on the difference $t-s$. Therefore, one can assume that $\beta(t,s) \equiv \beta(t-s) \equiv \beta(\tau)$. This function remains at 1 until $\tau = 30$, then drops down to 0.9 over 50 years, vanishing after 70 years. Power consumption $p(t)$ for 2000 is consistent with the reported data (177 907 MW). Between 2001 and 2050, the demand for electricity is expected to grow at a rate of 2% annually at the beginning of the forecast period, declining to 1% by the year 2050.

The data assumed for specific costs are given in Table 2. They reflect the projected increase in specific capital costs and the potential reduction in specific fuel consumption due to the transition to relatively expensive, environmentally friendly power plants. The values of costs are not adjusted for inflation.

The coefficients of growth in operating costs $u_1(t-s) \equiv u_1(\tau)$ as the equipment ages are given as follows:

$$u_1(\tau) = \begin{cases} 1, \ \tau \le 30, \\ 1.03^{\tau-30}, \ \tau > 30. \end{cases}$$

Thus, after the standard equipment lifetime is achieved, an exponential increase in operating costs is expected. The costs discount coefficient a is 0.97.

Solving problems (1)–(6) based on real-life data with various parameter variations is discussed in detail in [15, 16]. These studies utilize a heuristic algorithm to find a long-term generation capacity input strategy. They rely on a class of piecewise linear functions, reducing the problem to a linear programming formulation, which is solved using the General Algebraic Modeling System (GAMS). GAMS is a software environment designed for modeling linear, nonlinear, and mixed-integer optimization problems [17]) with the OSL solver. In this paper, we propose solving the same problem using a genetic algorithm.

III. APPLICATION OF GENETIC ALGORITHM TO PROBLEM (1)–(6)

Genetic algorithms are a type of evolutionary computation that solve optimization problems using natural evolution techniques such as inheritance, mutation, selection, and crossover. The basic operators of genetic algorithms include selection, crossover, and mutation. Crossover (the process of combining two parents to create offspring) plays a central role in genetic algorithms. Due to the flexibility of the algorithm, it can be applied to a wide range of problems.

The stages of the simplest genetic algorithm include:

1) Creation of the initial population;

2) Evaluation of the fitness for each individual in the population;

3) Crossover of the individuals;

4) Mutation of the individuals;

TABLE 2. Specific Operating and Capital Costs, USD/kW

Year	$u_2(t)$	$k(t)$
1960	220	
1970	200	
1985	175	
1995	175	900
2005	170	850
2010	165	800
2020	160	900
2030	150	1 000
2040	140	1 100
2050	130	1 200

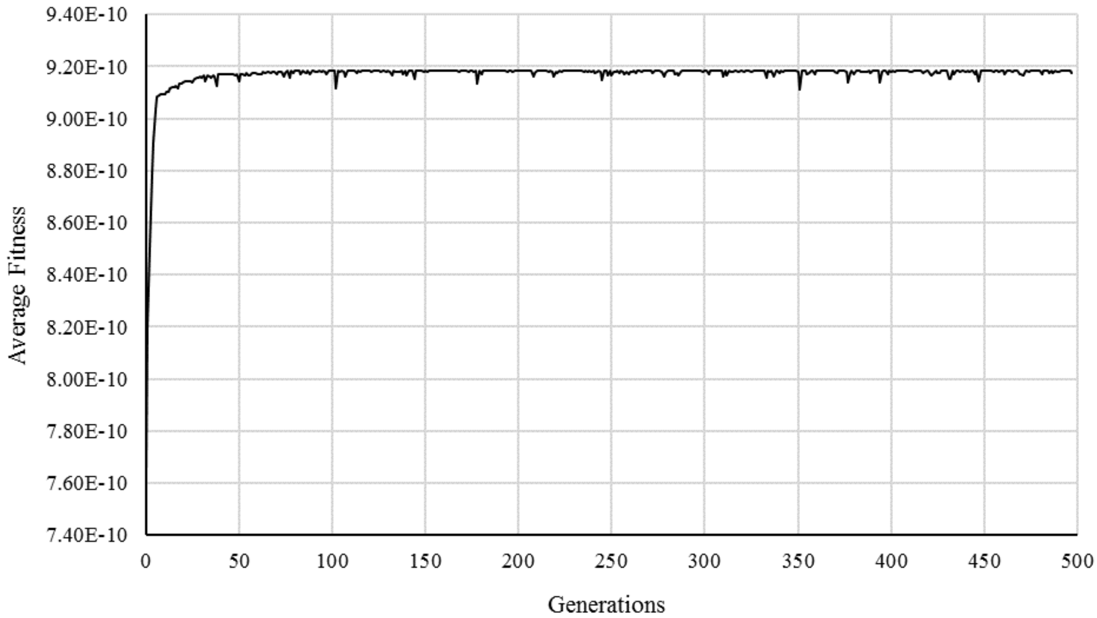

Fig. 1. Dynamics of average fitness.

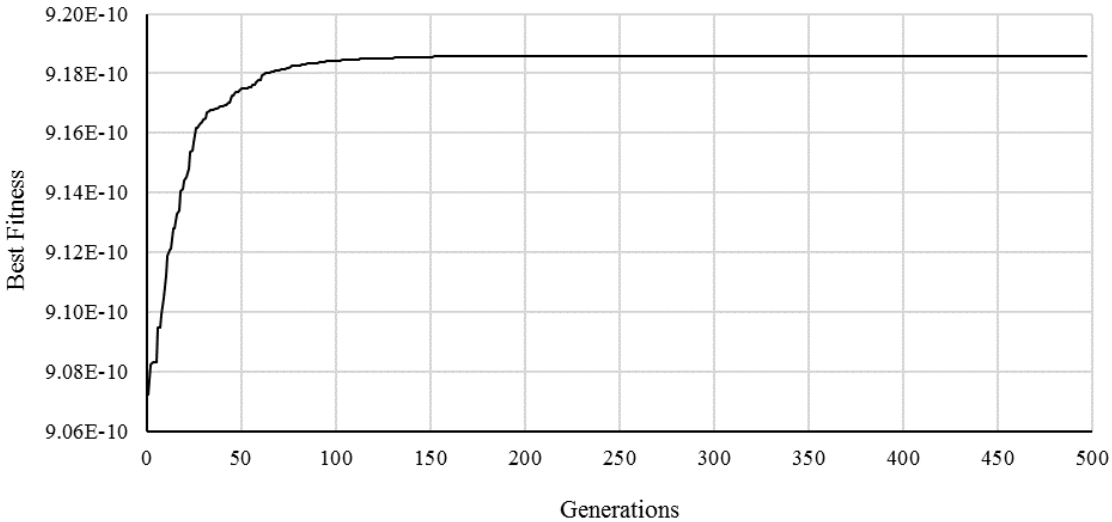

Fig. 2. Dynamics of best fitness.

5) Formation of a new generation.

These steps are repeated until the result meets the specified requirements or until one of the following conditions is satisfied:

- The number of generations (cycles) reaches a predetermined maximum;
- The allotted solving time reaches a predetermined maximum;
- A predefined stopping criterion is met.

Consider the application of a genetic algorithm to problem (1)–(6), using data from [15, 16]. In the first step, an initial population is created. According to the data from [16], the forecast period in the problem spans 50 years, from 2000 to 2050 ($[t_0, T] = [2000, 2050]$), which means that each individual will consist of a set of 50 “genes,” i.e., values corresponding to the maximum equipment lifetime in the forecast year. These genes are generated randomly but following the lifetime constraints specified in (6). The number of individuals in a population for problems solved using genetic algorithms is chosen arbitrarily. However, a larger population provides greater genetic diversity and, consequently, the potential for more optimal solutions. In this case, each population consisted of 100 individuals.

After creating the population, it is necessary to calculate the fitness value for each individual. Since the optimization problem aims to minimize equipment operation costs, the fitness of a particular individual is computed as the inverse of the costs associated with the use of that individual's genes in the objective function (5).

Once the fitness of each individual in the population is evaluated, they are ranked from the most to the least fit. Then, random individuals are paired and crossed to create a new population. In this problem, a single-point crossover is employed, where a single random point is selected on both parent gene sequences. The genes are cut at this point, and the segments beyond the point are exchanged between the parents, resulting in two new offspring that inherit genes from both parents. The parent selection operator used is panmixia — both parents are chosen randomly from the population with equal probability. The crossover probability was set to 0.7. After two parents are selected, there is a 70% chance they will produce two offspring that are transferred to the next population, and a 30% chance that the parents themselves will be passed to the next population unchanged. Before crossover, it is necessary to ensure that the constraints specified in (6) are not violated.

To prevent stagnation in local optima and premature convergence of the population in genetic algorithms, the concept of mutation is implemented. Mutation is typically applied after crossover and involves changing an individual's genes to randomly selected values within the specified constraints, with a predetermined probability. Since each gene of an individual can undergo mutation, it should occur with a sufficiently low probability to avoid turning the method into a purely random search. In this problem, mutation was set to occur with a probability of 0.01 and was designed not to violate the lifetime constraints specified in (6).

Next, it is necessary to select individuals that will participate in the next iteration of the algorithm from those resulting from crossover and mutation. To ensure that the new population is at least as good as the previous one and that optimal solutions are not lost during evolution, the concept of elitism is implemented. This involves transferring five individuals with the highest fitness values directly to the next generation without any changes. The remaining members of the population are filled with individuals produced through crossover and selected via tournament selection: a subset of the best solutions is randomly chosen, their fitness values are compared, and the winner is transferred to the new population. The size of one tournament is 2, the individuals are compared pairwise.

The stopping criterion for the algorithm is population degeneration, i.e., a situation where diversity within the candidate solutions decreases to such an extent that most individuals become very similar or even identical. To monitor this, each iteration compares the fitness of the best individual in the current population with that of the best individual in the previous generation. If the difference

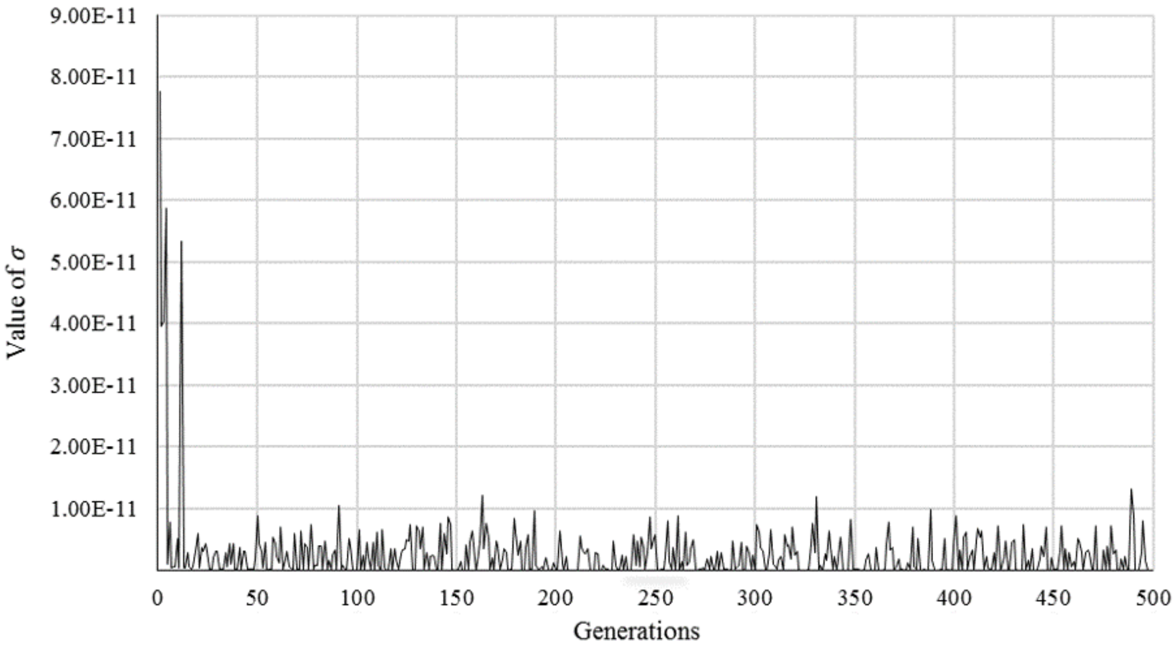

Fig. 3. Dynamics of population diversity σ ***.***

between these fitness values is less than a predefined threshold, the algorithm terminates and outputs the individual with the highest fitness observed throughout the entire cycle. As an additional constraint, the maximum number of generations was 500. Ideally, during degeneration, only one most fit individual and its genetic equivalents remain in the population.

The convergence of the algorithm was assessed using graphs of fitness variation over generations. The best and average fitness values were calculated for each population (see Figs. 1 and 2).

The population diversity metric was defined as the standard deviation of fitness values among individuals:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(f_i - \overline{f}\right)^2}\,, \tag{7}$$

where f_i is the fitness of the *i*-th individual, $\overline{f}$ is the mean population fitness, and N is the population size. Since the fitness function was defined as the inverse of the cost value, the absolute values of σ were extremely small (on the order of 10^{-11}). Nevertheless, the dynamics of σ across generations allow for the correct assessment of relative diversity and identification of premature convergence tendencies: a drop of σ toward zero indicates population degeneration, while stable values point to the preservation of variability (Fig. 3).

To check for the premature convergence, the population diversity metric σ and the best fitness were monitored. The algorithm was considered prematurely converged if σ approached zero and no improvement in the best fitness was observed over the subsequent 50 generations.

In this study, the fitness reached all-time high values within the first 100 generations, with the most significant improvement occurring around generation 30, where σ also dropped sharply to near-zero. After this point, the best fitness remained stable while diversity fluctuated near zero. This indicates that the algorithm quickly found near-optimal solutions and that further increases in diversity do not improve the performance. Therefore, despite the low σ values, the algorithm demonstrates rapid and correct convergence rather than premature stagnation, which is supported by the fact that the algorithm consistently produced near-optimal solutions after 20 consecutive simulations.

To assess the accuracy of the sample mean, a 95% confidence interval was calculated. The confidence interval for the mean improvement value μ with a sample size of $n = 20$ was determined using the formula:

$$\overline{x} - t_{\alpha/2,n-1}\frac{s}{\sqrt{n}} \le \mu \le \overline{x} + t_{\alpha/2,n-1}\frac{s}{\sqrt{n}}\,, \tag{8}$$

where $\overline{x}$ is the sample mean, s is the sample standard deviation, $t_{\alpha/2,n-1}$ is a critical value of Student's *t*-distribution at a significance level of $\alpha = 0.05$ and $n-1$

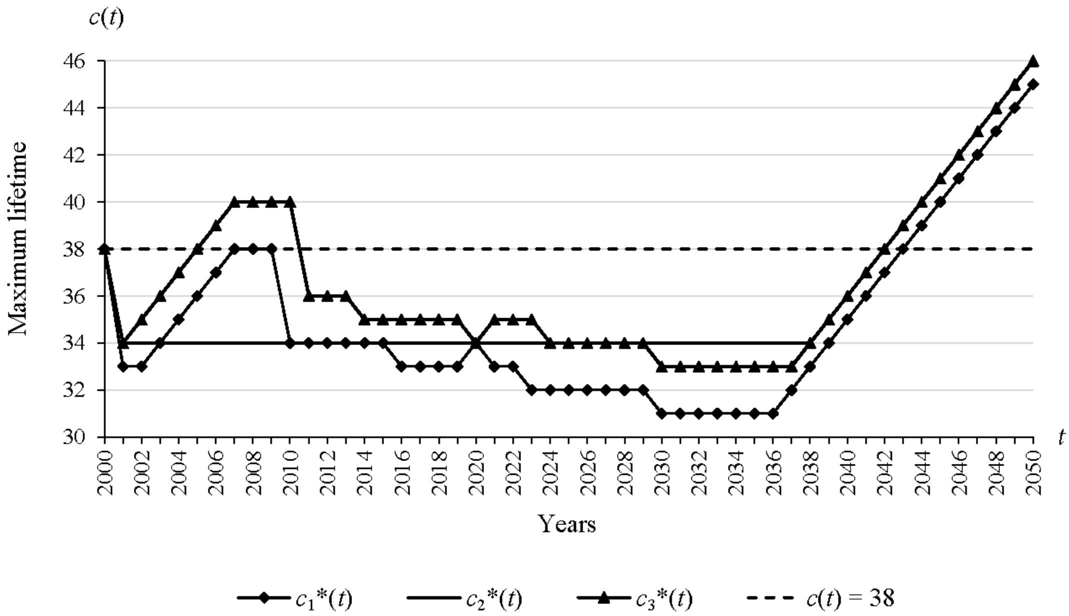

Fig. 4. Dynamics of optimal equipment lifetime.

degrees of freedom.

The statistics obtained for the sample of 20 simulations were the following: the sample mean improvement $\bar{x} = 1.450$ and the standard deviation $s = 0.368$. At a 95% confidence level and 19 degrees of freedom, the critical value of Student's *t*-distribution was $t_{0.975,\,19} = 2.093$.

Thus, the 95% confidence interval for the mean improvement value is $1.450 - 2.093\frac{0.368}{\sqrt{20}} \le \mu \le 1.450 + 2.093\frac{0.368}{\sqrt{20}}$, i.e., $1.277 < \mu < 1.623$. This suggests that with the 95% probability, the true population mean improvement lies within the calculated interval.

IV. Results of the Computational Experiment

The results of the conducted computational experiment and those obtained earlier [16] were compared in [18]. Figure 4 [18] shows the dynamics of the lifetime $c_1^*(t)$ obtained using the genetic algorithm. This strategy reduces the initial value of the objective function $I(38)$ (the average equipment lifetime assumed in 2000) by 1.72%. The lifetime dynamics $c_2^*(t)$ were determined by a systematic exhaustive search within the class of piecewise linear functions [16]. As a result, the total costs decrease by 1.47%. The lifetime dynamics $c_3^*(t)$ were obtained by reducing the original problem to a linear programming problem and solving it using GAMS [17]. The integral costs for this strategy are lower than $I(38)$ by 1.52%. Thus, the use of the genetic algorithm provides a variation of equipment lifetime $c(t)$, exhibiting the best result among those presented.

V. Further Development of the Work and Conclusions

The modern approach to operating complex dynamic objects is implemented through the concept of digital twins [19]. This concept involves not only the use of mathematical models based on physical laws of operation but also virtual data reflecting the structure, performance, technical condition, and other production characteristics. Thus, digital twins facilitate both creating a virtual prototype of a real-life technical device or technological process and testing control strategies for its lifecycle, considering the specific stage of the dynamic object's evolution. A key feature of today's energy sector is intelligent systems, which are currently defined as the unity of cyber-physical systems, software, and hardware, including those implementing the concept of digital twins.

The relevance of developing a methodological approach to constructing digital twins that relies on ontological engineering of the subject area is undeniable. Systems with a large number of sensors to monitor their operation are susceptible to interference or damage. Adapting semantic modeling techniques for resource-constrained devices can be useful for solving such problems [20]. The availability and performance of ontologies based on semantic modeling, particularly focusing on applications in resource-constrained devices are discussed in [20]. The study highlights the necessity of developing suitable ontologies and importance of their availability for the energy domain [22].

A key challenge in modeling complex systems is managing the combinatorial complexity of operational parameters, configurations, and potential failure conditions. Genetic algorithms offer a powerful approach to address this challenge, enabling the exploration of large solution spaces and the discovery of optimal or near-optimal strategies for system operation and control. In this context, genetic algorithms represent system components, operational decisions, or control parameters as genes within candidate solutions, while chromosomes represent a full configuration or control strategy for the system over a defined period.

For complex dynamic systems, genetic algorithms can interact directly with the digital twin: the twin provides realistic evaluation of each candidate solution, simulating system behavior under physical and operational constraints.

A promising tool for implementing a conceptual approach to modeling complex dynamic systems is high-level Petri nets. A method for interpreting coloured Petri nets is proposed in [23] to design static and dynamic event processing systems within the framework of the Semantic Web based on the SPARQL language [24]. The ontology of coloured Petri nets is considered at the level of TBox (terminological box) and ABox (assertion box). Specifically, a general description such as "There is X such that $P(X)$" contains the subject X and predicate $P(X)$ from the TBox, as well as x_i, $P(x_i)$ from the ABox, where x_i belongs to X, and $P(X)$ is a predicate that performs different functions in both the TBox and ABox. Additional insights from [25] enrich the syntactic description of the Petri net with semantic information by transitioning to categorical attribute statements [26], which are free from ontological assumptions, where an object $Y = P(X)$. This enables the relationship between X and $P(X)$ to be interpreted in terms of logical relations. Integration of Petri nets into digital twin models within the energy sector is explored in numerous studies, with researchers employing varying levels of model complexity and considering the hierarchical structure of energy systems [27]. In particular, [28] presents an aggregation process based on the Unified Modeling Language (UML), illustrated in [Fig. 4, 28] titled “DDHPN Integration in Digital Twin Model.” A dedicated block presented in this Figure suggests the use of empirical methods to optimize operating parameters. This optimization process relies on inputs from two other components: the “Energy Behavior Model” and the “Production Demand Information” blocks. Optimization of operating parameters can be handled through a genetic algorithm. By encoding Petri net states or transition priorities as genes, the genetic algorithm can optimize control strategies dynamically, identifying sequences of events or operational adjustments that maximize system performance or reliability.

Thus, the approach to constructing digital twins using coloured Petri nets and optimizing them with the genetic algorithm ensures a comprehensive framework for simulating, analyzing, and optimizing complex dynamic systems. This approach facilitates iterative exploration of operational strategies, automated adaptation to changing conditions, and the discovery of solutions that might be difficult to identify using conventional methods.

This study numerically solves an optimization problem of the generation equipment dismantling dynamics. The mathematical formulation of the problem is represented though the Volterra integral equation of the first kind with variable integration limits. A genetic algorithm was implemented and tested for solving the problem. The algorithm factors in the constraints on both the commissioning of generation equipment during the forecast period and the extension of the equipment lifetime. The effectiveness of the proposed approach was demonstrated through its comparison with the previously used methods.

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