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Application of a genetic algorithm to solve the problem of scaling hydrogen systems.

The work aims to develop a robust tool for scaling hydrogen systems and their energy consumption using a genetic algorithm.
Relevance. The most common method of hydrogen production is water electrolysis, which requires a sufficient amount of electricity. If electricity sources are insufficient, this can put additional strain on the power grid, especially during peak consumption periods. Since 87% of hydrogen plants currently use hydrogen on-site (instead of generating it and then transporting it for use), there is a need for optimization in this area to improve energy efficiency and sustainability.
Current research analyzes the improvement of hydrogen systems in terms of the cost-effectiveness of systems using renewable energy sources and the reduction of hydrogen logistics costs by applying linear programming and particle swarm optimization methods.
However, these works are mainly focused on hydrogen production systems based on a single electrolyzer and do not aim to assess the feasibility of using multiple units. As a result, the topic of cost optimization and maintenance strategies for multi-electrolyzer systems remains less explored, as well as the related problem of their dispatching.
Research methods. Stochastic methods were used to solve the problem of finding the best startup queue for electrolysis units, and the effectiveness of the genetic algorithm for solving this problem was tested.
Results. A model for optimizing the peak power consumption of an electrolysis system was built, and the configuration evaluation function and objective function for system optimization were determined. The choice of a stochastic optimization method is justified by checking the objective function for the properties necessary for the effectiveness of traditional optimization methods, namely, continuity, differentiability, smoothness, and convexity. The effectiveness of the genetic method was tested in comparison with the gradient descent method on examples with different configurations of electrolyzers (similar and different types).
Conclusions. These calculations have confirmed that the genetic algorithm has stable results and is effective in finding the global optimum, while the gradient descent may stop at local minima and require additional adjustments to achieve the optimal solution. Using the genetic algorithm method, we obtain results that give an approximate optimal result for a fixed number of steps. This approximate result, as shown in the problem with the placement of 10 electrolyzers, gives significant results — the peak electricity consumption has decreased by almost 40%.
Further research can be aimed at improving the parameters of the algorithm, in particular, adaptive tuning of the mutation and crossover operators to increase the convergence rate.
keywords: *Optimization, Stochastic (non-deterministic) methods, Genetic Algorithm, power consumption, hydrogen systems, electrolysis unit.*

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1 Introduction

Green hydrogen is one of the most promising sources of clean energy. Growing demand for energy, the need to reduce greenhouse gas emissions, and the desire for sustainable development are driving the active implementation of hydrogen technologies. The most common method of hydrogen production is the electrolysis of water, which requires sufficient electricity [1]. If electricity sources are not enough, this can cause an additional load on the power system, especially during peak consumption periods.

The simultaneous use of several appliances creates a large electrical and mechanical load on the power system. Unevenly distributed power consumption can lead to an increase in peak power and the occurrence of shock mechanical loads on the power system (which in turn can cause an impact on the turbines of the generating unit and cause their failure).

To avoid such scenarios, installations need to have a controlling entity (controller) that will manage the startup queue in such a way as to minimize the amount of power used simultaneously and avoid shocks during the completion of the installation's cycles. This controller performs the task of finding the best possible startup queue.

2 Problem formulation and literature review

Optimization techniques are crucial in engineering, business, and science because they help improve efficiency, reduce costs, and enhance performance. Optimization techniques ensure better performance, lower costs, and smarter decision-making across industries.

As 87% of existing hydrogen-generating plants currently use hydrogen on-site (instead of generating and then transporting and selling it)[1], there is a need for optimization in this area to improve energy efficiency and sustainability.

The most common method of hydrogen production is the electrolysis of water, which requires sufficient electricity [2]. If electricity sources are scarce, this can put additional strain on the power grid, especially during peak consumption periods.

Optimization helps to reduce energy consumption and carbon footprint.

The most promising method for this is the integration of a smart grid-based control system that optimizes the distribution of electricity. [3, p.1]

Various optimization and computational intelligence techniques has already been incorporated into large-scale grids; for example using artificial intelligence, heuristic, and evolutional optimization to analyze optimal power flow, power flow, SE, stability, and unit commitment.

In his guide to smart grids, James Momoh notes that: The classical optimization tools currently used cannot handle the adaptability and stochasticity of smart grid functions. Thus, the computational tools and techniques required are defined as a platform for assessment, coordination, control, operation, and planning of the smart grid under different uncertainties. [3, p.100]

In modern studies, improvements in hydrogen systems are analyzed from the perspective of cost efficiency in systems utilizing renewable energy sources [4,5] and the reduction of hydrogen logistics costs [6,7] through the application of linear programming and PSO methods.

However, it is important to note that these works primarily focus on hydrogen production systems based on a single electrolyzer and do not aim to assess the feasibility of using multiple units. As a result, the topic of cost optimization and maintenance strategies for multi-electrolyzer systems remains less explored, along with the associated challenge of their dispatching.

If we abstract from the hydrogen-specific context and focus on dispatching as an optimization objective, insights can be drawn from dispatching methodologies applied in power systems [8,9,10], emergency management [11], and construction [12]. These fields offer a well-established foundation for the practical application of stochastic optimization algorithms such as Lyapunov optimization, PSO, and GA in solving complex optimization problems.

3 The research aim and problem statement

The purpose of this study is to develop a mathematical and software tool to minimize the amount of power consumed by a hydrogen-generating system.

An optimization problem is a mathematical task in which it is necessary to find the best (optimal) solution among all possible options, taking into account certain constraints and the optimality criterion (objective function).

The optimality criterion in determining the best start-up shift for electrolysis units is the lowest peak power consumption by the hydrogen generating system.

Task variables:

- n - number of units.
- t - time
- $Af(t)$ - function that describes the voltage change for the electrolysis unit
- $\overline{Af}$ - a vector of functions that describe the voltage change for each unit in the system
- $\overline{I}$- a vector describing the number of amperes used by each unit to produce hydrogen
- $\overline{\varpi}$ - start time offset vector of each unit

Equation (3.1) is a function that characterizes the system costs (power) at a point in time, further Sf. Of(3.2) - an estimation function of a specific system configuration.

$$Sf\ (t, \overline{Af}, \overline{I}, \overline{\varpi}, n\ ) = \sum_{i=0}^{n} |(Af_i\ (t + \varpi_i) \cdot I_i)| \tag{3.1}$$

$$Of\left(\overline{Af}, \overline{I}\ \overline{\varpi}, n\right) = max_{t\in[0,2\pi]} Sf\ (t, \overline{Af}, \overline{I}, \overline{\varpi}, n\ ) \tag{3.2}$$

Sf is a function that estimates a specific system configuration at a specific shift. The configuration consists of three main components. First, a set of functions $\overline{Af}$ describes the voltage change for each unit. Second, a vector $\overline{I}$ represents the number of amperes each unit uses to produce hydrogen. Finally, a vector $\overline{\varpi}$ defines the start time offset for each unit.

The functions describing the voltage change $\overline{Af}$ and the vector describing the number of amperes $\overline{I}$ are defined as the input conditions of the problem, and the start time offset vector $\overline{\varpi}$ is a parameter generated from the optimal solution space.

- M - a matrix of start time offset vectors of each unit or a function that generates a start time offset vector
- K - is the number of shift vectors.

$\mathrm{F}(\overline{Af}, \overline{I}, M, n, k)$ (3.3) - is the estimation function by which the optimization is performed, $\min \mathrm{F}\left(\overline{Af}, \overline{I}, M, n, k\right)$ - objective function.

$$\mathrm{F}\left(\overline{Af}, \overline{I}, M, n, k\right) = min_{i\in[0,k]}\ Of\ (\overline{Af}, \overline{I}, M_i, n\ ) \tag{3.3}$$

When minimizing, we are interested in the amount of power consumed, since it is this amount that determines the restrictions on the grid, so we use the modulo power consumption in the following. Next, we need to define an estimating function that measures the amount of consumption.

The estimation function for this task is the maximum power value during the operation of the electrolysis system - the peak amount of power consumed. Accordingly, the objective function of optimization is the smallest peak power consumption.

4 The research aim and problem statement

The task of choosing an optimization method is to determine the most efficient approach for a particular class of problems, taking into account their mathematical properties and computing resources. Since different optimization methods have their limitations and peculiarities, choosing the right method depends on the characteristics of the objective function and constraints. In general, optimization methods can be classified into the following two types: Traditional (deterministic) methods and Stochastic (non-deterministic) methods.

Traditional (deterministic) methods are not always able to solve optimization problems efficiently. They are usually based on such properties as continuity, differentiability, smoothness, and convexity of the objective function and constraints (if any). The absence of at least one of these properties makes it difficult to apply traditional optimization methods [13]. Therefore, to further search for a solution to this problem, we checked these properties.

Continuity. The functions that describe the power consumed by the electrolyzer are periodic and without discontinuities. They are represented as the sum of sinusoidal functions (sines and cosines) with different frequencies and amplitudes. Since sines and cosines are continuous functions, their sum also retains this property. In addition, the set of possible values for the maximum of the approximation functions is compact (closed and bounded), which confirms the continuity of the corresponding function.

Differentiability. The minimum function of the target function is not differentiable since it may have a fracture at the minimum point. For example, if a pure sinusoidal signal models the behavior of an electrolyzer, then when the startup is shifted by 90 degrees, the problem equivalent to max(sin(x), cos(x)) arises. At the points where these functions are equal, a sharp transition occurs, making it undifferentiable.

Because of this, traditional optimization methods cannot be applied to this problem.

Using a direct search of possible shift operations is also inefficient because it generates numerous variants to be checked. To solve the problem in this way, it is necessary to check all possible combinations of startup time shifts of n units with k number of shifts. Accordingly, the number of such combinations is the number of placements with repetitions of n elements by k elements [14 p.14]. $A_n^k = n^k$.

Therefore, for 3 units and 21 offset options (from 0 to 60 minutes in increments of 3), the number of combinations will be ., for 4 units 194481, and for 5 units 4084101. When the quality and number of units change, the complexity of the execution time increases significantly. In this case, the complexity is $\Theta(\phi) = n^k \cdot t$ (where t is the number of steps required to calculate the estimation function).

Therefore, one of the stochastic algorithms should be chosen instead. The choice of a stochastic optimization method depends on the characteristics of the problem, such as the dimensionality of the solution space, the differentiability of the function, the constraints, and the required accuracy.

It is worth noting that due to the ability to work with complex, multidimensional or discrete optimization problems with many local optima, evolutionary algorithms are often used to solve scheduling problems. [15, p.4 Table 1].

That is why it was decided to select a genetic algorithm to solve this problem.

5 Genetic algorithm

A genetic algorithm is an evolutionary search algorithm used to solve optimization and modeling problems by sequentially selecting, combining, and varying the desired parameters using mechanisms that resemble biological evolution. The specific feature of the genetic algorithm is the emphasis on the use of the “crossover” operator, which performs the recombination of candidate solutions, the role of which is similar to the role of crossing in living nature [16].

```
population = INIT() //Initialize the population using.
best_solution = None
best_fitness = negative infinity.
FOR Number_of_generations:
    // the fitness of each individual in the population
    fitnesses = [FITNESS(population)]
    if max(fitnesses) > best_fitness:
        best solution, best_fitness = max(fitnesses)
    new_population = []

    FOR population_size / 2:
        parent1, parent2 = SELECT(population)
        child1, child2 = CROSSOVER(parent1, parent2)
        child1, child2 =MUTATE(child1, child2)
        new_population.add[ child1, child2]
    // Replace the old population with the new population.
    population = new_population
// Return the best solution and its fitness.
return best_solution, best_fitness
```

Scheme of the genetic algorithm in the form of pseudo-code

The main stages of the genetic algorithm:

Creation of the initial population. The first step is to create an initial set of solutions (chromosomes) that can be generated randomly or based on certain assumptions. In our case, it is assumed that the values are generated randomly in the range from 0 to 60 minutes (from 0 to 2). The number of chromosomes in each group corresponds to the number of electrolysis units, and the total number of solution groups is set manually and can be increased to improve search efficiency.

Performing iterations until the stop criterion is reached. The process is repeated until the algorithm's stopping criterion is met (in this case, reaching a certain number of generations or steps).

Evaluating the suitability of solutions (fitness function). For each element of the population, a fitness function value is calculated that reflects the quality of the solution in the context of the problem. In this case, the estimation function $Of(\overline{Af}, \bar{I}\,\overline{\varpi}, n)$ is used.

Selecting individuals for the next generation ("selection")

The chromosomes that will be used to create the next generation are selected. Tournament selection is used in this process: several chromosomes are selected, and the best one moves on.

Crossover and/or mutation

In this implementation, both mechanisms are used.

- **Crossover:** new chromosomes are formed by combining pairs of initial solutions. Universal crossing is used (5.1), in which each gene (the offset of a particular unit i) is inherited from the parents in proportion to a random value within [0;1]:

$$\varpi_{ni} = \alpha \cdot \varpi_{1i} + (1-\alpha) \cdot \varpi_{2i} \qquad (5.1)$$

- **Mutation:** a random introduction of minor changes to the genes of a chromosome. In this case, a Gaussian mutation is used, which involves changing the value of a gene within the permissible range.

Formation of a new population. A new population is created, consisting of the resulting descendants (the results of crossing and mutation) that replace the previous population.

6 Numerical results

To validate the proposed method, we will test the proposed solution to the problem of producing $354.538m^3$ of hydrogen per hour. The function $Af(t)$ describing the voltage change for the electrolysis unit is given in Table 1, and the approximation based on this table $Af(t)$ (6.1).

$$Af(t) = -\frac{0.58}{2} - 0.46\cos(t) + 1.63\sin(t) + 0.19\cos(2t) - 0.15\sin(2t) + 0.44sin(3t) \qquad (6.1)$$
$$+4cos(4t) + 0.03six(4t) + 0.06cos(5t) + 0.2 * sin(5t)$$

Table 1. time series of voltage changes of the full cycle of hydrogen and oxygen production during electrolysis using the Fe electrode assembly (sponge). Current density: I = 0.015 A/cm^2

Таблиця 1. Зміна напруги повного циклу виділення водню і кисню під час електролізу з використанням електродної збірки Fe (губчасте). Щільність струму: I = 0,015 A/см^2

T	0	1,5	3	4,5	6	7,5	9	10.5	12	13,5	13,5	15	16,5
U	0	0.31	0.37	0.41	0.47	0.51	0.61	0.68	0.77	0.88	0.88	1.01	1.2
T	18	19,5	21	22,5	24	25,5	27	28,5	30	31,5	33	34,5	36
U	1.31	1.42	1.51	1.57	1.71	1.4	0	-0.43	-0.78	-1.13	-1.43	-1.62	-1.71
T	37,5	39	40,5	42	43,5	45	46,5	48	49,5	51	52,5	54	
U	-1.76	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	0	

To produce $1m^3$ of hydrogen, our electrolyzer consumes 4.24 kW of electricity [17]. Therefore, to produce $354.538m^3$ of hydrogen, we need to spend 1503.244 kW of electricity.

In order to verify the suitability of the genetic algorithm, the first exercise compares its results with the results that can be obtained using the gradient descent algorithm. Consider a situation in which 10 identical electrolyzers produce the required amount of hydrogen, each of which has a plate area of $75162.2cm^2$. The use of the direct search method is not advisable since 60^{10} possible combinations need to be checked to calculate qualitative results (with a time step of at least 1 minute). The results of the calculations are shown in Table 2.

Table 2: Comparison of the peak power obtained by 5 rounds of optimization using the genetic algorithm and the gradient descent method.

Таблиця 2: Порівняння пікової потужності, отриманої за 5 раундів оптимізації з використанням генетичного алгоритму та методу градієнтного спуску.

genetic algorithm	gradient descent method
915.43	1011.83
903.64	953.05
918.53	952.18
913.32	1000.05
924.14	984.40

The best result obtained with gradient descent in this configuration has a maximum peak power of 952 kW (startup queue: 46.69 min, 7.09 min, 37.81 min, 32.92 min, 53.29 min, 22.43 min, 20.36 min, -0.26 min, 11.62 min, 39.56 min). The genetic algorithm provided the best result with a peak power of 903 kW (start-up queue: 15.26 min, 27.31 min, 6.55 min, 18.07 min, 30.72 min, 51.77 min, 2.54 min, 42.52 min, 53.78 min, 38.82 min).

We also investigated the algorithm's effectiveness in two more cases. The first is a configuration of three identical electrolyzers, each with a plate area of $125270.3cm^2$, and the first electrolyzer with a plate area of $375811cm^2$. The second half of the production is covered by two identical electrolyzers, given by Table 1 and Equation 1, and two PEM electrolyzers, given in Equation below (6.2).

$$\begin{gathered}Af(t) = 8.13 — 2 + 1.00 * \cos(1 * t) + 0.34 * \sin(1 * t) - 4.61 * \cos(2 * t) \\ -4.37 * \sin(2 * t) - 0.94 * \cos(3 * t) - 1.70 * \sin(3 * t) + 0.27 * \cos(4 * t) \\ + 2.73 * \sin(4 * t) + 0.13 * \cos(5 * t) + 0.85 * \sin(5 * t) + 0.01 * \cos(6 * t) \\ -0.33 * \sin(6 * t) - 1.04 * \cos(7 * t) - 0.23 * \sin(7 * t) + 0.17 * \cos(8 * t) \\ + 0.02 * \sin(8 * t) + 0.90 * \cos(9 * t) + 1.01 * \sin(9 * t) + 0.01 * \cos(10 * t) \\ + 0.34 * \sin(10 * t) + 0.21 * \cos(11 * t) - 0.64 * \sin(11 * t) \\ + 0.35 * cos(12 * t) - 0.35 * sin(12 * t) \end{gathered} \tag{6.2}$$

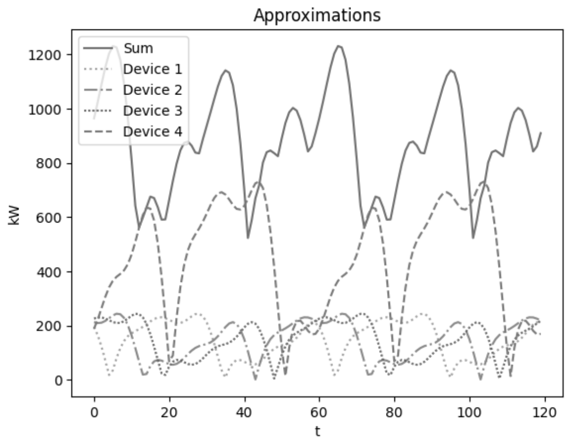

Figure 1. Optimization of a configuration of 3 identical electrolyzers, each with a plate area of $125270.3cm^2$ and an electrolyzer with a plate area of $375811cm^2$ using a genetic algorithm.

Рисунок 1. Оптимізація конфігурації 3 однакових електролізерів, кожен з яких має площу пластини 125270,3 〚см〛 ^2 , та електролізера з площею пластини 375811 〚см〛 ^2 за допомогою генетичного алгоритму.

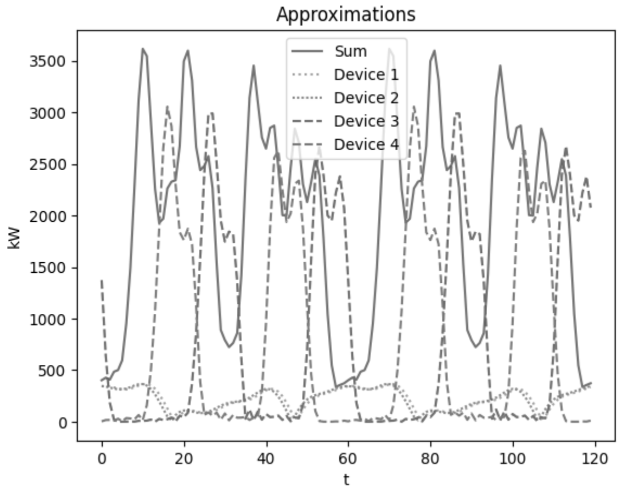

Figure 2. Optimization of a configuration of 2 identical membrane-less electrolyzers and 2 PEM electrolyzers using a genetic algorithm.

Рисунок 2. Оптимізація конфігурації 2 ідентичних безмембранних електролізерів та 2 PEM електролізерів за допомогою генетичного алгоритму.

Table 3: Numerical results of optimization of the startup queue for configurations of systems with several electrolyzers using the genetic algorithm and the gradient descent method.

Таблиця 3: Числові результати оптимізації черги запуску для конфігурацій систем з декількома електролізерами з використанням генетичного алгоритму та методу градієнтного спуску.

Configuration	Genetic algorithm	Gradient descent
3 identical electrolyzers, each with a plate area of 125270.3 cm^2, and 1 electrolyzer with a plate area of 375811 cm^2	903.64	926.81
2 identical membrane-less electrolyzers and 2 PEM electrolyzers	3256.94	3315.41

The analysis of the numerical results (presented in Table 3 and Figures 1 and 2) confirms that the genetic algorithm demonstrates higher efficiency than the gradient descent method. This is observed regardless of the number of electrolysis units in the configuration and the type of units used.

In particular, the genetic algorithm consistently provides the best values of optimized parameters, which indicates its ability to effectively find global optimal solutions, even in cases with high dimensionality of the search space and complex dependence of input parameters.

7 Conclusion

The study substantiated the feasibility of using a genetic algorithm to solve the optimization problem of calculating the effective start queue of electrolyzers in a hydrogen production system. The analysis of its effectiveness in comparison with the gradient descent showed that the genetic algorithm demonstrated better quality of the obtained solutions, especially in conditions when the function is non-uniform, has local minima, or is not differentiable.

These calculations have confirmed that the genetic algorithm has stable results and is effective in finding the global optimum, while the gradient descent may stop at local minima and require additional adjustments to achieve the optimal solution. The results confirm the feasibility of using a genetic algorithm to solve similar optimization problems, where traditional gradient methods may be less effective due to their sensitivity to local minima.

The results confirm that the genetic algorithm is a promising approach to solving optimization problems in cases where traditional methods have limitations.

By using the genetic algorithm method, we obtain results that give an approximate optimal result for a fixed number of steps. This approximate result, as shown in the problem with the placement of 10 electrolyzers, gives significant results — the peak power consumption decreased by almost 40%.

Further research can be aimed at improving the parameters of the algorithm, in particular, adaptive tuning of the mutation and crossover operators to increase the convergence rate.

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Застосування генетичного алгоритму для розв'язання задачі масштабування водневих систем

Метою роботи є розроблення надійного інструменту для масштабування водневих систем та їх енергоспоживання за допомогою генетичного алгоритму.

Актуальність

Найпоширенішим методом виробництва водню є електроліз води, який вимагає достатньої кількості електроенергії. Якщо джерела електроенергії є недостатніми, це може створити додаткове навантаження на енергосистему, особливо в періоди пікового споживання. Оскільки 87% водневих станцій наразі використовують водень на місці (замість того, щоб генерувати його, а потім транспортувати для використання), існує потреба в оптимізації в цій галузі для підвищення енергоефективності та сталого розвитку. У сучасних дослідженнях вдосконалення водневих систем аналізуються з погляду економічної ефективності систем, що використовують відновлювані джерела енергії, та зниження витрат на водневу логістику шляхом застосування методів лінійного програмування та оптимізації рою частинок. Однак важливо зазначити, що ці роботи в основному зосереджені на системах виробництва водню на основі одного електролізера і не ставлять за мету оцінити доцільність використання декількох установок. Як наслідок, тема оптимізації витрат і стратегій технічного обслуговування багатоелектролізерних систем залишається менш дослідженою, а також пов'язана з цим проблема їх диспетчеризації.

Методи дослідження

Для розв’язання задачі пошуку найкращої черги запуску для електролізних установок використані стохастичні методи, та перевірено ефективність генетичного алгоритму для розв’язку цієї задачі.

Результати

Побудована модель оптимізації пікового споживання електроенергії електролізною системою, визначено оціночну функцію конфігурації та цільову функцію для оптимізації системи. Вибір стохастичного методу оптимізації аргументовано за допомогою перевірки цільової функції на властивості які необхідні для ефективності традиційних методів оптимізації, а саме — неперервність, диференційованість, гладкість та опуклість. Ефективність генетичного методу перевірено у порівнянні з методом градієнтного спуску на прикладах з різними конфігураціями електролізерів (однотипних та різнотипних).

Висновки

Ці розрахунки підтвердили, що генетичний алгоритм має стабільні результати і є ефективним для пошуку глобального оптимуму, в той час, як градієнтний спуск може зупинятися на локальних мінімумах і вимагати додаткових налаштувань для досягнення оптимального розв'язку. Використовуючи метод генетичного алгоритму, ми отримуємо результати, які дають наближений оптимальний результат за фіксовану кількість кроків. Цей наближений результат, як показано в задачі з розміщенням 10 електролізерів, дає значні результати — пікове споживання електроенергії зменшилося майже на 40%. Подальші дослідження можуть бути спрямовані на покращення параметрів алгоритму, зокрема, адаптивне налаштування операторів мутації та кросовера для збільшення швидкості збіжності.

Ключові слова: *оптимізація, стохастичні (недетерміновані) методи, генетичний алгоритм, енергоспоживання, водневі системи, електролізер.*

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