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HEURISTIC CONTROL OF POWER CONSUMPTION BY UP TO 1000 V ELECTRICAL LOADS AT MINING ENTERPRISES

Purpose. To develop a method for synthesizing the structure and algorithm of the system for automated control of power consumption by up to 1000 V electrical receivers at mining enterprises with iron ore underground mining methods. This enables direct control of the load connection to the industrial power grid to ensure minimum power costs depending on its cost per day ahead.

Methodology. The problem of controlling power consumption of electrical receivers at iron ore underground mines is formalized as a binary form of mixed integer programming. To solve it, a binary implementation of the heuristic genetic algorithm is used. The mathematical modeling method analyzes the impact of genetic algorithm settings, such as the number of phenotypes in the population, the number of elite phenotypes that pass unchanged to the next generation, and the method of phenotype crossover on its quality.

Findings. As a result of the research, it is found that the most effective way to control the process of power consumption based on an evolutionary genetic algorithm is to use the Laplace crossover function and keep the percentage of elite phenotypes in the population at 10 %. Moreover, at the smallest population size, the best accuracy is observed when using the Laplace function, while at one- and two-point crossover functions, it worsens, but not significantly (no more than 0.2 %). However, as the number of elite phenotypes increases, the duration of the evolutionary search in the control process is reduced by almost a factor of two in the case of one- and two-point crossovers.

Originality. For the first time, the structure of a heuristic system for automated control of power consumption by underground electrical receivers with a supply voltage of up to 1000 V at iron ore underground mines has been developed on the basis of an evolutionary genetic algorithm. Depending on the designed volumes of ore production and the daily power cost per day, this allows determining the optimal power load schedule of underground distribution substations in advance, which, subject to the accepted limits on hourly and daily power, minimizes the cost of purchasing power, and thus reduces the cost of the final product.

Practical value. The architecture of a heuristic system for controlling power consumption by electrical receivers with a voltage of up to 1000 V based on an evolutionary genetic algorithm is developed and recommended when optimizing the power load schedule of transformer substations of mining and metallurgical enterprises, in particular, of iron ore underground mines operating in this voltage class.

Keywords: *power, up to 1000 V electrical receivers, heuristic algorithm, genetic algorithm, underground mine*

Introduction. The enactment of the Law of Ukraine "On the Power Market" [1] creates conditions for a fundamental change in the operation of the Integrated Power System of Ukraine. At the same time, the modernization of the power system as a 'power producer-power consumer' complex can and should be implemented in two key areas. One is the creation of small-scale distributed generation power plants to decentralize the power grid, and the other is the transformation of the wholesale market model with a single buyer into a competitive one. While the first direction is only stimulated by the Law of Ukraine, the other is mandatory and has already been put into effect.

It should be noted that a competitive market implies a complete change in the approach to mutual settlements for consumed power between power supply companies and consumers. Thus, the Law creates an intraday segment of the power market with hourly pricing, i.e. the day-ahead tariff system. Moreover, prices change each day depending on the results of the market's buying and selling trades. This 'variable' approach to tariff setting introduces significant uncertainty into consumers' operations that plan their work for a long time, such as mining and metallurgical enterprises. Such a group of enterprises includes, among others, those engaged in underground mining (underground mines). To reduce the level of power consumption payments, enterprises artificially modify consumption modes of mainly energy-intensive consumers in a primitive form, by increasing power consumption during economic hours of the day and decreasing it during peak hours. This gives a certain material effect, but also adds a number of negative aspects [2, 3]. In order to achieve the desired effect in the power and energy sector of operating iron ore mining enterprises, it is necessary to change available approaches to both labor organization and management of consumed power during the day [4, 5].

Traditionally, underground mines rely on electrical equipment to extract ore, which can potentially be adjusted within a fairly narrow timeframe, as it depends on monthly production. Under the three-zone tariff system differentiated by time of day, which was in effect before the introduction of the Law of Ukraine "On the Power Market", power consumption was reduced during peak tariff hours, whenever possible. After the creation of the intraday market, when the price of electricity fluctuated hourly and the high price hours did not coincide from day to day. So, it became quite difficult to save money because power consumption was not controlled as such or was controlled manually, not automatically. Thus, there is an urgent need to develop such a control system.

Literature review. The issue of controlling power consumption by domestic and industrial facilities is considered in a fairly wide range of works. Of these, [6, 7] are devoted to a comprehensive review of the problem, analyzing advantages and disadvantages of ways to solve it using common science-based methods.

Three main areas can be distinguished according to the conditions for setting tasks for solving the problem of power consumption control and the methods for solving them. The first is the application of classical methods of mathematical programming, as defined in [8, 9]. The second involves the use of heuristic methods and the third includes methods based on artificial intelligence principles. What they all have in common is that they are controlled on the consumer's side, outside the balance sheet, i.e. in their own power system.

A significant amount of research is devoted to the use of heuristic methods. They formalize the problem of power control as an optimization problem of planning operation periods of electrical equipment over a certain time period. The majority of the research is based on algorithms that determine the optimal solution by imitating the principles by which wildlife systems function, like genetic algorithms [10, 11], the particle swarm method [12, 13], the ant colony algorithm [14], the ant lion algorithm [15], the cuckoo search algorithm [16], the gray wolf hunting optimization algorithm [17], the symbiotic organisms search algorithm [18], the hybrid genetic-air optimization algorithm [19], and the whale search algorithm [20].

[21] compares the quality of solving an optimization problem of power consumption control using a cockroach colony, a sparrow search algorithm, and a binary orientation algorithm. We would like to highlight the works that propose heuristic algorithms that do not involve the principles of biological systems. These are [22, 23]. The former deals with a multi-agent optimization system, and the latter with a two-stage iterative algorithm.

Recently, other approaches to solving the problem of power control have also become widespread, in particular, those that apply the neural-fuzzy principle in building control systems. Moreover, artificial neural networks are mainly used to predict power consumption [24, 25] in a hybrid system, and fuzzy logic [26, 27] is used to regulate the power receiver capacity or to decide whether to disconnect it from the power grid or reconnect it to it.

However, the literature analysis shows that the issue of optimizing power consumption by electrical receivers in ore underground mines, in particular, those with voltages up to 1,000 V, has not been studied to date. This is what makes this research relevant.

Main material presentation. Substantiation of the methods used. To solve such problems, the optimization method of mixed-integer linear programming (MILP) is used. This approach has a high speed of solution and accuracy. However, these advantages mostly apply to cases where there are no restrictions or they are not strict enough. Also, the method is not very suitable for operational control, which will be required to implement the smart grids concept in the industrial power system with its smart metering and smart switching approaches. The genetic algorithm, which belongs to the class of evolutionary algorithms, does not have these disadvantages. In solving optimization problems, it uses the mechanisms of selection, crossover, reproduction, and mutation, similar to biological evolution in living nature, and is well suited for solving MILP problems [28].

We synthesize a heuristic system for controlling power consumption by technological equipment at an iron ore underground mine and analyze its quality indicators. We consider electrical equipment of several blocks of an underground mine level as an object. The list of equipment and its technical data is shown in Table 1.

An analysis of the list of equipment (Table 1) shows that the equipment can be divided into two categories: with a floating (variable) and fixed work schedule. The former include those that create conditions for the safe work of mine employees, such as local ventilation fans and lighting, while the latter category includes all other equipment.

Results and discussion. Let us set an optimization problem of controlling power consumption of the mine level to solve it with an optimization algorithm. As a variable for each technological unit, we use a binary value that determines the state of connection to the power grid, which will take one of two values: 1 – electrical equipment consumes power from the industrial power system, 0 – electrical equipment is disconnected. Thus, the MILP problem is reduced to a binary form (Binary MILP). The involvement of a genetic algorithm becomes even more relevant because the

Table 1

Electrical equipment of the mine level

No	Consumer	Total power	No	Consumer	Total power
Block 1			*Block 3*		
1	Scraper winch 30LS-2S	120	19	Scraper winch 30LS-2S	60
2	Scraper winch 55LS-2S	110	20	Scraper winch 55LS-2S	55
3	Scraper winch 17LS-2S	74	21	Scraper winch 30LS-2S	90
4	Scraper winch 30LS-2S	60	22	Fan SVM-6M	14
5	Fan SVM-6M	28	23	Drilling rig NKR-100M	8
6	Drilling rig NKR-100M	24	24	Vibro-manhole AShL	30
7	Vibro-manhole AShL	60	25	Welding transformer STN-500	33
8	Welding transformer STN-500	33	26	Other	5
9	Lighting	10			
Block 2			*Block 4*		
10	Scraper winch 30LS-2S	120	27	Scraper winch 30LS-2S	60
11	Scraper winch 55LS-2S	110	28	Scraper winch 55LS-2S	55
12	Scraper winch 17LS-2S	37	29	Scraper winch 17LS-2S	37
13	Scraper winch 30LS-2S	30	30	Scraper conveyor KS-2	120
14	Fan SVM-6M	14	31	Vibrating machine VL-2 (PVS)	90
15	Drilling rig NKR-100M	8	32	Drilling rig NKR-100M	8
16	Vibro-manhole AShL	45	33	Fan SVM-5M	27.5
17	Welding transformer STN-500	33	34	Fan SVM-6M	28
18	Other	7.5	35	Lighting	18

most common type of phenotype encoding is two-bit, i.e. when one gene in a phenotype chromosome can be either 0 or 1.

The objective function whose extremum is to be determined has the following form

$$\underbrace{\operatorname{argmin}}_{x_{ij}\in Z_2} J(x_{ij}) = \sum_{i=1}^{N_T} C_i \sum_{j=1}^{N_L} P_{ij} \cdot x_{ij}, \quad (1)$$

where N_L is the number of consumers of the mine level; N_T is the number of gaps in the time interval under consideration; i is the index of the time period; j is the consumer index; x_{ij} is a variable of the state of connection of the j^{th} electrical equipment to the industrial power grid at the i^{th} time interval; C_i is the power price at the i^{th} time interval, UAH/kWh; P_{ij} is the installed power of the consumer, kW.

According to the objective function (1), the optimization algorithm establishes a schedule of electrical loads at the underground mine substation to ensure the minimum daily cost of purchasing power from the power supply company.

According to the Law of Ukraine "On the Power Market", the power market segment is intraday with hourly pricing, so as a time period, the research will consider a day with hourly intervals. It is also convenient to plan production for the day ahead.

When solving the optimization problem of power consumption control, the following restrictions are imposed:

1. The daily consumption power should not exceed the volumes ordered the day before from the day-ahead distribution (DAM) operator

$$\sum_{i=1}^{N_T} \sum_{j=1}^{N_L} P_{ij} \cdot x_{ij} \le P_{DAM}.$$

2. The total power of consumers simultaneously connected to the grid should not exceed the total rated capacity of mobile sectional underground substations (MUS), i.e. the transformer load factor should not exceed one

$$\sum_{j=1}^{N_L} P_{ij} \cdot x_{ij} \le P_{ratedMUS},$$

where P_{ij} is the power of the j^{th} consumer in the i^{th} time interval.

3. To ensure the required ore extraction productivity, each consumer should work for a set period of time

$$\sum_{i=1}^{N_T} x_{ij} = n_j,$$

where n_j is the duration of the j^{th} consumer's operation during the day, hours.

The operating time allows considering the planned rock mass extraction productivity as a ratio of extraction volumes to the productivity of the j^{th} unit. We assume that n_j takes only an integer value over a period of time.

Thus, the form of the optimization problem indicates that the system for controlling power consumption of electrical equipment for stopping and preparatory workings has a MISO-type. The input variables are the production rate and the hourly power price, the output variable is the daily cost of purchasing power, and the state variable is the state of connection of the equipment to the power grid.

We evaluate the quality of the minimum search for the objective function (1) using an evolutionary genetic algorithm subject to constraints. Let us use the *ga* function from the MATLAB/Global Optimization Toolbox.

Let us analyze the impact of genetic algorithm settings on its quality. The number of phenotypes in the population, the number of elite phenotypes that pass unchanged to the next generation, and the method of phenotypes crossover is subject to change. These settings are proven to have the greatest impact on the quality of the limit search and are used for variation [29].

During the research period, the number of phenotypes in the population is defined as 100 and 200, the number of elite phenotypes that passed to the next generation without crossover or mutation is 0, 5, 10, 20 and the one-, two-point crossover functions and the Laplace crossover function [30], defined as

$$x = p_1 + b_1 |p_1 - p_2|; \quad x = p_2 + b_1 |p_1 - p_2|, \quad (2)$$

where b_1 is a random number obtained from the Laplace distribution.

The Laplace crossover function is considered to be the most adapted for solving mixed integer linear programming problems.

The conditions for the evolutionary algorithm to terminate are the achievement of either the maximum number of generations or the average relative change in the lowest value of the objective function. They are set at 300 and 10^{-8}, respectively.

The average power value always remains constant at 377.958 kW. This because the power consumption of the process plants is not regulated, only the distribution of their operation over time.

During the experiments, the power cost is considered as a random variable with a normal probability distribution law. Its parameters are chosen based on the following assumptions. According to the analytical materials of the power market operator [31], the peak cost of power as of the current date of March 06, 2023 is 3,949.48 UAH/MWh and this price remains for most of the day from 07.00 to 24.00. The power supply company takes this value as a basis and adds its own markup to it. Therefore, the mathematical expectation is set to $M[X]$ = 5,000 UAH/MWh. Also, looking at the trends, it can be argued that the peak value on the day-ahead market will increase to this value, since, for example, a year before, on March 05, 2022, the peak price was 2,646.25 UAH/MWh, i. e. the increase is 49.25 % over the specified period. This is explained by the state of Ukraine's Integrated Power System. The situation has stabilized, so we can predict that growth will continue, but at a slower pace. The cost allocation will have its own peak values, which will model either force majeure circumstances of the power system or a deliberate price increase by the power supply company to increase profits.

To adequately compare the efficiency of the heuristic control system with different settings, the pseudorandom number generator is fixed in the same state, so the cost distribution is the same.

Indicators of power consumption control by the electrical equipment of preparatory and stopping workings are shown in Table 2 and Figs. 1–8.

Genetic algorithm parameters: the population includes 100 phenotypes, the number of elite phenotypes is 10. First, let us apply the following settings to the genetic algorithm: population size per generation is 100 phenotypes, the number of elite phenotypes in the population is 10 (10 % of the total phenotypes), and the crossover function is one-point. In Fig. 1, *a*, the results of optimizing the electrical load schedule using the objective function (1) are presented.

The minimum value of the criterion during the test made 42,516.6 UAH/day. The schedule of changing the objective function value, produced by the best phenotype in each generation (Fig. 1, *b*), indicates that the evolution begins with the value of 43,303.3 UAH/day. This is calculated for the start population. Also, it is obvious that the populations' evolution ends at population 114, when the change in the objective function value is almost absent. The genetic algorithm control system cuts electric power costs for the underground mine by 1.817 %. Apart from that, after generation 24, when the value of 42,599.7 UAH/day is reached, i. e. decreased by 1.625 % from 43,303.3 UAH/day, the algorithm reduces the costs insignificantly, only by 0.195 %. Totally, 164 generations are needed to implement the condition of algorithm termination.

The power load schedule (Fig. 2, *a*) shows that the peak power consumption of 708.5 kW after the final planning of working hours occurs at 5 a.m., while the minimum power consumption of 217.5 kW occurs at midnight. It should be noted that during these specific hours, the power price is neither highest, nor the lowest. The most expensive and the cheapest

Table 2

Efficiency indicators of the heuristic system for controlling power consumption during the day at different settings of the genetic algorithm

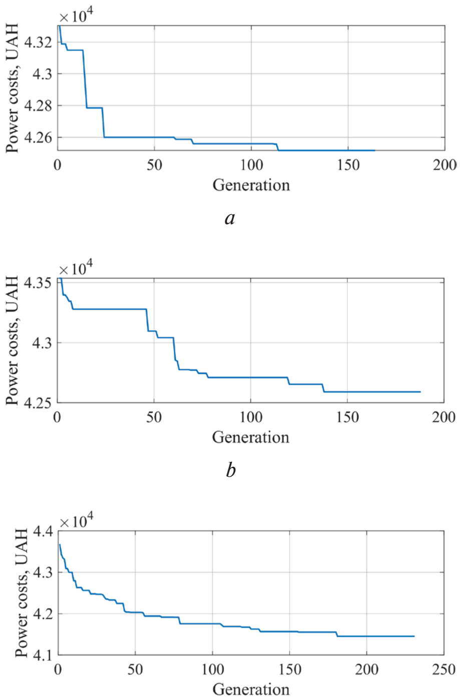
Population size	Number of elite phenotypes	Crossover function	Power costs, UAH/day	Final generation	σ, kW	P_{max}, kW	P_{min}, kW
100	10	One-point	42,516.6	114	104.12	708.5	217.5
100	10	Two-point	42,590.23	138	92.8202	592.5	173
100	10	Laplace	41,454.99	181	111.3152	654.5	199
100	5	One-point	42,337.16	131	114.7072	661.5	229
100	5	Two-point	42,681.84	108	96.6943	560	218
100	5	Laplace	42,499.92	46	101.265	566	214.5
200	20	One-point	42,515.63	54	95.3207	599	211
200	20	Two-point	42,518.40	80	117.9157	724	221.5
200	20	Laplace	41,661.27	91	102.3352	567.5	184
200	0	One-point	43,470.55	300	80.1435	574	264
200	0	Two-point	43,430.45	300	88.2164	624.5	237
200	0	Laplace	42,878.01	300	104.6009	669.5	232.5

tariffs are used at 4 p.m. and at midnight respectively, with the power consumption of 310.5 kW, i.e. 93 kW higher than the minimum and 460 kW, i.e. 248.5 kW lower than the maximum.

Let us find a two-point crossover function without changing the sizes of population and the number of elite phenotypes, and compare the results of controlling power consumed by the electric equipment at the underground mine level (Figs. 1, *b*; 2, *b*).

According to the schedule (Fig. 1, *b*), under such settings of the genetic algorithm, the best phenotype in the initial population makes the objective function value of 43,535.8 UAH/day. Afterwards, generation by generation, the phenotype quality improves evolutionally and reaches 42,590.2 UAH/day when terminating the algorithm, i.e. the costs reduce by 2.172 %, which is higher in percentage expression than in the one-point crossover function. However, in this case the search lasts longer, namely 138 generations (114 for one-point crossover function), which is 24 generations or 21.053 %. Moreover, the algorithm termination occurs in generation 188. The final result is worse than that with the one-point crossover: 42,590.2 UAH/day compared to 42,516.6 UAH/day. Daily expenses are 0.1731 % greater, and so is the duration.

The power load schedule (Fig. 2, *b*) indicates that peak power consumption of 592.5 kW occurs at 9 p.m., and the minimum of 173 kW occurs at 4 p.m. Thus, the lowest consumption rate is when the electric power price is the highest. The maximum power consumption does not coincide with the time of the minimum price. At noon, when the power price is the highest, the power consumption is 366.5 kW, being



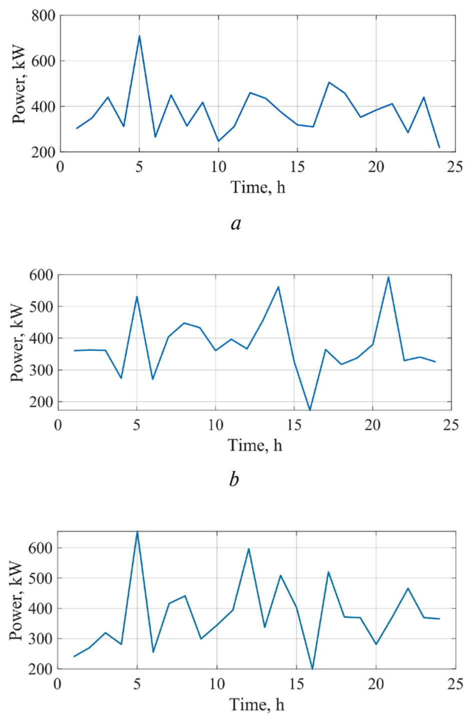
a

b

c

Fig. 1. The dynamics of changes in the optimal value of the objective function during the evolutionary execution of a genetic algorithm with a population size of 100 phenotypes and 10 elite phenotypes in the population:

a – one-point crossover function; b – two-point crossover function; c – Laplace crossover function



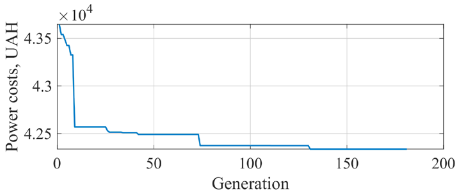
a

b

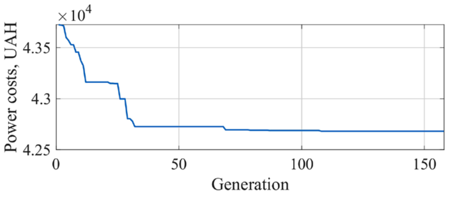
c

Fig. 2. Power load schedule in the course of power consumption control applying the genetic algorithm for a population size of 100 phenotypes and 10 elite phenotypes in the population:

a – one-point crossover function; b – two-point crossover function; c – Laplace crossover function



a



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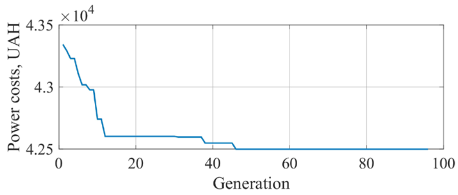

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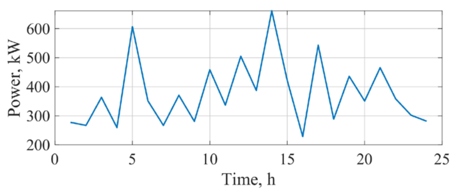
Fig. 3. Dynamics of changes in the optimal value of the objective function during the evolutionary execution of the genetic algorithm with a population size of 100 phenotypes and 5 elite phenotypes in the population:

a – one-point crossover function; b – two-point crossover function; c – Laplace crossover function



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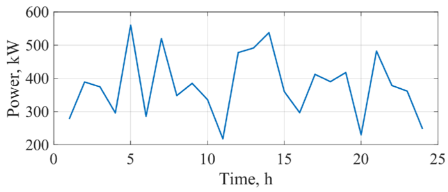

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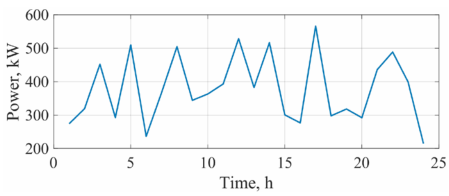

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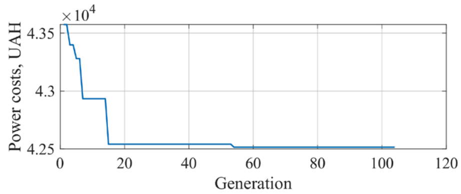
Fig. 4. Power load schedule in the course of power consumption control applying the genetic algorithm for a population size of 100 phenotypes and 5 elite phenotypes in the population:

a – one-point crossover function; b – two-point crossover function; c – Laplace crossover function



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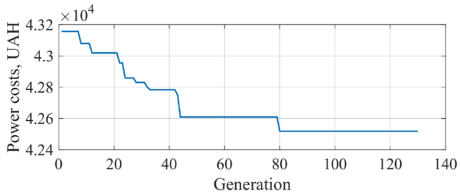

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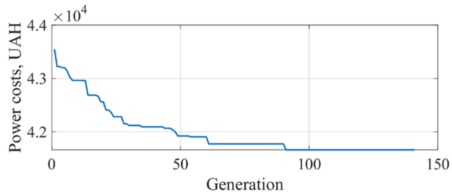
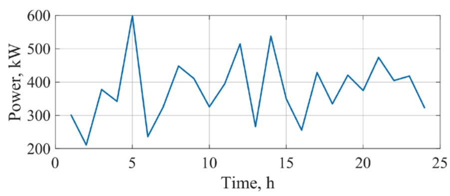


c

Fig. 5. Dynamics of changes in the optimal value of the target function during the evolutionary execution of the genetic algorithm with a population size of 200 phenotypes and 20 elite phenotypes in the population:

a – one-point crossover function; b – two-point crossover function; c – Laplace crossover function



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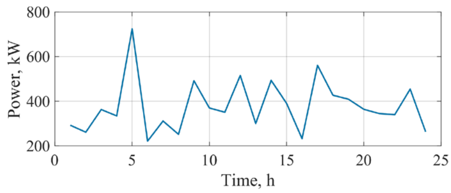

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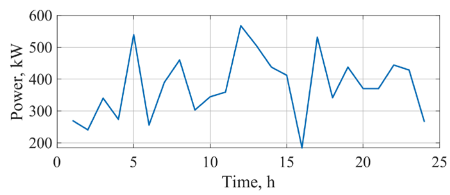

c

Fig. 6. Power load schedule in the course of power consumption control applying a genetic algorithm with a population size of 200 phenotypes and 20 elite phenotypes in the population:

a – one-point crossover function; b – two-point crossover function; c – Laplace crossover function

38.143 % lower than the peak one. Compared to the one-point crossover algorithm, the two-point crossover demonstrates smaller peak and minimum consumption by 16.373 and 25.723 %, respectively. The standard deviation of 92.8202 kW indicates the greater grouping of power in relation to the mean value of 377.958 kW.

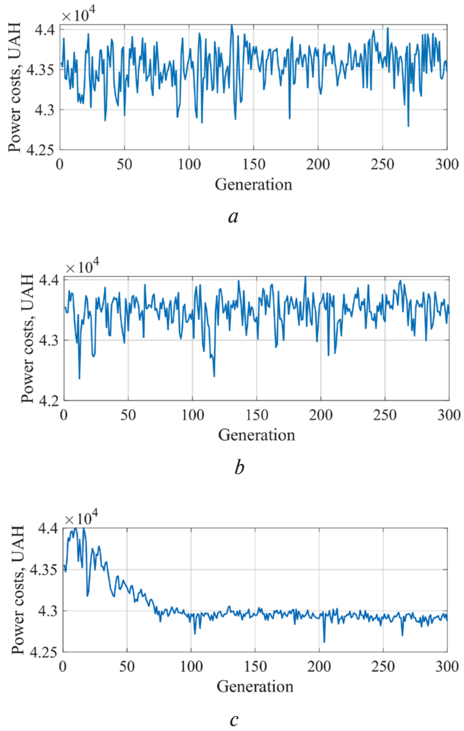

Fig. 7. Dynamics of changes in the optimal value of the objective function during the evolutionary execution of the genetic algorithm with a population size of 200 phenotypes without elite phenotypes in the population:

a – one-point crossover function; b – two-point crossover function; c – Laplace crossover function

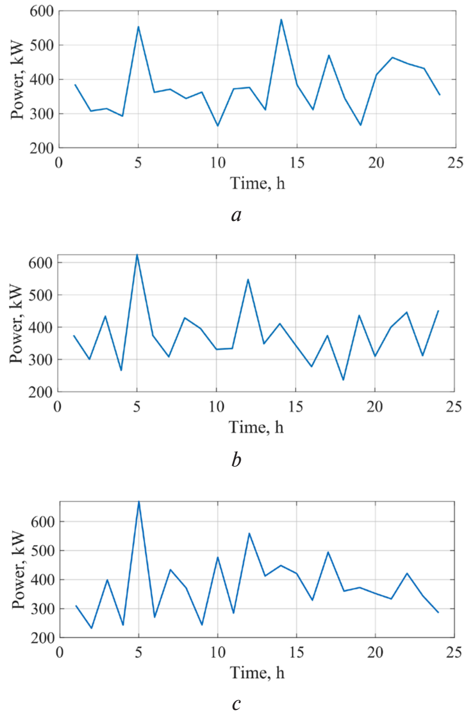

Fig. 8. Power load schedule during power consumption control applying a genetic algorithm with a population size of 200 phenotypes without elite phenotypes in the population:

a – one-point crossover function; b – two-point crossover function; c – Laplace crossover function

Let us change the two-point crossover function into the Laplace crossover one (expression 2) and analyze the operation of the genetic algorithm (Figs. 1, *c*; 2, *c*).

Fig. 2, *c* proves that the start population has the most qualitative phenotype, producing the value of the objective function of 43,682.4 UAH/day at the Laplace crossover function. During evolutionary search for the optimum solution, the value of 41,454.99 UAH/day is reached. Thus, power costs are reduced by 5.099 %. Furthermore, there is the lowest index of the objective function of the all three analyzed crossover functions, e.g. 2.497 % lower than at the one-point crossover and 2.665 % at the two-point crossover. But the evolution process itself is the most long-lasting and enumerates 181 generations before obtaining the optimum result and 231 generations before reaching the condition for algorithm termination. It is 67 generations longer (37.017 %) than the one-point crossover and 43 generations longer (23.757 %) than the two-point crossover.

The power values shown on the power load schedule (Fig. 3, *c*) obtained after genetic algorithm termination are 654.5 kW at 5 a.m. and the minimum value of 199 kW at 4 p.m. It is worth mentioning that the lowest consumption is again, like at the two-point crossover, when the electric power price is the highest. The peak power consumption does not coincide with the minimum price hour, but it is the second cheapest. It can be claimed that the power load schedule is more optimal than that obtained at other crossover functions. The standard deviation here is the biggest – 111.3152 kW. This indicates that the algorithm adheres more to the daily price distribution, by increasing consumption at the low price and decreasing it at the high one. That is, the power load schedule becomes more uneven.

Genetic algorithm parameters: the population includes 100 phenotypes and 5 elite phenotypes. Let us reduce the number of elite phenotypes in the population of up to 5, while maintaining the population size of 100 phenotypes, and compare the quality of evolutionary optimization with three crossover functions. The results are shown in Table 2, Figs. 3 and 4. The entire series will be considered and compared at once.

Figs. 3, *a–c* shows the process of changing the objective function value produced by the highest-quality phenotype in the generation. A decrease in the number of elite phenotypes causes a deterioration in the quality control for the two-point crossover and the Laplace crossover functions. Costs in these crossover options increase by 0.215 %, from 42,590.23 to 42,681.84 UAH/day, and by 2.52 %, from 41,454.99 to 42,499.92 UAH/day respectively. However, the search itself becomes shorter: for the two-point crossover, it is reduced by 30 generations (21.74 %), and for the Laplace crossover function – by 135 generations (3.93 times). The quality improves with the one-point crossover. Power costs decrease by 0.422 %, from 42,516.6 to 42,337.16 UAH /day. Moreover, the evolutionary process is longer by 17 generations (by 14.91 %).

The change in the quality of populations has the same trends as in the cases when the number of elite phenotypes is 10 %. Due to the evolution, the one- and two-point crossover functions divide the population into two groups. With the Laplace crossover function, the entire population becomes more qualitative.

Comparing the power load schedules obtained with the heuristic control (Figs. 4, *a–c*), we can see that peak power consumption decreases as the percentage of elite phenotypes in the population decreases: from 708.5 to 661.5 kW (6.634 % decrease) for the one-point crossover, from 708.5 to 661.5 kW for the two-point crossover, from 592.5 to 560 kW (5.485 % decrease) and from 654.5 to 566 kW (13.522 % decrease) for the Laplace crossover function. The minimum power of each crossover functions increases from 217.5 to 229 kW (5.287 %), from 173 to 218 kW (26.012 %) and from 199 to 214.5 kW (7.789 %).

Parameters of the genetic algorithm: the population includes 200 phenotypes and 20 elite phenotypes. Let us increase the population size to 200 phenotypes, maintaining a percentage ratio of 10 % (20 phenotypes) between the number of elite phenotypes and their total volume, and apply the three crossover functions. The results are shown in Figs. 5, 6 and Table 2. We compare the control indicators with the most effective case when the population consists of 100 chromosomes and the number of elite phenotypes is 10.

As the schedules (Figs. 5, *a–c*) show, the power costs, after the algorithm terminates, decrease by 0.00228 and 0.169 % at one-point and two-point crossover types, respectively. The duration of the evolutionary search is also reduced from 114 to 54 generations (by 52.6 %) for the one-point crossover and from 138 to 80 (42.03 %) for the two-point crossover. For the Laplace crossover function, there is a 0.498 % increase in power costs, but a 49.72 % decrease in the duration of the genetic algorithm execution (from 181 generations to 91). Given the slight increase in costs in the latter case, increasing the number of populations shows better results. However, the calculation time for a single generation increases, but since the interval for data calculation and control is long (up to 30 minutes in ASKOE systems), this moment does not impair the genetic algorithm operation.

As can be seen from the power load schedules (Figs. 6, *a–c*), for the one-point crossover and the Laplace crossover functions, both peak consumption and minimum consumption decrease when the population size is 200 units and the number of elite phenotypes is 20 units. For each crossover function, peak consumption decreases by 15.46 and 13.29 %, while minimum consumption decreases by 2.989 and 7.538 %.

Genetic algorithm parameters: the population includes 200 phenotypes without elite phenotypes. Finally, we conduct an experiment when elite phenotypes are absent. The population size is 200 phenotypes. Figs. 7, 8 and Table 2 show the results of the algorithms' operation for the three crossover functions.

Considering the dynamics of changes in the optimal value of the target function in each generation (Fig. 7), it is possible to notice that the genetic algorithm without elite phenotypes, especially at the one- and two-point crossovers is very unstable. As a result, the algorithm terminates only when the set maximum number of generations is reached.

Table 2 lists the cost values at the final moment of the algorithm's operation. They are the largest of all ever obtained. But these are not the minimum values recorded in the course of evolution.

For the one-point crossover, the lowest costs are with generation 270 making 42,792.1 UAH/day; for the two-point crossover - generation 12, which is very early, 42,363 UAH/day; and for the Laplace crossover function – generation 204, making 42,619.6 UAH/day, which are not the worst results. Only for the last crossover function (Fig. 7, *c*), a gradual movement to the objective function minimum is observed.

The power load schedule (Fig. 8) for one-point and two-point crossover types is more uniform, as evidenced from the lowest indicators of the standard power consumption deviation.

Thus, without elite phenotypes, the algorithm has poor performance indicators and therefore cannot be recommended for controlling.

Conclusions. In power consumption heuristic control, based on the evolutionary genetic algorithm, the use of the Laplace crossover function and the observation of 10 % of elite phenotypes in the population are the most effective. Moreover, for the smallest population size, accuracy improves when using the Laplace function, and worsens, though not significantly (less than 0.2 %), when using one- and two-point crossover types. With an increase in the number of elite phenotypes, the duration of the evolutionary search in the course of control at some crossover functions becomes almost twice as short.

As the percentage of elite phenotypes in the population decreases, the quality of the algorithm deteriorates for the two-point crossover and the Laplace crossover function, and improves for the one-point crossover, which is explained by longer evolution than in the case of a larger number of elite phenotypes in the latter case and shorter in the first two cases.

The option with no elite phenotypes at all demonstrates the worst quality. Such a genetic algorithm is not stable, the movement to the minimum of the objective function is not carried out at all for one- and two-point crossover types, and is very slow at the Laplace crossover function. This happens because the random generation is repeated at each generation without taking into account the previous state of the search, i.e. as in the start population, so the minimum value at each generation depends only on whether the randomly generated phenotype enters or does not enter the minimum region.

The hourly power consumption during the day is distributed by the genetic algorithm in such a way that it does not exceed the permissible limit of 800 kW. In none of the considered options for settings, the peak power consumption at the mine level does not coincide with the time when the power price is minimal. But, mostly, the minimum power consumption is provided by the algorithm at the time of its highest cost. With the Laplace crossover function, the power load schedule corresponds largely to the daily distribution of the power price. Its application provides high quality to the genetic algorithm.

The conducted research reveals that the heuristic control system for connecting power consumers of mine levels to the industrial power grid allows determining the optimal power load schedule to minimize power costs and reduce this component in the cost of iron ore underground mining.

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Евристичне керування споживанням електроенергії електроприймачами напругою до 1000 В гірничодобувних підприємств

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Мета. Полягає у розробці методу синтезу структури та алгоритму роботи системи автоматизованого керування процесом споживання електроенергії електроприймачами з напругою живлення до 1000 В гірничорудних підприємств із підземними способами видобутку залізної руди, що дозволить здійснювати пряме управління підключенням навантаження до промислової енергосистеми для забезпечення мінімуму витрат на придбання електроенергії залежно від її вартості на добу наперед.

Методика. Задача керування споживанням електроенергії електроприймачами залізорудних шахт формалізується як бінарна форма змішаного цілочисельного програмування. Для її розв'язку застосовується бінарна реалізація евристичного генетичного алгоритму. Методом математичного моделювання проводиться аналіз впливу налаштувань генетичного алгоритму, як от число фенотипів у популяції, число елітних фенотипів, що переходять незмінними у наступне покоління, і метод схрещування фенотипів на його якість.

Результати. У результаті проведення досліджень установлено, що найбільш ефективними при керуванні процесом споживання електроенергії на базі еволюційного генетичного алгоритму є застосування функції Лапласа для схрещування і задіянням дотриманням відсотка числа елітних фенотипів у популяції на рівні 10 %. При чому, за найменшого розміру популяції спостерігалася краща точність при застосуванні саме функції Лапласа, а при одно- і двоточковому схрещуванні – гірша, але не значно (не більше 0,2 %). Але зі збільшенням числа елітних фенотипів скорочується тривалість еволюційного пошуку у ході керування, при одно- і двоточковому схрещуванні, практично, у два рази.

Наукова новизна. Уперше розроблена структура евристичної системи автоматизованого керування споживанням електроенергії підземними електроприймачами з напругою живлення до 1000 В залізорудних шахт на основі еволюційного генетичного алгоритму, що дозволяє в залежності від планових обсягів видобутку руди і вартості електроенергії на добу наперед визначити оптимальний графік електричних навантажень підземних дільничних підстанцій, котрий, при дотриманні прийнятих обмежень на погодинну й добову потужність, забезпечує мінімізацію витрат на придбання електроенергії, тим самим зменшуючи собівартість кінцевого продукту.

Практична значимість. Розроблена архітектура евристичної системи керування споживанням електроенергії електроприймачами напругою до 1000 В на базі еволюційного генетичного алгоритму, котра рекомендується для застосування при оптимізації графіку електричних навантажень трансформаторних підстанцій гірничо-металургійних підприємств, зокрема, залізорудних шахт, що працюють на цьому класі напруги.

Ключові слова: *електрична енергія, електроприймачі до 1000 В, евристичний алгоритм, генетичний алгоритм, шахта*

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