ISBN 978-83-66216-71-6

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PREVENTIVE THESES TO OPTIONS FOR DEVELOPING SMART CONTROL SYSTEMS

FOR POWER FLOWS DISTRIBUTION AMONG CONSUMERS OF IRON ORE UNDERGROUND MINES

Edited by DSc. (Engineering), Prof. Sinchuk O.M.

Monograph

iScience

Warsaw, Poland - 2023

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UDC 621.313-57

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Recommended for publication by the Academic Council of Kryvyi Rih National University of the Ministry of Education and Science of Ukraine
(Minutes #2, September 27, 2022)

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PREVENTIVE THESES TO OPTIONS FOR DEVELOPING SMART CONTROL SYSTEMS FOR POWER FLOWS DISTRIBUTION AMONG CONSUMERS OF IRON ORE UNDERGROUND MINES /Monograph/ I. Sinchuk, A. Kupin, K. Budnikov, M. Baranovska. – Warsaw: iScience Sp. z.o.o. – 2023. – 92 p.

The research materials presented in the monograph continue to accumulate the ‘stock’ of the search results developed by Prof. Sinchuk’s scientific school from Kryvyi Rih National University (Ukraine) devoted to the issue of increasing energy efficiency of mining enterprises with an underground method of mining iron ore raw materials.

To do this, the researchers of the above-mentioned scientific school have all the grounds to study basic system-creating enterprises of Ukraine’s industry – mining and metallurgical ones – by applying their professional potential and expertise.

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CONTENT

INTRODUCTION

Due to a number of factors, including historical and political ones, Ukraine is currently among those countries the economy of which is still developing. It is based on the raw material base, the main one for extracting and processing of iron ore raw materials, which are annually exported to 12-15 foreign countries, thus replenishing the country's foreign currency reserves by over 60 %

In Ukraine, iron ore mining is carried out by both open-pit/surface (followed by raw ore concentration at mining and concentration plants) and underground mining methods.

Over 30% of total iron ore in Ukraine is mined by underground methods. This and a number of other important factors make underground mining enterprises quite promising in terms of iron ore production. Meanwhile, iron ore mining costs are increasing, both for objective (increased mining depth exceeding 1500m, with an outlook for 2000m-2300m) and some subjective reasons [1-4]. One of such factors is a constant increase in prices for power consumed by enterprises, including its component – electric power. It is the electric power segment that is the main excitatory factor, as an indicator of low energy efficiency of iron ore mining enterprises, which in the final version leads to an increase in the cost of iron ore production [2-5].

This dependence is explained by the fact that iron ore mining enterprises, as well as the mining and metallurgical industry as a whole, are energy-intensive [6-11]. Analysis of the prime cost components for underground iron ore mining indicates that power costs constitute about 30% of total ones. In turn, electricity covers over 95% of these costs. Besides the problem of electric energy efficiency due to installed significant power capacities, underground iron ore mining enterprise’s activity is also complicated by great fluctuations in power consumption levels during the day, months, and seasons. Daily variations in power consumption are the largest [12-19]. As it is established in [12, 13], the range of existing fluctuations in daily hours by levels of power consumption at Ukrainian iron ore mines on average exceeds four multiple values. Such fluctuations are not observed in any other types of industrial enterprises, even including those similar to iron ore underground mines – coal, shale, salt mining and other types of mines.

In turn, the load factor of transformers of main step-down substations (MSDSs) of mining enterprises at night reaches 5-12 %. This fact generates negative changes in quality indices of power because of fluctuations (decrease) in load power at specified hours of the day, which causes generation of the reactive component of power in the network.

In 2019, the existing three-rate tariffs ("peak", "half-peak", "night") were actually terminated for industrial enterprises in accordance with the Law of Ukraine [20], this greatly deteriorating the economic situation at iron ore underground enterprises. Transition to an hourly tariff, in fact denoting transition from a three-rate tariff to a two-rate one, caused an acceleration of the growth of the power cost segment in the total cost of iron ore production [22-30].

Increasing the depths of iron ore mining will inevitably contribute to increasing power consumption. It is an equally important factor in deterioration of the situation with power engineering of national iron ore mining enterprises. For iron ore underground mines, the mining depth has crossed the mark of 1500 m with the prospect of 2000-2300 m. As established, lowering the depth of production for every 70 m up to 1500 m requires additional power costs of 1100 kW/t of extracted iron ore materials, and up to 2300 m – by 2400 kW.

To a large extent, the state of energy efficiency of iron ore mining enterprises depends on certain mining technology used by iron ore mining enterprises. Taking into account the prospects of Ukraine's iron ore industry, it should be noted that in the following 30-50 years no new mining enterprises are going to be built. Therefore, one should not expect introduction of new technologies into mining practices as a way of reducing energy intensity of production of this type of minerals.

The life of operating iron ore mines in Ukraine, as well as their electric power systems, is over 50-60 years [1-6, 9-11]. If we take into account the fact that over the past 20-25 years the electric power systems of these enterprises have almost not been upgraded, the reason for their low economic efficiency will be understandable.

Considering the dominant role of the power consumption segment in forming the modern structure of the target cost of iron ore production, in the last 5-10 years mining enterprises have somewhat changed their attitude to the internal power engineering. Some efforts are taken to find ways, and, most importantly, implement a number of energy-saving measures at operating mining enterprises.

Unfortunately, these measures were and are mostly of purely managerial character, which implied an a priori change in the format of functioning of some of the most energy-intensive power consumers. However, in reality, such measures are not enough. Among other reasons for this, there is also the fact that these measures, for the most part, were not always scientifically substantiated.

Despite a certain imperfection of these measures, they temporarily gave enterprises a certain savings in payment for the consumed power and enabled them to restrain the growth rate of energy intensity of iron ore production. In the future, preventive measures of mining enterprises to improve the energy efficiency of iron ore production were supplemented by energy management services included in the structure of enterprises. The services use accounting tools to control power consumption and adopt appropriate measures according to the results obtained.

In modern conditions, it is logical that in relation to electricity as a basic component in formation of iron ore costs, only to control the levels of electricity consumption is not enough both for pure economic reasons and from the viewpoint of developing the mining industry itself. Currently, it is necessary to control this process as a set of components of mining technology designated for this type of minerals.

In addition, it would be appropriate to note that the problems of power engineering of mining enterprises of any type are not solved even after their closure or conservation [13-16]. This is another of important additional impulses to the relevance and necessity of timely study of ways to improve energy efficiency of these enterprises in the integrated direction of the search goal.

Directions for improving energy efficiency of mineral mining are basically known and formed [1-8, 10, 11][1]. Moreover, in the last 5-10 years, the 'line' of directions has increased. However, as a rule, this applies to those mining enterprises that are being designed or globally re-equipped. As for the existing ones, this problem is far from being solved. So, it is logical to conduct scientific research to improve existing power complexes of operating mining enterprises.

Real directions for improving energy efficiency of existing underground mines in the current vision of the problem include modernization of power supply systems, installation of machines and mechanisms with energy-efficient electric drives, optimization of power consumption processes of both local energy-intensive facilities and the entire electric power complex of enterprises with further adaptive management of this process.

Of the above directions, the first one has been more or less investigated and contains effective, but still very limited aspects of its

[1] Note. According to state standards of Ukraine, under the concept of energy efficiency, we mean a degree for assessing the level of achievable energy efficiency. To do this, weight (degree of energy efficiency) can be expressed in various ways, including that of mining enterprises - a tonne of extracted minerals per unit (kW*h) of a particular type or total power consumed.

application. Therefore, it seems relevant to conduct a set of studies, with an emphasis on the second of the above-mentioned areas.

In practice of well-known scientific researches in this area, the closest are the studies conducted at coal underground mines and other types of mining and industrial enterprises [1-8].

Meanwhile, the difference in mining technologies at coal and iron ore underground mines, and especially at different industrial enterprises, does not allow transferring the research results, even in the first approximation, from "coal" to "ore".

All this determines the difference in formation and implementation of requirements both to structures and parameters of power supply systems, as well as to operating modes of technological electrical equipment, which is a determining and, at the same time, the main factor in personalizing the approach to forming such a solution to the problem of increasing energy efficiency of power use for special conditions of coal and iron ore underground mines.

The analysis of the above-mentioned, as well as a number of scientific studies that were not covered in this study, and yet were subject to a certain analysis, allowed the authors to formalize and differentiate searches according to their orientation, technological conditions of the enterprises for which and on the basis of which they are performed. Such a gradation, according to the specifics of mining technology and the research aim, makes it possible to cross out areas that were not fully covered, or subject to research at all, and which are aimed to be used at iron ore types of enterprises.

Of course, maximum energy efficiency of mining enterprises can be achieved because of a comprehensive solution. However, without rejecting this version of the approach from the list of possible ones, we note that both in scientific research and in practical implementation of its results in the structure of mining enterprises in general, and, mining in particular, in the above-mentioned context, it is a very difficult task with a long investment period. A step-by-step solution to this complicated problem with an unconditional emphasis on such an interpretation of the finality of the solution seems logical.

It is logical that one of the first among those directions that will increase energy efficiency of iron ore mining enterprises with a short investment period is to restrain and reduce price pressure for consumed power. This statement is based on the fact that it is underground iron ore mining enterprises, unlike their other analogues, that are characterized by significant fluctuations of levels of power consumption in time ranges. Advantage should be taken of the existing grid of zone tariffs for the consumption of this type of energy.

A positive point among others in terms of efficiency of this tendency is that in the general structure of the energy-intensive power system of underground iron ore mining enterprises, their fullness is based on a limited number of energy-intensive consumers. Consuming 90-95% of the total power of the enterprise, these consumers form the current technology of iron ore mining. In other words, the task of improving energy efficiency of the entire underground iron ore enterprise is solved by redistributing power flows among energy-intensive consumers within the framework of established tariffs.

The automatic control system (ACS) of power consumption should become an expected result of searching for ways to increase the electric power efficiency of underground iron ore mining enterprises. The structure of the algorithm functioning of the ACS should provide for forecasting the volume of managerial decisions in this direction.

Thus, theoretical substantiation, evaluation and development of methods for ensuring required and possibly affordable energy efficiency aimed at maximum realization of mining enterprises' power potential by developing the ACS of electric power consumption for current and designed enterprises of underground iron ore mining not only in Ukraine, but also in other countries are relevant and timely research tasks.

SECTION 1
ANALYSIS AND ESTABLISHMENT OF FACTORS AFFECTING ENERGY-ORIENTED MODES OF POWER CONSUMPTION BY WATER DRAINAGE FACILITIES OF IRON ORE UNDERGROUND MINES

1.1. Water drainage facilities in the structure of the power supply complex of iron ore mining enterprises

As to their intended purpose, water drainage facilities of mining enterprises are divided into main (central), auxiliary (site) and temporary (shaft-sinking). The main ones include installations designed to intercept and pump out all or most of the expected water flow from underground mine workings to the surface into special reservoirs of technical water. Site and shaft-sinking water drainage facilities pump water from the relevant areas to the central drainage system. The scheme of drainage of the closed mine Hihant-Hlyboka (Kryvyi Rih) is shown in Fig. 1.1

According to this classification, in terms of water pumping technology and power consumption, main drainage facilities, which receive power from the grid with a 6 kV voltage are noted for significant levels of installed electrical capacities (Table 1.1) and power consumption averaging up to 40% of the total power consumed by an iron ore underground mine.

The main water drainage system of each modern operating iron ore underground mine is usually located on two to three underground levels and consists of four to five stages, which include reservoirs, a pumping chamber, a substation chamber, etc.

Water drainage is an electricity receiver, the modes and consumption of which actually do not depend on the volume of iron ore production, but mainly on the natural level of groundwater inflow. As can be seen from the above graphs, the volumes of water pumped out by water drainage facilities do not have a stable dependence on extraction of iron ore raw materials, and in recent years, with a slight decrease in these volumes, there has been a slight increase in water inflow.

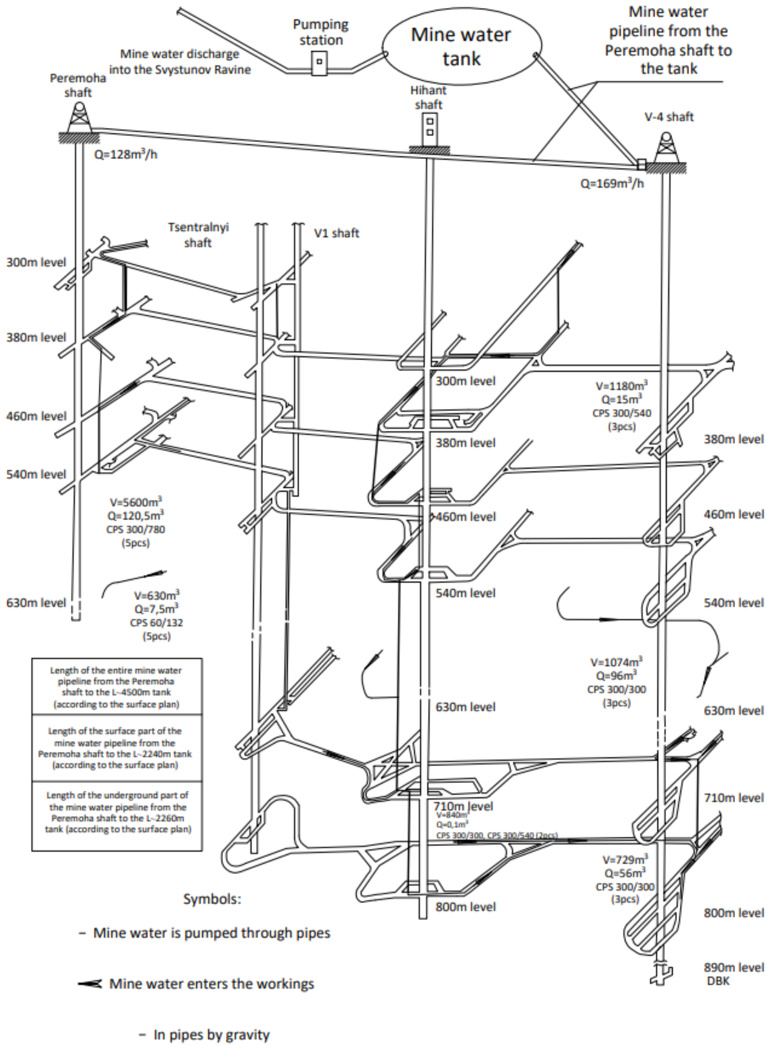


Fig. 1.1. Structure of water drainage facilities of the closed Hihant-Hlyboka underground mine (Kryvyi Rih)

Table 1.1 – Power indices of electric motors of electric drives of main water drainage facilities of underground mines in Kryvyi Rih region

№	Underground mines	Motors		
		Capacity, kW	Number	Total installed capacity
1	Ternivska	800	9	7200
		315	4	1260
		250	4	1000
		Total 9460		
2	Kazatska	800	9	7200
		630	3	1890
		500	1	500
		315	3	945
		Total 10535		
3	Pokrovska	800	8	6400
		400	8	3200
				Усього 9600
4	Kryvorizka	800	20	16000
		560	6	3360
		Total 19360		

The volumes of water flow of iron ore underground mines of the Kryvyi Rih iron ore basin are presented in Fig. 1.2.

According to the analysis of indices for the underground mines, the difference in the volume of water inflows differs almost four times. This significantly affects the volume of power consumption of each facility.

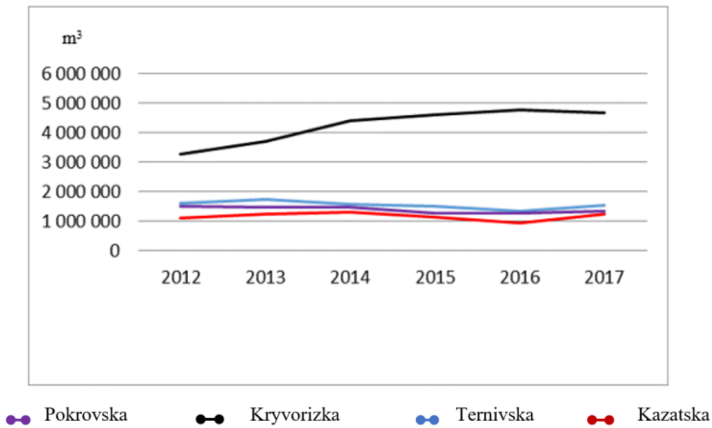


Fig. 1.2. Water flow of iron ore underground mines (Kryvyi Rih, Ukraine)

To analyze parameters of water drainage functioning, the ratio of the annual water inflow (m^3) to the volume of annual iron ore production is used (Fig. 1.3).

As the graph in Fig. 1.3 indicates, this coefficient is not constant and for individual underground mines (Kryvorizka) is characterized by a significant level of fluctuations. This is an additional component in choosing search parameters to solve the problem of improving energy efficiency of a particular underground mine.

Graphs of active power consumption by water drainage facilities per day at iron ore underground mines of the Kryvyi Rih iron ore basin are in Fig. 1.4. The graphs show that the pumps do not constantly work in the nominal mode. When the reservoirs are large enough to accumulate water, it is pumped at night only (Kazatska). When the capacity is insufficient to collect all the water, the staff is forced to turn on water drainage facilities in the daytime (Kryvorizka and Pokrovska).

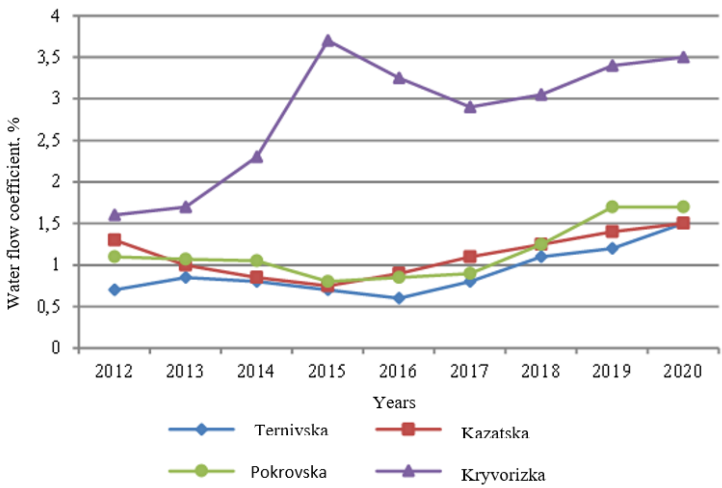


Fig. 1.3. Water flow coefficient of iron ore underground mines of Kryvyi Rih iron ore basin

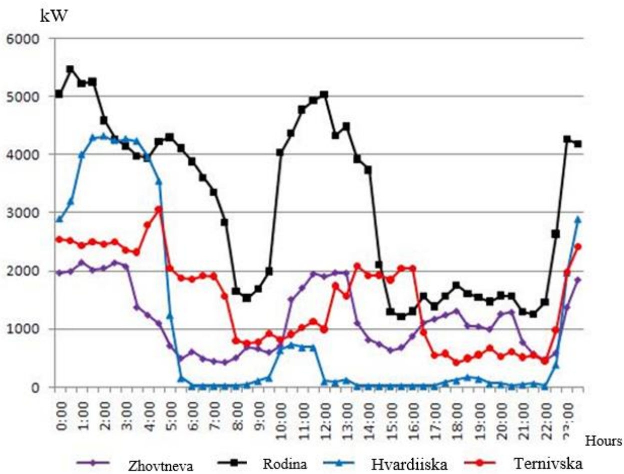


Fig. 1.4. Daily curves of active power of water drainage facilities of iron ore underground mines of Kryvyi Rih iron ore basin

Figures 1.5 – 1.8 show the graphs of power consumption of water drainage facilities of various underground levels of underground mines of Kryvyi Rih iron ore basin.

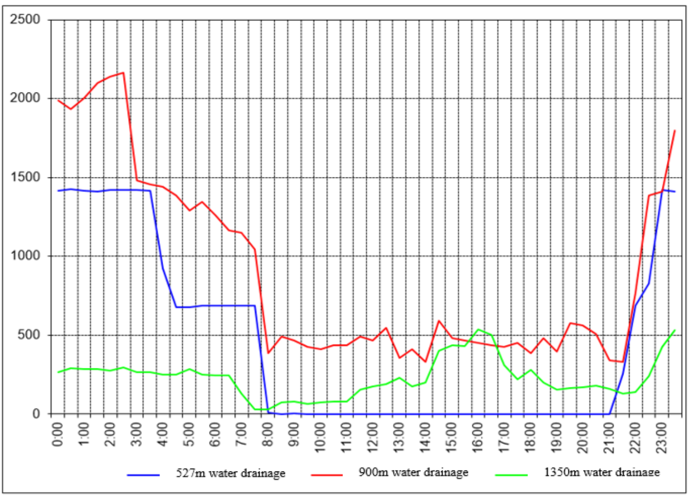


Fig. 1.5. Daily curves of water drainage facilities of Ternivska underground mine (Kryvyi Rih) on January 2, 2018

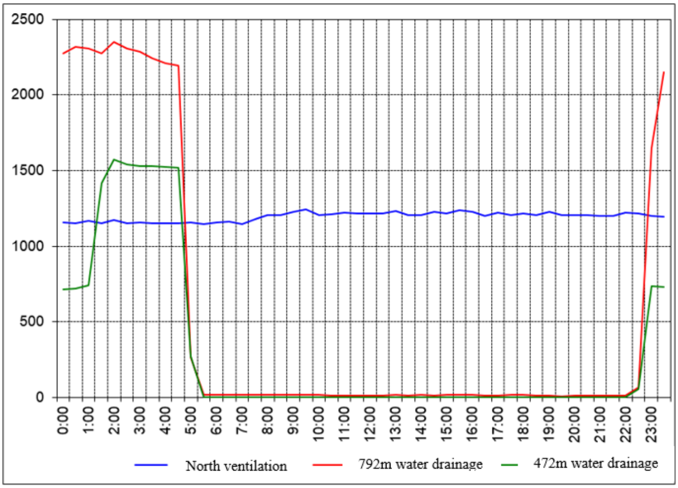


Fig. 1.6. Daily curves of water drainage facilities of Kazatska underground mine (Kryvyi Rih) on January 2, 2018

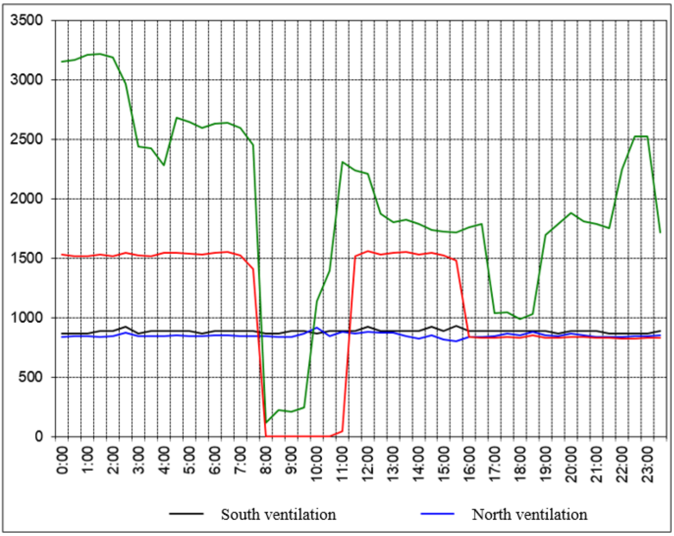


Fig. 1.7. Daily curves of water drainage facilities of Kryvorizka underground mine (Kryvyi Rih) on January 2, 2018

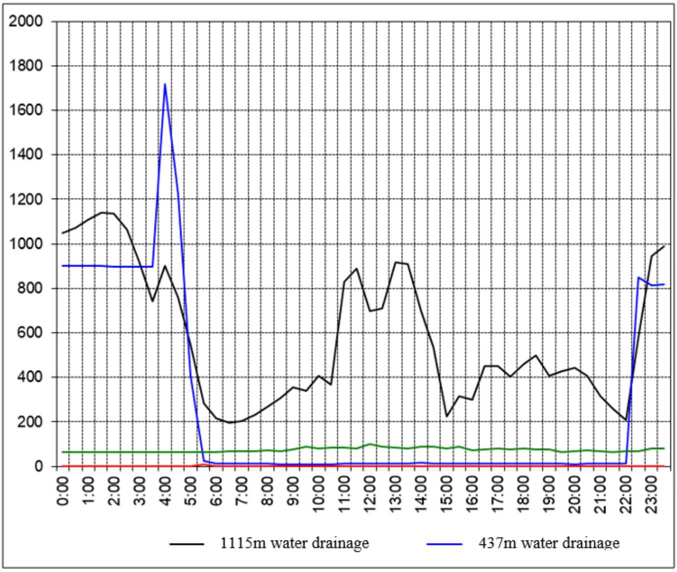


Fig. 1.8. Daily curves of water drainage facilities of Pokrovska underground mine (Kryvyi Rih) on January 2, 2018

Analysis of power consumption curves during the operation of water drainage facilities for 24 hours at different iron ore underground mines shows that the levels of power consumption fluctuate significantly and do not have a stable dependence [83-85].

The values of the coefficients ($K_{saf.factor}$ = 0.49÷0.57, K_m = 2.04÷1.75) are due to the mode of operation mainly during the hours of the minimum tariff (night) to reduce electricity fees. To implement this mode one requires almost twofold supply of power and performance of drainage units, as well as an increased capacity of water reservoirs. More profound control is carried out at the Kazatska and Ternivska underground mines, less profound – at Kryvorizka and Pokrovska underground mines.

Discrepancies in power consumption by water drainage facilities of the corresponding iron ore underground mines during a day indicate ambiguity of mining and geological conditions of the underground mines, which causes different volumes of water inflow. In this regard, these discrepancies affect economic indices of energy efficiency of water drainage facilities during the day, but also the economic situation of an enterprise as a whole.

To complete assessment of the operating modes of the analyzed types of power consumers, Fig. 1.9 shows the yearly of load curve of water drainage facilities of underground mines of Kryvyi Rih iron ore basin. As can be seen, fluctuations in the load of water drainage facilities during the year are insignificant, which is caused by a change in water inflow.

Thus, comparing daily and monthly curves of power consumption and considering significant levels of power capacities of main water drainage facilities of iron ore underground mines and their basic components, it seems logical to decide on optimizing the curves and, therefore, power consumption primarily in hours of the day (according to daily tariffs for power consumed).

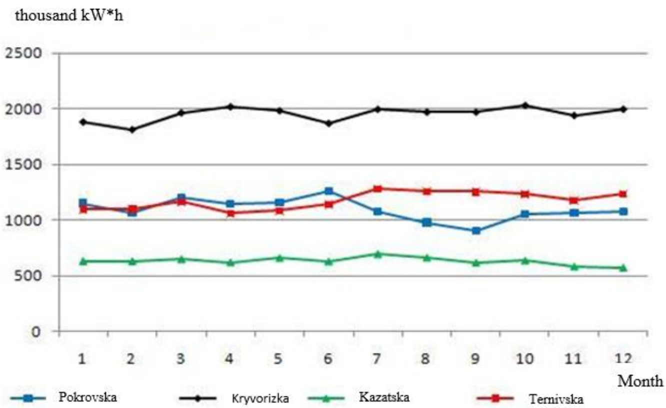


Fig. 1.9. Yearly load curves of main water drainage facilities of iron ore underground mines (2018)

The enterprises have decided and continue to solve this axiom in the context of a set of energy saving measures. Moreover, this preventive measure allows enterprises to obtain a significant effect (about 18%) by saving material costs for electricity consumed by water drainage.

Indeed, the analysis of daily operation of water drainage facilities in recent years allows us to conclude that most of the underground mines of Kryvyi Rih iron ore basin have redeveloped the operation of water drainage systems in order to increase work at night due to reducing costs in electricity payments.

As a result of the operation of water drainage facilities in the night zone, although its duration is 7 hours, power consumption is 40-55%, and during peak hours, lasting 6 hours – 22%. That is, water drainage facilities are some of the largest consumers of electricity during peak hours. At night, according to real possibilities, it is planned, as far as possible, to make the capacity of water drainage facilities maximum. As the analysis of water drainage in day zones in recent years showed, the planned and actual indicators have almost equalized and reach maximum values – 50% [12-19, 25-30].

The maximum effect is achieved if at night, the water is completely pumped out, and at other hours of the day, the pumps are not turned on. To do this, it is necessary to have a sufficient volume of reservoirs (which is problematic because of the mining technology available) and pump performance.

Meanwhile, the analysis conducted by the author and some other scientists and manufacturers showed that even with this approach, not all the potential is exhausted at iron ore underground mines in terms of implementation of these measures.

As a possible option to supplement the measures already applied, the following proposals can be given (Fig. 1.13). The above-mentioned measures will additionally reduce losses for the share of power consumed by the water drainage system by 10-15%

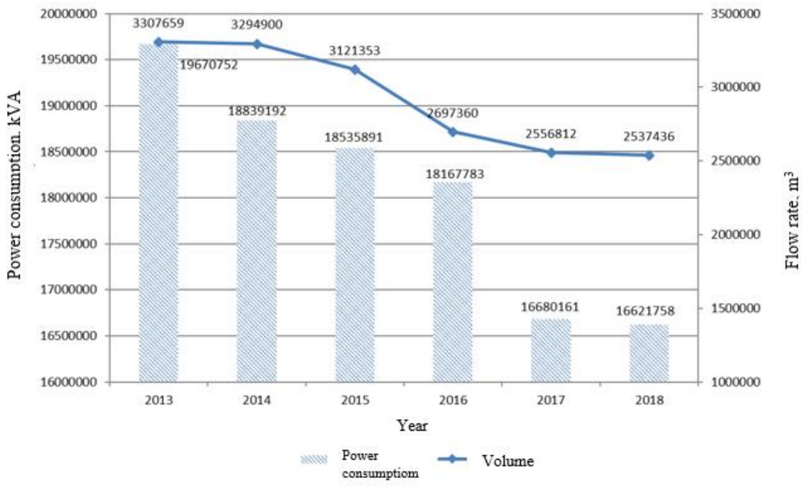
However, the forecast of the expected growth of water inflow volumes along with an increase in the mining depth in the near future may minimize these ‘organizational achievements’. Meanwhile, another natural possibility of mine water drainage systems, namely, their ability to work as reversible hydraulic units, has not yet been analyzed and exhausted. In other words, they can not only consume power, but also produce it for the needs of underground power consumers. This thesis seems urgent for another reason as well.

When analyzing the electric power consumption for water drainage of underground mining enterprises, it is necessary to note the fact that even with the closure (conservation) of underground mines, the water drainage facilities of these mines continue to work, since, as a rule, the inflow of water into mine workings continues to exist.

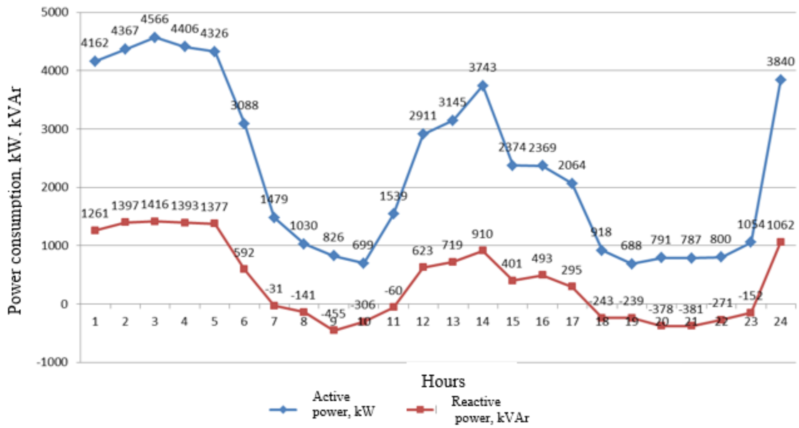
As an example Fig. 1.10 shows the levels of power consumption by the main water drainage systems of Hihant-Hlyboka underground mine (Kryvyi Rih) in 2013–2018. This mine was closed more than twenty years ago. According to the data [26-30], the levels of power consumption in this non-operating underground mine exceed the corresponding levels of operating ones. That is, the problem of water drainage at non-operating underground mines remains relevant. The capacity of electric motors of pumps and their types are given in Table 1.2.

Table 1.2 – Capacity of electric motors of pumps and types of complexes of main drainage systems

Pumps	Capacity of motors, kW	Number of motors	Total capacity, kW
TsNSA300/540	800	5	4000
TsNSA 300/300	500	7	3500
TsNSA 300/780	1000	5	5000
VP340/18	37	5	185
TsNSA 60/132	37	2	74
Total			12759
Power consumption by water drainage			
Average daily consumption			28950
Average monthly consumption			868500



a)



b)

Fig. 1.10. Power consumption by the main water drainage complex of Hihant-Hlyboka underground mine (Kryvyi Rih) on the yearly (a) and hourly basis – December 20, 2017 (b)

For more significant confirmation, a framework analysis of power consumption of this underground mine is carried out in accordance with Fig. 1.10. With a 23.3% decrease in the volume of water inflow from 2013 to 2018, power consumption decreased by 15.5%, i.e. in the forecast for the coming years, the volume of power consumption by this non-operating mine will decrease.

1.2. General problems and logistics of a comprehensive assessment of power consumption by water drainage facilities of iron ore underground mines

Over the past decades, production of power in Ukraine has been decreasing and at the beginning of 2020 it made 150 000 GW*h against 300 000 GW*h in 1990, i.e., it has halved. Meanwhile, the levels of installed capacities of Ukraine's power plants have not decreased compared to 1991, but, on the contrary, have increased and are actually equal to about 55 GW [55].

The potential capacities of the Ukrainian electric power industry make it possible to produce about 300 billion kWh of power per year.

The power balance of Ukraine is characterized by:

– decrease of power production volumes in 1990-2000 from 298.5

to 171.4 billion kWh, i.e. almost halved (including TPPs by 2.5 times) with the tendency of potential stabilization;

– reduction of power received from outside Ukraine;
– reduction of power consumption by the industrial sector;
– reduction of power supply outside the state;
– the trend of stabilizing power production volumes;
– stability of production volumes by nuclear power plants;
– growth of generating capacities.

Key requirements for modern general power engineering formed by the world community, include, in particular, its effectiveness declared as "maximizing efficiency of the use of all types of resources and technologies in production, transmission, distribution and consumption of power" [56-62].

Currently, in most countries of the world, the process of steadily reducing the amount of power used to produce a unit of GDP continues. This trend, although in a significant lag behind the EU countries, is also typical for Ukraine. As is known [63], energy intensity of this main economic indicator of the state is largely determined by part of the energy-intensive industry. In the last decade, power consumption by the industrial sector of Ukraine stabilized. Close to this option of stability came energy-intensive types of production, including enterprises of the mining and metallurgical complex.

Such "stability" restrains the pace of reduction of energy intensity of GDP necessary for the state's economy. However, this is not a verdict on the futility of further reducing energy intensity of GDP, but on the contrary, an impetus to intensify the tested and find new ways to solve this global problem for the state. The Law of Ukraine on the Power Market is also aimed at solving these problems [64].

The reform of Ukraine’s power market is associated with acquisition of the status of a Contracting Party in the Treaty establishing the Energy Community [65]. Fulfillment of the requirements of the Third Energy Package in a timely manner is the main priority for the next period of activity of the United Power System (UPS) of Ukraine within the Energy Community. In particular, with this package, the national regulatory authority is endowed with legal isolation and functional independence from any state, public, private persons, market interests, including persons responsible for management.

It should be noted that when following foreign countries’ experience, reforming (liberalization) of the power market and making it competitive leads as a rule to a significant increase in power prices, a decrease in investments in the industry, a subsequent decrease in the capacity reserve and reliability of power supply to consumers.

A number of national scientists in the field of power engineering [57-63] emphasize that at this stage of development of legislation, in particular the antimonopoly one, it is more expedient not to change the "current" model of the power market, but to improve it by introducing mechanisms of centralized impacts on development and functioning of the power system of Ukraine. It is also proved that concentration of market potential primarily in production of power (monopolization of generation) by a certain financial and industrial group contradicts the idea of forming market competition, which underlies the "new" model of functioning and management of the power market.

As evidenced by the results of the first years of reforms, a new already existing model of the wholesale energy market of Ukraine needs to be improved in terms of respecting the economic interests both of suppliers and consumers of power. An important component of this process should envisage optimization of power costs. Each manufacturer and supplier should be responsible both for their own balance sheet and for the imbalance of power, i.e. deviations from the contractual schedule of production or consumption.

By concluding bilateral contracts or buying power on the day-ahead market, power suppliers and producers are obliged to ensure their consumption and production at certain hours at the appropriate level. At the same time, they are parties that are responsible for the balance personally (or are included on a contractual basis in a certain balancing group).

In Ukraine, about 200 mining and metallurgical enterprises represent basic consumers of power. These types of enterprises have been operating in power market conditions for more than 3 years [64]. To switch to this format, power enterprises-consumers had to perform a significant amount of work to improve reporting forms of the automated power accounting system and update their energy services.

Until January 2019, at industrial enterprises, including mining ones, three-zone tariffs were used – "peak", "half-peak" and "night". The cost of power, for example, in April 2019 in the "peak" zone was UAH 2.94, in the "half-peak" zone – UAH 1.67, in the "night" zone – UAH 0.41. Enterprises had the opportunity to effectively adjust operation of drainage and hoisting at night, so they saved money on power costs due to the difference of more than seven times the cost of the peak and night zones. This had a positive impact on operation of power producing companies due to the unloading of peak zones, since energy-intensive consumers almost did not work in these zones.

With transition to the energy market, hourly tariffs began to operate, which are in fact two-zone tariffs – "day" and "night", differing from each other by almost half. For example, in April 2020, the cost in the "day" zone was UAH 2.05, in the "night" zone – UAH 0.96. Now enterprises do not use pauses in the morning and evening peak hours, so the load during these hours for energy companies increases.

If earlier power tariffs for enterprises were constantly and steadily only growing, now the market determines the levels of power costs. Therefore, it is expected that when the market in Ukraine will become reliable, it will have a positive impact on both energy companies and power consumers. However, to achieve such parity, it is necessary to approach the problem carefully from both sides based on the results of scientific researches.

At the same time, it should be remembered that the base-forming component of variability and energy-saving of both generating systems and consumers of power are forms of curves of power consumption [34, 37, 39, 66]. These curves can be daily, monthly, seasonal and yearly. The corresponding curves of generating systems depend on the trajectory of curves of power consumption by energy-intensive enterprises, therefore they can be adjusted in approximation to their optimal. As established [38, 41, 42], iron ore mining enterprises are noted for the greatest fluctuations compared to other industrial enterprises.

This dynamics of fluctuations is especially inherent in the daily curves of power consumption. Taking into account that according to the Law of Ukraine [64], tariffs for power consumption are determined by the energy market hourly for the day ahead, the problem of improving energy efficiency of mining enterprises (as well as other types of consumers) should be solved in this very perspective.

Along with the above arguments according to the state and prospects of Ukraine's energy sector in general and the power industry in particular, one should mention such a system-forming fact of our time as reliability and uninterrupted functioning of power supply systems of industrial enterprises and enterprises of housing and communal services of the state in extreme situations. This requires specific measures to be found, substantiated and developed in order to ensure stability and continuity of operation of power supply systems, including autonomous (backup) systems for generating power at enterprises, places of residence, etc.

1.3. Analysis of selecting criteria for optimal power consumption by energy-intensive components of iron ore mining enterprises

Based on the statement that any production system operates in conditions of limited resources, the level of achievement of the goal is limited and the optimal operating mode of the system involves the choice of the best vector of actions *X* on the set of its possible options. To do this, there should be an objective mathematical characteristic of action priority. Each version of the power consumption system, based on its limited resource, seeks to provide a set of actions that would bring the system closer to its goal to the greatest extent, that is, it would have the greatest benefit for this. The scheme is successfully implemented limited only by available resources.

Power consumption options cannot ideally correspond to the principle of maximum compliance of the consumed power and its cost, because there can always be certain errors and random deviations, but in the absence of certain possibilities, the nature of compliance as a whole does not change. Because of this, it is reasonable and logical to study this aspect of the production process based on the principle of optimality. In this case, it can be considered reasonable to assume that for power consumption, there is a certain criterion of optimality that regulates behavior of water drainage devices. This criterion should be called a target function of promoting goal achievement to maximize which all possible options for power consumption are striving.

It should be noted that such a definition of the target function is ambiguous. If $f(x)$ is the target function, and $\eta\left(f\left(x\right)\right)$ is the arbitrary monotonically increasing function of the argument $f\left(x\right)$, then any conditional maximum $f\left(x\right)$ will simultaneously correspond to the conditional maximum of the function $\tilde{f}\left(x\right)=\eta\left(f\left(x\right)\right)$.

Because of this, from the point of view of this definition of the target function, it is not possible to distinguish between functions $f\left(x\right)$ and $\tilde{f}\left(x\right)$, i.e. the target function is defined only with accuracy to monotonous transformation and therefore does not reflect any real quantitative value. This function only indicates which of the action sets takes precedence over the others. However, this is quite enough to study both power consumption and the problem of optimizing energy efficiency levels. From a methodological point of view, such ambiguity of the target function is convenient to use, because it allows you to choose one or another of its variants, depending on characteristics of the specific task under study.

Giving a geometric interpretation of the target function, it can be characterized by a set of hypersurfaces of indifference in the *n*-dimensional space *x*, on each of which the target function remains constant. The monotonous transformation of the target function does not affect the shape of these hypersurfaces, but only the value of the target function on each of them.

$$p \cdot x = d\,, \tag{1.1}$$

where $p = \left(p_1,\ p_2, ...,\ p_n \right)$ is the vector of the cost of power consumption;

$x = \left(x_1,\ x_2, ...,\ x_n \right)$ is the vector of target parameters or the vector of power consumption, which has an impact on the level of goal achievement of optimizing power consumption of water drainage devices of an iron ore mining enterprises;

d is the total resource volume (more precisely, the total cost of power consumed over the period of time analyzed).

Among all the possible vectors that satisfy (1.1), the iron ore mining enterprise will choose the one that provides the maximum value of the target function $f(x)$. The optimal value of the vector x, can be found using Lagrange factors, while allowing the differentiation of functions f(x):

$$L = f\left(x\right) + \lambda\left(d - px\right), \tag{1.2}$$

where λ is an arbitrary scalar multiplier.
Applying the Lagrange rule, we obtain:

$$\nabla f\left(x\right) = \lambda p\,, \tag{1.3}$$

or in the scalar form:

$$\frac{\partial f\left(x\right)}{\partial x_i} = \lambda p_i, \quad i = 1,2,....,n\,\cdot \tag{1.4}$$

This property of the target function can be used to analyze and predict the possibilities of ensuring power consumption. With the known function, dependence (1.4) can be applied to determining changes in the structure of target parameters when the cost and volume of power consumed changes, as well as to solving the inverse problem of determining the cost system that corresponds to the most desirable structure of the target parameters of power consumption. To solve partial problems, the functions of dependence of possibilities of power consumption on the volume of power consumed and the cost are used. Yet, to obtain a complete description of the structural elements, it would be necessary to jointly analyze the target functions for achieving the goal for each possible power resource.

Partial derivatives of the first order of the target goal achievement function (1.4) can be interpreted as values of the proportionate value of equilibrium. Assuming that $f(x)$ is twice differentiated:

$$\frac{\partial f(x)}{\partial x_i} = \frac{\partial}{\partial x_j}\left(\frac{\partial f(x)}{\partial x_i}\right) = \lambda \frac{\partial p_i}{\partial x_j}. \tag{1.5}$$

They characterize the dependence of the cost of equilibrium on the numerical values of all types of target parameters. If we assume that a square matrix $\left\|\frac{d^2 f(x)}{dx_i dx_j}\right\|$ characterizes the dependence of the value of equilibrium on the numerical values of all possible available target parameters, partial derivatives of the first (1.3) and second order (1.4) quite fully characterize the target function *f(x)* in the broad structure of the target parameters and the corresponding equilibrium value system. Based on this, you can get a quadratic model of the target function. Let $\overline{x}$ be some known structure of target parameters and the equilibrium value vector $\overline{p}$ corresponding to this structure is known.

We decompose the function $f(x)$ into a Taylor series near the point $\overline{x}$ and limit ourselves to the quadratic approximation of this decomposition:

$$f(x) = f(\overline{x}) + \nabla f(\overline{x})(x - \overline{x}) + \frac{1}{2}(x - \overline{x})\left\|\frac{d^2 f(x)}{d\overline{x}_i d\overline{x}_j}\right\|(x - \overline{x}). \tag{1.6}$$

The product of the vector ($x - \overline{x}$) on the matrix $\left\|\frac{d^2 f(x)}{d\overline{x}_i dx_j}\right\|$ and the vector $(x - \overline{x})$ is executed according to the rules of vector-matrix calculus, as a result of which the quadratic member would acquire the following scalar form:

$$\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \frac{d^2 f(x)}{dx_i dx_j}(x_i - \overline{x}_i)(x_j - \overline{x}_j). \tag{1.7}$$

By definition, the target function is defined with accuracy to a monotonous transformation, which allows you to discard constant terms and constant factors. Based on this, (1.7) can be written as follows:

$$f(\Delta x) = \overline{p}(\Delta x) + \frac{1}{2}\Delta x R \Delta x, \tag{1.8}$$

where $\Delta x = x - \overline{x}$, $R = \left\| z_{ij} \right\|$, $z_{ij} = \dfrac{\partial^2 f(x)}{\partial \overline{x}_i \partial \overline{x}_j}$.

The problem of the necessary consideration of a large number of types of target parameters in the practical use of the target function can be solved in at least two ways: by aggregation of types of target parameters, and by using partial target functions.

The numerical values of target parameter types for each *k*-th, where $k = 1,2,...,K$, of the group x^k can be determined using the coefficients of entry of each parameter of the *i*-th type of the detailed list α_i^k into the unit *k*-th numerical value of the target parameter of the enlarged list. In the scalar form, we will have:

$$x^k = \sum_{i \in k} p_i^k x_i^k. \tag{1.9}$$

The ratio between the costs of the detailed and the enlarged list of target parameters can be made through the corresponding cost indicators, similar to (1.10)

$$p^k = \sum_{i \in k} p_i^k \alpha_i^k x_i^k, \tag{1.10}$$

where p^k, p_i^k is the value equivalent of a unit of the numerical value of the target parameter according to the aggregated and the detailed list.

The second way to solve the large-dimensional problem is through introduction of partial target functions for specific groups of target parameters. Knowing the partial functions, which are obviously easier to build, you can build a general target function for achieving the goal, for example, in the following form:

$$f(x) = \varphi[f_k(x)], \quad k = 1,2,...,K. \tag{1.11}$$

The most significant factor affecting the form of the target function aimed to achieve the goal is peculiarities of structural combinations of targets. This makes it appropriate to build general target functions for each option, and then combine these functions in a suitable way into a single general target function, using the most realistic distribution of resources between different possible options for power consumption.

The second most important element of the criterion of optimality of power consumption by water drainage facilities is the corrective function $W(t)$, which should clarify in time the target function $f(x)$. The specific form of this function depends on the entire set of objectively existing factors. This function should reflect advantages of the target parameters in achieving the goal of the iron ore mining enterprise, seeking to achieve it as soon as possible and relying on both subjective and objective grounds.

When adjusting the function, it is also necessary to consider some uncertainty in interpreting power consumption, in particular consumption of power resources and production. There are many such influential factors that make the problem of building a corrective function quite complex and ambiguous. One of the promising approaches to building a corrective function is based on sliding long-term planning, which is closest to the real scheme of continuous solution.

The corrective function makes it possible to correct inaccuracies in subsequent calculations, but this is very erroneous. The wrong choice of the function $W(t)$ impairs the smoothness of the power consumption trajectory, which entails significant losses in efficiency of using power consumption resources and leads to an increase in time duration required for achieving the goal specified.

The most successful choice of the function $W(t)$ implies minimal total changes in the power consumption trajectory. This can be achieved as follows. Before calculating optimal power consumption, a preliminary calculation of several alternatives is carried out according to enlarged groups of target parameters, using reasonable options for the corrective function $W(t)$. This set will reveal production potential of power consumption by an iron ore mining enterprise in the period under analysis. Within these possibilities, a specific option is chosen, which in the future will ensure minimal deviations in the power consumption trajectory of the iron ore mining enterprise from the ideal.

The choice of a specific power consumption strategy also determines the variant of the corrective function $W(t)$, which will need to be used in calculations according to a detailed list of target parameters. Yet, it should be noted that such a choice of the corrective function inherently bears a significant amount of subjectivism. Objectivism is achieved by taking into account real conditions of mining production.

The optimal options for the power consumption strategy of an iron ore mining enterprise, calculated simultaneously for different variants of *W(t)*, are convenient to analyze and compare by means of determining parameters, which are time functions and clearly illustrate development of the production system. For each corrective function, determining parameters will take on a specific form and a specific version of the function *W(t)* is selected among them.

Meanwhile, determining parameters of the enterprise's development, including the energy sector, may be interpreted differently. The relative growth rate of the energy efficiency is proposed as such parameters. The first of them can be divided into several components depending on the direction of power resources use. The second of these parameters can be omitted with a sufficiently long time period.

Calculating the optimal strategy of power consumption of main water drainage facilities at an iron ore mining enterprise according to criterion (2.18), and solving the corresponding dual conditionally extreme problem of optimal planning of power consumption, one can obtain both quantitative indices of all types of target parameters for all points in time, and their optimal values, reduced to the point in time $t = 0$. The result of solving these problems can be a vector function of the optimal values of the target parameters $\hat{x}(t)$ and their corresponding optimal cost, determined by the vector function $p_x(t)$. Based on them, it is possible to determine the relative growth rate of efficiency of power consumption for a specific time *t:*

$$\alpha(t) = \frac{p_x(t)\dfrac{d\hat{x}(t)}{dt}}{p_x(t)\hat{x}(t)}. \tag{1.12}$$

Based on the type of this dependence, you can make the following comments. Time differentiation here does not apply to the cost, because it is necessary to compare two sets of values of target parameters for different points in time in comparative prices. In addition, we can conclude that expression (1.12) does not depend on the scale of prices, because prices are present in both the numerator and the denominator.

Having the vector function of the main $\hat{y}(t)$ and their optimal prices $p_y(t)$ for the optimal power consumption strategy, the relative growth rate of *β(t)* will be written as follows:

$$\beta(t) = \frac{p_y(t)\dfrac{d\hat{y}(t)}{dt}}{p_y(t)\hat{y}(t)}. \quad (1.13)$$

Similarly, it is possible to describe other parameters characterizing the relative growth rates for any other set of power resources.

Obviously, the parameters $\alpha(t)$ and $\beta(t)$ are significantly dependent on the corrective function *W(t),* because for each of its variants you can calculate the corresponding parameters $\alpha(t)$ and $\beta(t)$, which means that different results of such calculations are obtained for different functions *W(t).*

To calculate the coefficient of power consumption efficiency, we consider along with the given optimal prices up to one point in time t = 0, $p_x(t)$ and the unreduced optimal prices of the target parameters, which will be affected by the vector function. They are associated with the following ratio:

$$\overline{p}_x(t) = \gamma(t)\, p_x(t), \quad (1.14)$$

where $\gamma(t)$ is a monotonously increasing scalar function, the argument of which is time *t* and which can be interpreted as one of the indicators of energy efficiency of an iron ore mining enterprise.

The specification of the function $\gamma(t)$ is possible based on the dynamics of prices, the tendency of change can be expressed by the function $\delta(t)$. Taking this into account, you can write:

$$\overline{p}_x(t)x(0) = \overline{p}_x(0)x(0)\delta(t), \quad (1.15)$$

where $\delta(0) = 1$.

If $\delta'(t) < 0$, prices will reduce; at $\delta'(t) > 0$, prices will rise, and at $\delta'(t) = 0$, prices will remain unchanged.

The function $\gamma(t)$ for the optimal strategy of power consumption and the specifically selected function *W(t)* can be defined as follows:

$$\gamma(t) = \frac{\overline{p}_x(0)x(0)\delta(t)}{p_x(t)x(0)} \tag{1.16}$$

The relationship between the reduced and unreduced optimal prices is valid not only for the target parameters $x(t)$. It is also true for other factors, because otherwise prices will not be able to serve as a means of appropriate calculations, for calculating indicators of power consumption efficiency as well.

In the theory of optimal management, the concept of the level of efficiency acquires the most general sense. This efficiency in relation to power consumption is considered as a tool for bringing to one point in time the unreduced optimal prices of power resources for two adjacent single periods of time. For example, at the time *t*, the ratio of unreduced prices to the given ones is 5, and at the time (*t* +1)-6, the coefficient of power consumption efficiency is determined as follows:

$$\frac{\overline{p}_x(t)}{p_x(t)} = 5; \quad \frac{\overline{p}_x(t+1)}{p_x(t)} = 6; \quad \eta(t) = \frac{6}{5} - 1 = 0{,}2, \tag{1.17}$$

which corresponds to the 20% efficiency level.

When changing the time interval by Δt, the efficiency coefficient $\eta(t)$ can be determined from the following equations that are valid for all types of target parameters indicated by the index *i*:

$$1 + \eta(t)\Delta t = \frac{\overline{p}_i(t+\Delta t)}{p_i(t+\Delta t)} : \frac{\overline{p}_i(t)}{p_i(t)}, \tag{1.18}$$

or for small time changes of *dt*:

$$1 + \eta(t)dt = \frac{\overline{p}_i(t+dt)}{p_i(t+dt)} : \frac{\overline{p}_i(t)}{p_i(t)}. \tag{1.19}$$

Considering (1.19) and the fact that the value dt is quite small, we can write:

$$1 + \eta(t)dt = \frac{\gamma(t+dt)}{\gamma(t)} = 1 + \frac{d\gamma(t)}{\gamma(t)}, \tag{1.20}$$

or

$$\eta(t) = \frac{1}{\gamma(t)} \frac{d\gamma(t)}{\gamma(t)} = \frac{d}{dt} \ln \gamma(t). \tag{1.21}$$

This means that efficiency coefficients of economic processes are expressed as a logarithmic derivative of the function $\gamma\left(t\right)$.

Considering (1.20), you can write (1.21) in the following form:

$$\eta(t)=\frac{d}{dt}\ln\delta(t)-\frac{d}{dt}\ln p_x(t)x(0)\cdot \tag{1.22}$$

This means that the coefficient of power consumption efficiency depends on two factors: changes in the scale of unreduced optimal prices and the dynamics of changes in reduced prices. It should be noted that the efficiency coefficient depends on the function *W(t)* of criterion (1.22) and for each such function *W(t)* there is its own consumption strategy and, of course, its own efficiency coefficient.

Peculiarities of the process of selecting a corrective function can be reflected by investigating a simple model of optimal power consumption by variation calculation methods for the continuous argument *t*.

We will consider one type of target parameter, the rate of change of which at time *t* is denoted through *x(t)*, and the target function of achieving the goal – through *f(x)*. At the initial time *t* = 0, the rate of change of the target parameter is known and is determined by the value *x(0)*. One factor that may correspond, for example, to pump flow rate is considered. The pump flow rate is determined (for simplicity, let us call it in this case a production resource) at time *t* by a value of *y(t)*, and at time t = 0 – by the value of *y(0)*.

The production factor unit provides a change in the target parameter *x(t)* per unit of time. To expand a production resource per unit of time, you need *p(t)* units of this resource. It is considered that production resources are fully utilized. The share of the production resource *y(t)* used to change the target parameter *x(t)* is determined by the value *k(t)*, and to expand the production resource– (1-k(t)). At t=0, the value of *k(0)* is defined as follows:

$$k(0)=\frac{x(0)}{y(0)}.$$

It characterizes distribution of the production resource (capacity of resources) y for the initial moment of time.

The model of the described situation in the accepted designations will look like:

$$x(t)=k(t)y(t), \tag{1.23}$$

$$\frac{\partial y(t)}{\partial t}=\frac{\left[1-k(t)\right]y(t)}{\rho(t)}. \tag{1.24}$$

This model will use the optimality criterion as (1.25), only *x(t)* will be considered a scalar function of time. The essence of the problem is to maximize the optimality criterion

$$F = \int_0^{\infty} W(t) f[x(t), t] dt \text{,} \tag{1.25}$$

with restrictions:

$$x(t) = k(t) y(t) \text{,} \tag{1.26}$$

$$y'(t) = \frac{1 - k(t)}{\rho(t)} y(t) \text{.} \tag{1.27}$$

Excluding the function *k(t)* from (1.27) and expressing *x(t)* through *y(t)*, we can write:

$$x(t) = y(t) - \rho(t) y'(t) \text{.} \tag{1.28}$$

The functional (1.26), taking into account (1.27) and (1.28), will look like:

$$F = \int_0^{\infty} \Phi[t, y(t), y'(t)] dt \text{.} \tag{1.29}$$

The extreme value of functional (1.29) with the convex function *f(x)* exists and its finding is reduced to solving the Euler-Lagrange differential equation:

$$\frac{\partial \Phi}{\partial y} = \frac{d}{dt}\left(\frac{\partial \Phi}{\partial y'}\right) = 0 \text{.} \tag{1.30}$$

In our case, we consider the function Φ to be a subintegration function in (1.26), where *x(t)* is defined with (1.27). With this in mind, equation (1.30) will be rewritten as follows:

$$W(t) \frac{df[x(t)]}{dx(t)} + \rho(t) \frac{d}{dt}\left[W(t) \frac{df[x(t)]}{dx(t)}\right] = 0 \text{.} \tag{1.31}$$

The solution to this equation will be:

$$W(t) \frac{df[x(t)]}{dx(t)} = ce^{-\alpha(t)t} \text{.} \tag{1.32}$$

where *c* is an integration constant.

We denote $\frac{df[x(t)]}{dx(t)}$ by z=z(x) and define *c* and *p(t)* according to the specified initial conditions *x(0).* With this in mind, (1.31) can be written as follows:

$$z[x(t)] = z[x(0)]W^{-1}(t)e^{-\frac{1}{\rho}t}. \tag{1.33}$$

The solution to this equation would be as follows:

$$\hat{x}(t) = z^{-1}\left\{ z[x(0)]W^{-1}(t)e^{-\frac{1}{\rho}t} \right\}. \tag{1.34}$$

Thus, (1.34) determines the optimal value of the target parameter *x(t)* for all variants of the values of the function *W(t).*

The optimal program for accumulation of production resource *y(t)* can be determined by solving equations (1.34) in the following form:

$$\rho(t)y'(t) - y(t) = -\hat{x}(t)\cdot \tag{1.35}$$

The solution to this equation will be:

$$y(t) = y(0)e^{-\frac{1}{\rho}t} - \rho e^{-\frac{1}{\rho}t}\int_0^t \hat{x}(t)e^{-\frac{1}{\rho}t}dt = \hat{y}(t)\cdot \tag{1.36}$$

Using (1.33) to determine the optimal reduced prices, it should be remembered that this problem is not a linear programming problem to understand which optimal prices are interpreted. Yet, we assume that such prices exist and that they have similar properties.

Using the example of the model (1.33) – (1.36), the basics of the method of selecting the corrective function *W(t)* were illustrated.

Ratios were obtained to build determining parameters of the power consumption strategy for different variants of the corrective function. Conversely, to obtain the function *W(t)* according to specified variants of the determining parameters or by fixed ratios between them.

The research confirms that the corrective function is an objectively justified element of the optimality criterion of power consumption by water drainage facilities of an iron ore mining enterprise. In addition, it is illustrated that the corrective function has a rather narrow and specifically defined range of change. The direct relationship between the corrective function and determining parameters allows you to specify the adjustment of the function within its permissible values, based on the principle of minimum deviations from its optimal power consumption strategy at all subsequent points in time.

1.4. Simulation of assessing power consumption by water drainage facilities of iron ore underground mines

When studying formation of power consumption at iron ore mining enterprises, methods for measuring relationship are essential. Practice proves the expediency of applying correlation-regression analysis and non-parametric methods to determining appropriate relationships. These methods provide an opportunity to analyze power consumption by iron ore industrial enterprises in general and by main water drainage facilities in particular. It is advisable to determine the totality and content of indices that will allow a more reasonable assessment of the use of applied and consumed resources at all stages of operation; plan the current activities of power consumption by water drainage facilities of iron ore underground mines; identify reserves for increasing production, etc.

Thus, in today's conditions in the structure of the information space of power consumption by water drainage facilities of iron ore underground mines, analytical information should occupy a more significant place. In this regard, timeliness and reliability of relevant information becomes an important factor that provides an opportunity to increase efficiency of the entire process of power consumption.

According to some scientists, simulation is an effective way of knowing regularities and laws of the surrounding world. Simulation replaces a real process with a certain design, which is analytical ratios. They reflect the main features of the process while abstracting from non-essential components. That is, the result of simulation is an image of reality that has a simplified, schematic view. Naturally, when defining simulation as art, one should focus on simplification, but it is necessary to determine how and where it is necessary to simplify [12, 18, 26, 29].

By their nature, processes of power consumption of main water drainage facilities are stochastic, probabilistic, and uncertainty is their intrinsic property. The study of these processes, anticipation of the prospects for their further development, making optimal decisions on effective power consumption should use models that, under certain uncertainty conditions, ensure reliability and constancy of conclusions. Such models, in all respects, are statistical. These models belong to the class of mathematical. They are formed in the form of algorithms, functions, and equations. Solutions and their analysis combine probabilistic and logical-algebraic methods.

The statistical model represents a formally abstract scheme of relationships between quantities that determine features of a real process. The elaboration of these relationship schemes and the choice of features is carried out informally. A priori analysis regarding the nature of the process allows you to form hypotheses in accordance with regularities and properties.

The real process and the mathematical scheme of power consumption model are interconnected by a combination of two types of information:

1) the ratio and interrelation of logically substantiated hypotheses in accordance with the nature and properties of the process;

2) empirical data that determine the designated nature and properties.

The model allows you to imitate the corresponding mechanisms to form patterns. It finds out the correspondence of hypotheses and the population of facts. The use of models allows you to conduct experiments. Simulation results extend to real processes. To form a model, the defining requirement is adequacy of a real process.

The logic of statistical modeling can be represented by the following steps:

– definition of the purpose and object of simulation;
– analysis of initial data;
– general mathematical formalization of the model;
– evaluation of certain parameters of the model;
– verification for the adequacy of the formed model;
– analysis and interpretation of simulation results.

The first stage determines the purpose and the object of simulation. The purpose of the first stage is the final purpose of the model, e.g. process diagnostics, mechanism formation and analysis, trends in development of the process, etc. Naturally, the same process can be reflected by different models. It depends on the purpose of simulation.

The object of simulation is a statistical set. In such a set, a pattern is realized. It is known that formally any set exists to be represented as a ranked data set with the corresponding parameters n, m, T, where n is the number of elements of the population (j = 1, 2, ..., n), m is the number of features registered in the j-th element (i = 1, 2, ..., m), T is the calendar period with certain quanta of time (year, quarter, month, day, etc.). The information unit of the simulation object is the value of the i-th feature in the j-th element of the population in the t-th period – $x\_ij\ t\_ij$. Information is represented by the matrix n x m, if the population is formed in statics, and if in dynamics, then by the matrix t x m.

Characteristics of the simulation object contains the following components:

– selection of a single element of the population, which is considered the carrier of characteristic features for the pattern;

– formulation of spatial and temporal volumes of the simulation object;

– definition of the feature set of the model.

The degree of the simulation object depends on the choice of the primary element of the population. Power consumption can be studied at the level of the industry, individual enterprises, workshops and even individual workers. Naturally, in each case that is analyzed, the element of the population will be different. The boundaries of the simulation object are determined by the size of the population n for static models and the duration of the period T – for dynamic ones.

In determining the feature set X, a significant role is played by expert assessment of the significance and informativeness of individual features. It is necessary to take into account the possibility of accurate measurement, the complexity of collecting information, and the range of variation.

Statistical simulation involves considering the population as a sample, which can be classical or hypothetical. The classical sample is defined as part of a real population. A hypothetical general population is characterized by the number of possible consequences of the functioning of the simulation object, and not the number of elements. The definition of population is used when it comes to the volumetric, but finite set of objects that are being investigated.

In practice, as a rule, they deal with finite populations. In scientific research, it is noted that if the ratio of the volume of the population to the sample size is more than 100, then, according to Glass and Stanley, the evaluation methods for finite and infinite populations give the same results in the entity [12, 18, 26, 29]. The general population can be considered the full set of values of any feature. The main basis for assessing characteristics of the population is that the sample belongs to the population.

The main idea is based on the impossibility of a complete study of all objects of the general population, because it requires a lot of time and significant material costs.

Iron ore mining enterprises are quite specific in terms of power consumption, and therefore the choice of a model to study power is a complex and, to some extent, risky task.

In a market economy, a number of external and internal factors influence effectiveness of power consumption. Particularly significant influence is exerted by factors of adequacy of financing iron ore enterprises' activities, the cost of equipment update, consumption of power, etc., all this enabling to evaluate the results by applying economic and statistical methods. Application of these methods consists in conducting an in-depth analysis of the studied statistical indices and the results obtained by building a mathematical model.

A large number of factor values necessitates the use of methods of multiple correlation-regression analysis to isolate the most statistically significant factors and assess their relationship with the effective feature, which is ultimately presented in the form of a certain numerical expression.

Naturally, only some indices of power consumption efficiency of water drainage facilities is a large statistical population. That is, there is a feasibility of using appropriate economic and mathematical methods and software systems. Ignoring such a requirement can lead to not only unreliable results, but also an inadequate mathematical model.

As practice indicates, one of the most effective economic and statistical methods for identifying the influence of the most significant factors on the effective feature is correlation-regression analysis. Thus, there is an objective need to build and consistently analyze an appropriate adequate mathematical model.

The results of analyzing power consumption in a market economy are formed under the influence of many factors, the impact of which can be expressed using economic and statistical methods.

Meanwhile, the current state of information support creates preconditions for intensive use of multivariate models in order to establish relationships between the effective feature and major factors.

In order to study qualitative and quantitative assessment of internal and external relationships between the effective feature and the selected factors, it is advisable to apply correlation-regression analysis mainly to analyze the available statistical data of the studied features with the subsequent establishment of the relationship density using the calculated correlation coefficients.

To carry out multiple correlation-regression analysis and take into account the set of factors that have been selected, it is possible to build a linear equation of multiple regression, since there is a linear relationship between the effective feature and the factor indices:

$$\hat{Y} = a_0 + a_1 * X_1 + a_2 * X_2 + \cdots + a_n * X_n.$$

Multiple regression is a relationship equation with several independent variables [126]:

$$y = f(x_1, x_2, \dots, x_m) + \varepsilon$$

where y is a resulting, functional index (dependent variable);

x_1, x, ..., x_m are factor indices, factors that determine the value of the resulting index (independent variables).

To estimate the parameters of the multiple regression equation, the least squares method is used. For linear equations like

$$y = a + b_1 * \mathrm{x}_1 + b_2 * \mathrm{x}_2 + \cdots + b_\mathrm{m} * \mathrm{x}_\mathrm{m} + \varepsilon$$

the following system of normal equations is built, the solution of which allows obtaining estimates of regression parameters:

$$\begin{cases} \Sigma y = na + b_1 \Sigma x_1 + b_2 \Sigma x_2 + \ldots + b_m \Sigma x_m \\ \Sigma y x_1 = a \Sigma x_1 + b_1 \Sigma x_1^2 + b_2 \Sigma x_1 x_2 + \ldots + b_m \Sigma x_m x_1 \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \Sigma y x_m = a \Sigma x_m + b_1 \Sigma x_1 x_m + b_2 \Sigma x_2 x_m + \ldots + b_m \Sigma x_m^2 \end{cases}$$

The x parameters in linear regression are called ‘net’ regression coefficients. They determine the average change in the result of the corresponding factor per unit, while the values of other factors are unchanged.

The least squares method is also applicable to the multiple regression equation on a standardized scale:

$$t_y = \beta_1 * t_{x_1} + \beta_2 * t_{x_2} + \cdots + \beta_m * t_{x_m} + \varepsilon$$

where $t_y, t_{x_1} \ldots . t_{x_m}$ are standardized variables calculated as:

$$t_y = \frac{y - \bar{y}}{\sigma_y}$$

$$t_{x_i} = \frac{x_i - \overline{x_i}}{\sigma_{x_i}}$$

β_i is a standardized coefficient of regression;

$\bar{y}$ is the average value of the dependent variable;

σ_y, σ_{x_i} are RMS deviations of indicators;

$\overline{x_i}$ are average values of factor features.

Due to the fact that all variables are specified as centered and normalized, standardized regression coefficients β_i can be compared with each other. Comparing them with each other, you can rank the factors by the strength of their impact on the result. This is the main difference between standardized regression coefficients and ‘net’ regression coefficients that cannot be compared with each other.

Applying the MNC to the multiple regression equation on a standardized scale, we obtain a system of normal equations of the form:

$$\begin{cases} r_{yx1} = \beta_1 + \beta_2 r_{x1x2} + \beta_3 r_{x1x3} + \ldots + \beta_m r_{x1xm} \\ r_{yx2} = \beta_1 r_{x1x2} + \beta_2 + \beta_3 r_{x1x3} + \ldots + \beta_m r_{x1xm} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ r_{yxm} = \beta_1 r_{x1xm} + \beta_2 r_{x1xm} + \beta_3 r_{x1xm} + \ldots + \beta_m \end{cases}$$

where r_{yx_i} are $r_{x_i x_j}$ are pair and interfactor correlation coefficients.

The values of the b_i 'net' regression coefficients are related to the values of standardized regression coefficients β_i as follows:

$$b_i = \beta_i \cdot \frac{\sigma_y}{\sigma_{x_i}}.$$

Therefore, it is possible to move from the regression equation on a standardized scale to that on the natural scale of variables, with the parameter a defined as:

$$a = \bar{y} - b_1 * \overline{x_1} - b_2 * \overline{x_2} - \cdots - b_m * \overline{x_m} \qquad (1.37)$$

The considered meaning of standardized regression coefficients allows them to be used when screening out factors. The factors with the lowest value of β_i are excluded from the model.

The average coefficients of elasticity for linear regression are calculated by the formula:

$$\bar{E}_{yx_j} = \beta_j \cdot \frac{\bar{x}_j}{\bar{y}}. \qquad (1.38)$$

The values of the coefficients indicate how many percent on average the result will change, if the value of the corresponding factor changes by 1%. The values of average elasticity indices can be compared with each other and, accordingly, the factors can be ranked by the strength of their influence on the result.

The closeness of the joint influence of factors on the result is estimated by the multiple correlation index:

$$R_{yx_1x_2\ldots x_m} = \sqrt{1 - \frac{1-\sigma_{yocm}^2}{1-\sigma_y^2}}. \qquad (1.39)$$

The value of the multiple correlation index is in the range from 0 to 1 and it is necessary to be greater than or equal to the maximum paired correlation index:

$$R_{yx_1x_2\ldots x_m} \geq r_{yx_i} \quad (i = \overline{1,m})$$

With a linear relationship, the multiple correlation coefficient can be determined through matrices of paired correlation coefficients:

$$R_{yx_1x_2\ldots x_m} = \sqrt{1 - \frac{\Delta r}{\Delta r_{11}}}, \tag{1.40}$$

where $\Delta r = \begin{vmatrix} 1 & r_{yx1} & r_{yx2} & \ldots & r_{yxm} \\ r_{yx1} & 1 & r_{x1x2} & \ldots & r_{x1xm} \\ r_{yx2} & r_{x2x1} & 1 & \ldots & r_{x2xm} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ r_{yxm} & r_{xmx1} & r_{xmx2} & \ldots & 1 \end{vmatrix}$ is a determinant of the matrix of these correlation coefficients;

$\Delta r_{11} = \begin{vmatrix} 1 & r_{x1x2} & \ldots & r_{x1xm} \\ r_{x2x1} & 1 & \ldots & r_{x2xm} \\ \ldots & \ldots & \ldots & \ldots \\ r_{xmx1} & r_{xmx2} & \ldots & 1 \end{vmatrix}$ is a determinant of the matrix of the interfactor correlation.

With a linear dependence of features, the analytical expression of the multiple correlation coefficient can be represented by the following formula:

$$R_{yx_1x_2\ldots x_m} = \sqrt{\sum \beta_i \cdot r_{yx_i}}, \tag{1.41}$$

where β_i are standardized regression coefficients,

r_{yx_i} are paired coefficients of correlation of the result with each factor.

The quality of the built model as a whole evaluates the coefficient (index) of determination. The coefficient of multiple determination is calculated as the square of the multiple correlation index.

In order to more adequately characterize the closeness of the relationship, an adjusted multiple determination index is used, which includes an amendment to the number of degrees of freedom and is determined by the formula:

$$\hat{R}^2 = 1 - \left(1 - R^2\right) \cdot \frac{(n-1)}{(n-m-1)}, \tag{1.42}$$

where n is the number of observations;
m is the number of factors.

With a small number of observations, the unadjusted value of the multiple determination coefficient R^2 tends to overestimate the share of variation of the effective feature. As you know, this share is associated with the influence of factors included in the built regression model.

Private correlation coefficients (or indices) measuring the impact of the factor x_i on y when eliminating other factors, can be determined by the formula:

$$r_{yx_1 \cdot x_1 x_2 \ldots x_{i-1} x_{i+1} \ldots x_m} = \sqrt{1 - \frac{1 - R^2_{yx_1 \cdot x_1 x_2 \ldots x_m}}{1 - R^2_{yx_1 \cdot x_{i-1} x_{i+1} \ldots x_m}}} \tag{1.43}$$

or by the recurrent formula:

$$r_{yx_1 \cdot x_1 x_2 \ldots x_{i-1} x_{i+1} \ldots x_m} =$$

$$= \frac{r_{yx_1 \cdot x_1 x_2 \ldots x_{i-1} x_{i+1} \ldots x_{m-1}} - r_{yx_m \cdot x_1 x_2 \ldots x_{m-1}} \cdot r_{x_1 x_m \cdot x_1 x_2 \ldots x_{i-1} x_{i+1} \ldots x_{m-1}}}{\sqrt{\left(1 - r^2_{yx_m \cdot x_1 x_2 \ldots x_{m-1}}\right) \cdot \left(1 - r^2_{x_1 x_m \cdot x_1 x_2 \ldots x_{i-1} x_{i+1} \ldots x_{m-1}}\right)}}. \tag{1.44}$$

The private correlation coefficients calculated using the recurrent formula vary from -1 to +1, and according to the formulas through multiple coefficients of determination – from 0 to 1. Comparing them with each other allows you to rank the factors for closeness of their relationship with the result. Private correlation coefficients give a measure of the close relationship of each factor with the result in its pure form.

The significance of the multiple regression equation is generally estimated using the Fisher F-criterion:

$$F = \frac{R^2}{1 - R^2} \cdot \frac{n - m - 1}{m}. \tag{1.45}$$

The private F-criterion assesses the statistical significance of the presence of each of the factors in the equation. In general, for the factor x, the private F-criterion will be defined as:

$$F_{x_i} = \frac{R^2_{yx_1x_2...x_m} - R^2_{yx_1x_{j-1}x_{j+1}...x_m}}{1 - R^2_{yx_1x_2...x_m}} \cdot \frac{n-m-1}{1}. \qquad (1.46)$$

The actual value of the private F-criterion is compared with the tabular value level of α and the number of degrees of freedom: $k_1 = 1$, $k_2 = n - m - 1$. The inclusion of the x_i factor in the built model is justified. That is, the net regression coefficient of b_i under factor x_i is statistically significant if the actual value of F_{x_i} exceeds the tabular $F\ (\alpha, k_1, k_2)$.

The regression coefficient is statistically insignificant for this factor if F_{x_i} is less than the tabular one. That is, the additional inclusion in the model of the factor x_i does not significantly increase the proportion of the explained variation of the feature y. Thus, it is impractical to include it in the model.

The significance of the net regression coefficients is estimated by the Student's t-criterion. In this case, as in the paired regression, the following formula is used for each factor:

$$t_{b_i} = \frac{b_i}{m_{b_i}}. \qquad (1.47)$$

For the multiple regression equation, the mean quadratic error of the regression coefficient can be determined by the formula:

$$m_{b_i} = \frac{\sigma_y \cdot \sqrt{1 - R^2_{yx_1x_2...x_m}}}{\sigma_{x_i} \cdot \sqrt{1 - R^2_{x_1x_2...x_m}}} \cdot \frac{1}{\sqrt{n-m-1}}, \qquad (1.48)$$

where $R^2_{x_1x_2...x_m}$ is the coefficient of determination for the dependence of the factor x_i with all other factors of the multiple regression equation.

There is a relationship between the Student's t-criterion and the Fisher's private F-criterion:

$$|t_{b_i}| = \sqrt{F_{x_i}} \qquad (1.49)$$

The decision on reliability of differences is made if the calculated value of t exceeds the tabular value for a certain number of degrees of freedom. Publications or scientific reports indicate the highest level of significance of the three: $p < 0.05$; $p < 0.01$; $p < 0.001$.

At any numerical value of reliability of the difference between the averages, this indicator does not assess the degree of the identified difference (it is estimated by the very difference between the averages), but only its statistical reliability, that is, the right to disseminate the conclusion obtained on the basis of a comparison of samples that there is a difference to the entire phenomenon (the whole process) as a whole. A low calculated criterion of difference cannot be proof of the absence of a difference between two features (phenomena), because its significance (degree of probability) depends not only on the magnitude of the averages, but also on the number of compared samples. This indicates not the absence of distinction, but the fact that with such a sample size it is statistically unreliable: there is a very high chance that the difference under these conditions is random, very low probability of its reliability.

Based on the calculated adequacy indicators, the models find insignificant factor features and reject them. Thus, they build a new model with significant factor features, having previously calculated for it new estimates of regression parameters. On the basis of the new formed model, conclusions are formed about the influence of features on the resulting indicator.

Evaluation of power consumption by iron ore mining enterprises is a necessary stage in the analysis of main water drainage facilities' activities and relevant management. The proposed calculation method covers main internal processes of power consumption occurring in the internal environment of the iron ore mining enterprise in general and water drainage facilities in particular. As a result, a systematic inspection of power consumption is provided, which will allow identifying all the strengths and weaknesses, as well as introducing on this basis optimal zones of power consumption.

In a dynamic competitive economy, the process of power consumption depends to a decisive extent on the quality of information and analytical support. Development of market relations, formation of a new ownership structure, and changes in the management system require formation of information support adequate to these changes regarding power consumption, where the main role belongs to general quantitative indices, which are the basis for optimal power consumption by iron ore mining enterprises in general and water drainage facilities in particular.

In accordance with the above methods, we will carry out calculations for water drainage facilities at iron ore mining enterprises.

We divide all the work into parts, considering the system of statistical indices of power consumption:

1. Simulation of the system of indices for power consumption by water drainage facilities in Ternivska underground mine (Kryvyi Rih).

1.1. Forming a system of initial data (Table 1.3) and a table of intermediate calculations

Table 1.3 – System of initial data by water drainage facilities in Ternivska underground mines (Kryvyi Rih)

Year	kW/h.	m^3/h.	Level, m	Pump capacity, kW	Number of pumps, pcs
	Y	X_1	X_2	X_3	X_4
2014	3268.88	177.8	527	800.00	2.00
2015	4904.88	171.6	1050	800.00	3.00
2016	5920.88	175.9	1200	250.00	3.00
2017	10228.69	176.4	1350	315.00	3.00
2018	14609.02	169.8	1350	315.00	3.00
2019	11807.13	158.8	1350	315.00	3.00
2020	12897.05	164.1	1350	315.00	3.00

Let us single out the indices for which calculations will be carried out: Y is the volume of power consumption, kW/h, X_1 is water flow; X_2 is the mining level, m; X_3 is pump capacity, kW; X_4 is the number of pumps, pcs.

Let us find mean quadratic deviations of the features:

$$\sigma_y = 4{,}74;\ \sigma_{x_1} = 0{,}58;\ \sigma_{x_2} = 2{,}26;\ \sigma_{x_3} = 1{,}56.$$

We find the coefficients of net regression:

$$a = 1315.48;\ b_1 = 11.94;\ b_2 = -0.184;\ b_3 = -1.99;\ b_4 = 9.31.$$

Thus, we obtain the following equation of multiple regression:

$$\hat{y} = 1315.48 + 11.94 * x_1 - 0.184 * x_2 - 1.99 * x_3 + 9.31 * x_4$$

The regression equation shows that with an increase in water flow by 1% (with a constant level of the specific gravity of other factors), the volume of power consumption will increase by 11.94 kW*h.

After finding the regression equation, we form a new calculation table to obtain theoretical values of the average approximation error, the effective feature, the final variance (Table 1.4).

Table 1.4 – System of adjusted data Ternivska underground mine (Kryvyi Rih)

Year	*Y*	*Y`*	*Y-Y`*	$(Y-Y`)^2$	A_i, %
2009	713.93	1677.46	-963.53	928397.14	134.96
2010	780.07	1566.98	-786.91	619233.71	100.87
2011	1844.93	1393.87	451.05	203455.1	24.44
2012	3339.28	3811.41	-472.13	222913.47	14.13
2013	3113.22	2179.77	933.44	871315.74	29.98
2014	3268.88	3630.87	-361.99	131036.97	11.07
2015	4904.88	4470.29	434.58	188867.6	8.86
2016	5920.88	6637.32	-716.44	513291.28	12.1
2017	10228.69	9052.31	1176.39	1383894.1	11.5
2018	14609.02	16082.11	-1473.09	2169997.9	10.08
2019	11807.13	12021.79	-214.66	46080.7	1.81
2020	12897.05	10903.75	1993.29	3973212.4	15.45
Total	73427.99	73427.99	4.96811^{-10}	11251696	375.31
Average	6118.99	6118.99	4.1401^{-11}	937641.35	3.12

$\sigma^2_{\text{ост}}$ = 0,93; $\overline{\text{A}} = 3.127$.

The quality of the model, based on calculated relative deviations for each observation, can be considered good, since the average approximation error does not exceed 10%. In accordance with the value of the final variance indicator, the degree of influence of random factors is low.

We find the standardized coefficients of the regression equation:

β_1 = 1.456; β_2= -0.087; β_3= -0.655; β_4= 0.337.

That is, the equation will look like this:

$$\widehat{t_y} = 1.456 * t_{x_1} - 0.087 * t_{x_2} - 0.655 * t_{x_3} + 0.337 * t_{x_4}.$$

Since it is possible to compare standardized regression coefficients with each other, it can be argued that the water flow has the greatest impact on the volume of production, and the depth of the level is the smallest.

It is also possible to compare the influence of factors on the result using average elasticity coefficients:

$\overline{E_1}$= 0.569; $\overline{E_2}$= 0.115; $\overline{E_3}$= 0.532; $\overline{E_4}$= 0.086.

Again, the greatest impact of the first factor is confirmed – water flow, and the slightest impact – the depth of the level on power consumption.

1.2. Finding partial correlation coefficients characterizing the closeness of the relationship between the result and the corresponding factor in elimination of other factors included in the regression equation (Table 1.5).

Table 1.5 – Partial correlation coefficients for indices of water drainage facilities of Ternivska underground mine (Kryvyi Rih)

	Y	X_1	X_2	X_3	X_4
Y	1				
X_1	0.881	1			
X_2	-0.272	-0.114	1		
X_3	0.144	0.546	0.309	1	
X_4	-0.755	-0.674	0.546	0.096	1

The coefficient of multiple correlation is determined through matrices of paired correlation coefficients:

$R_{yx_1x_2x_3x_4} = 0.978.$

The multiple correlation coefficient indicates a very strong relationship of the entire set of factors with the result.

1.3. The value of the unadjusted coefficient of multiple determination characterizes the proportion of the variance of the result due to the factors presented in the regression equation. The value of the particle is 97.8% and indicates a fairly high degree of conditionality of variation relative to the result of the variation of factors. That is, there is a very close relationship of factors with the result.

The adjusted multiple determination coefficient $\widehat{R^2}$= 0.934 determines the closeness of the relationship, taking into account the degrees of freedom of general and residual variances. It characterizes assessment of the closeness of communication, which does not depend on the number of factors. That is, the value can be used to compare according to different models with a different number of factors. Both coefficients indicate a fairly high determination of the result *y* in the model by factors.

1.4. Assessing reliability of the regression equation as a whole and the indicator of the close relationship by the Fisher F-criterion:

F = 40.18; F_{table}= 4.12 at $f_1 = 4$, $f_2 = 7$.

The actual value is greater than the tabular one, so probability of accidentally obtaining such a value of the F-criterion does not exceed the permissible significance level of 5 %. The resulting value is not accidental, it was formed under the influence of significant factors, i.e. the statistical significance of the entire equation and the indicator of the close relationship is confirmed.

1.5. Assessing statistical significance of the parameters of net regression using the Student's t-criterion.

t_{b_1}=0.159; t_{b_2}=2.158; t_{b_3}=3.431; t_{b_4}=8.051; Table

t_{table}= 2.3646 at $f = 7, p = 0.95$.

The calculated value of the criteria $t_{b_2,} t_{b_3}$ and t_{b_4} are greater than the tabular one, and therefore parameters b_2, b_3, b_4 are statistically significant, while the value of the criterion t_{b_1} is less than the tabular one, and therefore the parameterb_1 is random by nature of formation.

We build confidence intervals:

11.963	$\leq$ b1$\leq$	12.025;
-27.882	$\leq$ b2 $\leq$	27.514;
-6.0588	$\leq$ b3 $\leq$	2.062;
7.2573	$\leq$ b4 $\leq$	11.349.

1.6. Based on Fisher's private F-criteria, assessing feasibility of including factors x_1, x_2, x_3, x_4 in the multiple regression equation:

F_{x_1}= 0.025; F_{x_2}= 4.658; F_{x_3}= 11.775; F_{x_4}= 64.822; F_{table}= 4.12 at $f_1 = 4$, $f_2 = 7$.

We exclude the first factor from consideration, since it is uninformative (i.e. the calculated value of the private F-criterion is less than the tabular one).

1.7. Building a new model. To do this, we will form a new table of source data (Table 1.6).

We find the coefficients of pure regression:

1.7. Building a new model. To do this, we will form a new table of initial data (Table 1.6).

Table 1.6 – Updated table of initial data Ternivska underground mine (Kryvyi Rih)

Year	Y	X_2	X_3	X_4
2009	713.93	3966.06	6108.27	709.10
2010	780.07	4821.09	6963.87	740.00
2011	1844.93	7430.61	6366.10	728.00
2012	3339.28	8947.83	2951.87	728.90
2013	3113.22	1447.36	2723.92	546.89
2014	3268.88	1519.72	2860.11	574.23
2015	4904.89	2154.78	3188.10	469.62
2016	5920.89	2366.78	3338.10	719.62
2017	10228.70	3049.93	4430.73	379.45
2018	14609.03	1818.99	5308.26	144.17
2019	11807.14	4217.96	5478.56	491.09
2020	12897.05	4235.99	6607.05	582.75
Total	73427.99	45977.10	56324.94	6813.82
Average	6119.00	3831.42	4693.75	567.82

We find the coefficients of net regression:

a = 15632.34; b_2= 0.277; b_3 = 0.559; b_4 = -23.254.

So, we have a new equation:

$\hat{y} = 15632.34 + 0.277 * x_2 + 0.559 * x_3 - 23.254 * x_4$.

A 1% increase in the factor feature of the level depth will lead to an increase in power consumption by 0.277.

Partial correlation coefficients are:

r_{yx_2}=0.272; r_{yx_3}=0.143; r_{yx_4}=0.656.

According to the Cheddock scale, the most noticeable relationship force is present between factor X_4 and Y, a weak relationship is between factors X_2 and Y, X_3 and Y.

A similar simulation method is applied to Kryvorizka, Pokrovska, Kazatska underground mines (Kryvyi Rih).

Among the components of optimal provision of power consumption are the assessment of quality, which can be expressed by cost indices. When optimizing the optimality criterion, a certain target function of a set of private criteria is formed, which is called a quality function and characterizes the suitability of an object to meet certain needs in accordance with the purpose. We believe that such a function exists and is a continuous function of many variables, which does not decrease with an increase in the values of private criteria. We also consider that the criteria are independent and their influence on the generalized criterion is linear. Then it becomes possible to represent the function in a linear additive form

$$W(\varpi) = \sum_{j=1}^{m} \varpi_j \upsilon_j , \tag{1.50}$$

where $\upsilon_j = \frac{\partial W}{\partial \varpi_j} = \frac{\partial W}{\partial p_j} p_{j0}$ is a parameter characterizing sensitivity of assessing the relevant criterion to the variations of the corresponding partial criteria around some point $p_0 = (p_{10}, ..., p_{m0})$, taken as the initial for comparison.

Components

$$\varpi_j = \frac{p_j - p_{j0}}{p_{j0}}, \tag{1.51}$$

where $p_{j0} \ge p_j$ characterizes reduction for each of the j-x criteria.

The vector $p_0 = (p_{10},..., p_{m0})$ is an ideal solution for which all *j-i* criteria are taken as the best values in the area of their possible changes. In general, such a solution does not exist and should be considered as hypothetical, that is the standard.

We assume that the closer the estimate is to the reference one, the better the solution and the higher the quality level of the compared object. To establish the measure of proximity of the solution to the ideal (reference) one, we use the principle of optimality, called the principle of "equivalent concession". When using this principle, it is assumed that near each local optimum *j*-th criterion, you can specify the following Δ_j areas (actions) that equally reduce the quality of the solution.

In other words, these concessions are equivalent in their impact on the value of the total estimate. Then the coefficient υ_j determines the "price" or "weight" of the concession for the *j*-th criterion. The weighting coefficient is not the same for private criteria of different significance, since it depends on the influence of each of the criteria on the value of the total estimate.

Let us consider the way to find the weighting factors. To do this, we represent the *j*-th partial derivative through the ratio of increments $\Delta W / \Delta p_j$. Increments Δp_j determine the value of absolute concessions equivalent in the value of equality of increments of estimates ΔW according to the *j*-th criterion. The corresponding series of equivalence $\Delta p_1 \approx ... \approx \Delta p_n$ (where $\approx$ is equivalence) characterizes the interchangeability of the criterion (consumer, operational and other) properties of the object. Equivalent are also relative increments $\Delta_j = \Delta p_j / p_{j0}$. Then, solving the equation

$$\sum_{j=1}^{m} \frac{\Delta W}{\Delta p_j} p_{j0} = 1 \tag{1.52}$$

relative to ΔW (subject to normalization of weights $\sum_{j=1}^{m} \upsilon_j = 1$), we obtain the following calculation formula for the weighting factor:

$$\upsilon_j = \frac{\Delta_j^{-1}}{\sum_{j=1}^{m} \Delta_j^{-1}}. \tag{1.53}$$

Note that the weighting factor, which is calculated according to this formula, is not a direct analogue of the significance of the *j*-th private criterion, since its value depends on the value that takes the criterion at the point of the local optimum, i.e. from p_{j0}. The weight coefficient takes the greater the value, the smaller the value of the relative increase is.

To find the values of concessions, an informal procedure is used and experts are involved. Each expert should indicate the ratio of equivalence (($\cong$) for pairs of compared criteria that differ in their values, i.e.

$$\begin{pmatrix} p_{i0} - \Delta p_i \\ p_{j0} \end{pmatrix} \cong \begin{pmatrix} p_{i0} \\ p_{j0} - \Delta p_{j^*} \end{pmatrix}, \tag{1.54}$$

where Δp_j^* is the value of the change in the *j*-th criterion, which compensates for the difference Δp_i. The equivalence of increments Δp_i and Δp_j corresponds to the expert's ideas about interchangeability of these increments. The procedure for finding the equivalence ratio of pairs of compared criteria and formation of equivalence segments is an iterative process described in the form of an algorithmic procedure.

The practical use of the method requires a preliminary stage in identifying the priority of the criteria for the advantage of changing their ranges, i.e.

$$\begin{pmatrix} \overline{p_i} \\ \underline{p_j} \end{pmatrix} \left\{ \overset{>}{\underset{<}{\cong}} \right\} \begin{pmatrix} \underline{p_i} \\ \overline{p_j} \end{pmatrix} => \left\{ \overset{1}{\underset{-1}{0}} \right\} \tag{1.55}$$

where $\underline{p_i}(\underline{p_j})$ i $\overline{p_i}(\overline{p_j})$ are limits of the ranges of the corresponding criteria;

signs $(>, \cong, <)$ are relative advantages (better, equivalent, worse).

On the basis of the preference system established in this way, a matrix of paired comparisons is compiled, which is used to determine the ranks of the criteria. The highest rank corresponds to a large sum of elements in the matrix rows. The rank of the criterion determines its place in a number of comparable sequences of pairs of criteria:

$$(p_1^1, p_2^1), (p_2^2, p_3^2), \ldots, (p_j^j, p_{j+1}^j), \ldots, (p_{m-1}^{m-1}, p_m^{m-1}), \tag{1.56}$$

where the inferior index is the rank of the criterion and the upper index is the ordinal number of the comparison pair. Thus, the criteria adjacent in the rank are preferred for comparison.

After identifying pairs of comparison of the criteria, it is necessary to develop *m*-1 procedures for finding equivalence segments on these pairs. In order to maximize approximation of the function, one of the segments is selected equal to the range of the criterion change. As a result, the following set of pairs of equivalence segments is formed:

$$(\Delta p_1{}^1 \approx \Delta p_2{}^1), \tag{1.57}$$

$$(\Delta p_2{}^2 \approx \Delta p_3{}^2),\ldots,(\Delta p^j{}_j, \Delta p^j{}_{j+1}),\ldots,(\Delta p_{m-1}^{m-1}, \Delta p_m^{m-1}), \tag{1.58}$$

where $\Delta p^j{}_{j+1}$ is the change range of the (*j*+1)-th criterion,

$\Delta p^j{}_j$ is a compensating difference of the *j*-th criterion.

In general, obtaining the values of equivalence segments for two adjacent series members are not the same, i.e. $\Delta p_j{}^{j-1} \neq \Delta p_j{}^j$. To build a series of equivalences, it is necessary to develop a sequential alignment of segments. The following transformations are used:

$$\tilde{\Delta} p_j{}^{j-1} = \Delta p_j{}^j; \;\; \tilde{\Delta} p_{j-1}^{j-1} = \Delta p_{j-1}^{j-1}\left(\frac{\Delta p_j{}^j}{\Delta p_j^{j-1}}\right). \tag{1.59}$$

An equivalence series found as a result of alignment

$$\tilde{\Delta} p_1 \approx \tilde{\Delta} p_2 \approx \ldots \approx \tilde{\Delta} p_m$$

that is the initial for calculating weighting factors.

Assessment consists in comparing the designed or actual values of power consumption indices with the basic ones, taken as a basis for comparison. In cases when not all indicators of the variant evaluated are better than the basic ones, the problem of a comprehensive assessment arises, i.e. using one generalized criterion. When conducting a comparative assessment of options, instead of optimal values p_{j0}, the best values of indicators for a set of these options appear. Previously, it was assumed that the best indicator of power consumption corresponds to the highest value of the *j*-th criterion. Practically, there are indices for which the best indicator corresponds to the smallest possible value of the criterion.

If there are assessment options, then the difference $\Delta W = W_1 - W_2$ (W_1 and W_2 are estimates of two options) shows how much the quality level of one option is better (positive sign) or worse (negative sign) than another criterion. It is often necessary to determine how many times the option is evaluated better or worse than any other option. The value of the relative indicator Δ_{rel} is recalculated from the difference estimate according to the formulas:

$$\Delta_{rel} = 1 + \Delta W, \text{ if } \Delta W \geq 0; \quad (1.60)$$

$$\Delta_{rel} = \frac{1}{1 - \Delta W}, \text{ if } \Delta W \leq 0. \quad (1.61)$$

In this case, the estimates take a value greater than 1 if the option evaluated is better than the one chosen for comparison, and the smaller units (always positive) – otherwise.

The methodological basis for analyzing power consumption efficiency is a comparison of the results of using two options. Therefore, in calculations, options are compared, factors influencing the result identified, including quantitative and qualitative parameters. Compliance with the rule of comparison of comparable options is the main condition for the reliability of power consumption calculations.

It should be noted that expert assessment of power consumption is expensive and difficult to implement.

It is impossible to ignore the cost indicators for power consumption by main water drainage facilities, namely power consumption during peak hours, when the cost is maximum, along with the payment. The operating mode of the power supply system can also be improved, i.e. voltage and power losses reduced, the coefficient improved:

$$E_v = \rho g W(Z_1 - Z_2) + W(P_1 - P_2) + 0{,}5\rho W(\beta_1 v_1^2 - \beta_2 v_2^2)$$

where E_v is water flow energy in an area, J;

t – is time, s;

g – acceleration of the free fall, m/s;

ρ is density of the liquid, kg/m, for water flow with clean water ρ = 1000 kg/m;

W is volume of water flow, m;

Z_1 and Z_2 are geometric heights above the plane of comparison in levels, m;

P_1 and P_2 are pressure in the intersections of levels, Pa;

v_1 and v_2 are average water speed in levels, m/s;

ρ is the coefficient of kinetic energy (Kopiolica).

Thus, the power of the water flow can be determined from the formula:

$$N = \frac{E_v}{I}.$$

These findings will be used in further dissertation research.

Having initial statistical information on power consumption by water drainage facilities, we consider it appropriate to conduct a generalizing analysis.

The graphs visually show the components-characteristics of the operation of water drainage facilities, namely the amount of power consumed and the power cost at two- and three-zone tariffs (Fig. 1.12).

The maximum power consumption in the period from 0.00 to 6am, and 10am to 2pm; 11.30pm -11pm is typical. Accordingly, the cost of power consumption is the highest in the period from 10am to 2pm and 11.30pm - 11pm at two- and three-zone tariffs. The total daily cost of consumption at a two-zone tariff exceeds that at three-zone tariffs (Fig. 1.13).

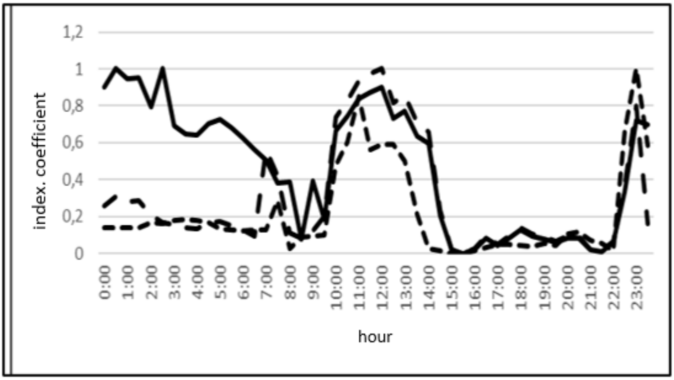


Fig. 1.12. Power consumption and cost for water drainage facilities at Kryvorizka underground mine (Kryvyi Rih)

Statistical data in accordance with power consumption and cost at two- and three-zone tariffs gives grounds to draw the following conclusions. The highest power consumption corresponds to the time period from 11am to 12.30 and from 10.30 pm to 11.30 pm. The same periods of the day correspond to the highest cost of power both at two-zone and three-zone tariffs. The total daily cost of consumption at a two-zone tariff exceeds that at three-zone tariffs (Fig. 1.14).

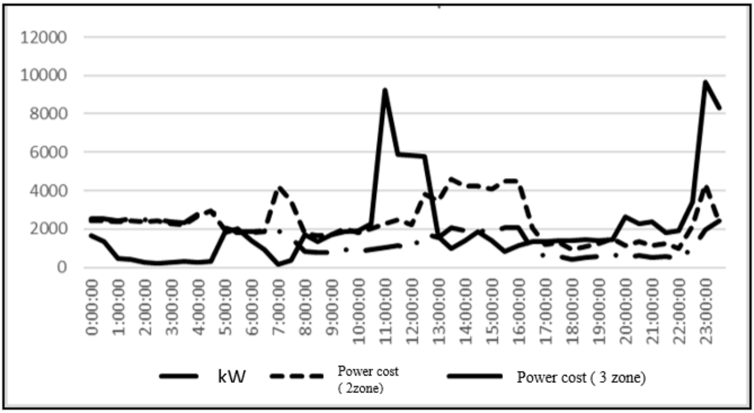


Fig. 1.13. Power consumption and cost for water drainage facilities at Ternivska underground mine (Kryvyi Rih)

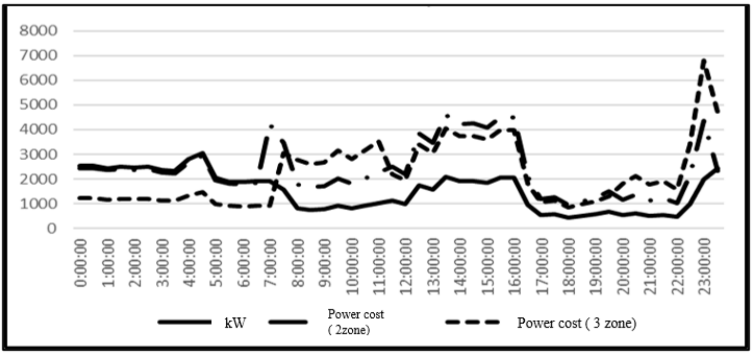


Fig. 1.14. Power consumption and cost for water drainage facilities at Kazatska underground mine (Kryvyi Rih)

Visual analysis of the graph indicates the highest power consumption in the period from 0.00 to 5am and from 11pm to 11.30pm. But most of all the cost of power at two-zone and three-zone tariffs corresponds to the period of time from 01pm to 3pm and from 10.30pm to 11.30pm. The total daily cost of power consumption at a two-zone tariff exceeds that at three-zone tariffs.

The preliminary research gives grounds to assert that there is no general scientific and technical substantiation for optimal distribution of power consumption relative to water drainage facilities. The daily cost of power consumption at a two-zone tariff exceeding the cost of consumption at three-zone tariffs is common to all iron ore mining enterprises under study. Each individual enterprise consumes power in accordance with individual technical needs, without conducting appropriate research, which is the key to reducing cost indices of power consumption. Such studies should form the basis of a general scientific approach to optimizing consumption indices by main water drainage facilities, followed by adoption of specific search options.

CONCLUSIONS TO SECTION 1

1. The level of efficiency of functioning of main water drainage complexes of iron ore underground mines at daily designed tariffs is under analysis. Information on power consumption by iron ore underground mines indicates complexity of analyzing the results obtained. An innovative approach to the use of statistical material of the corresponding indices of power consumption of the corresponding cost, water flow, level depth, the number of pumps and their capacity is proposed, synthesizing mathematical models as complex objects by deeper study of statistical material substantiating the results obtained.
2. For the first time, multivariate regression models were used, taking into account multicollinearity and nonlinearity in terms of pump capacity, to study the effect of pump capacity on the cost of power by using an elasticity coefficient. Analysis of the results of mathematical simulation in accordance with the statistical material using the algorithm for studying the dependence of the cost of consumed power on capacity of pumps indicates the presence of critical values that qualitatively change the corresponding impact. This allows determining the most promising trends in development of water drainage facilities of iron ore underground mines and ensure effective management of energy efficiency processes.
3. In accordance with the proposed methodology, a multiple correlation-regression model of power consumption modes by electromechanical complexes of water drainage facilities of underground mines is built and analyzed. It is established that the greatest impact on power consumption is performed by the factor of water flow, and the smallest – by the level depth. It is determined that with an increase in water flow by 1% (with a constant level of the specific gravity of other factors), the volume of power consumption will increase by 11.94%. The use of the proposed model will determine the optimal level of factors influencing the power consumption and offer appropriate technical and analytical solutions to the problems that may arise during the operation of water drainage facilities of underground mines.

SECTION 2
DEVELOPMENT OF AUTOMATED CONTROL OF WATER DRAINAGE FROM IRON ORE UNDERGROUND MINES AS A SUBSYSTEM OF THE INTEGRATED SMART ACS OF POWER SUPPLY-POWER CONSUMPTION

2.1. Prerequisites for applying the approach and setting the task

As stated in the first section of this research, the achievement of the desired level of energy efficiency of mining enterprises is possible on the platform of the integrated smart ACS of Power Supply-Power Consumption*.

According to the previously presented research results of the authors [12-19, 21-30], it is argued that controlling locally only one process and/or a limited number of energy-intensive production components of the technological complex of an iron ore underground mine is not an appropriate and effective solution. Systematic consideration of all management decisions of individual consumers in the format of building a generalized structure of the ACS, taking into account the entire complex of parameters of their influence on the general technology of functioning and formation of relevant management decisions, is quite effective and logical.

In accordance with this, [12-19, 21-30] present a version of the general structure of the ACS of Power Supply-Power Consumption. It is also determined that local control over power consumption of main water drainage facilities should be carried out segmentally within the control subsystem of this complex on the platform of the general smart ACS. It can definitely be argued that the quality of final decision-making depends on the measure of its effectiveness. Therefore, the research process is structured in this direction, the results of which are presented in the subsequent sections of this work.

2.2. Formalization of tasks for controlling water drainage at iron ore underground mines

In the previous section, the structure and basic principles of creating the ACS for the technological and energy process of main water drainage facilities of iron ore underground mines are substantiated according to their individual specificity as a type of enterprises with underground methods of mineral extraction.

At the same time, according to the logic of scientific thinking and the results of a number of scientific studies [12-19, 21-30], it is clear that a sufficient level of energy efficiency potential of the *Power Supply - Power Consumption* complex of such an energy-intensive and technologically complex production operation as an iron ore underground mine cannot be implemented only by a local solution by creating energy systems with a personalized sub-variant. The solution should be comprehensive. At the same time, as an option, the structure of such ACS can be built on the basis of the corresponding local subsystems, with their subsequent unification into a single management complex. Therefore, in the preventive version, the ACS should be generalized, and the process of power supply to consumers should be controlled by a generalized ACS management algorithm based on the algorithms of the corresponding subsystems - components of the general structure of the *ACS of Power Supply - Power Consumption* of an iron ore underground mine [26-30].

According to the globally accepted model of integration of the standard of control levels (IEC-1131), a trivial hierarchy scheme establishes general subordination of lower-level subsystems to higher-level systems and determines priorities in information exchange. Namely, each subsequent level of the hierarchy is subordinate. At the same time, higher-level ACSs can set tasks and control the work of lower-level ACSs due to higher priority.

Automated smart control of power supply in the conditions of a typical underground mine belongs to the third level of the hierarchy according to the IEC-1131 standard. Therefore, in accordance with such a hierarchy, its subsystems should subordinate local ACSs of lower levels 1 and 2, as well as form tasks (control settings) and criteria for their work. Feedback between the general ACS and the local ACS of levels 1 and 2 is carried out through control functions of the corresponding subsystems.

In turn, the ACS is subordinated to systems of a higher level of hierarchy, namely to levels 4 and 5. Information exchange in the forward and reverse direction between them is carried out in a similar way to the above, taking into account the appropriate hierarchy.

On the basis of the above-mentioned requirements, a functional scheme for implementing smart control of power supply at underground mines can be recommended, shown in Fig. 2.1. The scheme shows structural and informational relations within the entire hierarchy of the ACS.

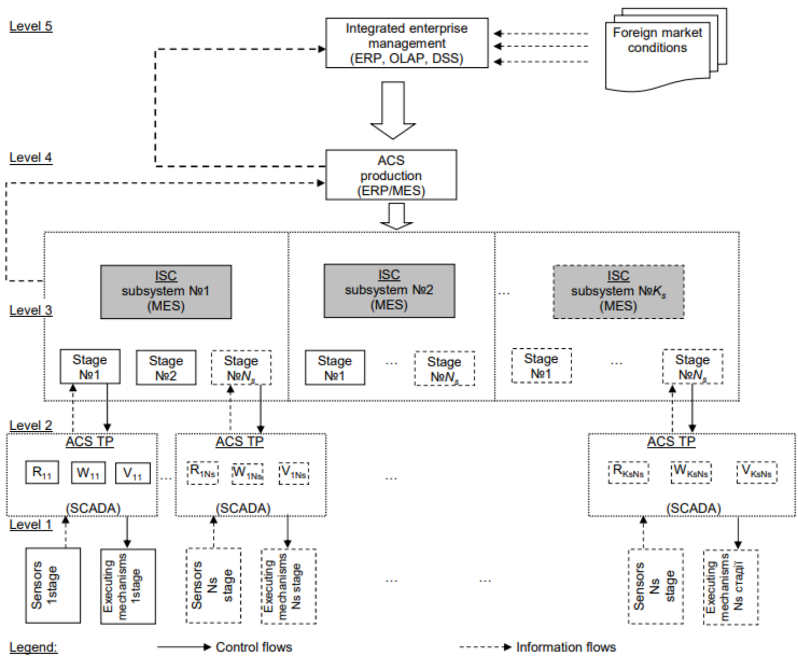


Fig. 2.1. Interaction of subsystems of the *ACS of Power Supply* - *Power Consumption* of an iron ore underground mine in the general hierarchy according to the IEC-1131 standard: *Ks* is the number of subsystems in the mine; *Ns* is the number of stages of information collection

It is in this context of the hierarchy of the underground mine's the *ACS of Power supply* - *Power Consumption* that it is logical that in this version of the ACS structure, the water drainage facility management segment, as a mandatory component of the system, should be in the form of a subsystem.

From the point of view of formalizing the tasks of managing such an object, this process can be represented by a structural diagram (Fig. 2.2).

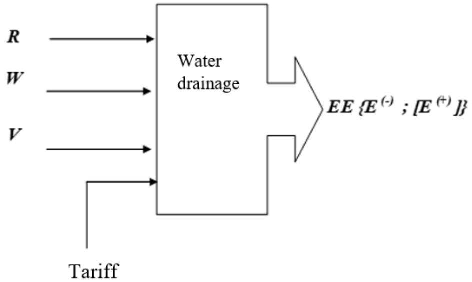


Fig. 2.2. Water drainage as a control object: *R* – ore mining; *W* – water consumption; *V* – air consumption in ventilation; $E^{(+)}$ – power generation, $E^{(-)}$ – power consumption

In view of rationality of production activity of underground mining enterprises, it is necessary to minimize power consumption to ensure energy efficiency (including due to power generation by underground mines). On the other hand, as a non-alternative option, it is necessary to provide water drainage in the minimum permissible volume along with ensuring air ventilation of underground workings, hoisting of extracted iron ore, etc.).

Given all these factors as efficiency criteria of the water drainage ACS, it makes sense to select

$$\left\{\begin{array}{l} E^{(-)} \Rightarrow Min \\ E^{(+)} \Rightarrow Max \\ \bar{W} = \sum_{i=1}^{24} W_i \geq W^* \end{array}\right\} \qquad (2.1)$$

where $\overline{W}$ is average daily water drainage; W_i is hourly water drainage (i=1…24); W^* is a certain optimal value of average daily water drainage.

The method of determining the last parameter was studied by the authors under the guidance of DSc. (Engineering), Professor Sinchuk during the last several years at different daily tariffs for power consumption [26, 27, 30], technological schemes of work, and specific iron ore underground mines of Ukraine.

Therefore, the next task is to develop a version of the structure of the smart ACS and the corresponding algorithm for its operation with the final analysis of the system's operation by means of computer simulation.

Therefore, the next task is to develop an option of the structure of the smart ACS and the corresponding algorithm for its operation with the final analysis of the system's operation by means of computer simulation.

2.3. Generalized algorithm of multifunctional smart control

Let us consider the possibilities of building a generalized algorithm the *ACS of Power Supply* - *Power Consumption* for two realistically possible cases: 1 – a selective tariff with restrictions on daily power consumption based on agreements or 2 – a variable tariff (hourly/24).

To clarify and understand the research tactics, we note that development of the structure and parameters of the algorithm of the underground mine’s *ACS of Power Supply* - *Power Consumption* includes a substructure (subsystem) of managing the water drainage process.

Based on the above-mentioned tasks of smart control of the electric power complex at underground mining enterprises, a corresponding generalized algorithm of multifunctional control of power consumption is developed [26-30].

2.3.1 Generalized description of blocks of the *ACS of Power Supply* - *Power Consumption* algorithm

The generalized algorithm of the automated multi-functional system for power consumption control of an iron ore underground mine is shown in Fig. 2.3.

Block 1 informs about the start of the system.

In block 2, the current regulatory framework of Ukraine concerning power consumption and supply is updated. Also here, initial information (current parameters) is input according to current control criteria and problem statement (1) - (10).

Block 3 checks whether the enterprise has a valid agreement (contract) with the power generating company for power supply. If the agreement exists, the algorithm proceeds from block 4.

Otherwise (there is no agreement), further calculations can be made on a general basis or conclusion of such an agreement in the future can be initiated (i.e. block 5.1, Category ={«A»}and block 6).

Similarly, block 4 checks whether the enterprise has a valid agreement (contract) with the power transportation company for power transportation. If such an agreement exists, the algorithm proceeds from the next block (5.2). Otherwise (there is no agreement), this algorithm is terminated, and further calculations can be made on a general basis or conclusion of such an agreement can be initiated in the future.

Block 5.1 and block 5.2 enable an industrial consumer to select a category (either "A" or "B"), i.e. Category = {"A", "B"}.

Block 6 provides an opportunity for the enterprise to select (order) a daily tariff (Td) and designed power consumption volume from the power generating company. It is desirable to maintain the ordered volume as accurately as possible because non-fulfillment or, conversely, over-fulfillment of the ordered volume may cause potential economic losses of the enterprise.

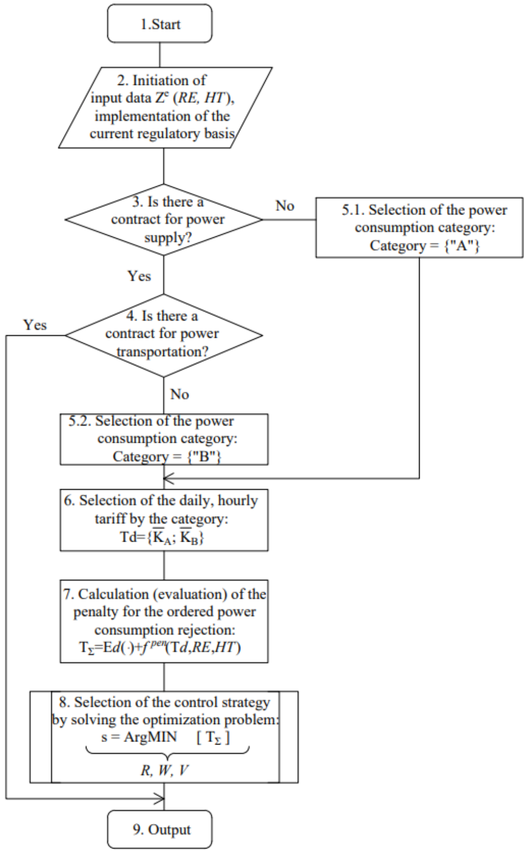


Fig. 2.3. Generalized algorithm of operation of the *ACS of Power Supply - Power Consumption* of an iron ore underground mine. Multi-functional control option

Taking into account requirements for implementing declared power consumption, in block 7, an integrated assessment factor ($T_{\sum}$) is formed, which considers actual power consumption and a special function *penalty*. The value of the penalty should approach 0 (there is no penalty or it is minimal), if there are no such deviations. Otherwise, in case of positive or negative deviations, the function begins to increase sharply, i.e. the penalty is maximized. An example of the penalty function is

$$f^{penalty} = r\sum_{i=1}^{NS}\left[\frac{\left|\overline{T}_i - T_i^{rest.}\right| + (\overline{T}_i - T_i^{rest.})}{2}\right]^2, \quad (2.2)$$

where $\overline{T}_i$ is an average daily value of the *i-th* tariff; $T_i^{\partial on.}$ is a restriction on deviations in power consumption when applying the *i-th* tariff to the system; *NS* – is the number of established tariff intervals; *r* is the penalty factor (an empirically chosen integer).

$$I = \left[Ed(R,W,V) + f^{penalty}(\mathrm{T}d, E^{(-)}, E^{(+)})\right] \to MIN, \quad (2.3)$$

where I is the resulting target function; $Ed = \left(E^{(-)} + E^{(+)}\right)$ is evaluation of actual power consumption-generation balance according to (2.1); $\mathrm{T}d$ is the current tariff.

Block 8 is actually designed to select an optimal strategy (*s*) of power control by solving the optimization problem with certain parameters of the state vectors (Fig. 2.2). Considering basic algorithms (Fig. 2.4, 2.5), the actual solution includes parameters of ore flows, water drainage and ventilation (R,W,V) to achieve the minimum value of the target functional of (2.3) type:

$$\mathrm{s} = \underbrace{\mathrm{ArgMIN}[I]}_{R,W,V}, \quad (2.4)$$

where s is the number of the optimal control strategy according to the algorithm (Fig. 2.4).

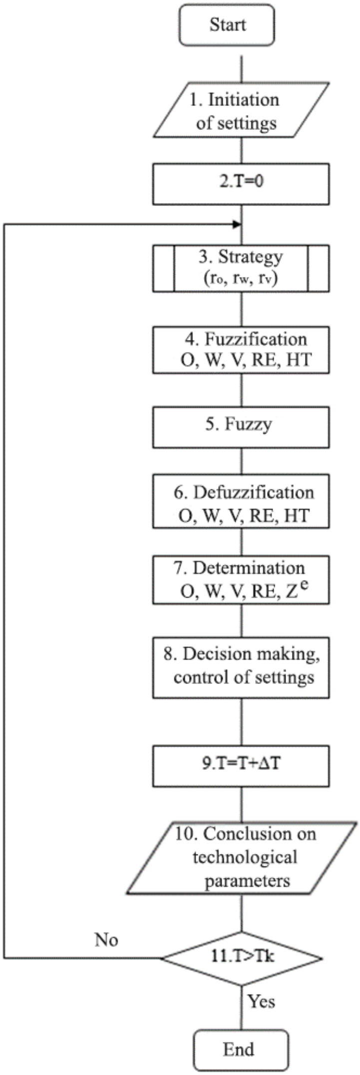


Fig. 2.4. Algorithm of operation of the option of the fuzzy *ACS of Power Supply* - *Power Consumption* of an iron ore underground mine. Multi-functional control option

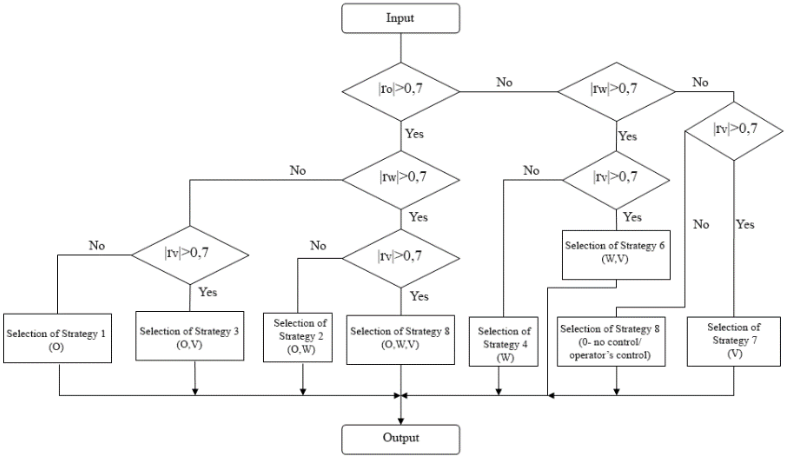


Fig. 2.5. Algorithm for selecting the control strategy (channels)

Final block 9 of the algorithm actually ceases the corresponding calculation and allows us to implement more complex smart approaches to controlling the power consumption process in the future:

$$Z^{e} = F\left(RE, HT\right) \Rightarrow \min, \qquad (2.5)$$

where Z^{e} is total costs of the enterprise for the consumed power (hourly, daily), UAH; *RE* is power consumption (hourly, daily), kW; *HT* is an hourly (0-24) tariff, UAH/kW; $F\left(\cdot\right)$ is some established functional dependence.

Total power consumption in the system as a whole or in individual processing stages can be found from target function (2.3) as

$$RE = f\left(R, W, V\right), \qquad (2.6)$$

where $f\left(\cdot\right)$ is a function or approximation.

2.3.2 Development of the smart control algorithm for power consumption

Considering the above preconditions of nonlinear characteristics, incomplete data, multi-channeling in real production situations, modern smart approaches to introducing automated fuzzy logic-based control are promising [26-30].

This approach provides an algorithm for a fuzzy control system (Fig. 2.3), to implement several control strategies (i.e. multi-channeling), namely

$$\mathrm{S} = \left\{R, R+W, R+V, W, 0, W+V, V, R+W+V\right\}. \tag{2.7}$$

Each strategy determines the number of possible control actions (channels) to be further implemented in the ACS. For example, according to (2.7), the number of parameters can be 0 (no control or the manual mode), 1, 2 or 3. However, it should be noted that using this method, the number of channels can be further increased if necessary.

It should also be noted that according to (2.7), the main controlled factor is the enterprise's potential power cost Z^e, which, in turn, depends on power consumption *RE* and the hourly (time-of-day) tariff *HT*.

The algorithms include a cascade of conditional operators checking the corresponding correlation coefficients between [*R*, *W*, *V*] and [*RE*] (in pairs) followed by an aggregation of AND/OR relations. Exceeding the threshold value, i.e. $|r_{xy}>0.7|$, indicates the need to consider this control channel (action) in the resulting strategy. Thus, the output results in a specific control strategy that corresponds to the number of control channels (actions) – 1, 2 or 3, i.e. "for ore", "for ore and water", "for ore, water and ventilation".

2.3.3. Floating daily tariff

The second case advanced at the beginning relates to the *floating* daily tariff, which varies every hour, i.e. *NS* = 24 in accordance with (2.2)-(2.3). There is also a restriction on power consumption, namely exceeding the declared volume as well as reduced consumption is undesirable (penalty).

Analysis conducted reveals that for this case, the value of specific power consumption per 1t of pumped water at water drainage should be used as a basic indicator of the target function (2.1), i.e. considering (2.3) – (2.7)

$$I = \frac{RE}{W} + f^{\,penalty}(RE, HT), \tag{2.8}$$

where $RE = \left\{E_1, E_2, \ldots, E_{24}, E_\Sigma, E_\Sigma^{rest}\right\}$ is a set of power consumption indicators for the 1st hour of the day, the 2nd, . . . , the 24th; $E_\Sigma = E_1 + E_2 + \ldots + E_{24}$ is total daily power consumption; E_Σ^{rest} is a restriction on daily power consumption (the actual order); $W = \left\{W_1, W_2, \ldots, W_{24}, \overline{W}\right\}$ is the set of water drainage per hour for the 1st hour of the day, the 2nd, . . . , the 24th; $\overline{W}$ is average water drainage; $HT = \{T_1, T_2, ..., T_{24}, \overline{T}\}$ are tariffs for power consumption per hour for the 1st hour of the day, the 2nd, . . . , the 24th; $\overline{T}$ is the average daily tariff.

Then, for the penalty function we can apply the expression

$$f^{penalty}(RE, HT) = r\frac{\overline{T}}{\overline{\overline{W}}}\sqrt{\left[\frac{\left|E_\Sigma - E_\Sigma^{rest}\right| + \left(E_\Sigma - E_\Sigma^{rest}\right)}{2}\right]^2}. \qquad (2.9)$$

Considering the above, we obtain the final expression for the target function

$$I = \left[\frac{1}{24}\sum_{i=1}^{24}\frac{E_i \cdot T_i}{W_i} + r\frac{\overline{T}}{\overline{\overline{W}}}\sqrt{\left[\frac{\left|E_\Sigma - E_\Sigma^{rest}\right| + \left(E_\Sigma - E_\Sigma^{rest}\right)}{2}\right]^2}\right] \to MIN. \qquad (2.10)$$

Some vectors W^*, E^* of water drainage indicators and corresponding power consumption of the following type are the solution of the target function

$$\begin{aligned} W^* &= \{W_1, W_2, ..., W_{24}\} \\ E^* &= \{E_1, E_2, ..., E_{24}\} \end{aligned}. \qquad (2.11)$$

In addition, it should be noted that according to [25], there is a close correlation between ore production, drainage and power consumption at many deposits. So, it is possible to calculate these indicators on the basis of established regression equations like

$$\begin{aligned} W_i &= f_{\beta pe}(E_i) \\ E_i &= f_{\beta ep}(W_i) \end{aligned}, \qquad (2.12)$$

where $f_{\beta pe}(E_i)$, $f_{\beta ep}(W_i)$ are appropriate regression models for water drainage based on power consumption and/or appropriate power consumption based on the volume of water drainage.

Therefore, to solve the optimization problem on the basis of the target function of type (2.10) and find corresponding vectors (2.11) certain optimization methods should be applied. Given the significant number of unknown quantities, finding an exact solution to such a problem is quite difficult. Therefore, for an approximate solution, we use the stochastic optimization approach [6]. With this in mind, the corresponding algorithm for an approximate solution to optimization problem (2.10) contains the following stages.

1. Start the algorithm.

2. Set the initial data:

– the maximum number of iterations for the optimization algorithm (N_Σ);

– the maximum hourly power consumption ($E_i^{\max}$) for the random value generator;

– the minimum hourly power consumption ($E_i^{\min}$) for random value generator;

– admissible (recommended or optimal) daily power consumption (E_Σ^{rest});

– the variative coefficient for the penalty function (r).

3. Initialize primary values for working data of the algorithm:

– the suboptimal value of the target function ($I = +\infty$);

– the suboptimal value for specific hourly power consumption ($\frac{E_i^*}{W_i^*} = 0$);

– the number of the current iteration of the algorithm (j =1).

4. Generate 24 random values of hourly power consumption ($E_i, \left[i = 1 \div 24\right]$) with the regular distribution law $\xi_i = RND(0 \div 1)$ at the interval $\left[0 \div 1\right]$ and expand it for the required interval $\left[E_i^{\min} \div E_i^{\max}\right]$:

$$E_i = E_i^{\min} + \left(E_i^{\max} - E_i^{\min}\right)\xi_i, \text{ i.e.}$$

$$\left\{\begin{array}{l} E_1 = E_1^{\min} + \left(E_1^{\max} - E_1^{\min}\right)\xi_1 \\ E_2 = E_2^{\min} + \left(E_2^{\max} - E_2^{\min}\right)\xi_2 \\ \dots \\ E_{24} = E_{24}^{\min} + \left(E_{24}^{\max} - E_{24}^{\min}\right)\xi_{24} \end{array}\right\}$$

5. Calculate the corresponding 24 values for water drainage ($W_i, \left[i = 1 \div 24\right]$) based on the corresponding regression models [25]

$$\left\{\begin{array}{l} W_1 = f_{\beta pe}(E_1) \\ W_2 = f_{\beta pe}(E_2) \\ \ldots \\ W_{24} = f_{\beta pe}(E_{24}) \end{array}\right\}$$

6. Determine the required average ($\bar{T}, \bar{W}$) and total (E_Σ) values for further calculation of the current target function (2.10)

$$\bar{T} = \frac{1}{24}\sum_{i=1}^{24} T_i ,$$

$$\bar{W} = \frac{1}{24}\sum_{i=1}^{24} W_i ,$$

$$E_\Sigma = \sum_{i=1}^{24} E_i .$$

7. Calculate the new current target function (I) on the basis of (2.10).

8. If $I < I^*$, re-determine the suboptimal value of the target function and the corresponding vectors of power consumption and water drainage:

$$E_i^* = E_i, W_i^* = W_i, i = 1 \div 24.$$

9. Add the number for the next iteration $j = j + 1$, if $j \le N_\Sigma$, proceed to the next cycle (iteration) starting from block 4. Otherwise, if the last iteration of optimization is achieved, proceed to the final block of the algorithm.

10. Print or enter into the database suboptimal values of the target function, power consumption and water drainage vectors: $I^*, E_i^*, W_i^*, i = 1 \div 24$.

11. Finish the optimization algorithm.

Fig. 2.6 – 2.8 present the results of optimization using the above algorithm. This suggests dynamics of changing the target function values (I, I^*), specific power consumption (E_i^* / W_i^*) and the penalty function ($f^{penalty}(\cdot)$) depending on the iteration number (calculation step j).

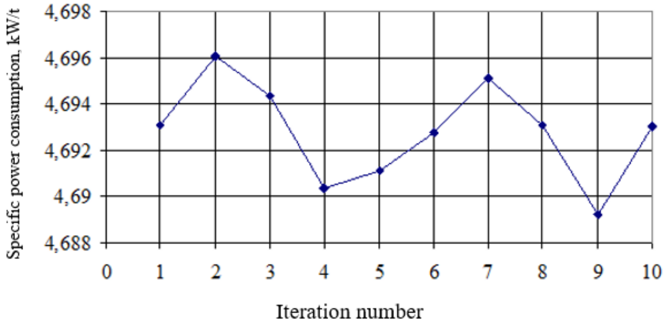


Fig. 2.6. Change in the average value of hourly specific power consumption in the optimization process

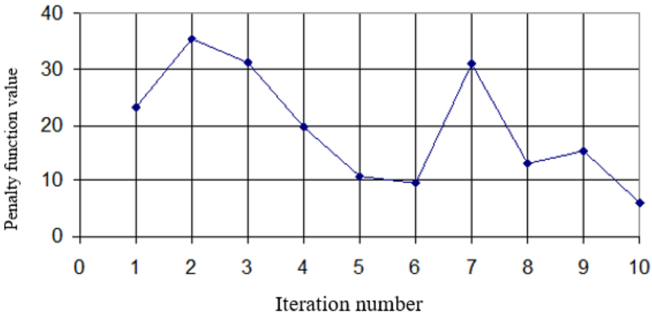


Fig. 2.7. Change in the values of the penalty function for excessive or insufficient power consumption

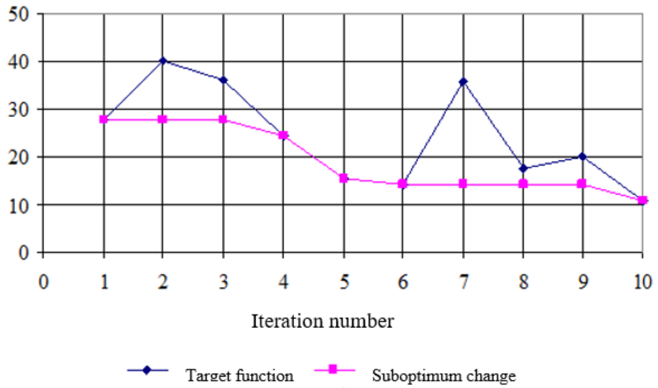


Fig. 2.8. Change in the target function values (*I*) and the corresponding suboptimum (*I**)

2.3.4. A prior evaluation of proposed algorithms efficiency

1. Analysis of stochastic optimization results (Fig. 2.9, 2.10) indicates that even if a fairly small number of iterations $N_{\Sigma}=10$ is applied, it is possible to improve the primary solution by over 60% (the initial value of the target function *I**=27.7 and the final value at the last iteration *I**=10.7).

2. According to the modelling, there are determined necessary vectors for daily hourly water drainage (*W**) and appropriate power consumption (*E**), which corresponds to the suboptimal value of the target function (*I**). The obtained results can be used for recommendations on more efficient planning of enterprise activity. To obtain a better solution, it is necessary to increase the number of iterations by 2-3 orders of magnitude.

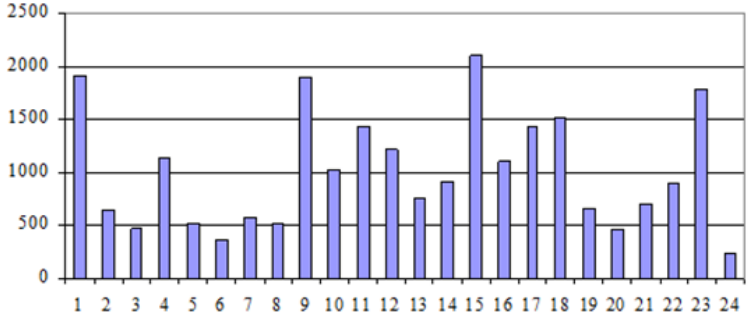


Fig. 2.9. Value of the hourly (daily) power consumption vector (*E**), which corresponds to the suboptimum of the target function (*I**) on the example of Pokrovska underground mine statistics (Kryvyi Rih)

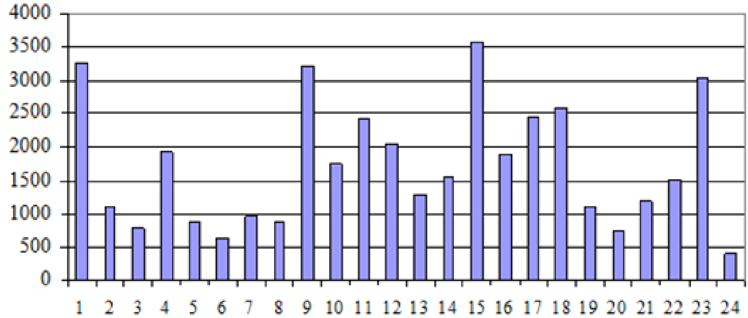


Fig. 2.10. Value of the hourly (daily) water drainage vector (*W**), which corresponds to the suboptimum of the target function (*I**) on the example of Pokrovska underground mine statistics (Kryvyi Rih)

2.4. Development of the structure of the smart FL-based ACS

According to the previous subsection and [26-30], to build a smart ACS, Fuzzy Logic methodology should be applied with the following mandatory stages: fuzzification, FL-inference and defuzzification.

2.4.1. Principles of fuzzification and formation of the inference logic rulebase with the single-channel control (for the two-rate "Night/Peak" type).

We determine linguistic variables (terms) for all the above fuzzy parameters:

$$T_1^{Power} = \left\{ \frac{MIN}{NB}; \frac{mean}{Z}; \frac{MAX}{PB} \right\}, \qquad (2.13)$$

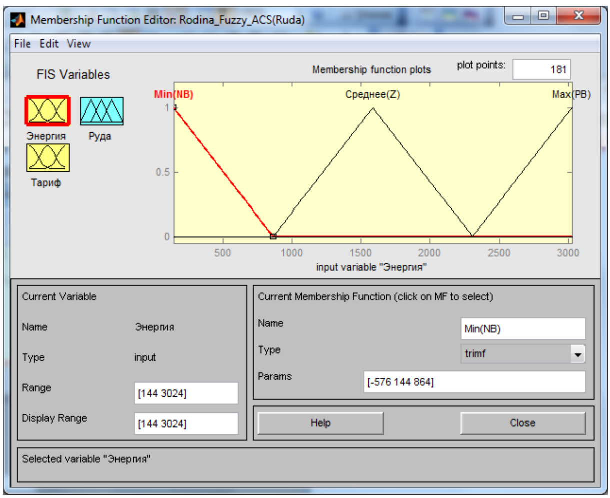
$$T_2^{Tariff} = \left\{ \frac{Night}{NS}; \frac{Peak}{PS} \right\}, \qquad (2.14)$$

$$T_3^{Ore} = \left\{ \frac{MIN}{NB}; \frac{mean}{Z}; \frac{MAX}{PB} \right\}, \qquad (2.15)$$

where T_1^{Power}, T_2^{Tariff}, T_3^{Ore} are identifiers of numerous terms for fuzzy variables: power consumption, tariff formation and ore flow; {{*MIN*, *mean*, *MAX*}+{*Night*, *Peak*}, {*NB*, *Z*, *PB*}+{*NS*, *PS*} are complete or shortened identifiers for corresponding values of these terms.

As can be seen from (2.13) – (2.14), a three-digit scale is used for parameters of power consumption and ore flow, and a two-digit scale – for the tariff variable. However, if necessary, quantitative values of all these scales can be changed.

Subsequently, standard triangular membership functions are selected for fuzzification of fuzzy variables of (2.13) and (2.15), and tangential ones – for (2.14). An example of parameterization of these variables and functions is performed in MATLAB. In Fig. 2.11, an example of such parameterization based on statistics of Rodina underground mine is shown.



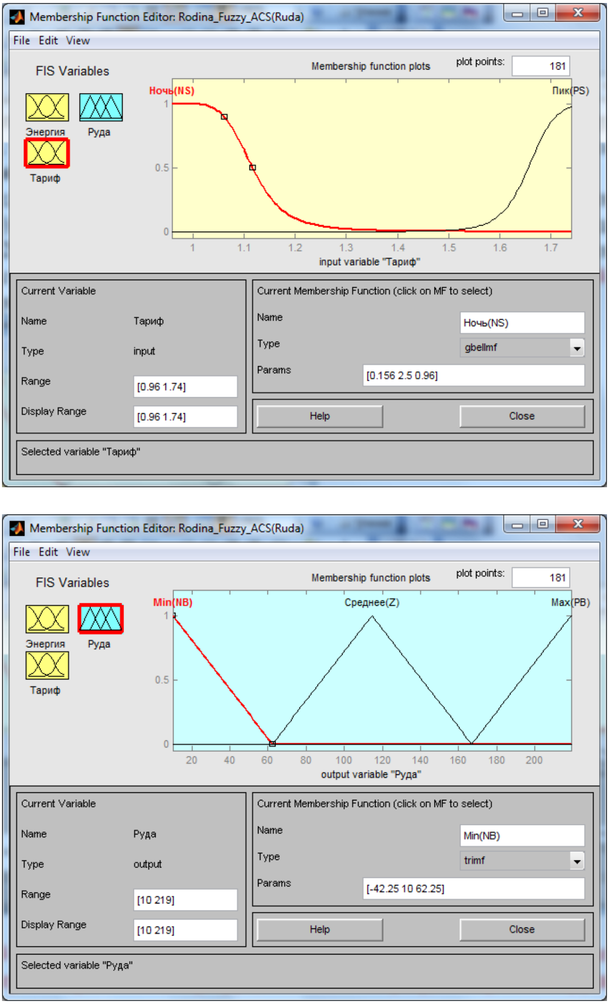


Fig. 2.11. Fuzzification based on statistics of Rodina underground mine (the two-rate tariff)

Fuzzy sets and corresponding terms (2.13) – (2.15) of fuzzy inference rules are as follows:

1) IF "Power Consumption" (β_1) = "MIN" (NB) AND (И) "Tariff" (β_2) = "Peak" (PS) THEN "Ore Flow"= "MIN" (NB);

2) IF "Power Consumption" (β_1) = "MAX" (PB) AND "Tariff" (β_2) = "Night" (NS) THEN "Ore Flow"= "MAX" (PB);

…

The complete base of the rules is in Fig. 2.12 reproduced as a Matlab code.

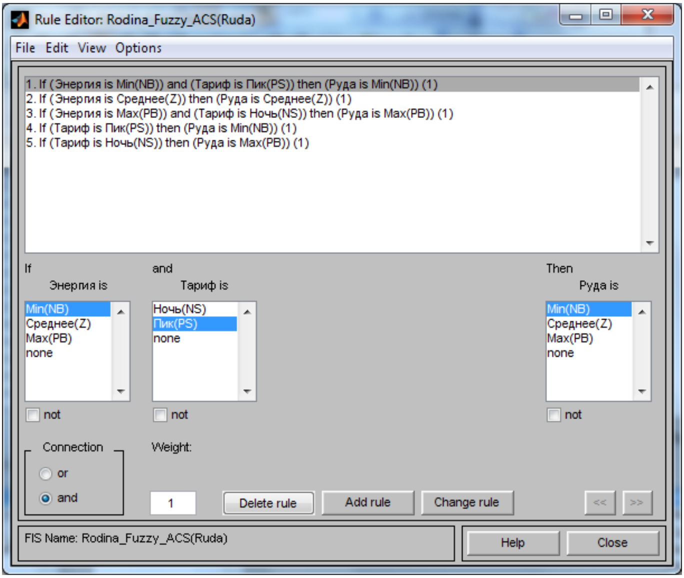


Fig. 2.12. Formation of the rulebase for decision-making

The standard Mamdani method is adopted as a basic algorithm for defuzzification.

2.4.2. Principles of fuzzification and formation of the inference base for the two-channel control

This type of control is implemented by two of possible control actions ("ore/water"). According to the algorithm (Fig. 2.5), these can be strategies 2, 3 or 6. Strategy 2 ("Ore + Water Drainage") realizes general principles of fuzzification and formation of the inference base for the two-channel control. Other strategies are implemented in the same way. The control action here is the ore flow *R* and water drainage *W*; the controlled parameter is power consumption from (2.1). Parameters of air supply for ventilation are classified as disturbing.

We expand basic fuzzy sets (2.13)-(2.15) to implement the two-channel control. In this case, the set of the above expressions requires determination of the following term:

$$T_4^{water} = \left\{ \frac{MIN}{NB}; \frac{mean}{Z}; \frac{MAX}{PB} \right\}, \tag{2.16}$$

where T_4^{water} is the term indicator for the fizzy variable of water drainage.

Considering (2.13)-(2.16), several examples of forming fuzzy inference rules for this control type are provided:

1) IF "Power Consumption" (β_1) = "MIN" (*NB*) AND "Tariff" (β_2) = "Peak" (*PS*) THEN "Ore Flow"= "MIN" (*NB*);

2) IF "Power Consumption" (β_1) = "MAX" (*PB*) AND "Tariff" (β_2) = "Night" (*NS*) THEN "Ore Flow"= "MAX" (*PB*), "Water Drainage" = "MAX" (PB);

…

Other stages are performed in the above manner (2.4.1).

2.4.3. Principles of fuzzification and formation of the inference base for the three-channel control

This type of control is implemented by three control actions ("Ore + Water + Air"). In accordance with the algorithm (Fig. 2.5), it is strategy 8. The control actions here are the ore flow *R*, water drainage *W* and ventilation *V*, the controlled parameter is power consumption from (2.1). The air supply parameter remains disturbing. General fuzzification principles and formation of the inference base for the three-channel control are as follows.

Besides the above terms (2.13)-(2.16), it is necessary to additionally determine the term:

$$T_5^{Air} = \left\{ \frac{MIN}{NB}; \frac{mean}{Z}; \frac{MAX}{PB} \right\}, \tag{2.17}$$

де T_5^{Air} is the term identifier for the fuzzy variable ventilation.

Considering (2.13)-(2.16), several examples of forming fuzzy inference rules for this type of control are provided:

1) IF "Power Consumption" (β_1) = "MIN" (NB) AND "Tariff" (β_2) = "Peak" (*PS*) THEN "Ore Flow"= "MIN" (NB), "Water Drainage" = "MIN" (*NB*), "Ventilation" = "MIN" (*NB*);

2) IF "Power Consumption" (β_1) = "MAX" (*PB*) AND "Tariff" (β_2) = "Night" (*NS*) THEN "Ore Flow"= "MAX" (*PB*), "Water Drainage" = "MAX" (*PB*), "Ventilation" = "MAX" (*PB*).

Other stages are performed in the above manner (2.4.1).

2.4.4. Principles of building fuzzy controllers of smart ACSs

The above fuzzy variables, fuzzy sets (2.13)-(2.17) and membership functions (Fig. 2.11) in the FIS editor enable setting input and output parameters. It means that the Mamdani algorithm is used for further defuzzification.

Fig. 2.13 contains an example of a multichannel ("Ore/Water/Air") fuzzy controller for the smart ACS of power supply. The two-rate "Night/Peak" tariff is used as the basic one. Any single- or two-channel controller is an appropriate private case from this.

Depending on the input values of *R, W, V* (as potential controlling actions in the smart ACS) and the selected tariff, the actual power consumption $\{E^{(-)}\}$ is determined by a fuzzy logic inference. In case of the enterprise's own additional power generation $\{E^{(+)}\}$, this is also considered in the final energy balance of the enterprise during the day.

Algorithmic and software implementation of various smart fuzzy controllers and their further testing by computer modelling is carried out on real data from underground ore mines of Kryvyi Rih iron ore basin (Kryvorizka, Pokrovska, Kazatska, etc.). Some results of such tests are given in [15-19].

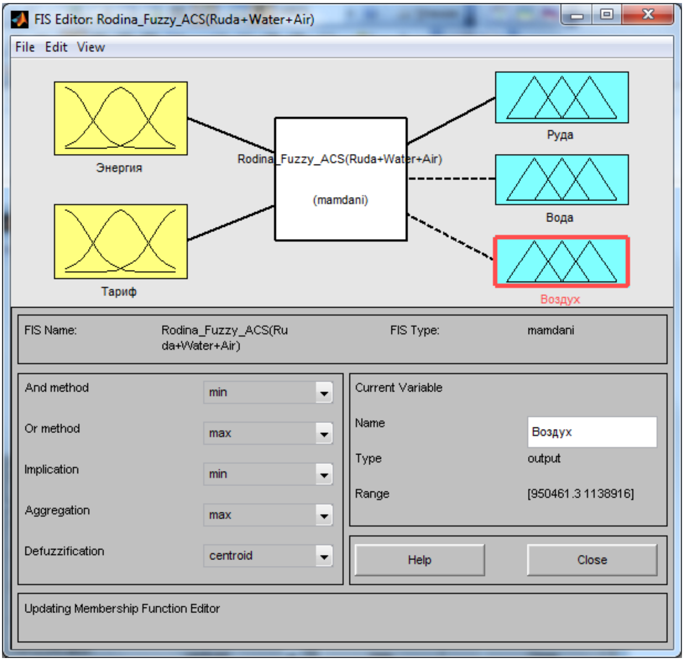


Fig. 2.13. Creation and definition of fuzzy multichannel controller settings

2.5 Simulation of the ACS in the water drainage mode

Basic principles of modelling or simulating such systems and proving their adequacy are discussed in detail in [23-25, 27, 29].

To model ACS operation of mine power consumption, we apply the Fuzzy Logic Toolbox (FLT) module from the well-known MATLAB software mathematical package. To do this, we use the standard fuzzy modelling method described in [23-25].

The fuzzy controller is built on the example of the single-channel control of the "Water Drainage-Power Consumption" channel based on statistics of Rodina underground mine (Kryvyi Rih). Considering some of the above fuzzy variables, fuzzy sets (2.13)-(2.17) and membership functions in the FIS editor, input and output parameters are set. As shown above, it means that for further defuzzification, the Mamdani algorithm is used (Fig. 2.13).

The next step is to determine the rulebase for a fuzzy inference. Examples of these rules are given above (2.3), and the full list of these rules is provided in Fig. 2.12.

According to the data on this mine [25, 26], during fuzzification, the corresponding maximum and minimum daily parameters are determined:

– power consumption (144; 3024) kW/day;

– water consumption (10; 219) t or m^3/day.

On the basis of such data, a 3D surface model is obtained for the fuzzy inference of the developed fuzzy model (рис. 2.14).

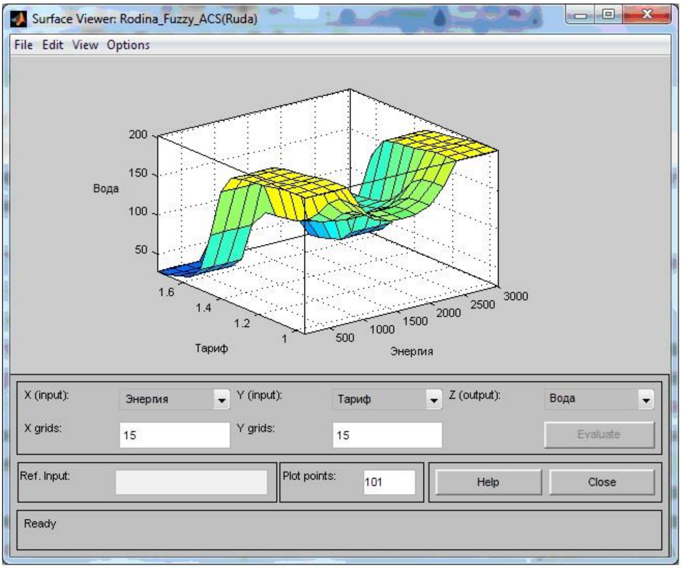
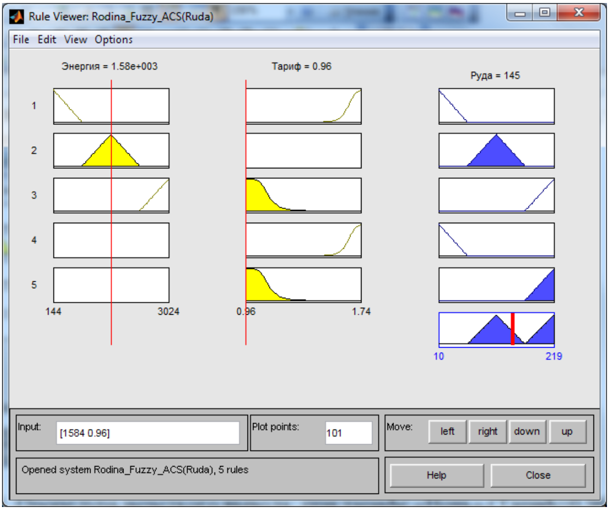
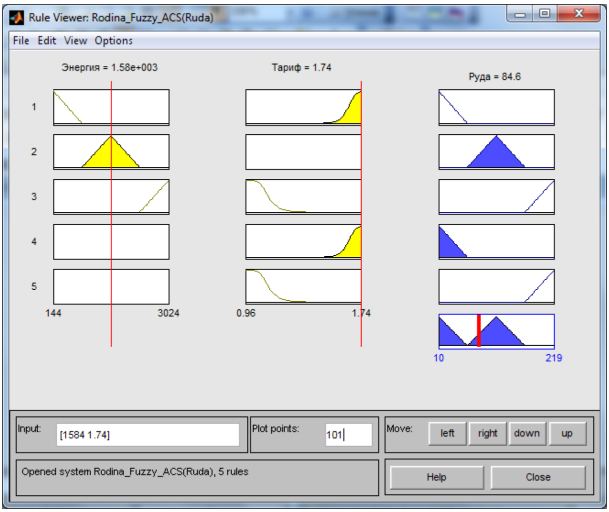


Fig.2.14. 3D surface model for the fuzzy inference of the fuzzy model (according to the data on Kryvorizka underground mine for the two-rate tariff)

Using the appropriate MATLAB FLT mode for modelling fuzzy inference procedures, we check operation of algorithms (Fig. 2.3, 2.4), and then calculate the expected reaction of the fuzzy controller to control actions (Fig. 2.15). At the same time, different values of the two-rate tariff for power consumed are used. The current data on DTEK "Dniprooblenerho" for the 1st category industrial consumers is used as basic tariffs.



(1)



(2)

Fig.2.15. Procedure of the fuzzy regulator on controlling impacts: Ekonom tariff; Peak tariff (Tariff=1.74)

Thus, on the basis of repeated use of this module, all the necessary data is calculated for further visualization and analysis of relevant dependences (water and power consumption, tariffs, costs, etc.).

2.5.1. Single-channel control simulation

Fig. 2.16 contains the results of modelling operation of the fuzzy single-channel ACS of power consumption on the basis of a single control action – daily water drainage distributed over time. The discreteness of the controller modelling is 30 minutes. In modelling, initial data from operating iron ore underground mines is used. Other approaches to smart control for such enterprises (including those with alternative tariffs and/or control channels) are demonstrated in [23-25].

Analysis of the modelling results (Fig. 2.16) and analytical calculations reveal that two-rate tariff application causes a 12.88% increase in power costs (without the ACS). The use of the FLC-based ACS on the basis of minimax criteria of (2.1)-(2.2) at Kryvorizka underground mine allows increasing daily water drainage by 11.9%. At the same time, daily power consumption similarly increases by 11.9%, and power costs decrease by 4.31% considering the two-rate tariff due to a more efficient redistribution of temporary zones.

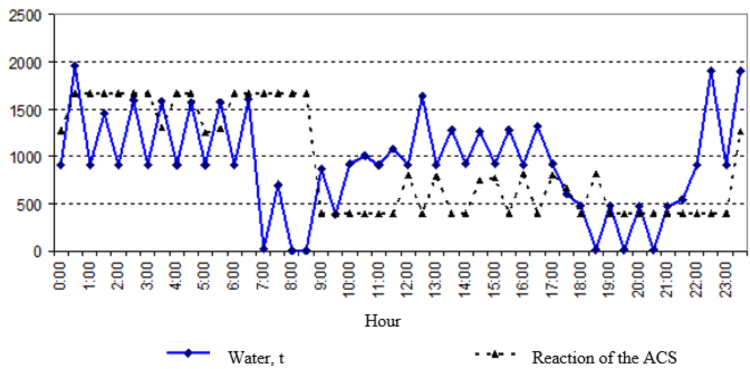


Fig. 2.16. Dependences of water drainage at Kryvorizka underground mine as a single control channel and designed water drainage with the latter maximized by criterion

2.5.2. Multichannel control simulation

Basic principles of building fuzzy controllers (including fuzzification, fuzzy logical inference, defuzzification, etc.) as well as their operation algorithms for multichannel control conditions are described above. In this subsection the results of modelling automated control of power consumption for three control channels ("Ore", "Water", "Air") are given. Main calculations are based on Kryvorizka underground mine's statistics. However, according to the analysis and the given methodology, these results can be similarly reproduced for all algorithm strategies (Fig. 2.3, 2.4) and at other mining enterprises (underground mines).

Thus, implementation of multichannel control in the MATLAB environment using the structure of a fuzzy smart controller (Fig. 2.13) on the basis of initial real production data shows results similar to the previous case (Fig. 2.15). In particular, the "Ore/Water" model with minimax control based on criterion (2.3) is in [26-30].

The analysis results of other calculated values show that under the two-rate tariff, daily costs increase by 7.1% against alternatives. Minimax control (minimized power consumption with maximized daily water drainage) causes a 6.97% increase in daily consumption. However, according to [26], it is fully compensated by an increase in daily production of raw materials (approximately +508 t/day) [26-30].

Fig. 2.13 shows the structural scheme of the two-channel FL-controller ("Ore-Water-Air") implemented through applying basic principles, algorithms and rules presented in 2.4, their full formalization given in [26-30].

Considering the fact that implementation of the first two control channels ("Ore-Water") is completely similar to those demonstrated earlier, there are provided the results of computer modelling for the third channel "Air" (Fig. 2.17) for all three processing stages, i.e. extraction, water drainage, ventilation.

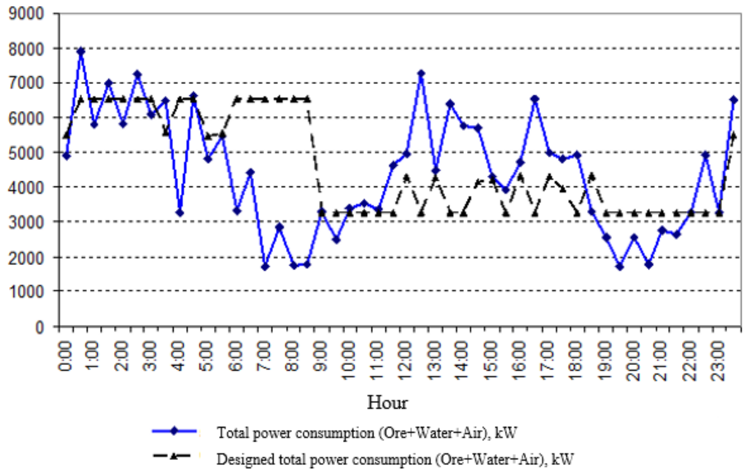


Fig. 2.17. Results of three-channel control ("Ore-Water-Air") over total power consumption at Rodina underground mine with the two-rate tariff

The results of analyzing the obtained dependences indicate that unlike the single- and two-channel control when applying a two-rate tariff to power consumption, the use of minimax control causes a predicted increase in daily power consumption by about 4.45%. However, as shown in calculations [26-30], this is fully compensated by an increase in total production efficiency. At the same time, the daily cost of consumed power reduces by 2.5% due to a more efficient distribution of ore/water/air-flows according to the main processing stages. Consequently, the use of the three-channel fuzzy control which is potentially coordinated (ore flow, drainage and ventilation) is the most effective for underground mining of iron ore materials.

2.6 Simulation of the ACS in the power generation mode

According to [12, 13, 15-17, 23-30], one of the effective means of improving energy efficiency of iron ore production is by using autonomous power generating on enterprises' own fuel and energy resources. Let us dwell on the frame version of implementation of this idea within the *ACS of Power Supply – Power Consumption* of underground mines.

The mode of additional power generation enables to partially compensating for the total power consumption due to additional energy provided by hydraulic storage sources. In Fig. 2.18, 2.19, there are provided examples of modelling operation of such enterprises (Kryvorizka and Pokrovska underground mines) in 4 modes.

Analysis of modelling results indicates the possibility of reducing power consumption by 26%-35% when applying more advanced modes 3 – 4 (Kryvorizka underground mine). Similar results are shown when modelling conditions for Pokrovska underground mine (Fig. 2.19).

Analysis of modelling results indicates the possibility of reducing power consumption in modes 3 and 4 by 15% – 24% (Kryvorizka underground mine).

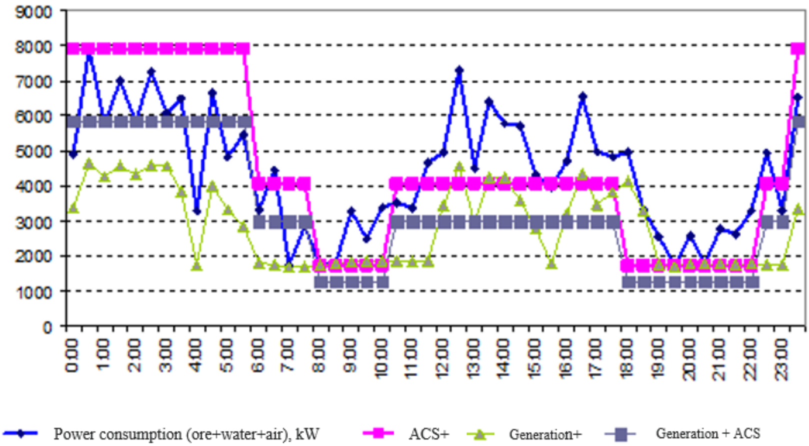


Fig. 2.18. Results of modelling operation of Kryvorizka underground mine in the following modes: 1) normal mode (without smart control and additional generation); 2) using smart control and additional generation; 3) using additional generation without smart control; 4) using smart control and additional generation

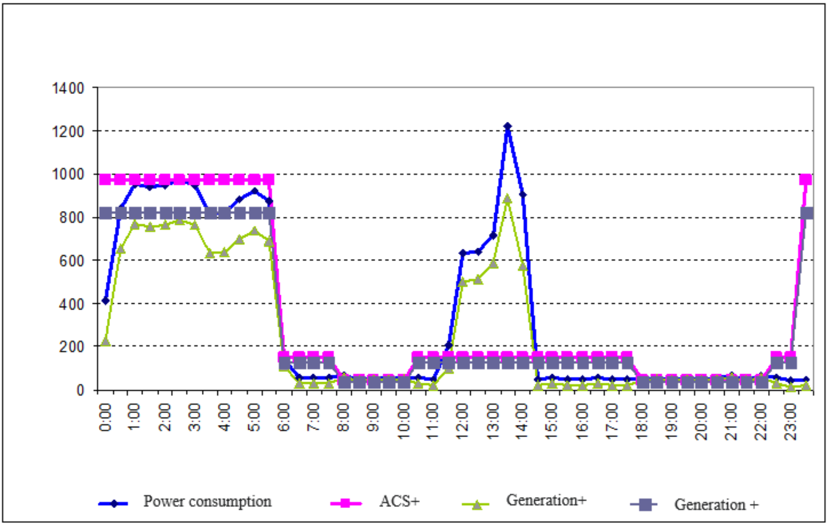


Fig. 2.19. Results of modelling Pokrovska underground mine operation in the following modes: 1) normal mode (without smart control and additional generation); 2) using smart control and additional generation; 3) using additional generation without smart control; 4) using smart control and additional generation

CONCLUSIONS TO SECTION 2

1. Through retrospective analysis of known sources of information and subsequent systematization of the results, the relevance of implementation of smart control of the local water drainage process as part of the integrated automated control system of the power system at iron ore underground mines is substantiated. In the future, development of the structure, algorithms of such a system, as well as proving effectiveness of its functioning by computer simulation is carried out.
2. Analysis of stochastic optimization results (Fig. 2.9, 2.10) shows that even with a small number of iterations N_{Σ} =10, it is possible to improve the primary solution by over 60% (the primary value of the target function I^*=27.7 and the final value at the last iteration I^*=10.7).
3. Application of a two-rate ("Ekonom/Peak") tariff without using smart fuzzy ACS causes a 12.88% increase in daily costs for consumed power with single-channel water drainage control and, accordingly, a 7.1% increase with two-channel control of ore and water drainage simultaneously. However, application of fuzzy controllers enables compensation of these losses.
4. Application of the fuzzy 3-channel ACS ("Ore, Water Drainage, Ventilation") allows reducing power costs with the two-rate tariff due to more efficient redistribution at daily intervals. For example, according to the data on Rodina underground mine, with a 4.45% increase in daily power consumption total costs are reduced by 2.5%.

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SCIENTIFIC PUBLICATION

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MONOGRAPH

Edited by DSc., Professor Oleh Sinchuk

Subscribe to print 10/12/2022. Format 60×90/16.
Edition of 300 copies.
Printed by “iScience” Sp. z o. o.
Warsaw, Poland
08-444, str. Grzybowska, 87
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ISBN 978-83-66216-71-6
9 788366 216716