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Algorithm and Methods for Analyzing Power Consumption Behavior of Industrial Enterprises Considering Process Characteristics

Pavel Ilyushin [1,*], Boris Papkov [2], Aleksandr Kulikov [3] and Konstantin Suslov [4,5]

1 Department of Research on the Relationship Between Energy and the Economy, Energy Research Institute of the Russian Academy of Sciences, 117186 Moscow, Russia
2 Department of Electrification and Automation, Nizhny Novgorod State University of Engineering and Economics, Knyaginino, 606340 Nizhny Novgorod, Russia; boris.papkov@gmail.com
3 Department of Electroenergetics, Power Supply and Power Electronics, Nizhny Novgorod State Technical University n.a. R.E. Alekseev, 603950 Nizhny Novgorod, Russia; inventor61@mail.ru
4 Zhejiang Baima Lake Laboratory Co., Ltd., Hangzhou 310000, China; dr.souslov@yandex.ru
5 Department of Hydropower and Renewable Energy, National Research University "Moscow Power Engineering Institute", 111250 Moscow, Russia
* Correspondence: ilyushin.pv@mail.ru

Abstract: Power consumption management is crucial to maintaining the reliable operation of power grids, especially in the context of the decarbonization of the electric power industry. Managing power consumption of industrial enterprises by personnel proved ineffective, which required the development and implementation of automatic energy consumption management systems. Optimization of power consumption behavior requires comprehensive and reliable information on the parameters of the technological processes of an industrial enterprise. The paper explores the specific features of non-stationary conditions of output production and assesses the potential for power consumption management under these conditions. The analysis of power consumption modes was carried out based on the consideration of random factors determined by both internal and external circumstances, subject to the fulfillment of the production plan. This made it possible to increase the efficiency of power consumption in mechanical engineering production by taking into account the uncertainty of seasonal and technological fluctuations by 15–20%, subject to the fulfillment of the production plan. This study presents a justification for utilizing the theory of level-crossings of random processes to enhance the reliability of input information. The need to analyze the specific features of technological processes based on the probabilistic structure and random functions is proven. This is justified because it becomes possible to fulfill the production plan with technological fluctuations in productivity and, accordingly, power consumption, which exceeds the nominal values by more than 5%. In addition, the emission characteristics are clear, easy to measure, and allow the transition from analog to digital information presentation. The algorithm and methods developed to analyze the power consumption patterns of industrial enterprises can be used to develop automatic power consumption management systems.

Keywords: industrial enterprise; technological process; analysis of power consumption behavior; power consumption management; theory of level-crossings of random processes; random function

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1. Introduction

The decarbonization of the global electric power industry is progressing in phases, driven by the widespread development of power plants that utilize renewable energy sources (RES) [1–3]. The largest share of commissioned renewable energy generation capacity comes from the wind and solar sectors [4]. In countries with the necessary volume of hydro resources, hydropower development continues through the construction and commissioning of new hydroelectric power plants and pumped-storage power plants. The unit installed capacity of hydroelectric power plants is constantly increasing, making a significant contribution to the balance of electricity in the power systems [5,6].

In the context of the stochastic production of electricity by wind and solar power plants, it is necessary to maintain a balance between active power production and consumption within energy systems [7,8]. This can be achieved by increasing the maneuverability of generation equipment of conventional power plants, integrating energy storage systems, and managing the electricity consumption in industrial enterprises [9–11].

It is important to note that the reliability indicators of equipment used in wind and solar power plants have a significant impact on the reliability of the energy systems. In [12], it is noted that photovoltaic modules in solar power plants in moderate climates begin to fail en masse after about 10–12 years due to exposure to dust, high humidity, vibration, and other factors. Failures of photovoltaic modules often cause damage to multi-string inverters, which reduces the reliability indicators of solar power plants.

Power consumption management is highly effective because it facilitates a quick restoration of active power balance in the power grid by disconnecting less critical power loads at industrial enterprises [13,14]. However, it is essential to take account of the specifics of technological processes, as changes in the power consumption of consumers involved in a continuous production process can lead to product defects, accompanied by substantial losses [15,16].

The advancement of digital technologies changes the principles of interaction between electricity producers, such as power plants and generation companies, and industrial enterprises. This process is enabled by the adoption of modern measuring, communication, and information and computing systems, alongside data collection, transmission, and processing systems [17,18]. Modern power supply systems leverage cutting-edge technologies, such as cyber-physical devices, the Internet of Things, artificial intelligence, robotics, and augmented and virtual reality [19–21]. Intelligentization of the electric power industry requires vast amounts of data, which, when processed, create a qualitatively new information framework for the development and implementation of automatic power consumption management systems [22,23].

The digitalization of the electric power industry requires a revision of existing approaches and models for planning, forecasting, and managing electricity consumption, as well as ensuring the reliability and economic efficiency of industrial consumers. All these factors have a direct impact on the technological process and overall product output [24,25].

An analysis of human-induced impacts, including cyberattacks, on power industry facilities reveals that levels of electricity consumption and its structure can vary dramatically, exhibiting both increases and decreases [26,27]. Fluctuations in electricity consumption are also possible in cases where fulfilling the production plan is a priority. Administrative and market mechanisms currently used to manage electricity consumption prove ineffective in today's landscape, while new management algorithms have yet to be adequately developed and tested [28,29].

These conditions justify the need to develop modern methods of planning, forecasting, and optimization of power consumption behavior as well as algorithms for managing power consumption of industrial consumers. The ongoing evolution of network topology and operating parameters within power grids and power supply systems of industrial consumers necessitates the advancement of new mathematical models and algorithms, which are crucial for making informed decisions on managing electricity consumption, tailored to the specific features of technological processes.

The study [30] focuses on a model for forecasting energy consumption based on the assessment of electricity consumption parameters relying on the Bayesian estimation method and the Markov Monte Carlo method in order to reduce electricity costs. In [31], the authors explore methods to lower the auxiliary consumption of thermal power plants. The study considers various factors, including the types, capacity, and duration of operation of peak electric loads; the fuel used; and the capacity of the power plant; as well as the external conditions. In [32], a statistical analysis based on the probability theory is proposed for analyzing electricity consumption in order to determine the "energy efficiency index". This index is used to assess the loss of energy resources during production processes for reducing environmental fines. In [33], a system of energy efficiency indicators is designed to facilitate energy audits in coal mining enterprises. The study also involves systematizing the factors that influence the consumption of energy resources and their reduction and investigating the barriers that hinder the implementation of energy-saving measures. The use of artificial intelligence methods, in particular artificial neural network methods, including the long-short-term memory (LSTM) method, is proposed in [34] to improve the accuracy of forecasting electricity consumption at industrial enterprises. The research also highlights the importance of utilizing the Gaussian distribution principles along with normalization and scaling techniques for primary data processing. In [35], the authors suggest using cluster analysis methods to examine electricity consumption measurement data across various parameters while considering load fluctuations and typical load curves. Electricity consumption is forecast based on the LSTM neural network, factoring in the influence of meteorological data on the accuracy of load forecasting. A system of differentiated tariffs for industrial consumers is proposed in [36] to reduce electricity supply costs by shifting the load curve to off-peak hours across the day. This brings down the cost of production by reducing electricity expenses by at least 1.5 times and enables power grid companies to receive a uniform load on power lines and transformers throughout the day, preventing emergency overloads. A particle swarm optimization algorithm is used in [37] to forecast and analyze the changing trend of industrial electricity consumption, which increases the adaptability of the model. The authors propose utilizing the forecasting results to plan the expansion of energy systems and enhance the operation of the electricity market. In [38], various scenarios for reducing the network load during emergency situations are examined by leveraging advanced information and communication technologies. This approach relies on the methods for optimizing and modernizing the generation of emergency commands.

In [39], the problem of positive stabilization of linear continuous singular systems of both proportional and proportional derivatives of state feedback is considered. In [40], a control strategy is presented for an isolated hybrid DC microgrid that includes photovoltaic systems, piezoelectric elements, and storage batteries. An approach to model predictive control supplemented by reinforcement learning is proposed to optimize the performance of a hybrid DC microgrid that can be used in industrial power supply systems. In [41], a new combined method for long-term forecasting of consumer power supply systems development is proposed, which allows taking into account their features when planning the development of power systems. In [42], a new hybrid method is proposed that allows for improving the accuracy of short-term load forecasting, which is based on the use of an artificial neural network and an artificial bee colony algorithm. This method allows for taking into account historical data and weather conditions.

The considered methods of power consumption analysis are used to improve the economic indicators of industrial enterprises by enhancing the efficiency of power use, reducing environmental fines, planning the expansion of power systems, enhancing the operation of the electricity market, as well as shedding load at the dispatcher's command in the event of emergencies [43,44]. The studies discussed do not take into account the specific features of the technological process, but this is essential to predict the possibility of its completion in order to fulfill the production plan in accordance with the contract.

The aims of the study are (1) to analyze the features of technological processes at industrial enterprises, (2) to analyze the possibilities for fulfilling the plan for production output under conditions of changing speed of the technological process and power consumption, (3) to study the characteristics of the random function of power consumption and the law of distribution of emissions of the random process, and (4) to develop an algorithm and methods for analyzing the modes of power consumption of industrial enterprises taking into account the features of technological processes for their use in automatic power consumption control systems.

The paper is organized as follows. Section 2 examines the characteristics of non-stationary conditions of producing products and power consumption by industrial enterprises and discusses methods for analyzing and making decisions on power consumption management. Section 3 presents an algorithm designed to analyze the current state of the technological process and power consumption behavior. This section also justifies the need to factor in potential fluctuations in the system parameters when managing power consumption and outlines the conditions for specifying power consumption patterns and parameters. Section 4 focuses on the findings and potential areas of research in the field of power consumption management. The conclusion encapsulates the key results of the study.

2. Materials and Methods

The operating conditions of modern power systems, which integrate conventional power plants (thermal, nuclear, hydroelectric), renewable energy power plants, distributed generation facilities, and energy storage systems, differ significantly from the planned ones [45,46]. This situation stems from the changes in the topology and operating conditions that result from emergency shutdowns of equipment at power plants and in electrical networks, limitations in the transfer capability of electrical network equipment, as well as changes in electricity consumption for various reasons [47,48]. In this context, accurately forecasting electricity generation to meet the demand of industrial enterprises for power both in volume and quality becomes increasingly challenging [49,50].

The size of the electricity consumption of an industrial enterprise depends on the characteristics of the technological processes and the output plan [51]. Technological processes are also affected by random factors, leading to a probabilistic nature of electricity consumption at various stages [52]. The technologies for managing power consumption that are widely used in industrial enterprises prove ineffective because their implementation relies on personnel, even when integrated with automated process control systems. Control actions are aimed at disconnecting some of the less critical process equipment [53,54]. It is quite difficult to assess the technical and economic consequences of changing the power consumption behavior with high accuracy under these conditions.

Monitoring the compliance with process regulations and fulfillment of the production plan in all stages of the process is essential to manage power consumption. Since power consumption management has a significant impact on the process parameters and production volumes, it is necessary that the algorithms for power consumption management be designed based on an in-depth analysis of the control object. Reliable information on the state and permissible operating conditions of power supply systems is required to manage power consumption [55–57]. This will eliminate significant losses.

In [58], the authors present diagrams of power consumption management systems, which take account of the interaction between power grids and power supply systems of industrial enterprises, including scenarios of emergency power shortages in power grids. This facilitates the analysis of the transition of a technological process to a new state characterized by a new power consumption behavior. The listed problems can be solved through the use of the mathematical apparatus of probability theory, mathematical statistics, and the theory of level-crossings of random processes.

The permissible operating conditions, productivity, and the degree of influence of external and internal factors vary depending on the specific technological process. Therefore, it is crucial to analyze the current state of the technological process to prevent failures in both the technological process and the power supply system operation [59,60].

The solution to the formulated problem is determined by the following:

- The types, quantity, and parameters of controlled components.
- The sequence, duration, and frequency of analysis of the state of the technological process and its power supply system.
- The accuracy of assessment of current parameters of the production process and its power supply system.
- The accuracy of forecasting the state of the technological process and its power supply system [61,62].

The state of the technological process and its power supply system should be forecast based on trends in the change of conditions and parameters of the technological process. This will facilitate informed decisions on managing the parameters of the technological process and power consumption behavior. In this case, it is important to assess the probability of the process parameters going beyond the permissible limits because this assessment affects the capacity to meet the production targets, the change in the power consumption behavior, and the probability of level-crossings of random processes.

The ability to fulfill the production plan is associated with several random factors determined by both internal and external circumstances. One of them is the amount of power consumed (P, kW) at the current time. The second is the power consumed (W, kWh) over the period t_{pl} required for the timely fulfillment of the production plan, provided the power supply conditions are met.

In [63], the study reveals that the relationship between the output volume B and the electricity consumption W at the surveyed industrial enterprises is not functional $B = f(W)$ but probabilistic and is determined based on correlation coefficients changing in the range $r_{B,W} = 0.43 - 0.89$. This is mainly characteristic of enterprises that produce small-scale products while simultaneously manufacturing a large range of products in various stages of the technological process. Large industrial enterprises, where production processes vary in duration and complexity, are also influenced by the indicated factors.

Here are examples of how to calculate the correlation coefficient for two industrial enterprises with different technological processes and different power consumption.

Example 1. *During 4 days (n = 4), one of the enterprises of the chemical industry has the volume of output production B (kg) with daily power consumption W (MWh), which are given in Table 1.*

Table 1. Data of the volume of output production and power consumption of the chemical industry enterprise.

***B*, kg**	1000	1100	1220	1350
***W*, MWh**	5.6	6.6	7.0	7.8

Estimates of the mathematical expectation, dispersion, standard deviations, and correlation coefficient are calculated using known equations:

$$M^*(B) = \frac{\sum_{i=1}^{4} B_i}{n} = 1167.5 \text{ kg};\; M^*(W) = \frac{\sum_{i=1}^{4} W_i}{n} = 6.75 \text{ MWh};$$

$$D^*(B) = \frac{\sum_{i=1}^{4} [B_i - M^*(B)]^2}{n-1} = 22922 \text{ kg}^2;$$

$$\sigma_B^* = \sqrt{D^*(B)} = 151.4 \text{ kg};$$

$$D^*(W) = \frac{\sum_{i=1}^{4} [W_i - M^*(W)]^2}{n-1} = 0.837 \text{ MWh}^2;$$

$$\sigma_W^* = \sqrt{D^*(W)} = 0.915 \text{ MWh};$$

$$r_{B,W}^* = \frac{\sum_{i=1}^{4} [B_i - M^*(B)] \cdot [W_i - M^*(W)]}{(n-1)\sigma_B^* \sigma_W^*} = 0.98.$$

The obtained value of the correlation coefficient (0.98) indicates a fairly close (close to functional) dependence between the volume of output of an industrial enterprise and its electricity consumption. The value $n - 1$ in the denominator of the equations for calculating the dispersion and correlation coefficient eliminates the bias of their estimates at a small number of observations.

Example 2. *At one of the enterprises of the metalworking industry, the study of the dependence of the volume of output production B (ton) on the value of electricity consumption W (MWh) was carried out. The results of measurements for 15 days (n = 15) are shown in Table 2.*

Table 2. Data of the volume of output production and electricity consumption of the metalworking industry enterprise.

№	***B*, ton**	***W*, MWh**	**№**	***B*, ton**	***W*, MWh**	**№**	***B*, ton**	***W*, MWh**
1	70.3	7.9	6	98.4	0.8	11	81.9	11.2
2	85.0	0.9	7	59.2	6.0	12	97.1	0.5
3	100.0	3.7	8	86.8	7.2	13	68.2	4.6
4	78.1	8.1	9	70.1	8.8	14	92.1	9.7
5	77.9	6.9	10	42.2	10.2	15	91.2	1.0

To reveal the dependence between B and W, their ordering is required. For the purpose of visualization, the paired values for 15 days $(w_1; \text{B}_1)$, $(w_2; \text{B}_2)$, …, $(w_{15}; \text{B}_{15})$ are graphically represented in the Cartesian coordinate system in Figure 1.

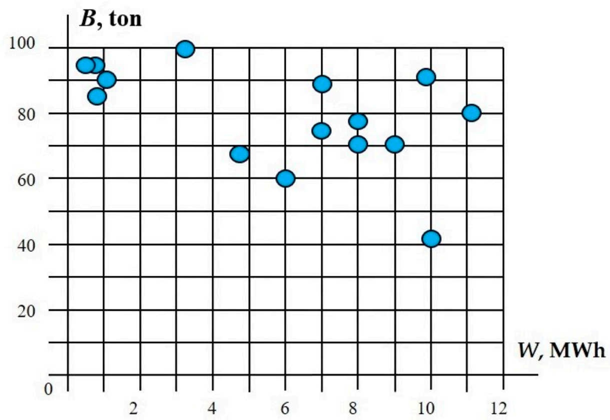

Figure 1. Graphical representation of paired values (w_i; B_i) from Table 2.

The analysis of Figure 1 shows that there is no clear functional dependence between the values of w_i and B_i. However, it is obvious that smaller values of w_i in most cases correspond to larger values of w_i. This allows us to conclude that power consumption increases when the technological process functions with reduced productivity.

Estimates of the mathematical expectation, dispersion, standard deviations, and correlation coefficient are calculated using the known equations:

$$M^*(B) = \frac{\sum_{i=1}^{15} B_i}{n} = 5.8 \text{ ton}; \; M^*(W) = \frac{\sum_{i=1}^{15} W_i}{n} = 299.6 \text{ MWh};$$

$$D^*(B) = \frac{\sum_{i=1}^{15} [B_i - M^*(B)]^2}{n-1} = 13.7 \text{ ton}^2;$$

$$\sigma_B^* = \sqrt{D^*(B)} \approx 3.7 \text{ ton};$$

$$D^*(W) = \frac{\sum_{i=1}^{15} [W_i - M^*(W)]^2}{n-1} = 255.6 \text{ MWh}^2;$$

$$\sigma_W^* = \sqrt{D^*(W)} \approx 16 \text{ MWh};$$

$$r_{B,W}^* = \frac{\sum_{i=1}^{15} [B_i - M^*(B)] \cdot [W_i - M^*(W)]}{(n-1)\sigma_B^* \sigma_W^*} = -0.54.$$

The given examples substantiate the necessity of taking into account the peculiarities of technological processes at industrial enterprises of different industries when analyzing the modes of power consumption.

Let us consider the process of producing output based on probabilistic analysis methods. It is obvious that deviations of process parameters and power consumption values may differ between two contracts producing the same volume of identical products. For two contracts that have the same deviations from planned values ΔB and ΔW at time t, the differences may be significant if in one case the technological process is in the initial stage, and in the other case, the process is in the final stage. Figure 2 presents an example schedule to fulfill the production plan for output B with a power consumption level W for a single technological process.

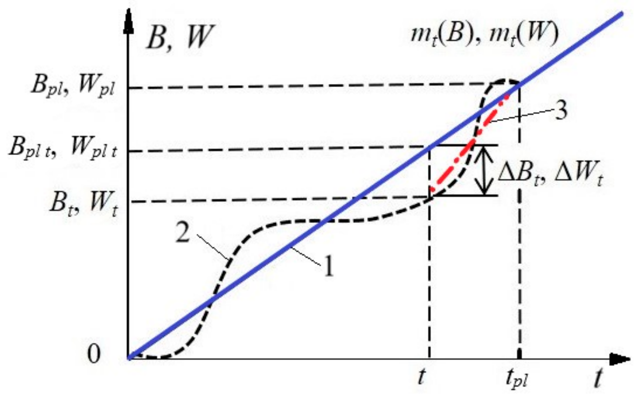

Figure 2. Schedule of the production plan for the output B with power consumption W for a single technological process: 1—planned schedule; 2—potential option for production output; 3—alternative option for production output in one of the stages.

In general, Figure 2 shows a non-stationary random process [64], assuming that the planned values $B_{pl}(t)$, $W_{pl}(t)$ at time t are represented by mathematical expectations for the volume of production output and the amount of electricity consumption, which can be calculated using Equation (1):

$$m_B(t) = B_{pl\ t} \neq \text{const};\ m_W(t) = W_{pl\ t} \neq \text{const}. \quad (1)$$

The expected state of the technological process is characterized by the probability of completing the scope of work $p(B_t)$ and, accordingly, the probability of power consumption $p(W_t)$ at time t. The automatic power consumption management system records the actual values B_t and W_t at time t. The probability of producing the planned output level in accordance with the contract is determined by the probability of producing any shortfall during time $t_{pl} - t$ [64].

The production of output in accordance with the plan may be disrupted or adjusted for various reasons—administrative, technological, and electrical. This may be related to the untimely supply of raw materials and components, failures of process or electrical equipment in the power supply system, and an active power shortage in the power grid. If the delay in the output plan ΔB_t and the undersupply of the required amount of electricity ΔW_t at time t (Figure 2) are large enough, they cannot be compensated for by the available reserves over the period of time $t \div t_{pl}$.

To simplify the analytical model, we assume that at time t, the listed causes are mutually independent events. Then, the probability of fulfilling the production output plan $p_t\left(B_{pl}\right)$ can be determined as the product of the probabilities according to Equation (2) [65]:

$$p_t\left(B_{pl}\right) = p(\Delta B_t) = p_t(A) \cdot p_0\left(t, t_{pl}\right) \cdot p_A\left(t, t_{pl}\right), \quad (2)$$

where $p(\Delta B_t)$ is the probability of compensation for deviation ΔB_t over the period of time $t_{pl} \div t$, provided that all technological regulations are adhered to; $p_t(A)$ is the probability of absence of technological equipment failures by time t that would lead to non-fulfillment of the plan; $p_0\left(t, t_{pl}\right)$ is the probability of fulfilling the plan for the supply of raw materials and components; and $p_A\left(t, t_{pl}\right)$ is the probability of failure-free operation of process equipment over the period of time $t \div t_{pl}$.

Similarly, we assess the probability of having an adequate amount of electricity to fulfill the production plan $p_t\left(B_{pl}\right)$, which depends on the power supply system of the industrial enterprise, namely, on the possibility of compensation for ΔW_t over the period of time $t \div t_{pl}$ and the availability of power reserves in the power grid. Then, the probability of fulfilling the production plan $p_t\left(B_{pl}\right)$ can be calculated using Equation (3):

$$p_t\left(B_{pl}\right) = p(\Delta W_t) = p_t(E) \cdot p_r\left(t, t_{pl}\right) \cdot p_{PG}\left(t, t_{pl}\right), \tag{3}$$

where $p(\Delta W_t)$ is the probability of compensation for deviation ΔW_t over the period of time $t_{pl} \div t$ given the possibility of compensation for ΔW_t on the part of the power supply system of the industrial enterprise and the power grid; $p_t(E)$ is the probability of the absence of failures of electrical equipment in the power supply system by time t that would lead to non-fulfillment of the plan; $p_r\left(t, t_{pl}\right)$ is the probability of the presence of a power reserve in the power grid; and $p_{PG}\left(t, t_{pl}\right)$ is the probability of failure-free operation of electrical equipment in the power grid over the period of time $t \div t_{pl}$.

Analysis of Figure 2 shows that the production of the output, as per the technological regulations, is carried out at the planned (calculated) speed V_{pl}, which can be calculated using Equation (4):

$$V_{pl} = B_{pl}/t_{pl}. \tag{4}$$

If the technological process operates without deviations from the planned (calculated) speed V_{pl}, the mathematical expectation of fulfilling the production plan by time t can be calculated using Equation (5):

$$m_B(t) = V_{pl}t. \tag{5}$$

If the technological process operates underloaded (or overloaded) with a corresponding lack or surplus of electricity, the speed of output production can be calculated using Equation (6):

$$m_B(t) = \overline{V_t}t, \tag{6}$$

where $\overline{V}_t$ is the average speed of output production over the time interval $0 \div t$.

In general, the speed of output production is a function $V(t)$, which can be calculated using Equation (7):

$$m_B(t) = B_{pl}(t) = \int_0^t V(t)dt, \tag{7}$$

which in real conditions corresponds to the production plan for the planned value of electricity consumption at time t.

Given that the technological process may experience random deviations in output $\Delta B_t = B_{plt} - B_t$ and power consumption $\Delta W_t = W_{plt} - W_t$ (Figure 2), it is necessary to switch to a new speed of output production (dash-dotted line 3 in Figure 2), which can be calculated using Equation (8):

$$V_t = V_{pl} + \Delta V = V_{pl} + \Delta B_t/\left(t_{pl} \div t\right). \tag{8}$$

Then, the probability of compensation for the deviation $p(\Delta B_t)$ over the period of time $t \div t_{pl}$ is determined by the probability of transition of the production process to speed V_t, which is a random variable. If the distribution law $p(V)$ and its parameters are known, the probability of compensating for the deviation in the output $p(\Delta B_t)$ and electricity consumption from the power grid $p(\Delta W_t)$ can be determined as the probability that the actual speed of fulfilling the output plan B_{pl} with electricity consumption W_{pl} in the remaining time $t \div t_{pl}$ will take the value $V \geq V_t$. This value can be calculated by Equation (9):

$$p(\Delta B \geq \Delta B_t) = p(\Delta W \geq \Delta W_t) = p(V \geq V_t) = \int_{V_t}^{V_{\max}} p(V)\mathrm{d}V, \tag{9}$$

where $V_{\max}$ is the maximum speed of output production.

Analysis of the factors $p_t(E)$ and $p_{PG}\left(t, t_{pl}\right)$ in Formula (3) reveals a significant difference in technical and economic ramifications of electrical equipment failures in the power supply system of industrial enterprise or power grid in the initial stage of the technological process and at its end. With equal repair (replacement) times t_{rep} for electrical equipment, the probability of fulfilling the plan in the first case is significantly higher. Therefore, it is crucial to take into account that the probabilities $p_t(E)$ and $p_{PG}\left(t, t_{pl}\right)$ depend on the timing of equipment failure.

The minimum time in which the production plan can be fulfilled when operating at maximum speed $V_{\max}$ can be determined using Equation (10):

$$t_{\min} = B_{pl}/V_{\max}. \tag{10}$$

If a unit of electrical equipment in the power supply system fails at the beginning of the technological process for a time t_0 (delay for the time of repair of the equipment unit), then the plan can be fulfilled by operating at maximum speed $V_{\max}$. In this case, t_0 can be calculated using Equation (11):

$$t_0 = t_{pl} - t_{\min} = t_{pl} - B_{pl}/V_{\max}. \tag{11}$$

Let us assume that at time t, with known B_t and W_t, there is a delay in the production output for a period of time $t_1 - t$ (Figure 3), provided that the speed of production output is then increased to $V_{\max}$. In this case, the power consumption $P_{\max}$ will increase but the final value of power consumption W_{pl} will remain unchanged, as shown in Figure 3.

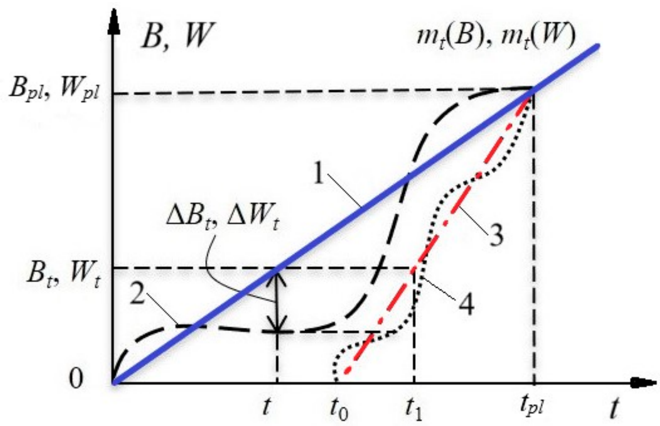

Figure 3. Schedule of the output plan $\underline{B}$ and electricity consumption W with a delay caused by the repair of an electrical equipment unit: 1—planned; 2—possible option for the output production; 3—option for the output production at speed $V_{\max}$; 4—alternative option for the output production at speed $V_{\max}$.

As seen in Figure 3, if a failure of a unit of electrical equipment in the power supply system occurs at time t, then when it is restored in time $t_r = t_1 - t$, it becomes possible to fulfill the output plan. However, the closer the time t is to the end of the established deadline for implementing the plan t_{pl}, the shorter the time interval remains for restoring the failed unit of electrical equipment (Figure 3).

Therefore, $t_{r\ all}$ is the allowable time for repairing the failed unit of electrical equipment, which can be calculated using Equation (12):

$$t_{r\ all} = t_{pl} - t_1 - t. \tag{12}$$

Analysis of fluctuations in productivity and power consumption of various technological processes showed that their deviations by no more than 5% from the nominal value do not lead to deviations from the production plan. In continuous technological processes of the chemical, metallurgical, and oil refining industries, the productivity of individual mechanisms can be reduced only to 50% of the nominal. Otherwise, this will lead to a complete stop of the technological process. In addition, an increase in the speed of production, in accordance with Equation (8), at these industrial enterprises is practically impossible. At industrial enterprises of the mechanical engineering and light industry, an increase in the speed of production is possible due to the use of technological equipment located in a cold reserve, as well as a time reserve (organization of second and third work shifts at an industrial enterprise).

The consequences of eliminating deviations in output production from the plan should be assessed based on the technical and economic damage $Y = f(\pm\Delta B_t,\ \pm\Delta W_t)$, taking into account all the factors considered [66,67].

Thus, we propose using models based on a probabilistic structure and random functions to examine electricity consumption while taking into account the specific features of the technological process. The use of the theory of level-crossings of random processes in the analysis of electricity consumption enhances the reliability of the initial information, which is essential for the operation of the automatic electricity consumption management system.

3. Results

An algorithm was designed to analyze the current state of the technological process and the power consumption behavior. It takes into account the specific features of the process and assesses all intermediate and resulting indicators, including technical and economic damage. The algorithm block diagram is shown in Figure 4.

To illustrate the work of the algorithm (Figure 4), an assembly shop of one of the enterprises of the machine-building industry that fulfills an order during the time t_{pl}, taken as 100%, was selected.

1. By the time of control t, 65% of the planned production volume with power consumption $\left(B_{pl\ t},\ W_{pl\ t}\right)$ should have been produced.
2. The actual process state (as measured by sensors and electricity meters) by control time t corresponds to an output of 50% (B_t, W_t).
3. The remaining amount of work to fulfill the output plan with the corresponding electricity consumption is determined to be 50%.
4. Actual deviations from the plan on output and power consumption $\Delta B_t, \Delta W_t$ amounted to 15%.
5. It is required to increase the speed of the technological process, compared to the planned (calculated), to complete the task of production in the established time for a time equal to 35% of the total time of work $\left(t_{pl} - t\right)$.
6. If there are no restrictions on the amount of power consumption, then by increasing the speed of the technological process by 43% at the time interval $\left(t_{pl} - t\right)$, provided that all the technological regulations are observed, the plan for production output can be fulfilled by the time $t_{pl} - t$.
7. If at the time interval $\left(t_{pl} - t\right)$, there are failures of technological or electrical equipment in the power supply system, disruptions in the receipt of raw materials and components, as well as there is a deficit of active capacity in the power system, it is necessary to assess the probability of transition to a mode with increased speed of the technological process. According to retrospective statistical data for the enterprise

under consideration and on the basis of the probability multiplication theorem for independent events $p(\Delta B_t) = p(\Delta W_t) \leq 0.04$.

8. If technological regulations allow the maximum speed of the technological process (due to the introduction of reserve equipment) to exceed the nominal one by 80%, then the minimum time $t_{\min}$ required to fulfill the plan for production output by the time t_{pl} will be 56% of t_{pl}.
9. Based on this, it is possible to calculate the maximum time of possible delay in the start of production $(0 \div t_0)$, which for the considered enterprise will amount to 44% of t_{pl} at the nominal speed of the technological process.

The issues of techno-economic evaluation of damage from deviations in the technological process and power consumption were not considered in this study.

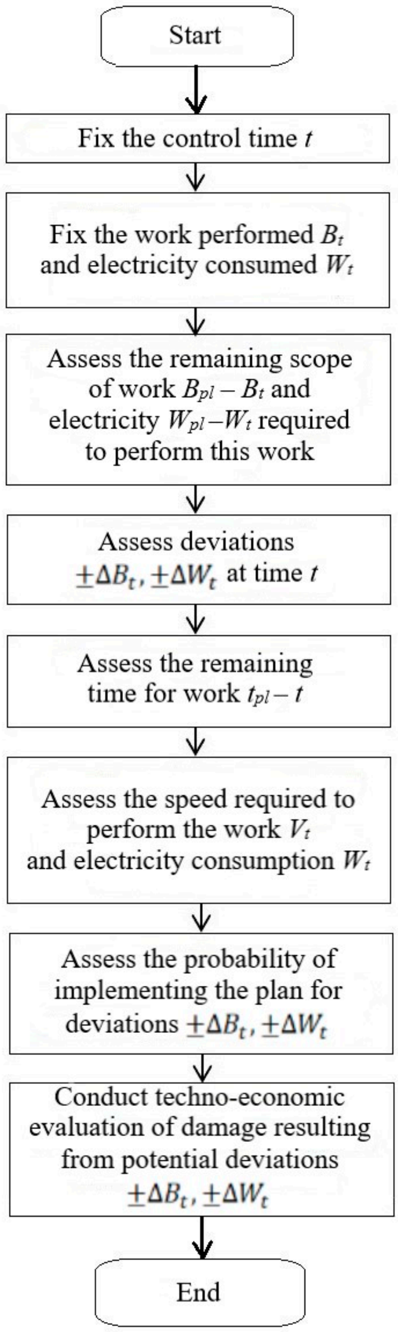

Figure 4. Block diagram of the algorithm for analyzing the current state of technological process and power consumption behavior.

The initial data used in developing the algorithm (Figure 4) included information received from process state sensors, an automated system for monitoring power quality indicators and electricity meters, as well as technical and economic information, and the results of expert assessments.

Implementation of the algorithm presented in Figure 4 in the automatic power consumption management system facilitates monitoring of current deviations $\pm\Delta B_t$, $\pm\Delta W_t$, along with the corresponding techno-economic assessment of damage, in any stage of the production process. Deviations can be local (process line, workshop) or system-wide (industrial enterprise). The information gathered allows for making informed decisions regarding power consumption management, changes in the speed of output production, introduction of additional reserves, and switching the equipment to another operating mode.

The algorithm for analyzing the current state of the technological process and the dynamics of power consumption (Figure 4) takes into account the emergence of new initial data. This allows for the accumulation of retrospective information for managing the technological process and power consumption modes, as well as forecasting.

Let us analyze the fluctuations of a system parameter, which can be effectively used in automatic power consumption management systems [68,69]. Increasing the frequency of analyzing power flow parameters (voltage, current, power, frequency) within the power supply system enables effective real-time management of power consumption [70]. This is important because deviations in the power flow parameters can increase the probability of the power consumption value going beyond the permissible limits of the planned one (the mathematical expectation of a random process). If the value of power consumption W_1 changes by ΔW_1, which is recorded during a control measurement at moment t_1, then it is essential to assess the probability of power consumption going beyond the permissible limits in subsequent time intervals. Consequently, it is necessary to forecast level-crossings of random processes. The need to use the characteristics of level-crossings of random processes originates from the limiting conditions of technological processes because manufacturers do not envisage redundancy in their process lines.

The requirements for safety, reliability, and efficiency of the technological process must be met regardless of power consumption levels (maximum and minimum) and under all permissible operational conditions [71,72]. This is important because the technological process needs to operate under critical and extreme conditions, which can be achieved through an in-depth analysis of the probabilistic structure of random processes. The graph of possible fluctuations in the system parameter is shown in Figure 5.

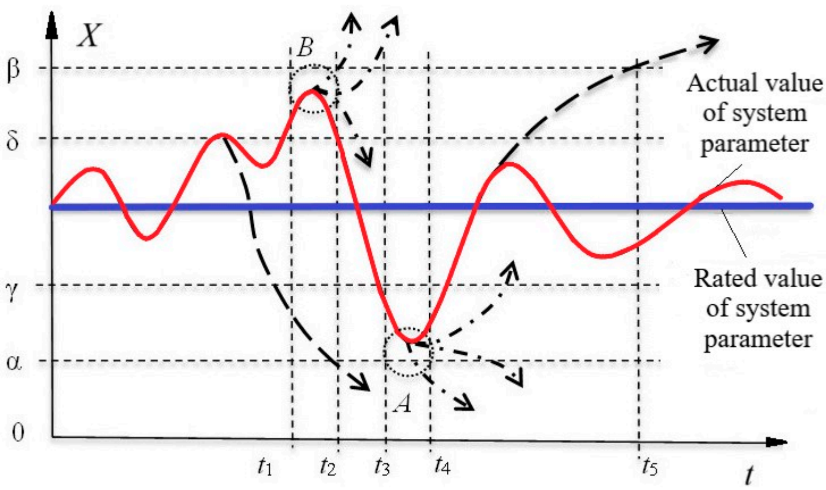

Figure 5. Graph of possible fluctuations in the system parameter *X*.

Since the question of the probabilities of rare random events in scientific and technical literature, due to the lack and uncertainty of factual information, was discussed mainly only in theoretical terms, this study uses the methodological approaches outlined in [73,74].

The range of permissible variations in the system parameter X, corresponding to the values of power consumption (voltage, current, power, frequency) lies within the interval $\{\alpha, \beta\}$. As long as its value does not go beyond $\alpha < X < \beta$, the technological process retains its integrative property, including integrity (the unity of the interrelations and interactions of components) and emergence (irreducibility of the system's properties to the properties of individual components). When X goes beyond the interval $\{\alpha, \beta\}$, it is impossible to maintain the dynamic equilibrium of the technological process through coordinated control. When integrativeness is lost at $t > t_5$ (Figure 5), the technological process is disrupted due to the activation of protection devices that prevent damage to the process line [75–78].

The partial components of the system parameter X can take values $\{\gamma > \alpha,\ \delta < \beta\}$, which defines the area of partial homeostasis $\{\gamma < X < \delta\}$. At $\{\gamma < X < \alpha\}$ or $\{\delta < X < \beta\}$, the technological process normally shifts to a new qualitative state, while maintaining its functionality. This occurs in the time ranges $\{t_1,\ t_2\}$ and $\{t_3,\ t_4\}$. The approach of the system parameter to the maximum permissible values (areas A and B in Figure 5) can lead to a disruption of the technological process. It is worth noting that when the technological process enters the bifurcation zone, predicting its further state becomes impossible.

Let us consider additionally the conditions specifying the behavior and parameters of power consumption. The actual value of power consumption W (system parameter) is one of the realizations of the random function $\xi(t)$. In most problems of power consumption management, it can be assumed that with a fixed value t_{pl} and fluctuations of instantaneous values of power consumption $w(t)$, the consumed power $p(t)$ also fluctuates proportionally, i.e., $w(t) \propto p(t)$. Since any random function is defined by a collection of sample realizations on a certain time interval $t \in [t_0,\ t_0 + T]$, and under the assumption of stationarity and ergodicity of the random function, it is sufficient to consider a single sample function $\xi(t)$ of a continuous random process.

The graph of the sample realization of the random function $\xi(t)$ along with the characteristics of the level-crossings of its trajectory $W(t)$ as it crosses the critical level $W_{cr\ \max} \propto P_{cr\ \max}$ is shown in Figure 6.

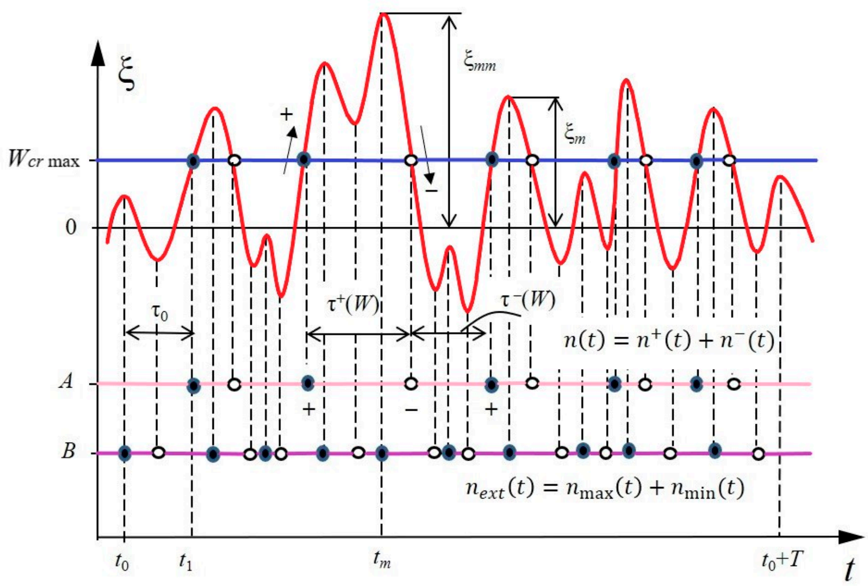

Figure 6. Graph of a sample realization of the random function $\xi(t)$ and characteristics of its trajectory level-crossings $W(t)$.

Let us explain the parameters shown in Figure 6: τ_0 is the time when the given boundary is first reached; ξ_{mm} is the amplitude of the absolute maximum; ξ_m is the amplitude of the local maximum; $n(t)$ is the number of times the random function crosses the level $W_{cr\ \max}$; $n_{ext}(t)$ is the number of maxima and minima of the random function $\xi(t)$; $\tau^+(W)$, $\tau^-(W)$ are durations of level-crossings of the random function $\xi(t)$ at the level $W_{cr\ \max}$ [78].

A set of "special" points is identified to describe the behavior and introduce numerical characteristics of random function. At a critical level of power consumption $W_{cr\ \max}$, the realization of the random function $\xi(t) = w(t)$ is characterized by its positive $n^+(W_{cr\ \max}, T)$, negative $n^-(W_{cr\ \max}, T)$, and overall $n(W_{cr},\ T) = n^+(W_{cr\ \max}, T) + n^-(W_{cr\ \max}, T)$ crossings on the interval $t \in [t_0,\ t_0 + T]$ (Figure 6).

The quantities $\tau^+(W) = \tau_{+-}(W)$ and $\tau^-(W) = \tau_{-+}(W)$ are the durations of positive and negative level-crossings between positive (+) and negative $(-)$ crossings of the critical level W_{crmax}. At the moment t_1, the trajectory $\xi(t)$ first goes beyond the limit $W_{cr\ \max}$, and the time it takes to reach it is τ_0. The function $\xi(t)$ on the interval $T < \infty$ has a finite number of maxima $n_{\max}(T)$ and minima $n_{\min}(T)$ with different amplitudes ξ_m. At the moment t_m, the trajectory $\xi(t)$ reaches the absolute maximum ξ_{mm}. This approach makes it possible to describe the trajectory $\xi(t)$ by a certain number of its extreme amplitudes with an indication of the duration of the intervals between individual extremes. This is important to design algorithms for managing power consumption when developing automatic power consumption management systems.

The characteristics of the random function $\xi(t)$ can be analyzed based on a sequence of singular points of the trajectory $\xi(t)$, representing a random sequence of level-crossings (maxima), as shown in Figure 6. The set of points t_i^+ and t_i^-, randomly distributed on the axes A and B of time t, form a flow of random events. Then, the probability of the absence of an event t_i is equivalent to the probability that the random variable ξ_i will not exceed the threshold value W_{crmax}, which can be calculated using Equation (13):

$$p^- = P(\xi_i < W_{cr\ \max}) = F_\xi(W_{cr\ \max}) = 1 - p^+. \tag{13}$$

Thus, the values of the sample function $\xi_1,\ \xi_2,\ \ldots, \xi_n$ of the random sequence $\{\xi_n,\ n = \overline{1,\ n}\}$ reflect the probabilities of occurrence p^+ and non-occurrence $p^- = 1 - p^+$ of a specific event at moments $t_1, t_2, \ldots, t_n$ when the critical level of power consumption $W_{cr\ \max}$ is exceeded. This approach is consistent with the classical Bernoulli scheme [79,80], where a random variable $n^+(W_{cr\ \max})$ is characterized by a binomial distribution:

$$p_k(n^+) = P\{n^+(W_{cr\ \max},\ n) = k\} = C_n^k (p^+)^k (p^-)^{n-k},\ k = 0,\ 1,\ 2,\ \ldots,\ n, \tag{14}$$

where $C_n^k = n!/k!(n-k)!$ is the number of combinations of n elements by k.

Distribution (14) is used to estimate the probability $P\{n^+(W_{cr\ \max},\ n) = k\}$ that exactly k exceedances of the electricity consumption threshold level $W_{cr\ \max}$ will occur in a sequence of n independent measurements for time moments $t_1, t_2, \ldots, t_n$ and, accordingly, values of the random function $\xi_1,\ \xi_2,\ \ldots, \xi_n$. The mathematical expectation and variance of the number of possible exceedances of the electricity consumption level $W_{cr\ \max}$ are calculated using Equation (15) [79], known from probability theory:

$$N^+(W_{cr\ \max},\ n) = M\{n^+(W_{cr\ \max},\ n)\} = np^+;\ D[n^+(W_{cr\ \max},\ n)] = np^+(1 - p^+). \tag{15}$$

Practical experience in analyzing the power consumption in technological processes shows that there can be several increasing stages of critical power consumption levels $W_{cr\ \max}$. Each of these levels may be crossed by the sample function $\xi_1,\ \xi_2,\ \ldots, \xi_n$ at random moments in time t_i. The sequence of crossings is considered a separate realization $t_1, t_2, \ldots, t_n$ of a random point process $\{t_i(W_j)\}$ of exceeding the power consumption level W_j. The graph of power consumption for a technological process with two critical power consumption levels $W_2 > W_1$ corresponds to the boundaries $\{\gamma < X < \alpha\}$ and $\{\delta < X < \beta\}$ (Figure 5) and is shown in Figure 7.

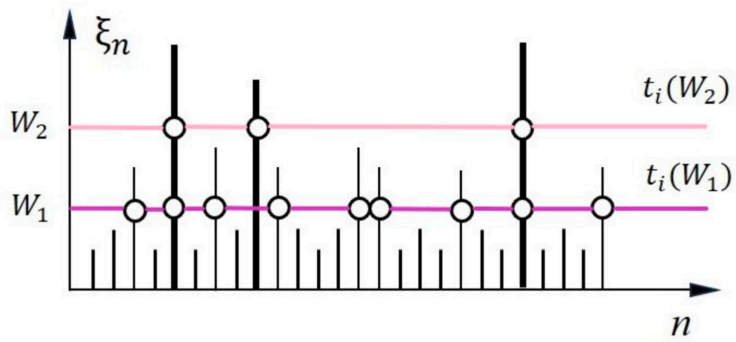

Figure 7. Graph of the random process of exceeding two critical levels of power consumption.

Given that the quantities ξ_i are independent, the conditions of the Bernoulli scheme are satisfied. In this case, the number of exceedances $n^+(W_j, n)$ of the power consumption level W_j follows a binomial distribution, similar to Equation (14). The mathematical expectation and variance of the number of possible exceedances of the power consumption level W_j can be calculated using Equation (15).

An analysis of Figure 7 suggests the conclusion that the random point process $t_i(W_2)$ at level W_2 is the result of "thinning out" the flow $t_i(W_1)$ from level W_1. Consequently, the probabilities of the mathematical expectation and the variance of the number of possible exceedances of level $p^+(W_j)$ will decrease. Their difference is information about the probability that the values of the random sequence ξ_n under study lie in the range of levels $\xi \in (W_1, W_2)$, which can be calculated using Equation (16):

$$P\{\xi \in (W_1, W_2)\} = p^+(W_2) - p^+(W_1) \tag{16}$$

which is shown in Figure 5 by boundaries $\{\gamma < X < \alpha\}$ and $\{\delta < X < \beta\}$.

Thus, process control comes down to changing the output plan deadlines, redistributing raw materials and components, and altering the amount of power and electricity consumption.

The intricate nature of the control object (technological process), coupled with the potential to change the structure and connections, as well as the ability to vary the range of products manufactured at an industrial enterprise, alongside random external and internal factors, significantly complicate the decision-making process for managing electricity consumption.

4. Discussion

Adhering strictly to contractual obligations concerning output production enables industrial enterprises to minimize reputational risks and remain a reliable supplier for their partners.

Each industrial enterprise has unique technological processes that necessitate their thorough analysis to manage power consumption effectively. An enterprise can simultaneously manufacture a large range of products, which requires multiple technological processes that vary in duration and power consumption. By considering the specific features of these processes when managing power consumption, enterprises can reduce product defects and, accordingly, minimize damage to the industrial operation, which is critically important.

Finding a balance between the reliability and efficiency of technological processes at industrial enterprises by selecting optimal technological conditions requires selecting appropriate algorithms for managing power consumption, in particular through the implementation of automatic power consumption management systems.

Widespread adoption of the "demand response" technology allows industrial enterprises to reduce electricity consumption by the volume and time specified by the power system dispatcher. Many industrial enterprises across various countries are actively involved in this process. This offers them financial advantages either through a discount on electricity or through compensation for services that help reduce electricity consumption on the power grid. The integration of automatic power consumption management systems streamlines this process and reduces the likelihood of human errors when taking steps to lower electricity consumption. In this case, it is only necessary to enter the amount of electricity consumption reduction (MW or %), and the automatic power consumption management system will select the optimal control actions. The implementation of such control actions will foster the reduction in electricity consumption by an industrial enterprise in the required volume while fulfilling the output plan with minimal delays.

Technological processes operate under extreme power and process flow conditions, often affected by random external and internal factors. Requirements for safety, reliability, and efficiency of the technological process must be observed under all power consumption levels, including maximum and minimum, and under all process conditions.

In the event of frequent power supply interruptions of the technological process caused by electrical equipment failures in the power grid or unforeseen active power shortages, it is crucial for the owner of the industrial enterprise to consider investing in the construction of their own distributed generation facility [81,82]. This will ensure a reliable power supply to the technological process in the minimum volumes necessary to fulfill the output plan [83].

The technical solution for implementing an automatic power consumption management system, along with the developed algorithms, can be effectively replicated in industrial enterprises with similar production processes. However, each industrial enterprise will need to customize the algorithms for analyzing and managing power consumption behavior. Industrial enterprises in other sectors will also need to revise the algorithms for analyzing and managing their power consumption patterns. The authors' methods and algorithms for analyzing power consumption behavior will be highly effective in industrial enterprises within the mechanical engineering sector, for which they were specifically designed.

Potential Areas of Development

The types and sizes of control actions for managing electricity consumption need to be elaborated to meet the specific features of various technological processes and electrical circuits within the power supply systems of industrial enterprises.

It is essential to further refine the methods for analyzing the probabilistic structure of a random function for automatic power consumption management systems to enhance the reliability of forecasting the number and magnitude of deviations, as well as their consequences.

The methods and algorithms developed for analyzing the power consumption behavior of industrial enterprises, given the unique features of their technological processes, are planned to be implemented in the automatic management system at one of the industrial enterprises. Following the pilot phase and industrial operation of the automatic power consumption management system, we will publish the results achieved and pinpoint areas for further research.

5. Conclusions

Managing the power consumption behavior of industrial enterprises requires comprehensive and reliable information about the features of their technological processes. In addition, it is necessary to consider random factors determined by both internal and external circumstances, which must be taken into account. This will reduce power usage throughout the technological process while still meeting the planned output targets.

Analysis of trajectories and level-crossings of random processes when analyzing the power consumption behavior of industrial enterprises fosters the estimation of the main numerical characteristics of the binomial distribution at different critical levels of power consumption. This allows us to evaluate and estimate the relative durations of random function realizations within critical ranges, assess the probability of the trajectories $w(t)$ exceeding permissible limits, and analyze various.

The algorithm and methods designed to analyze power consumption behavior can be used in the development of automatic power consumption management systems for industrial enterprises.

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