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A New Approach to Risk Management in the Power Industry Based on Systems Theory

Dariusz Gołębiewski [1], Tomasz Barszcz [2], Wioletta Skrodzka [3], Igor Wojnicki [4] and Andrzej Bielecki [5,*]

1 PZU S.A., Jana Pawla II 24 Ave., 00-133 Warsaw, Poland
2 Faculty of Mechanical Engineering and Robotics, AGH University of Science and Technology, Al. Mickiewicza 30, 30-059 Kraków, Poland
3 Faculty of Management, Częstochowa University of Technology, Armii Krajowej 19B, 42-200 Częstochowa, Poland
4 Faculty of Electrical Engineering, Automatics, Computer Science and Biomedical Engineering, AGH University of Science and Technology, Al. Mickiewicza 30, 30-059 Kraków, Poland
5 Institute of Security and Computer Science, Faculty of Exact and Natural Sciences, Pedagogical University in Kraków, Podchorążych 2, 30-084 Kraków, Poland
* Correspondence: azbielecki@gmail.com

Abstract: Contemporary risk management is based on statistical analysis. Such an approach has a few crucial disadvantages. First of all, it has limited applicability to new technological solutions. In this paper, a new idea for risk evaluation and management is put forward. The proposed approach is based on the autonomous systems theory. The theoretical foundation of the proposed idea is described and its prospective applications are discussed. The proposed measures of risk are based on the idea of the controllability of the system—the greater the level of controllability, the lower the risk. Various aspects of controllability are analyzed—economic, technological, and industrial. For each aspect of controllability, the problem of defining adequate measures for the level of risk is discussed. The proposed approach allows the risk assessor to analyze the system deeply. As a consequence, the analyst can assess the risk based not only on a posteriori statistics but also on an analysis of the crucial properties of the system. This allows the investigator to predict a priori possibilities of critical events. The proposed methodology is applied to the power industry.

Keywords: autonomous systems; risk analysis; controllability; risk measure; power industry

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1. Introduction

There are several approaches to risk analysis—see, for instance, refs. [1–4] for more detailed considerations. However, based on discussions, two aspects of the problem are regarded by all researchers as crucial. First of all, risk concerns humans and is studied from a human point of view. Furthermore, risk is connected with both the limited possibilities of predicting the future and the consequences of some events. Moreover, the more negative potential consequences that threaten and the more unpredictable the future, the greater the risks taken.

Since risk accompanies a lot of enterprises, there is a great demand for working out the tools that would allow us to manage risks. A good measure of risk is necessary in order to manage it effectively. Such a measure enables us to compare different options with respect to risk, among others. A new approach to risk analysis, as well as a proposal to create new measures of risk, is the main topic of this paper. The proposed approach concerns the power industry and is based on the fact that each human industrial activity is about having control. Therefore, a cybernetic approach based on the theory of autonomous systems [5,6] is introduced.

Cybernetics considers cybernetic systems, i.e., the systems that act in their own environment, interact with it using well-defined inputs and outputs, and process information and energy. Thus, the economic aspects of economic entities, such as companies, power systems, and countries, can be regarded as cybernetic systems. Therefore, rules according to which a cybernetic system acts can be applied to economic systems.

The proposed approach allows the risk assessor to analyze the system deeply. As a consequence, the analyst is able to assess the risk based not only on a posteriori statistics but also on the analysis of the crucial properties of the system. By analyzing the various aspects of controllability, such as system inertia, its stability, the ability to compensate for negative environmental influences, the degree of system autonomy, etc., it is possible to precisely define quantitative measures of the degree of system controllability (see Section 5). The values of these measures give information about the level of risk resulting directly from the cybernetic properties of the system. This allows the investigator to predict a priori possibilities of critical events.

According to the main thesis of this paper, risk is related to the controllability of the system—the greater the controllability, the lower the risk. An application of the proposal to power plants is discussed here because the plants can be regarded as autonomous systems and their controllability can be precisely defined. The relationships between the proposed idea and the energy market are also discussed. The thesis of this paper can be formulated in the following way: the autonomous systems theory can be used as a universal basis for risk analysis in all aspects of the industry, technological, production, economic, as well as other levels, from a single unit of a firm, a whole firm, or a network of interacting firms acting at the market and the whole market levels with the agents operating on it. In this paper, a theoretical basis is proposed and discussed. Furthermore, various levels of the power industry are studied in the context of the proposal.

2. Motivations

The current approach to risk analysis, in particular in the power industry, is based on predictions of future events. On the one hand, these predictions concern random adverse events and are based on a statistical analysis of the frequency of past events of this type. Such an analysis allows us to estimate the probability of similar events in the future. On the other hand, the predictions can also be based on an analysis of the properties of processes and structures. The assessment of the fatigue progress of the materials of the machines in the mechanical system of a wind turbine, for instance, is an example of this approach. If such an assessment is accurate, it allows managers to work out an effective timetable for maintenance and, as a result, reduces the probability of failure.

Both the aforementioned approaches have a significant level of uncertainty, which can be a source of mistakes in such predictions. Referring to the above-mentioned example, it turned out that the load on the mechanical system of a wind turbine has a chaotic character and causes a greater level of machinery fatigue than the one predicted by experts [7]. This was caused by a lack of chaotic aspects in models of wind turbine loads. The current approach, based, in general, on predictions of future events, which are based on past events, can be reinforced significantly by a complementary approach that is based on a deep cybernetic analysis of the considered system.

It should be stressed that in the statistical approach, important aspects of the function of the power industry are neglected. In the context of industry, risk has three aspects: technological, production, and economic. All three aspects are connected and should be studied at various levels: the single module level such as a wind turbine, the power plant level, and the level of the power network and energy market. At each level, numerous processes occur and have an impact on the environment. The processes are controlled and the level of controllability is related to the risks. The control is, among others, based not only on models of the processes but also models of the environment and an analysis of the structure of the system. Cybernetics provides the possibility to analyze these aspects consistently.

Contemporary research regards risk assessment or risk-based optimization as being carried out usually for a single aspect and single level only. For example, considering the economic aspect, a game-theory-based approach can be applied to integrated electricity and heat systems [8] or probabilistic [9] or stochastic [10] frameworks for power plants. The economic aspect is tackled as well at the power dispatch level [11,12]. Multiple technical aspects are also covered separately, for example, pump failure risk assessments [13], cyber security [14] for power plants, or robustness and resilience [15] at the power grid level. In contrast with the above, the proposed cybernetic approach is multi-aspect and multi-level.

These are the topics of this paper that are subsequently discussed in detail.

3. Power Industry Specifics

In this section, a few aspects of the power industry are discussed. Risks in the power industry, the legal and organizational aspects of the power industry, and the risk measures for energy markets are the topics of the subsequent subsections.

3.1. Risks in the Power Industry

The ability to define what can happen in the future and choose the best alternatives is the foundation of risk management. It is impossible to know with certainty which alternative is the best as there are threats and uncertainties involved [16]. The resulting prediction of each alternative by analyzing the outcomes as direct losses (immediately visible, e.g., health, property, environment, society), indirect losses (profits, reputation), and secondary costs (costs that weaken the affected country's economy) can be used to make an optimal decision.

In traditional engineering applications, risk is a physical property to be analyzed and estimated in the risk analysis process. The power industry has made a significant contribution to the development of risk analysis as part of the critical infrastructure sector, where safety and resilience are very important challenges. In 1975, the U.S. Nuclear Regulatory Commission completed the first study of the probabilities and consequences of severe reactor accidents in nuclear power plants. For this objective, a probabilistic risk analysis was used [17]. An accident at the Three Mile Islands power plant in 1979 was the reason for the further development of the methodologies of risk analysis in the power industry. In the general approach, risk is expressed as a combination of the potential accident and event probabilities, as well as the magnitude of the undesired consequences. The probabilities of potential accidents are the mean values of the probability distributions used. Although event frequencies cannot be described by a single value but as probability distributions, Monte Carlo simulations are used to produce a total probability distribution for the final event (see the Risk Management Guidelines, Companion to AS/NZS 4360:2004).

Risk analysis in the power industry is a useful tool for predictions of undesired consequences of events. It is also most valuable for decision making when it presents a realistic assessment of the conditions and then provides a realistic presentation of the uncertainties. The crucial problem with the implementation of risk analysis methodology is the inadequacy or lack of historical data on events. To use this approach, the observational data must be judged relevant and the number of observations must be large in a statistical sense. In practice, data applied in risk models are given in the form of occurrences of the outcomes of trials, registered during similar activities or observations of similar units in the past. The similar activities and unit meanings in the case of prototype devices in the power industry, e.g., thermal power sources and other significant developments in technology and efficiency such as ultra-supercritical power plants, can be problematic. In most cases, the data do not reflect the specific surrounding and risk factors of the system, e.g., those related to maintenance and the organizational culture, as well as environmental and political issues [18]. This additional information is integrated by experts who can understand how much the different factors contribute to statistical data and how to assess their influence in a risk model [19]. Therefore, the role of expert elicitations is growing. Instances of comprehensive historical data on events in the energy sector gathered by the Paul Scherrer Institute are published in the Energy-Related Severe Accident Database [20]. Establishing a risk model for more general levels seems to be even more challenging since the scarcity of data increases. Although it is hard enough to assess a single plant, it becomes even harder to assess a distribution or transmission grid.

3.2. Legal and Organizational Aspects of the Power Industry

According to Directive 2009/72/EC, "Member States shall ensure the monitoring of the security of supply issues". This includes the balance of supply and demand on the national market, expected future demand, and plans for commissioning additional capacities. The monitoring also includes the quality and level of maintenance of the networks, peak demand, and shortfalls of suppliers. Addressing any identified issues is also expected. Thus, it forces network operators and producers to closely monitor their infrastructures, analyze their functioning, and draw conclusions to increase the security of supplies. The Council of European Energy Regulators periodically surveys and analyzes the quality of such supplies (Council of European Energy Regulators, fifth CEER benchmarking report on the quality of electricity supply, technical report, Council of European Energy Regulators, 2011).

Parties involved in smart grid management are identified as either operators or consumers. The operators are responsible for managing the grid. They are subdivided further, mainly into transmission system operators (TSOs), distribution system operators (DSOs), and energy generators (producers). There are two main observable drivers for customer satisfaction and compliance with regulations. Customer satisfaction drives all stakeholders; however, after analyzing it, it turns out that it regards different, even opposing goals such as income maximization and energy bill reduction. The main assessments of this driver are non-interruptible delivery, better power quality, and wise energy usage. Non-interruptible delivery and better power quality contribute to the SO's (i.e., TSO or DSO) main goal, which is maintaining grid operations. Wise energy usage contributes to income maximization for the seller, as well as energy bill reduction for the customer. Compliance with regulations drives the SO. It is a complex driver whose main components can be characterized as being related to distributed generation, renewables, CO_2 emissions, and reliability. Compliance is usually forced upon DSOs by regulators and laws. Assessing this compliance results in non-interruptible delivery and better power quality, which consider the goals of maintaining grid operations and income maximization, which are the main objectives for the DSOs and sellers, respectively.

So, as can be seen from the above discussion, these three parties and their goals are highly entangled. Fulfilling these goals is a great challenge in power dispatch. In particular, optimizing grid operations is a complex requirement, which consists of providing dynamic tariffs, restoring services after a failure as soon as possible while minimizing the number of disconnected loads, and stabilizing the grid to provide uninterrupted operations, among others. Such actions are inevitably burdened by risk. Managing risk becomes an important issue. What is more, due to the aforementioned complexity of the system, it is challenging to establish viable risk models, which is a motivation for this research.

3.3. Risk Measures for Energy Markets

To quantify risk, risk analysis theory distinguishes between three groups of measures: volatility measures, sensitivity measures, and downside risk measures. The volatility measures reflect changes in the prices or rates of return of a financial instrument. The sensitivity measures determine the influence of the risk factors on the level of prices or rates of return. The downside risk measures pertain to the assessment of possible negative deviations in prices or rates of return. The best-known risk measure reported in the literature is value at risk (VaR), which is an estimation of a p-quantile of a given distribution function [21,22]. The expected shortfall acts as a complementary tool to the VaR in order to quantify the losses that are not covered by the VaR under its confidence level [23–26].

To date, research into the assessment of the VaR measure has mostly concentrated on the estimation of risk concerning the stock and currency markets [27–30]. In volatile markets, risk prediction is usually limited to the historical time series of the same markets [25,26,31]. Some authors take into account the spillover effects between the markets [32–35]. Using the BEKK-MGARCH model, Yousaf examined the risk transmission from COVID-19 to the precious metal and energy markets [36].

As for the markets for energy materials, we can point out those that only determine VaR for individual instruments using the ARMA, GARCH, and APARCH class models [30,37] and FIGARCH, FIAPARCH, and HYGARCH class models [38]. The assessment of value at risk concerning the future of energy materials is described in [39], among others, where non-parametric, semi-parametric, and parametric volatility models are used. On the other hand, in [40], the use of AR-GARCH models for one-dimensional series is described and the associative distribution of two-dimensional series is modeled with the use of the copula function. Selected markets are analyzed using a wavelet-based VaR estimation in [41]. A heterogeneous autoregressive quantity model is applied to forecast the VaR of the Chinese market [26].

When it comes to the energy market, the assessment of VaR using classic methods and their evaluation is conducted in [30,37,38]. Their works embrace a wide scope of models [42,43]. One-day-ahead value at risk (VaR) and the expected shortfalls for Saudi Arabian, Abu Dhabi, and Kuwaiti energy stock prices over short and long trading positions using three different long-memory autoregressive conditional heteroskedasticity (ARCH) and generalized(G)-ARCH models are also estimated in [44].

4. Autonomous Systems Theory

Cybernetics is a science that considers systems interacting with the environment in which they act. The interaction is realized by using the inputs and outputs of the system. The cybernetic system receives signals, energy, and matter from the environment using the inputs and affects the environment using the outputs. The signals, information, and energy are processed by the system, firstly in the context of its control. The functional as well as the structural properties of such systems are investigated in the framework of cybernetics.

As shown in the previous section, risk management is studied in the context of the activities of economic subjects. Economic and, more generally, social organizations can be considered cybernetic systems [45–47]. The systems can be controlled externally or internally. In the latter case, it is called an autonomous system. The theory of autonomous systems was introduced by Polish cybernetician Marian Mazur in the 1960s, where he applied it to engineering [5] and psychology [6]. In the twenty-first century, Mazur's approach was applied to the analysis of healthcare systems [48]. Moreover, the theory was improved and applied to the analysis of life phenomena [49]. In this paper, Mazur's theory of autonomous systems is applied to the analysis of economic subjects in the context of risk management.

Let us briefly recall the ideas of Mazur's autonomous systems theory—see [5,6,49] for more details.

The autonomous system is a system that has a specific structure and consists of the following elements.

The receptor is an input module that receives signals (stimuli) from the environment and translates them into the internal code of the system. Thus, receptors are responsible for signal reception, transformation, and transfer.

The alimentator is an input module that receives energy from the environment.

The effector is an output module that generates reactions in the system.

The accumulator is an inner module that stores resources, i.e., energy and matter, and processes them into forms that can be consumed directly by the system.

The correlator is an inner module that processes and stores information.

The homeostat is an inner module that secures the functional balance of the system.

In cybernetic systems, energy enables the system to sustain its existence and operation. Thus, apart from physical energy, in economic systems including industrial ones, money is also a form of energy in the cybernetic sense. The alimentator, accumulator, and effector constitute the energetic line of the autonomous system, whereas the receptor, correlator, and effector constitute its information line. The structure of the system is presented in Figure 1. The disorganization of the structure would prevent self-control so the autonomous system prevents the disorganization of its structure to preserve functional balance. The tendency of the system to keep a functional balance is called homeostasis. The set of feedback loops is aimed at keeping the functional balance in the system. As a result, an autonomous system counteracts the factors that may lead to its disorganization, as well as the factors that prevent the system from achieving its aims. Thus, an analysis from a cybernetic point of view consists of the analysis of the flows of signals, energy, and resources between the modules of the system. Furthermore, the modules are defined at a cybernetic level and, therefore, in a cybernetic analysis, their functional specificity is independent of specificities characteristic for the branch to which the considered system belongs. Moreover, Mazur's theory goes far deeper than the cybernetic theories of systems that could be considered alternatives to Mazur's approach, for instance, the theory proposed by Ackoff [50–52].

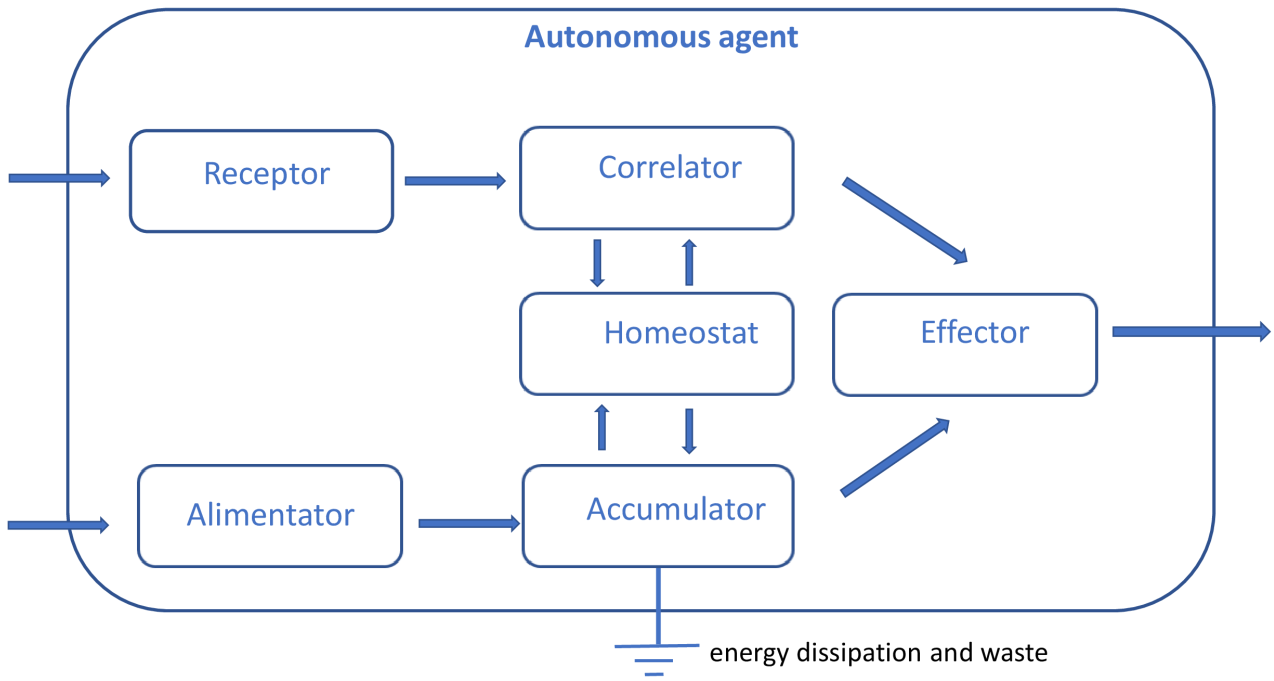

Figure 1. The structure of the autonomous system (autonomous agent) according to Mazur.

5. Risk in the Frame of Autonomous Systems Theory

As mentioned above, the current approach to risk management is based on predictions of future random events using statistical methods. Furthermore, it has, in a way, a passive character, i.e., it is based on an analysis of past events. Therefore, numerous processes that are crucial to risk analysis and management are not taken into consideration.

In this section, a complementary approach is proposed. Let us assume that an object for which risk is considered is a cybernetic system that is externally controlled or self-controlling. The risk is connected with the possibility that the aim may not be achieved. Since risk is strictly related to the occurrence of undesirable events or states of the system, the possibility of the avoidance of risk reduces the level of risk. The mentioned possibility is a result of the control of the system. The higher the level of controllability, the lower the level of risk. Let us analyze the controllability of cybernetic systems in reference to risk management. It is important to stress that the proposal of the measures of the level of controllability and, as a consequence, the measures of risk are some of the crucial points in the approach presented below. The proposed measures have an exemplary character.

This new approach is complementary to the one based on probability and statistics that is widely used in the classical approach to risk assessment.

The control of the system has the following basic aspects:

1. *The direct changing of the parameters.* The action of a controlled system is characterized by the set of its properties. The ones that can be expressed by numerical parameters are the basic characteristics. They can be analyzed at the most basic level of cybernetic systems analysis. More general cases, however, are also possible, an example being the properties that describe the system's stability (see point 5). Such complex properties can be expressed in mathematical terms but are usually expressed in terms more general than a single numerical parameter or a vector that has numerical components. In the context of controllability, the system has two basic aims—it should assure its acting and stability and it should achieve the determined goals. To perform these tasks, the system should maintain its characteristics in the given frameworks. In the case of numerical parameters, it means that their values should be kept in a priori-defined intervals. The ratio of the length x_1 of the interval for which the system acts properly to the length x of the interval of all values of the parameter that can be reached by the system is an example of the simplest measure of the controllability and, as a consequence, of the level of risk in a case when the system is controlled by only one numerical parameter. Thus, provided that C denotes the controllability of the system, we can use
$$C = \frac{x_1}{x} \tag{1}$$
In a case when the system is controlled using a set of n parameters, the lengths of the intervals should be replaced by the measures of the sets in R^n. The risk r can be expressed as $r = 1 - C$.
2. *The system inertia.* There are a few aspects of inertia in embodied systems. First of all, each embodied cybernetic system reacts with delays. The more delayed a reaction to the control signal, the lower the level of controllability. Thus, the size of the delay of the control, which is a measure of the system inertia, is at the same time a measure of its controllability and, as a consequence, of the level of risk. If a system depends on only one parameter and its dynamics can be modeled using a differential model,
$$\frac{df}{dt} = F(x, t - T) \tag{2}$$
where f is a function of the state of a system and F is its control term and the delay T is a measure of the system inertia. Thus, $\frac{1}{T}$ is a measure of controllability. The sensitivity s and reactivity r of a system are other measures of its inertia. Sensitivity is a relative measure of the changes in the state of a system depending on the input, whereas reactivity is a relative measure of the changes in the state of a system output depending on the input. Thus, in the simplest case, they are given by the following form:
$$s = \frac{R}{S} \tag{3}$$
$$r = \frac{\Delta f}{S} \tag{4}$$
where R denotes the value of a system's reaction (the state of the output of a system), S denotes the value of the stimulus (the state of the input of the system), and Δf denotes the change in the state of a system. The aforementioned aspects of the system inertia can be analyzed if a formal model of the system is given, for instance, in the form of a state equation. It should be stressed, however, that alternative models can be considered, for instance, a multi-layer artificial neural network in a case where the dependence between the value of the input and the value of the output has the form of a function, a recurrent artificial neural network if a system has inner dynamics, or a

rule system if a system can be described as the schema. It should be stressed, however, that in a system, the inertia can vary as it depends on the path of control. Therefore, the analysis of a system in reference to its inertia should be performed carefully. In particular, if the scheme of control is complex, for instance, multi-step, parallel, or if this scheme is described by a graph of flows of controls, then the pessimistic inertia level should be estimated. In complex systems, their inertia cannot be measured by a single parameter but by a more complex abstract structure, for instance, by a vector of pessimistic inertia of various paths of control. Considering the problem at the most general level, an analysis of the dynamical properties of the system can be performed. It should be mentioned that the mathematical tools of such an analysis are known as automation, for example, the transmittance of a system.

3. *Predictability.* Problems, such as the predictability of a system's reactions and, as a consequence, the predictability of the states that will be reached by the system, as well as the states of the environment and its pressure on the system, are strictly connected with the issues concerning the system's controllability [53]. First of all, a short-term forecast of the system's reaction is needed in the context of the system inertia discussed in the previous point. This means that a control algorithm has to take into consideration the delay effect to force the desired reaction effectively within the assumed time horizon. Predictability should also be taken into consideration in the context of creating a system strategy, which will allow the system to reach its goals. The possibility of predicting the future is related to the character of the processes that influence the predicted events. The problem of whether the considered process has a deterministic or stochastic character and whether it is chaotic or not are examples of crucial questions. These problems are related to the pressures of the environment—see point 4—and the models used by the system in the context of self-control—see point 7. There are well-defined mathematical measures that can be used to measure the system properties in the context of its chaotic nature and stochastic character. If the character of the process is analyzed indirectly, for instance, by analyzing the signals that are the effects of the process, then the characteristics of the string of signals considered as time series can be measured, for example, with random series tests or the fractal dimensions of the graphs of time series [7,54]. If the process can be studied directly, in particular, if its mathematical model is given, then measures, such as the Liapunov exponent of the studied dynamical system, Kolmogorov entropy of the system, or system ergodicity, are the strict mathematical measures that provide information about the character of the process and, as a consequence, the process's predictability. In the most general case, if any forecasts are performed, then the values of the forecasted parameters can be compared, ex post, with the actual values. This can be the basis for the calculation of the error of the prediction, which is also a measure of the predictability of the system.
4. *The pressure of the environment.* The environment of a cybernetic system puts pressure on it. The negative pressure, i.e., the pressure that disturbs the functional balance of the system or prevents the system from achieving its goals, should be compensated for by the system. The greater the capability to compensate for the unprofitable pressures of the environment, the greater the stability and self-controllability of the system. In the simplest case, if a magnitude of a given influence of the environment can be measured by a single numerical parameter, then the compensation capability of the system can be measured as a value of the ratio of the length of the interval of the value of the parameter for which the influence can be compensated for to the lengths of the intervals of all values that can be entered into the system output as the pressures of the environment. Furthermore, the greater the predictability of the environment, the greater the possibility to work out a strategy for compensation for its negative influence. Furthermore, it should be mentioned that the pressure of the environment is also connected with the variability of the environment—usually, the higher the variability, the greater the pressure. This problem, in particular, the adaptation to a

variable environment, is the topic of studies of biocybernetics in the context of the autonomy of biological systems—see, for example, [49] and the monograph in [55]. The results of these investigations can perhaps be adapted to industrial systems. The possibilities of the negative counteracting influence of the environment refer to the system inertia and compensation capabilities, the predictability of the environment, and the accuracy of the model that the system uses. The environment also consists of other autonomous systems—see point 8.

5. *The level of system stability.* The problem of the stability of a system, or more generally, its robustness, includes the stability of its processes and structures. The stability of the processes can be analyzed in the framework of dynamical systems theory, for instance, the structural stability of a process can be checked and discussed in the context of cybernetics—see [45], Section 9. Not only a single process should be stable but the network of processes should be robust as well. The robustness of the network is connected with the structural properties of the graph that models this network. Graph connectivity, both the vertex connectivity and the edge connectivity, is an example of a measure of the graph's resistance to damage. The stability of structures should be tested in the context of both their resistance to damage and the preservation of their functional properties after damage. For instance, artificial neural networks preserve their structural stability even if around 20% of neurons have been removed. Thus, if the control of the system is based on an artificial neural network, the control has high resistance to damage to the structure, which is the basis of the control algorithm. In general, the level of system stability depends on the effectiveness of the homeostasis of the system.
6. *Availability of resources and information.* A system needs means to solve the problems it is faced with. This is connected with the possibility of the effective operation of both of the autonomous system's lines—the energetic line and the information line. The energetic line can act if resources can be drawn from the environment, which is possible if there is a sufficient amount of them and they are achievable. Furthermore, exploitation has to be profitable and predictable. The information line needs pieces of information to update the content of the correlator. The necessary pieces of information, in contrast to the resources, are usually achievable, but the possibility of acquiring new pieces of information can be demanding for the development of the receptors including equipping the system with new types.
7. *The model on which the control is based.* The self-control of an autonomous system is based on the knowledge that is created and stored in the correlator. Since the control has to be performed in advance according to the inertia of each embodied system, the models of the environment, the inner and outer processes, as well as the relationships among them, are crucial parts of the correlator. The simplest models are used for creating direct relationships between the types of stimulus reactions and are implemented as a functional dependence. In engineering, automatic control and regulation are based on such models. The most complex models, which are based on symbolic representations that can be completely detached from actual circumstances, enable anticipatory planning, which is an important possibility in the context of the aforementioned system inertia. Furthermore, the complex, abstract models enable the system to work out complex strategies that allow the system to optimize its actions. In general, the more complex and abstract the model, the higher the level of controllability because the type of control is less fixed and, as a consequence, new combinations of actions and reactions can be created as a basis for new strategies. It should be stressed that studies concerning the types of models and their complexities, which are the basis of control in cybernetic systems, are conducted in the context of biological cybernetics and the application of biological mechanisms to technology—see [55,56], chapter 10.
8. *The character of the game.* Each autonomous system operates in its environment, which consists of other autonomous systems such as agents. The considered system interacts

with them in various ways. These interactions can both improve and reduce the functionality of the system. As a consequence, the possibility of the self-controllability of the system can increase or decrease. In such a context, the influence of the environment should be studied carefully in the framework of game theory and multi-agent systems theory. First of all, the payoff tables for various strategies should be analyzed, as well as the character of the whole game. The problem of whether the game is a zero-sum game and whether it is conducted against nature or not are examples of issues that should be considered. At the level of the relationships among agents, the existence of competition between them is crucial, as well as the possibility of cooperation. The network of flows of signals, means, and controls among agents should be investigated. The characteristics of agents should also be an element of the analysis of the whole system of agents. These aspects of cybernetic systems that consist of autonomous agents are analyzed in [48].

9. *Energy in the system.* The energy that is drawn from the environment is used to sustain and control the inner organization of a system. It can be used by the system more or less effectively, which is directly connected with controllability. Thus, the measure of the effectiveness of the utilization of energy is the measure of a crucial aspect of controllability and, as a consequence, the risk connected with the aspects of energy. The level of energy dissipation, conductivity of the energetic line in an autonomous system, efficiency of the accumulator and alimentator, time of the system relaxation after energetic exhausting, and the power of the system are examples of measures of energetic effectiveness. Furthermore, the capacity of the accumulator is also a crucial parameter that characterizes the accumulator. This also refers to the predictability of the whole system—the greater the capacity, the longer the run-time, which results in better predictability. All the specified measures are defined explicitly in the case of physical energy and can be defined by an analogy in the case of economic energy, i.e., money.

To sum up, crucial aspects of controllability have been discussed above. For each aspect specified as a separate point of discussion, examples of possible measures of the discussed aspect of controllability have been proposed. These measures can be the basis for the definition of the level of risk according to the aforementioned rule: the greater the level of controllability, the lower the level of risk. Let us notice that, in contrast with the contemporary approach commonly used, in the proposed analysis, the risk is assessed in the context of the cybernetic properties. Thus, it takes into consideration the functional possibilities of the system and, therefore, concerns its active aspects. The proposed approach provides a universal framework for risk analysis. The risk measures based on the proposed method can be expressed in mathematical terms, among others.

6. Application to Power Plants

The methodology of the analysis of a complex system in the framework of Mazur's theory is as follows:

1. Identification of the agents—each agent is analyzed in the framework of Mazur's theory.
2. Description of the agents:
    (a) The module identification, i.e., which modules in a system correspond to Mazur's autonomous agents and which modules correspond to their submodules.
    (b) The structures of the modules.
3. Analysis of the structure and properties of the environment
4. Specification of the mutual relationships between the agents and between the agent and the environment.

6.1. Power Plants as Autonomous Systems

Let us consider power plants as autonomous systems and apply the proposed method to risk analysis.

First, let us consider the specifics of the environment in which the power plant exists. There are three main levels of the environment. The first level is the power grid to which the energy produced by the power plant is supplied. The second level is the natural environment, which supplies the power plants with the raw materials for energy production. The power plant influences its environment at the natural level through the inevitable dissipation of energy in all physical systems related to the operation of the system and the release of industrial waste into the environment. This aspect of the operation of the power industry is analyzed in [57]. The last level is the economic level from which the requirements for the amount of produced energy and the money for the produced energy are supplied to the power plant. In the power plant, considered a cybernetic system, two autonomous agents can be distinguished at the highest organizational level—the economic agent and the technological agent. The diagram of their mutual relationship, as well as their relationship to the environment, is presented in Figure 2.

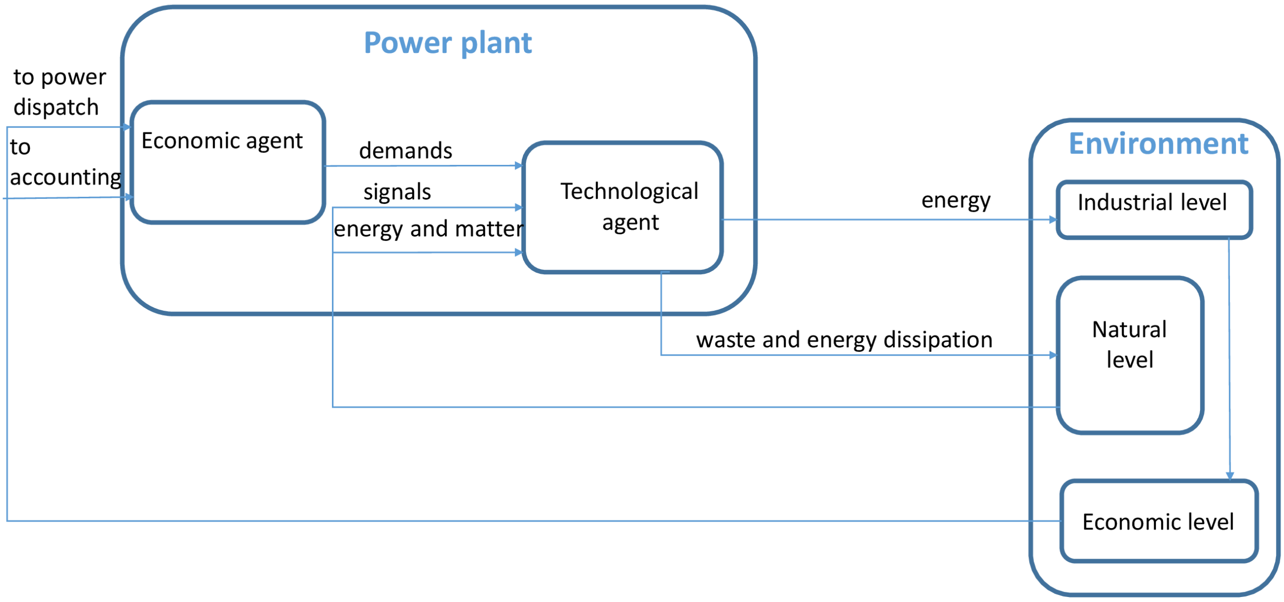

Figure 2. The organization of the thermal power plant and its relationship with the environment.

Assessing risk using the cybernetic model for each of the perspectives—technological, organizational, and economical—can yield varying results. Bear in mind that the model is very specific. Its parameters vary even for different power plant types. To show the applicability of the proposed approach, let us consider two examples—a thermal power plant, which is a very complex system, and a wind power plant, which is relatively simple.

Let us first discuss the technological level of a thermal power plant, which is presented in the framework of Mazur's theory in Figure 3. The alimentator is a set of devices and installations for collecting fuel, for instance, coal, through external transport means; the mechanization of fuel storage sites; initial fuel preparation such as sorting, coal crushing, mixing, and averaging; and transport to the boiler-side storage. It starts from the fuel intake, railway, or conveyor, and ends at the fuel storage. The accumulator is the coal storage, where storage is often sufficient for many days of operation, which defines the accumulator capacity, and, as a consequence, has an influence on the system predictability—see Section 5, points 3 and 9. Technologically, the accumulator's function can also be assigned to the reheater—a part of the boiler between the high- and intermediate-pressure parts, though the amount of steam is only sufficient for a dozen seconds. The effector is a complete set comprising the boiler, steam turbine, generator, and output transformer. The receptors are all the sensors in the power unit and are often a set that consists of more than 10,000 sensors. Both the correlator and homeostat are multi-layered systems. The homeostat is a control system that is based on the information stored in the correlator. The range of the parameters in which the system should be kept, which are written in a programmable logic controller (PLC), are examples of the information stored at the most basic level of the correlator. The procedures for the conservation of the modules of the power plant, as well as the procedures for action during a failure, are examples of information of the highest level encoded in the correlator. The basic level of the homeostat consists of lower-level controllers based on a PLC, which is responsible for the control parameters of the modules of a plant such as the level of water in the boiler or the pressure in a steam boiler. At the higher level of the control system, the homeostat is responsible for harmonizing all the processes to secure the safe and economic operation of the entire power plant [58].

Let us discuss the technological level of a wind power plant considered an autonomous system. A wind power plant is much simpler than a thermal plant but it can also be described and analyzed using the cybernetic approach. The alimentator is the rotor, which converts the power of the wind into mechanical torque. The wind turbine does not include any inherent accumulators, which is an important limitation of this power source. The rotor is the only component that partially fulfills this function. Its inertia, however, can store kinetic energy for only a few seconds. Therefore, studies to equip wind turbines with effective and economically viable energy storage are conducted intensively—see, for instance, [59]. The gearbox (if present) and generator with output power electronics constitute the effector. The other components are similar to the previous example but are simpler. The receptors consist of about a hundred sensors. The pieces of information that are stored in the correlator are specific to wind turbines and include the desired pitch angle values that are dependent on the wind direction and the algorithms for the wind speed prediction in a time horizon of a few seconds. The control algorithms that are set in the homeostat, which are specific to wind turbines, include the pitch angle control and the control of the turbine that is dependent on the wind conditions, taking into consideration the rotor inertia.

The economic aspect of power plants can also be described in terms of autonomous systems. It should be stressed, however, that it refers mainly to human resources. Therefore, sometimes, the cybernetic structure can differ from the physical structure of the system. The existence of such differences is characteristic of biological systems and systems that consist of biological subsystems, for instance, economic systems [56]. Since all resources that enable the system activity constitute energy in a cybernetic meaning, money is the main type of cybernetic energy at the economic level. Thus, the structures of the system that ensure revenue, for instance, accounting, play the role of actuators. The organization of a power plant, in particular, a thermal plant, in the framework of Mazur's theory is presented in Figure 4. The bank is the accumulator, whereas the management is the homeostat. The knowledge of the experts who work at a power plant, as well as the rules according to which the plant acts, constitute the content of the correlator. This is connected to the environment by a load-dispatching unit, among other things, which is a part of the receptor. Power dispatch, as well as the energy market, are parts of the environment at the economic level. A power plant proposes its offers via an energy trading unit. Usually, energy trading companies are brokers between power plants and the electricity market, and in such cases, they are a part of the environment of a power plant, and they are also autonomous systems. In order to work out the complex relationship between power plants and energy trading companies, the multi-agent systems theory should be used.

The brief discussion presented above showed the relationships between the modules of an autonomous system and the technological modules of two different types of power plants, as well as between the modules of an autonomous system and the modules of a power plant at the economic level. Such an approach allows us to analyze the problem of the controllability of the whole system in the context of the conductivity of the system lines, the robustness of the processes and their inertia, as well as the structure of the stored knowledge, availability of information, and effectiveness of the control algorithms. In particular, the isolation of the correlator allows us to analyze the system controllability in the context of data mining and knowledge management [60,61], whereas the isolation of the homeostat and definition of both the information and energetic lines, enable us to analyze the controllability of the system using dynamical systems theory and stochastic systems theory, as well as mathematical control theory.

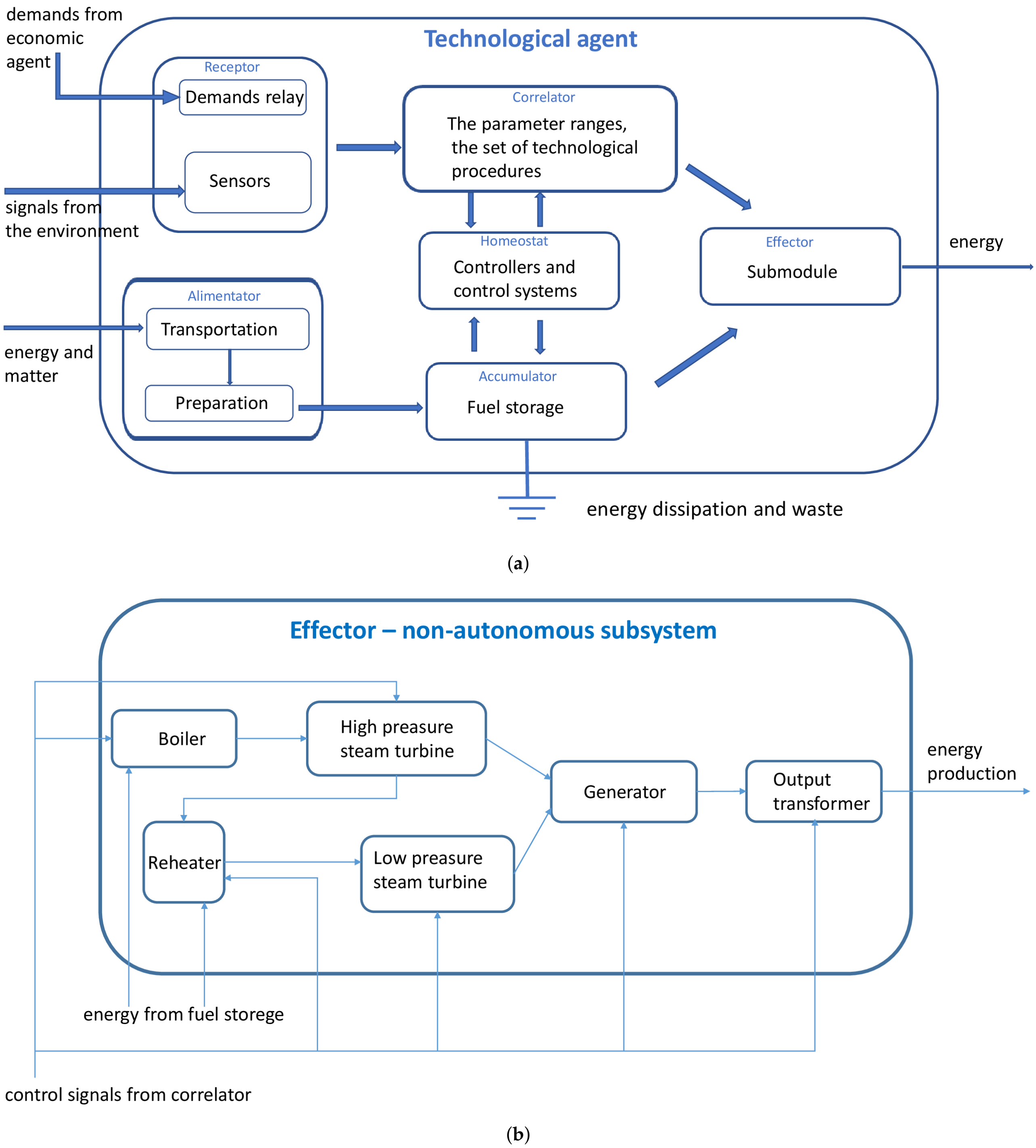

Figure 3. The thermal power plant—the technological agent in the framework of Mazur's theory. (**a**) The organization of the technological agent in the framework of Mazur's theory. (**b**) The effector as a non-autonomous subsystem of the technological agent.

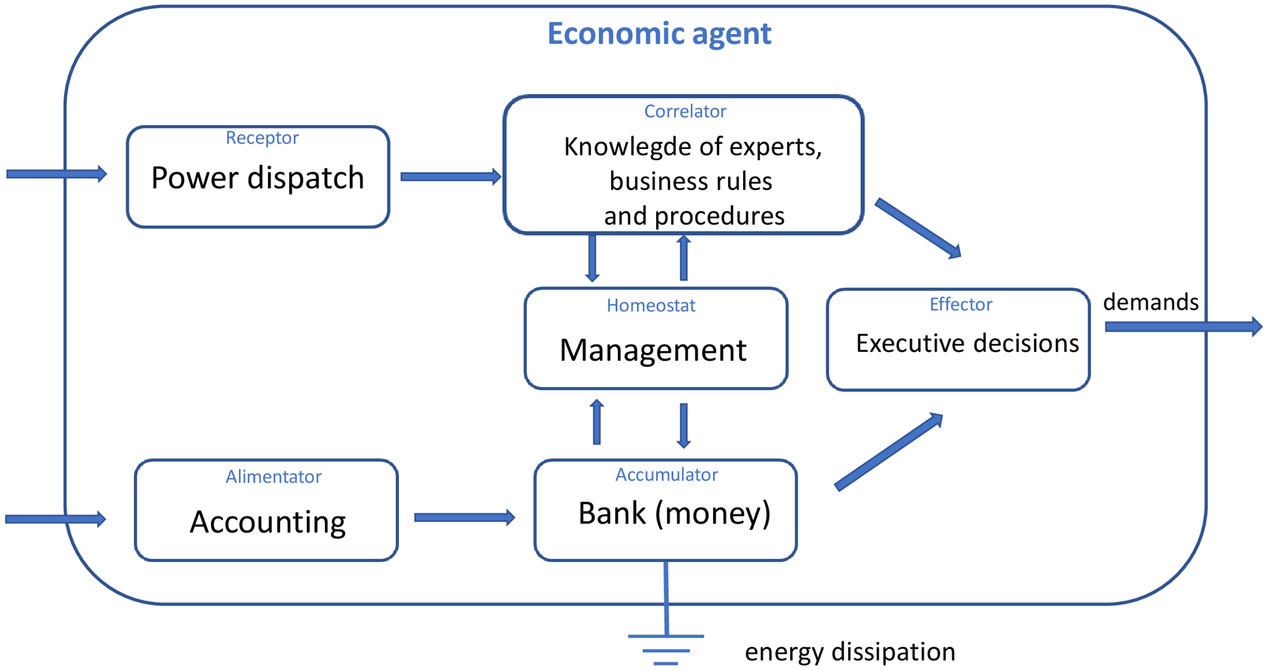

Figure 4. The power plant—the economic agent in the framework of Mazur's theory. The organization of the agent is common for all types of power plants.

To sum up, cybernetics in general and, in particular, the theory of autonomous systems, provides a universal tool for the analysis of various aspects of all types of systems. Such an approach allows researchers and analysts to understand the relationships within the system, including the interactions of its parts, as well as the relationships with the environment [5,50,52,60]. Moreover, the approach provides managers with universal tools that enable the analysis of the controllability of the system and, as a consequence, the effective management of risks.

6.2. Risk in Power Plants—A Cybernetic Approach

It should be stressed that this paper has a general character and the introduction of a new method of risk analysis and management is its main goal. The application of the proposed approach has a demonstrative and introductory character. This area is currently being researched and the following issues require further work:

1. There are a lot of parameters in a power plant that are changed directly during the control process. For thermal power plants, the combustion intensity is one of the basic parameters that determines the electric power output directly. The maximal intensity of the combustion and, as a consequence, the maximal power of the produced energy, is the measure of the controllability of the system. Production efficiency, measured in the described way, in comparison with the potential demand for energy, is the measure of risk that considers both the technological and economical aspects of power plant operations. From a cybernetic point of view, this is a problem with the energetic line's productivity such as the fragment that contains the accumulator and the effector.
2. Let us continue the example given in the previous point. Combustion in thermal power plants has great inertia, which means that the amount of produced energy cannot change quickly. The inertia of a wind plant is small in comparison. In particular, a wind plant can decrease the production of energy very quickly. In order to decrease the inertia of power plants, they are often equipped with modules that can take a surplus of the produced energy and dissipate it. From a cybernetic point of view, this is a problem with the inertia of the accumulator's reactivity.

3. The predictability of electric power demand is crucial for all players in the electricity market because the whole system acts in online mode. The consumption prediction is important in order to both plan short-term production in a one-day time horizon and work out a long-term production strategy since there is still no economically justifiable energy storage available for such applications. The prediction error is a good measure of prediction accuracy. From a cybernetic point of view, the possibilities of predictions performed by an autonomous system are determined by the accuracy of the models stored in the correlator.
4. The environment puts pressure on the system, for example, the overload of the drivetrain of a wind turbine caused by the irregularities of the wind speed including the chaotic character of the wind speed as a time series [7]. Chaotic overloads cause the quick fatigue of mechanical systems and, as a consequence, enhance the risk of system failure. Therefore, not only should they be monitored carefully but also should be taken into consideration in theoretical models and simulations [7]. From a cybernetic point of view, this problem is related to the capability of monitoring the negative influences of the environment on the system, as well as predicting, preventing, and compensating for them.
5. The stability of a cybernetic system has at least two aspects. The first, internal stability, consists of keeping the values of the parameters of the system inside the intervals in which the system remains in a functional balance. The system can counteract throwing out the functional balance passively or actively. The passive way regards the system inertia, which is disadvantageous in the context of system control, but it is advantageous in the aspect of keeping the balance. The active way consists of the active prevention of disadvantageous changes. Let us consider the resistance to overheating. The heat capacity of the system is an example of passive thermal stability, whereas cooling is an example of the active thermal stability of the system. The thermal stability of the generator is an example of the problem of stability. It should be mentioned that, in general, thermal stability is one of the crucial parameters in power plants and it is strongly connected with the risk of a disaster, especially for nuclear plants. The second aspect of cybernetic system stability, external stability, is related to the resistance of the system against the distortion of the trajectory of its states in the context of achieving goals. External stability can be measured using the tools from dynamical systems theory. In power plants, the production of a given amount of energy at a given time is an example of a goal. From a cybernetic point of view, the stability of the system refers to the effectiveness of its homeostat.
6. The availability of resources should be taken into consideration in the calculation of the risk of power plant exploitation in the context of its profitability. This problem is interesting, especially for wind plants. Theoretically, wind as an energy resource is widely available. On the other hand, however, wind turbines have a relatively narrow wind speed window, i.e., the wind speed intervals at which it operates safely and efficiently. The ratio of the length of the wind speed window to the length of the wind velocity in the terrain means the turbine is localized on the one hand and the ratio of the time in which the wind speed falls into the wind speed window to the time in which the wind speed does not fall into the window can be proposed as measures of controllability in the aspect of the availability of the resources of wind turbines. From a cybernetic point of view, this is a problem with the productivity of the energetic line such as the fragment that contains the alimentator and the accumulator.
7. The models on which the control of a system is based are kept in its correlator. The more accurate and detailed the model, the greater the possibilities for effective control, for example, the model on which wind turbine monitoring is based. In the simplest case of a monitoring algorithm, the alarm thresholds are fixed and set arbitrarily by an operator. The modeling of probability distribution functions for automatic threshold calculation is a more effective approach [62]. The complex fully automatic intelligent monitoring system, which consists of a few modules including

RBF or, alternatively, a mixture of Gaussian and ART neural networks [63,64], allows for an alarm at the very early stage of failure. From a cybernetic point of view, this problem is related to having the knowledge and based on this knowledge, creating an adequate model of the process. This problem should be solved by a module of the correlator.

8. The action of a power plant can be considered in the framework of game theory. The controllability of the system depends strongly on the character of the game. Games against nature and rational agents are some of the possible taxonomies of the types of games. In the first case, the opponent is not interested in victory and, as a consequence, the opponent either does not aspire to maximize the pay-off or the pay-off of the opponent cannot be defined, for instance, in a case when nature in the literal sense is the opponent. The strategy of the optimization of wind turbine control in the context of wind conditions is an example of such a game against nature. The possibility of wind speed prediction is limited because of the chaotic character of wind speed as a time series [7]. Thus, the controllability of the system is greater in cases where the behavior of the opponent is fully predictable. The more chaotic the behavior of the opponent, the lower the predictability and, as a consequence, the controllability of the system. The level of chaotic character can be measured mathematically using, for instance, entropy, Lyapunov exponent, or fractal dimension. From a cybernetic point of view, this problem should be solved by the module of the correlator, which is responsible for creating the strategy of the system.
9. As mentioned above, the alimentator is responsible for acquiring energy, whereas the accumulator stores and processes it. These issues have been discussed in points 1, 2, and 6. The capacity of the energetic line in a cybernetic system is another aspect of the problem. However, the control of the energy flows in the system in the context of consumption optimization is the most interesting cybernetic problem. It is crucial, especially for wind turbines with a vertical axis. In this type of turbine, the rotor cannot be started using wind energy but using electric energy. Thus, the control algorithm should take into consideration whether the turbine start is profitable in the context of potential energy production and wind conditions in a few minutes. From a cybernetic point of view, this issue is a problem with the control of the energetic line of the autonomous system by the homeostat.

As mentioned above, the presented discussion has an introductory character. The possibilities of the application of the proposed approach to the power industry both at the technological and economic levels have been outlined and presented in the framework of the points specified in the previous section. This discussion is a starting point for working out the problems in detail, as well as referring the approach to other branches of industry and economy and not only the power industry.

7. Concluding Remarks and Comments

The approach presented in this paper refers, in a way, to the behavioral analysis of risk that has so far been considered only in the context of human behavior [4] and the statistical analysis of events treated as random phenomena—see Sections 3.1 and 3.3. The proposed method enables the analysis of the behavior of industrial systems from a cybernetic point of view. It is a starting point for working out a consistent framework for risk measures for the power industry. The introduced methodology is sufficiently flexible to take into account all aspects of risk, i.e., technological, production, and economic. It also enables analyzing risk at various levels, i.e., the level of a single module such as a wind turbine, the level of a power plant, and the level of an energetic system and the energy market.

The innovation of the method consists of the fact that it is not based on a statistical estimation of events but on a cybernetic analysis of the system, first, taking into consideration its controllability. Such an approach enables the optimization of the functionality of the system and, as a consequence, allows for the reduction of risks. The proposed cybernetic approach does not eliminate the current methods based on statistical and probabilistic models because random, unpredictable events are immanent components of industrial processes. The introduced method reinforces our ability to analyze and reduce risk, as well as identify its sources, in the functional aspects of the analyzed system. It should also be mentioned that the proposed method is universal and can be applied to any branch of industry both at the technological and economic levels. Such an analysis of an industry and its modules, for instance, power stations, both in the context of system optimization and risk analysis can be conducted analogously as it was conducted for the healthcare system [48]. Furthermore, the completed Mazur approach, which is dedicated to the analysis of living systems—see [49]—can be applied to industrial facilities and systems that are created or developed, especially since structural and functional analogies between living and techno-industrial systems have already been analyzed in the scientific literature [65]. Publicly available data regarding the performance, technical, and economic factors of power systems are very limited due to their confidentiality. Nevertheless, the presented framework makes it possible to use the described approach to supplement risk assessment procedures by insurance companies and the management of industrial entities. Furthermore, a more detailed elaboration of the individual risk components postulated under the proposed cybernetic approach is planned—see Section 5. Moreover, depending on the availability of data, it is also planned to assess the risk for specific industrial entities.

The mentioned confidentiality of data is the reason why the comparison of our approach with the currently used methods is an issue. To overcome this, a synthetic benchmark is being formulated. Upon completion, it would enable us to provide a more quantitative comparison, which will be the subject of further research.

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Nomenclature

TSO	transmission system operators
DSO	distribution system operators
SO	system operators, i.e., TSO or DSO
VaR	value at risk
ARMA	autoregressive moving average model
GARCH	generalized autoregressive conditional heteroskedasticity model
ARCH	autoregressive conditional heteroskedasticity model
APARCH	asymmetric power ARCH model
FIGARCH	fractionally integrated generalized ARCH model
FIAPARCH	fractionally integrated asymmetric power ARCH
HYGARCH	hyperbolic GARCH model
RBF	radial-based functions (a type of artificial neural network)
ART	adaptive resonance theory (a type of artificial neural network)

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