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Case Report

Innovative Processes in Managing an Enterprise from the Energy and Food Sector in the Era of Industry 4.0

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Abstract: The paper analyzes issues related to production processes in learning organizations using innovative solutions based on the Industry 4.0 paradigm. This study was realized by surveys and observation of companies operating in the energy and food sectors. These are sectors that in recent years have started to intensively implement innovative solutions and are undergoing a transformation towards an intelligent (digital) enterprise, which uses virtual reality, supported by effectively controlling the non-player characters (NPCs). The presented examples can be inspiration for chief executive officer (CEOs), chief operating officers (COOs), and chief information officers (CIOs), the people managing companies for investment in innovative solutions. The implementation of Industry 4.0 solutions, as well as new machines design according state-of-the-art achievements of mechanical engineering rules, will allow companies to implement new products, achieve better results (e.g., more products with lower production cost), increase operational efficiency (e.g., lower energy and water consumption), and meet environmental requirements (e.g., reduce CO_2 emission, introduce zero-emission energy production).

Keywords: production processes; Industry 4.0; learning organization; machine to machine; circular economy; energy industry; food industry; mechanical engineering

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1. Introduction

The current industrial revolution aims to transform global economies by influencing issues such as process automation and the introduction of innovative technologies in companies based on the Internet of Things, machine learning, and blurring the boundaries between the digital and analog world. The combination of production machines with digital technologies allows the entire system, including employees, to efficiently transfer information relevant to each other at every stage of production. As a result of these activities, the production efficiency increases, because all data are transferred immediately and their transfer is independent of each other.

The paper presents the processes taking place in companies in the energy and food sector, which use elements of the Industry 4.0 paradigm, such as machine learning, Internet of Things, Big Data, or augmented reality. The example of an energy company shows how the latest technological solutions are used to meet the challenges of modern energy in the four main groups of processes: mining, production, distribution, and sale. The example of a food company shows how new technological development and new solutions enable the production of products with an increasingly higher level of added value, and how, for example, augmented reality increases production efficiency, ensuring a higher level of production or services.

In recent years, more and more research has been conducted in the field of adaptability of enterprises to the market environment, adaptation of production processes in the context of sustainable development, and implementation of innovative solutions in conjunction with artificial intelligence and augmented reality [1,2]. It is extremely important to undertake activities in the field of scientific research and to introduce advanced solutions in computerization and IT (Information Technology) in the energy and food sectors, in the broadly understood life sciences sector. For the life sciences, it is worth being at the forefront of mathematical, physical, and chemical, as well as management research and applications, and implementing solutions using the most advanced software and hardware applications of our time. Innovations and new technologies allow the companies to function, work, and develop in an ever-changing environment. Innovation can be understood as the introduction of a new product, process, or device. Innovation means something new that reduces operating costs and provides an improved product, service, or instrument that better meets the expectations of market participants [3]. In the era of numerous changes resulting from legal, political, technological, or ecological factors, companies face the challenge of adjusting their activities to the requirements of the external environment [4]. The dynamically progressing automation and robotization of many sectors of modern economies clearly shows that enterprises incur increasing costs of implementing instruments improving the quality of production processes [5], which is associated with setting the limits of process efficiency [6]. The issues related to the optimization and quality of production processes are developing dynamically and systematically. The importance of quality management in achieving the goals and tasks of each enterprise is growing. This requires managers (chief executive officers (CEOs), chief operating officers (COOs), chief information officers (CIOs)) to take these issues into account in the methods of enterprise management and coordination of its activities. These issues are important from the point of view of the company's performance [5].

The management cadre faces the challenge of managing production and processes that should be adaptable. Adaptability enables enterprises to effectively manufacture products and to actively react to changes [1]. For this purpose, it is necessary to use a system with functions intended for efficient planning, production, and control of the processes carried out in changing circumstances. Comprehensive planning is an adaptive process and includes planning decisions to be interrelated at all decision levels [7].

One of the biggest problems in production companies is the effective planning and re-planning of the use of materials, raw materials, and resources in the production process, which is adapted to the new requirements. The question that concerns the management of production processes in an enterprise can be formulated as follows: how to quickly plan and adapt production with the maximum level of production capacity utilization and ensuring adequate efficiency? This paper presents processes in companies in the energy and food sector. Both sectors are very important and very sensitive for innovative solutions from the high-tech range. Energy efficiency is a key issue for the food industry. In this industry, the consumption of electricity, water, and heat is high [8,9]. Improving the energy efficiency of the company translates into lower operating costs and brings benefits for the environment—an energy-efficient plant is less emission-intensive and significantly reduces environmental pollution.

In the energy sector, the use of Industry 4.0 solutions will improve operational efficiency, change the organization of work, improve efficiency, and enable the implementation of new operating standards and mechanisms for monitoring the environment and quickly reacting to changes that occur. Thanks to new technologies, decision making and analytical and reporting processes will also be accelerated. The energy sector also faces the challenges of decarbonization, which will be a complex process requiring capital-intensive investments focused on only low- and zero-carbon generation. RES (Renewable Energy Sources) and the conversion of coal fuel will reduce the impact on the natural environment and achieve climate neutrality by 2050. The reduction of the emission intensity of production will take place by changing the technology, expanding the RES portfolio, enabling active participation of customers (prosumers) and involving the entire industry in activities for the circular economy [1,9].

The presented research shows the direction that enterprises are recommended to follow to make production processes environmentally friendly and at the same time increase the efficiency of the company's operations.

2. The Processes in Companies in the Energy and Food Sector

2.1. The Enterprise as a Learning Organization

A learning organization is an emerging management theory that has been highlighted by many scientists and practitioners in recent years [10,11]. The challenge for enterprises is to move towards a learning organization that can transform the acquired knowledge into new cognitive perspectives, expectations, modernized procedures, and new organizational structures. A learning organization is also a new way of organizing an enterprise so that the tasks performed are a challenge to undertake subsequent tasks, so that innovations in both work processes and products lead to the creation of new competences. In this way, in a learning organization there is a positive feedback [12].

The new configuration of the enterprise, which is the result of the learning process, is a response to the constantly emerging adaptation needs. Thanks to learning, the company gains many positive features, such as:

- the ability to avoid and prevent errors and the ability to reduce the number of failures;
- overall increase in productivity and efficiency;
- increasing competitiveness by flexible adaptation to the preferences of various customer groups and to the conditions on different markets;
- the ability to make quick adjustments by taking appropriate steps and trying out new opportunities; and
- the ability to quickly adjust structures and react depending on customer preferences and market's trends.

All the above-mentioned features are extremely important in the adaptation process, as they greatly facilitate the possibility of potential changes within the company and the reaction to the changes in the environment [13]. Some factors that may affect the form of an organization include external environment, business strategy, technology and its transformation, the state and scale of the organization, and institutional culture [11].

In a rapidly changing market environment, companies should act quickly and update their skills and learning strategies on an ongoing basis [14]. The organization should make continuous adjustments accordingly and properly [11]. The importance of a learning organization is recognized in business research. Depending on the sector and type of activity, measures are taken in the dimensions of the learning organization [15]. The concept of a "learning organization" is one of the most popular management ideas of the last few decades.

"Learning organization" has been given different definitions and meanings, so it is difficult to establish any unified understanding of what a learning organization really is [16,17]. There are several definitions and approaches to the learning organization issue in the literature. The level of interest in a learning organization among researchers has increased significantly in recent years and the usefulness of this concept is mainly based on its role in improving organizational culture, efficiency, and innovation capacity [10]. The selected definitions of learning organizations are presented in Table 1.

Table 1. Selected definitions of learning organization.

Definition of Learning Organization	Main Core of Definition
A learning organization is an organization in which a learning culture is fostered and the structure is strong enough to improve mindsets and enable learning of the entire organization by continuously transforming and innovating for sustainable development in a complex and uncertain environment [18].	Learning culture and supporting learning processes
A learning organization is an organization that is organized to search for information in its environment, create information on its own, and promote individuals to transform information into knowledge, and coordinate that knowledge among individuals to gain new insight [12].	Constantly transforming information into knowledge

Table 1. *Cont.*

Definition of Learning Organization	Main Core of Definition
A learning organization is an organization with the skills to create, acquire, and transfer knowledge and to modify its behavior to reflect new knowledge and insights [19].	The ability to create new knowledge based on previous experiences
A learning organization can be perceived as a learning organization by coding applications that result from the activities of the enterprise so far and building a certain routine guiding behavior [20].	Drawing conclusions from activities in a historical perspective
The learning organization is people who constantly develop their ability to create. These are organizations where people are constantly expanding their creative potential, where new and expansive thinking patterns are supported, and where collective aspirations are released [21,22].	Creative thinking and creativity of employees

In many industry documents, a learning organization is seen as a sign of a developed safety culture. Depending on the industry, the emphasis may be on other elements related to the learning organization.

In the energy sector and in nuclear power plants in particular, safety is the most important factor. For example, the definition developed by the International Atomic Energy Agency (IAEA) indicates a safety culture in which the building blocks are organizational attitudes and procedures and the implementation of ever better solutions [23]. The learning process compares the new solution to the previous one, and as you search for the next solution, several better solutions are available. In principle, any learning problem can be solved as an optimization task, i.e., a genetic algorithm [23]. From the management side, the emphasis is on practices and procedures (such as event-based learning, self-assessment, benchmarking, external operational experience, and external evaluations) that support learning in the organization [24].

In the food industry, first generated idea of using the plant as a kind of laboratory or learning model for the corporation were in mid-1968 during a meeting of General Foods managers in Wisconsin [25]. The learning organization is poorly researched and described, but one of the available examples is the General Foods Plant in Topeka, which used a pioneering system of the idea of self-managing teams who assumed responsibility and they had a high level of employee autonomy [19,26]. This plant was one of the most highly publicized examples of organizational innovation although some believe that the learning system did not fully work in this organization [25].

2.2. Machine Learning

Learning abilities at the organizational level positively influence the achievement of higher levels of operational efficiency of the company, which systematically supports learning and knowledge sharing at the organizational level. A learning organization may benefit more from adopting the latest technologies [27].

In addition to the learning organization, machine learning is an important element in the production process, which offers great hope for reducing the cost of products and services. Machine learning algorithms can prioritize and automate decision making. They can also signal opportunities and appropriate actions that should be taken immediately in the enterprise [28]. Due to the increased use of machine learning in companies, it is becoming more and more important to use deep neural networks, which depend mainly on a wide range of network architecture hyperparameter choices [29]. Machine learning and the development of artificial intelligence (AI) carry certain risks related to the protection of personal data [30]. Data processing with the use of technologies such as Big Data and artificial intelligence is, among other things, difficult manual intervention in the automatic decision-making process, which may have a built-in bias in its algorithm. AI bias is an anomaly in the output of machine learning algorithms, which may be due to the biases adopted during the algorithm development process or bias in the training data. Another threat related to artificial intelligence is the lack of transparency about what data is processed, through which process and who is responsible when the system makes decisions based on algorithms that artificial intelligence has developed itself. The occurrence of errors in AI has become the reason why many guidelines, reports, and scientific papers on ethics in artificial intelligence have been written in the last few years [31,32].

Predictive analysis algorithms can be used to detect potential malfunctions in engines, turbines, hydraulics, and other equipment, for example by analyzing an oil sample. Combined with the experience of analysts, machine learning has become indispensable for the maintenance and service life of equipment in manufacturing companies. The ability to accurately track machine operation and predict the possibility of failure before it actually occurs is a significant help for manufacturers to increase OEE (overall equipment effectiveness) and contribute to cost reduction and time wastage. Prediction models are created by leveraging statistical techniques, machine learning (ML), or data mining to extract behavioral patterns [33].

The switch to this type of activity paves the way for new and innovative business models, products, and services. In addition, machine learning allows you to speed up business processes and provide better customer service. Machine learning is recognized as one of the most important application areas in the era of unprecedented technological development, and its adoption is gaining momentum in almost all industries [34]. Machine learning ranges from face recognition to self-driving cars, and from speech recognition to introduction. Machine learning can be thought of as computational techniques for learning probability distributions from data [35]. Machine learning is an algorithm that will transform input data into output. The input data will be used to refine the manufacturing process. Production process with feedback (learning) is shown in Figure 1.

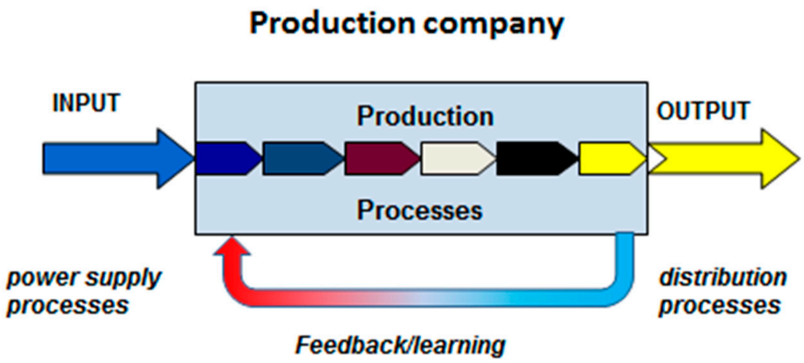

Figure 1. Idea of production processes in a learning organization using machine learning.

In the production process, you must have the ability to anticipate and the ability to reduce operational risk. In business management, managers should have knowledge of the demand for products and should have knowledge of what, when, and how much to produce [36]. Another important issue is the problem of designing a resistant food supply chain that will ensure the continuity of business operations in the event of threats or disruptions [37].

The performance of many machine learning methods is very sensitive to the multitude of design decisions, which is a significant barrier for new users. This is especially true in the dynamically developing field of deep learning, where engineers have to choose the appropriate neural architecture and training procedures [29]. Deep learning is a “deep” neural network that includes many layers of neurons and huge volumes of data. Deep learning allows computers to learn from experience and, thanks to the hierarchy of concepts, it allows you to learn and, based on simpler examples, create more complex concepts [38,39]. Neural networks have the ability to approximate any non-linear mapping with a given accuracy and are also characterized by the ability to generalize the knowledge acquired during the learning of the modeled system [40].

The last decade has seen an explosion in machine learning research and applications, in particular, deep learning methods that have enabled key advances in many application areas such as computer vision, speech processing, and image recognition [29]. Deep learning allows for a completely new approach—it is the transition from feature engineering to automatic representation learning from data. The main assumption and hope in deep learning techniques is that they can lead to predictive systems that generalize well, adapt well, can continuously improve as new data becomes available, and that they are more dynamic than predictive systems built on hard and deterministic business rules [41].

3. Industry 4.0 in Innovative Enterprises

Industry 4.0 allows manufacturers to take their production lines to a higher technological level through complete system integration and networking. Industry 4.0 has decentralized analytics, critical decision making, and increase in response time during productions [42]. Industry 4.0 solutions allow for communication between man and machine, giving wide opportunities to reduce production costs [43]. Industry 4.0 integrates employees and digitally controlled machines with the Internet and information technologies. According to the main assumptions, the materials used in production can always be identified; they also have the ability to constantly communicate with each other. Using machine learning algorithms to design predictive models in the Industry 4.0 environment is very useful [33]. In the new paradigm of Industry 4.0, the most optimal solution is machine learning and deep learning, which uses large datasets for the optimization process and obtains innovative solutions and new insights [44].

The concept of Industry 4.0 is inextricably correlated with, e.g., the Internet of Things, machine to machine (M2M) technology, and machine learning (ML), which allow for constant contact between machines, people, products, and even production materials, as shown in Figure 2.

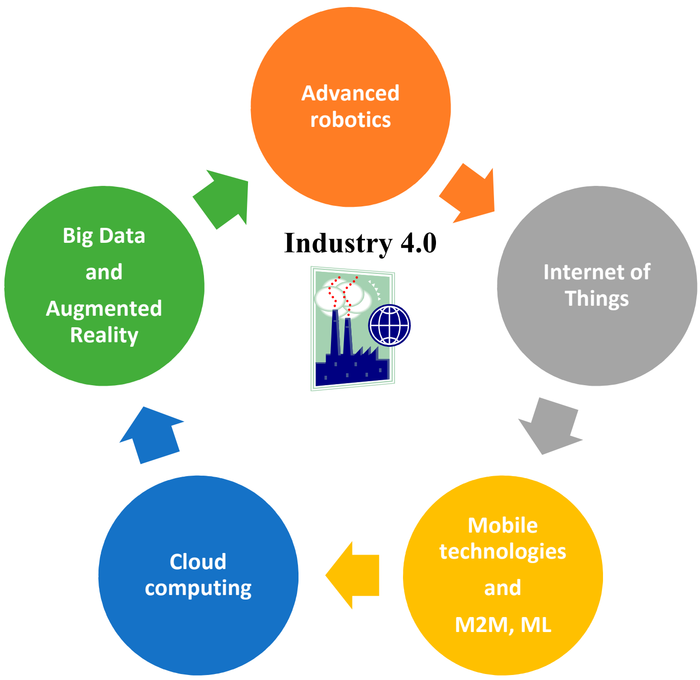

Figure 2. Idea of Industry 4.0.

The implementation of Industry 4.0 in a production company allows them to expand production capabilities, increase efficiency, and shorten the time of breaks and even eliminate them. As digitization continues, production models are changing through the use of intelligent technologies such as robotics, artificial intelligence (AI), Internet of Things (IoT), M2M, machine learning, etc. Artificial intelligence and its techniques and machine learning algorithms give huge possibilities to predict, improve outcomes, and better generalize the dataset [33].

The main purpose of machine-to-machine technology is to use sensor data and send it to the network. The main components of the M2M system include sensors, RFID (radio-frequency identification), Wi-Fi, or cellular link, and process control systems, which are essential for process automation and optimization. Autonomous data processing software programmed in order to assist a network device to interpret data and make decisions can trigger pre-programmed, automated actions [45]. Thanks to the use of these technical solutions, production companies have a real possibility to connect the previously isolated production elements with the rest of the process thanks to systems using radio waves for data transmission and protection against copying of product features. The above-mentioned technologies allow the implementation of digital information in the product, which, during the production process, enables the exchange of data between production machines about the condition of the product and its possible defects without human intervention. The information generated thanks to RFID systems allows for an ongoing description of the state in which the processed object or material is at a given moment. This information can be used at any stage of production. This allows for dynamic and autonomous development of the process during its duration. Data collected in this way allows the process to be designed and improved based on requirements [46].

Companies that have adapted to the Industry 4.0 paradigm are going through a new phase of automation that enables innovative and more efficient processes, products, and services. By using a combination of intelligent devices and machines, and by using self-learning solutions and increasing self-directional capabilities, it will be possible to reduce production costs, while increasing flexibility, quality, and speed of production. The possibilities of mass adaptation to market expectations will also improve [47].

The efficiency of processes is related to the measurement of processes, the determination of the desired value levels for individual process measures, and the assessment of the legitimacy of the implementation of activities in a specific system of processes [6]. Inventory logistics is also important in the food sector. In factories producing food, issues related to logistics 4.0 are considered. A smart factory helps to implement a sustainable production mode to meet global challenges [48]. A company that successfully implements the Industry 4.0 concept can accelerate by increasing the productivity of its production [49]. The ultimate goal is to identify new machine learning patterns in highly digitalized industrial work [47]. When implementing Industry 4.0 solutions, an important role is also played by production line operators who use real-time operational data technology, and they should be involved in the learning process from the perspective of a learning organization [50].

4. Methodology

The research methods used in the conducted research are secondary research (desk research) and research of primary observations and interviews [1,51]. Secondary research consisted of analyzing the collected information. The data necessary for the analysis were information collected on the basis of existing sources, published in reports, journals, and statistical yearbooks. On the other hand, the conducted observations constituted a qualitative research method used to analyze the behavior of enterprises.

The production companies belonging to the energy and food sectors were the exemplary material. Research materials about the energy company PGE were collected as desk research data. Research materials related to the food sector were collected during the observations and surveys. Answers for surveys, which were carried out in a rendering plant producing pork gelatin intended for food and pharmaceutical purposes, were collected from the accounting department and production section.

4.1. Energy Industry—PGE Capital Group

Enterprises in the energy sector face many challenges. On the one hand, there are low-emission trends and sustainable development, and on the other hand, there is the rationality of incurring transformation costs, operational efficiency, i.e., cost discipline and optimization of expenses. Measurement of efficiency becomes an important element in energy companies. Business performance measures should be considered based on the goals that the company intends to achieve in the short and long term.

Industry 4.0 and the external environment force the energy company to constantly adjust its goals, which is associated with increased and continuous measurements [52]. Energy production changes as technology advances. Production technologies as well as measurement technologies and measurement accuracy, including measurements of production efficiency indicators, are changing. Technological progress shows that, apart from production technologies, the management of energy production and transmission is also changing [53,54]. This is the direction in which Polish participants of the heat, power, and energy markets, who are currently facing profound changes and large investments, will follow [52]. Increasing energy efficiency is closely related to the circular economy, the development of renewable energy sources, and the reduction of emissions. In the era of depleting natural resources and progressive urbanization, circular economy is one of the most important directions of sustainable development. In the energy sector, it is also important to use products resulting from combustion. Combustion by-products are a valuable raw material widely used in various industries, including the most common in the construction (building) sector.

An example of an enterprise in the energy sector is the PGE Capital Group, which operates in the areas of central and eastern Poland. PGE has 5.33 million recipients and produces 58.32 TWh of energy [55], which accounts for 36.7% of the total electricity production in Poland in 2019 (158.76 TWh) [56]. The PGE Group plans to reduce the negative impact on the natural environment and achieve climate neutrality by 2050. PGE wants to realize these plans by integrating sustainable strategies assumed at the level of extraction, production, distribution, and sales departments. Moreover, PGE will continue developing distributed generation (DG) and will provide active support for distributed generation as well as storage service for distributed sources [57]. The reduction of the emissivity of generation will take place by changing the technology, expanding the RES portfolio, enabling PGE customers to participate in the transformation, and engaging in activities for the circular economy.

Due to increasing social pressure on environmental issues, stricter regulations, and a higher level of competition, the company takes environmental aspects into account in its strategic plans and is gradually shifting towards a circular economy. The circular economy (CE) will significantly contribute to achieving climate neutrality in the future [58,59].

All of the above-mentioned elements will require the implementation of new activities at PGE and reorganization of processes based on Industry 4.0 technology, supported by the idea of a learning organization. At PGE, core business is divided into mining (extraction), manufacturing, distribution, and sales. As part of these specified activities, it is possible to improve, modernize processes, and implement innovative solutions combined with elements of Industry 4.0 in order to achieve the assumed strategic plans.

4.1.1. Mining

Two elements can be distinguished within the mining activity: optimization of extraction and processing of the raw material, in which elements of Industry 4.0 are used.

Optimization of the mining process includes, among others, more accurate methods of resource identification, tools for numerical modeling of components of newly established opencast mines, diagnostic systems limiting the failure rate of machines and devices, and reducing the energy consumption of devices and subsystems.

Raw material treatment is a new method of improving the calorific value of the raw material, maintaining the assumed parameters for power units in real time, and monitoring the content of sulfur, ash, and humidity. Monitoring the sulfur content is important as the combustion of fossil fuels pollutes the environment and contributes to its systematic degradation. Coal, which contains a lot of sulfur, burns and releases it into the atmosphere as sulfur dioxide. SO_2 acidifies the environment and is responsible for acid rain that damages forests.

Coal ash includes a number of by-products produced from burning coal. The structure and composition of ashes depends mainly on the type of coal burned and the combustion temperature in power boilers. After combustion, the ashes contain potassium dioxide (K_2O) and silica (SiO_2). The ashes also contain chlorine (Cl), calcium (CaO), and magnesium (MgO). In order to assess the quality of the burned coal, it is also necessary to know the content of chlorine (Cl) and sulfur (S). A large amount of these elements causes corrosion and contamination of boilers, pipes, feed lines, and an increase in SOx, Cl_2, and HCl emissions. Chemical composition of ash from burning Polish brown coal coming from different mines is as follows (expressed as percent by weight): SiO_2 (33.47–51.20); Al_2O_3 (6.37–30.26); Fe_2O_3 (4.83–5.93); CaO (20.00–31.18); MgO (1.27–1.84); SO_2 (0.40–8.01); K_2O (0.11–2.64); Na_2O (0.15–1.05) [60].

4.1.2. Production

Manufacturing is another group. As part of the production, we can distinguish activities related to CO_2 and other harmful greenhouse gases.

Carbon dioxide utilization: CO_2 capture and storage technologies, CO_2 absorption process modeling, post-combustion separation methods. Reduction of NOx, SOx, Hg emissions etc. Methods of exhaust gas dedusting, emission reduction technologies (adsorption, absorption, catalytic). Energy companies have invested in flue gas desulphurization installations that ensure effective desulphurization of all fumes emitted during the operation of the power plant. Installations are made using the wet lime method. In addition to SO_2, the absorber additionally removes impurities such as hydrogen chloride, hydrogen fluoride, mercury, and ash. Another negative effect is the formation of nitrogen oxides as a result of coal burning too quickly at high temperatures. Nitrogen oxides, called NOx, are emitted into the atmosphere by power plants and combined heat and power plants (CHP). In order to reduce emissions of nitrogen oxides into the atmosphere, in line with the applicable standards, CHP plants are successfully developing the system of catalytic denitrification of selective catalytic reduction (SCR). The method consists in reducing nitrogen oxides to atmospheric nitrogen with a substance containing ammonia. The reaction takes place at the surface of the catalyst. The processing of by-products of combustion contributes to the creation of a waste-free industry. It also reduces the consumption of natural resources and reduces the amount of landfilled waste. The use of secondary raw materials such as combustion by-products gives a favorable CO_2 balance and reduces the degradation of the natural environment.

Improvement of production efficiency: predictive modeling and analysis of technical condition of devices, improvement of flexibility of the press of coal units. Fuel gasification: ground gasification technologies. Microcogeneration: cogeneration/diffuse trigeneration, improving production efficiency in combination.

4.1.3. Distribution

The third important activity in the enterprise is distribution. As part of distribution, Industry 4.0 can be used in the field of energy transmission, measurement, and storage.

Smart grid: optimization of transmission capacity, new methods of grid management, integration of RES with the distribution grid, use of data from balancing meters (advanced metering infrastructure—AMI) for grid monitoring.

Smart meters: DSR (demand side response) executive mechanisms, modern methods of reducing energy losses. The progressing digitization in energy enterprises will affect the optimization of the operation of the power grid (smart grid, smart metering) and will increase the possibilities of actively using the resources connected to the distribution grid.

The prosumer will not only generate electricity but will also become a participant in the energy market.

Energy storage: increasing the efficiency of energy storage, integrating storage facilities with renewable energy installations, increasing storage capacity, and service life. Work on energy storage technology has a key role to play in the transition to a carbon neutral economy in the future [54]. The energy storage system makes it possible to balance energy supply and demand.

4.1.4. Sale

The fourth element in an energy company is sales. As part of sales, the key is to know the customer and cooperate with him.

Customer information management: estimating customer value, grouping customers according to common features, prediction of customer behavior, customer migration management.

Smart facility: customer control of power consumption devices, planning and management of energy consumption, integration of the prosumer infrastructure with the distribution network.

E-mobility: integrating solutions for vehicles in individual and public transport, optimization of vehicle charging locations (including logistics).

Demand management: tools and functioning of ICT (information and communication technologies) used to aggregate the DSR (demand side response) potential of recipients.

The demand side in the energy sector are energy consumers who, in exchange for adequate remuneration, are able to voluntarily and temporarily reduce electricity consumption or postpone it. Therefore, it is worth encouraging consumers to introduce flexibility in the use of electricity. This is especially true for customers with inertial processes that are independent of the time of day/night, e.g., washing, cleaning, etc. These customers can shift periods of high consumption to periods of low electricity cost without disrupting their operations. Consumers shift their demand from daytime/nighttime from high to lower prices as part of continuous optimization [54]. The assumption of the smart grid system is the active participation of the end users of the power system in the market game and the possibility of controlled individual generation and storage of energy. The role of such a client changes into active participation consisting of both consumption and generation of energy. Energy consumption management will be important not only for retail customers, but also for manufacturing companies [61].

4.2. Food Industry—Gelatine Company

The term food industry refers to companies that produce, process, manufacture, sell, and serve food, drinks, and dietary supplements [62]. The food industry has recently faced rapid and continual change due to the current industrial revolution. Food is increasingly being produced efficiently and sustainably without harming the environment. Technological development has enabled the production of products with an ever higher level of added value and the high level of competition in the sector has resulted in higher performance requirements at the production stage. The use of innovative technological solutions that ensure a higher level of production or services [63] has a positive impact on the company and its environment [54]. In addition, modern technologies used in the enterprise are complex—apart from the production technology, they include a number of necessary peripheral installations, e.g., for environmental protection, such as modern sewage treatment plants or biofilters for odor treatment. The increase in processing capacity in a food enterprise reduces the energy consumption of the plant and at the same time increases the efficiency of production in the examined plant [9]. The implementation of new construction elements in the production process is based on mechanical engineering. Strength calculations allow you to increase efficiency, e.g., multi-stage pumps and complete systems that dose with the highest precision, even with back pressures of 20 to 50 bar. Mechanical calculations of the structure are also performed for pipelines in order to optimize the conditions or the mechanisms grinding meat waste are investigated [64,65]

The research was started in 2019 and finished in 2020 in the gelatin plant employing 144 people, including 120 production workers. The volume of all rooms was 32,350 m^3, including 21,456 m^3 of production rooms. In the factory, two types of processes in order to produce two types of gelatin are used. Type A gelatin is produced by acid processing of collagenous raw material; type B gelatin is produced by alkaline or lime processing. Mostly, type A gelatin is made from pork bones. The process includes macerating of bones and washing to remove extraneous matter and phosphorus, for four days in 5% solution of hydrochloric acid. The four to five extractions are made at temperatures increasing for 55–65 °C for the first extract to 95–100 °C for the last extract. Each extraction lasts about 4–8 h. Concentration to 20–40% solids is carried out, in several stages by continuous vacuum evaporation. The viscous solution is chilled, extruded into thin "noodles" (strips of gelatin), and dried at 30–60 °C on a continuous belt. Drying is completed by passing the strips through zones of successive temperature changes wherein conditioned air blows across the surface and through the gelatin strips mass. The dry gelatin is then ground and blended to specification. The process of gelatin production type A is presented in Figure 3.

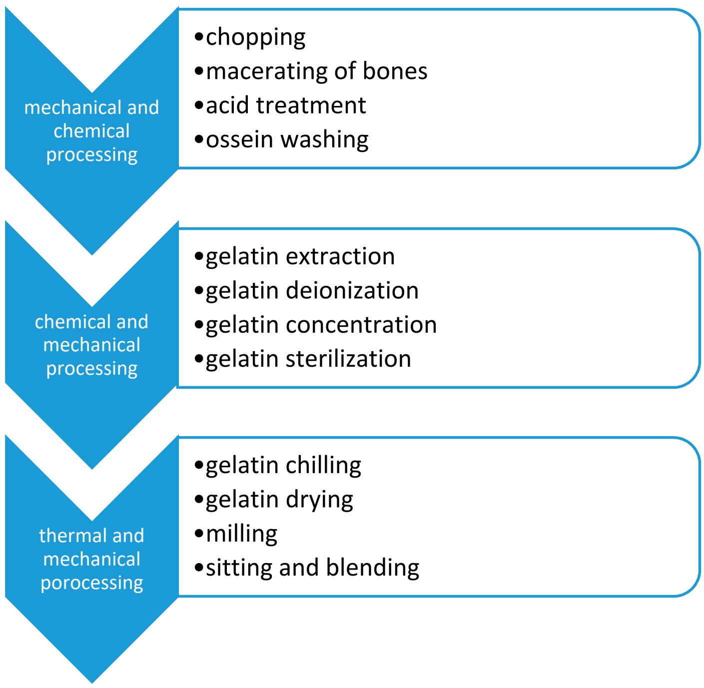

Figure 3. Process of gelatin production type A from porcine bones.

The conducted research shows that different amounts of energy and water are required in the production of type A and type B gelatins. The lowest consumption was in the production of type A pork gelatin using the acid method. The production of 1 kg of gelatin required 20–25 kg of steam, 3–5 kW·h of electricity, and approximately 150 dm^3 of water. The research was carried out as observation and survey investigation, on-site in this factory producing edible gelatin, and shows that the unit consumption of electricity and real water vapor was significantly lower than the available literature data by about 50–60%. Increased technological progress and the application of energy-saving production technology and apparatuses at individual stages of the transformation of energy carriers contributed to the reduced unit energy consumption. The company has the ISO 22000 certificate which indicates that a food safety management system is in place. This ensures customer confidence in the product and it is becoming increasingly important as customers demand safe food. For the discussed company producing pork gelatin, the next step in their development may be the production of gelatin based on fish or poultry waste and the implementation of modular production lines. Thanks to this, the company will be able to acquire new customers and enter new markets where pork gelatin is not widespread or is not allowed for cultural and religious reasons [66,67]. The larger a company's product portfolio, the greater the diversity, volume, complexity, or variety of national and international regulations that need to be met, the more digitization and Industry 4.0 technologies will be needed in creating a digital enterprise.

Industry 4.0 is a paradigm which mobilizes enterprises to use state-of-the-art technology, to be smarter in line with the world of Industry 4.0, to become a "smart factory". The technology used in the frame of Industry 4.0 will address issues such as food safety, security, control, instability, competitive pressure, and demand forecasting [68]. Industry 4.0 is driving profound changes in the overall dynamics of the industry. The "new industry" has become sensitive to the use of application tools such as the Internet, cloud computing, and augmented virtual reality [43]. The concept of augmented reality is shown on Figure 4.

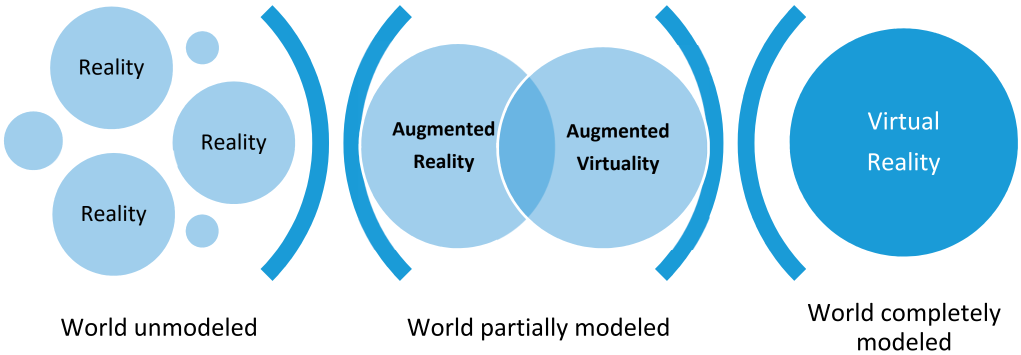

Figure 4. Augmented reality as a combination of virtual reality and the real world. Source: own elaboration based on [69].

New technologies are improving many areas in the food sector. An example is augmented reality (AR)—thanks to special digital glasses or tablets, the machine operator can see much more. The glasses show him production data and KPIs (key performance indicators) in real time. AR glasses are useful, for example, for cleanliness control in food production plants. The screen displays information on what needs special attention and where the critical points for the entire process are. As a result, the control is more efficient and all food products are much safer. AR is used by employees of the maintenance department, which allows to improve the performance of daily service duties and supports repairs. AR solutions provide visual guidance on where problems are and how to fix them when needed. This helps to reduce downtime and thus increase the overall equipment effectiveness (OEE) for the machine.

The introduction of these cutting edge business models requires new professional skills from the workforce in the food industry. A proactive industry-wide strategy has been put in place in the food sector to properly implement an effective digital transformation in the sector. To this end, the present and future key skills and competences required by each of the occupational profiles related to the food industry have been defined. In order to achieve higher employee competences and match skills with professional requirements, better-oriented lifelong learning programs [70] have been introduced. A learning organization whose organizational leadership is properly implemented contributes to the added value when leaders are able to constructively cooperate with each other and with their employees [71]. Effective leadership deals with issues of sustainable development and positively influences the learning of the organization and the generated results [72].

In the food sector, these benefits include technological development and economic dynamism, production flexibility, and reconfiguration. In addition, the implementation of Industry 4.0 increases the productivity and efficiency of resources in the entire process and radically traces the entire production process

Global economic development and changes in the functioning of products intended for processing, dynamic changes in the approach to process management, as well as a variety of differentiated products, increased customer service requirements, and shortening the product life cycle perform the functions of managing the efficiency of the flow of ingredients, finished products, and information [73]. Moreover, making AR tools available to the consumers themselves is becoming more and more popular. Thanks to this, the availability of knowledge takes completely new forms. Thanks to special applications, customers can find out everything about the selected products. They get to know their composition and nutritional values, and receive a lot of additional information about the manufacturer. Consumers are able to consciously choose the optimal food products for them.

5. Discussion and Conclusions

Due to the requirements of the market economy, the effectiveness of economic activity is determined by the rationality of decisions made, not only at the strategic and tactical level, but also at the operational level. In production companies, the efficiency of production planning and control determines the level of organization of production processes, which results in rational use of available resources. High consumption rates of raw materials and large amounts of waste products prove that the technological production process is underdeveloped [9]. Managing a production company requires computer support both for production preparation, supervision over its implementation, and auxiliary activities. The wave of transformation in the energy sectors is noticeable in most enterprises. The new, alternative models of energy market are implemented. Distributed generation (DG), also known as on-site generation, is the decentralized generation of electricity. In distributed power generation, electricity production is usually based on renewable or unconventional energy sources, often in combination with heat generation (distributed cogeneration). In terms of increasing energy efficiency in the power industry, innovative projects are implemented to increase the efficiency of electricity generation. An additional goal is to reduce the network loss ratio in transmission and distribution, including modernization of the existing networks and construction of new ones, replacement of low-efficiency transformers, and development of distributed generation, as well as increased energy end-use efficiency. Improving energy efficiency will also be a tool contributing to the reduction of greenhouse gas emissions [74].

The development of RES (water, wind, sun, and biomass, e.g., bamboo) and related technologies also leads to improvements in other sectors (e.g., the food sector). By investing in the development of high-tech technologies in the field of energy, companies are moving towards a circular economy with zero emissions and focus on the potential of electromobility [9,75,76]. The profound decarbonization efforts required to achieve climate neutrality imply a fundamental transformation at all stages regarding the energy company.

In the field of renewable energy sources, it is important to flexibly adjust the supply to the market needs and thus supplement the shortages of electricity. With the development of photovoltaics and wind energy, both of which are characterized by high fluctuation in production, energy storage is a key issue. Electricity storage is the key to solving the problem of using renewable energy sources. As wind, water, and sun only generate electricity when weather conditions (variable and unpredictable) allow, they must be integrated into an efficient energy storage system. Energy management is one of the main pillars of Industry 4.0. Similar results of the research were presented by Lang, who called the new stage of energy development "Energy 4.0". The energy industry is becoming one big and highly complex cyber-physical system composed of physical entities and controlled or monitored by computer-based algorithms [77]. The company's motivation in this respect comes from the combination of environmental aspects, cost pressure, European Union (EU) and national regulations, as well as proactivity in the field of energy efficiency. Moreover, the integration of different energy generation sources in an increasingly demanding and fragmented market will require technology that guarantees quality, sustainability, and efficiency [78]. Modern energy management systems will use a large amount of data collected by different types of meters, in different places, and these large amounts of data will also be constantly analyzed and decisions will be made on that basis [79]. Innovations for energy management and smart metering were also mentioned by Weiß and Goosen [80,81]. The use of sensors and automation systems for production management, monitoring and automation, machine learning, and Industry 4.0 will become the norm in the near future in most manufacturing companies to prepare the product for the next million new consumers who will expect further personalization of products while maintaining their high quality and attractive purchase costs. Novel methods are recommended for various products. Thanks to this, it is possible to look for and process new raw materials, if their processing has so far been considered impossible or economically unprofitable [82]. The situation in the entire food industry will change dynamically, and companies will follow these changes—producers will react quickly to new trends characterized by frequent changes in customers' eating habits, modern tools and eco-friendly farming methods [83], fashion for healthy food, or increasingly globalized supply chains.

Therefore, companies need modular production lines, the use of flexible processes and integration with high tech systems to create digital enterprises. Its main goal is to achieve the highest possible productivity with the possibility of personalization of mass production. Digital enterprise includes design using virtual reality, and integrated solutions for production automation and robotization. Realistic non-player controlled characters (NPCs) are essential for a virtual environment and are making the virtual world more real for users [84]. Realistic non-player characters are an important component of virtual environments. Dynamic NPC behavior supports work in enterprises in order to feel virtual reality (VR) as the realistic systems [85]. It can be useful not only in VR games, but also in companies, to prepare the movement path of real products in production process. Path-planning techniques based on machine learning are continuously used by enterprises. Companies are working and study a navigation mesh generation technique that more accurately controls the movement of NPCs by reflecting various physical properties such as sound, speed, and viewpoint [86].

6. Limitation and Recommendation

The theory was presented extensively, while research was limited to two interrelated key sectors of the economy. Many papers concerning the Industry 4.0 are expanding rapidly, and everyday new papers are published, but based on the review of the literature in the field of the food and energy industry, it can be seen that Industry 4.0 in both of these sectors is not yet discussed in depth and detail. Therefore, it is worth scientifically reflecting on these issues of the food and energy industry and continuing this kind of research.

In the next step, research can be carried out among the above-mentioned sectors as well as other industries, e.g., construction or finance, to investigate the importance of Industry 4.0 for the development of various sectors of the economy. The construction (building) sector is responsible for a high level of final energy consumption, while the financial sector is a pivotal one for the development of all economy and industry companies. Along with the development of technology, new generation production systems force a deep modification of the organizational behavior and the very core of production control systems. Steering systems emphasize the cooperation of autonomous and connected entities in the decision-making process. In the near future, it would be valuable for research development to move towards the holonic architectures needed to obtain full support for Industry 4.0.

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References

1. Borowski, P.F. New technologies and innovative solutions in the development strategies of energy enterprises. *HighTech Innov. J.* **2020**, *1*, 39–58. [CrossRef]
2. Patalas-Maliszewska, J.; Łosyk, H. An approach to assessing sustainability in the development of a manufacturing company. *Sustainability* **2020**, *12*, 8787. [CrossRef]
3. Freeman, C.; Soete, L. *Economics of Industrial Innovation*; MIT Press: Cambridge, MA, USA, 1997.
4. Borowski, P.F. Adaptation strategy on regulated markets of power companies in Poland. *Energy Environ.* **2018**, *30*, 3–26. [CrossRef]
5. Fraś, J.; Czyrka, K. Instruments for shaping the quality of production processes in the conditions of coopetition of enterprises. In *Advances in Intelligent Systems and Computing*; Springer: Cham, Switzerland, 2020; Volume 1216, pp. 235–244.
6. Cyfert, S. *System Granic Architektury Procesów Organizacji—Determinanty Kształtowania i Dysfunkcji w Definiowaniu [The System of Organizational Process Architecture Boundaries—Determinants of Shaping and Dysfunction in Defining]*; Wroclaw University of Economics: Wroclaw, Poland, 2014; Volume 340, pp. 243–250.
7. Ivanov, D. An adaptive framework for aligning (re)planning decisions on supply chain strategy, design, tactics, and operations. *Int. J. Prod. Res.* **2010**, *48*, 3999–4017. [CrossRef]
8. Borowski, P.F. Nexus between water, energy, food and climate change as challenges facing the modern global, European and Polish economy. *AIMS Geosci.* **2020**, *6*, 397–421. [CrossRef]
9. Wojdalski, J.; Krajnik, M.; Borowski, P.; Dróżdż, B.; Kupczyk, A. Energy and water efficiency in the gelatine production plant. *AIMS Geosci.* **2020**, *6*, 491–503. [CrossRef]
10. Hoe, S.L. The topicality of the learning organization: Is the concept still relevant today? In *The Oxford Handbook of the Learning Organization*; Oxford University Press: Oxford, UK, 2019; pp. 18–32.
11. Pan, T.; Hu, T.; Geng, J. View learning organization in a situational perspective. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *440*, 022026. [CrossRef]
12. Jensen, P.E. A contextual theory of learning and the learning organization. *Knowl. Process. Manag.* **2005**, *12*, 53–64. [CrossRef]
13. Borowski, P.; Kujawski, B. Adaptacyjność przedsiębiorstw sektora energetycznego. *Przegląd Organ.* **2012**, *8*, 24–27. [CrossRef]
14. Molavi, N. Powering Up the Energy, Utilities and Resources Workforce: Upskilling Initiatives Can Help Companies Address the Skills Gap, PwC. 2019. Available online: https://www.pwc.com/gx/en/industries/energy-utilities-resources/publications/powering-up-the-energy--utilities-and-resources-workforce.html (accessed on 6 January 2021).
15. Chang, S.; Lee, M. A study on relationship among leadership, organizational culture, the operation of learning organization and employees' job satisfaction. *Learn. Organ.* **2007**, *14*, 155–185. [CrossRef]
16. Örtenblad, A.R. *Background and Introduction*; Oxford University Press: Oxford, UK, 2019; pp. 2–18.
17. Warren, W. What Are Learning Organizations, and What Do They Really Do? Available online: https://www.chieflearningofficer.com/2017/02/22/37471/ (accessed on 6 January 2021).
18. Bui, H.T.M. On definitions of the learning organization: Toward a new definition of learning organization. In *The Oxford Handbook of the Learning Organization*; Oxford University Press: Oxford, UK, 2019; pp. 136–148.
19. Garvin, D.A. Building a learning organization. *Harv. Bus. Rev.* **1993**, *71*, 73–91.
20. Tsang, E.W. Organizational learning and the learning organization: A dichotomy between descriptive and prescriptive research. *Hum. Relat.* **1997**, *50*, 73–89. [CrossRef]
21. Reese, S. Taking the learning organization mainstream and beyond the organizational level. *Learn. Organ.* **2020**, *27*, 6–16. [CrossRef]
22. Senge, P. *The Fifth Discipline: The Art and Practice of the Learning Organization*; Doubleday: New York, NY, USA, 1990.
23. International Atomic Energy Agency. *Reload Design and Core Management in Operating Nuclear Power Plants*; IAEA-TECDOC-1898; IAEA: Vienna, Austria, 2020.
24. Koistinen, P. Toward learning organization—Practices in nuclear power plants. In *Human Factors in the Nuclear Industry*; Elsevier BV: Amsterdam, The Netherlands, 2021; pp. 239–247.
25. Whitsett, D.A.; Yorks, L. Looking back at Topeka: General foods and the quality-of-work-life experiment. *Calif. Manag. Rev.* **1983**, *25*, 93–109. [CrossRef]
26. Walton, R.E. Work innovations at Topeka: After six years. *J. Appl. Behav. Sci.* **1977**, *13*, 422–433. [CrossRef]
27. Tortorella, G.L.; Vergara, A.M.C.; Garza-Reyes, J.A.; Sawhney, R. Organizational learning paths based upon Industry 4.0 adoption: An empirical study with Brazilian manufacturers. *Int. J. Prod. Econ.* **2020**, *219*, 284–294. [CrossRef]
28. Czym Jest Uczenie Maszynowe (Machine Learning)? Available online: https://www.sap.com/poland/insights/what-is-machine-learning.html (accessed on 6 January 2021).
29. Hutter, F.; Kotthoff, L.; Vanschoren, J. *Automated Machine Learning: Methods, Systems, Challenges*; Springer: Cham, Switzerland, 2019; p. 219.
30. General Date Protection Regulation—GDPR. Available online: https://gdpr-info.eu/ (accessed on 6 January 2021).

31. Adamczyk, M. Etyczne Przetwarzanie Danych w Systemach Sztucznej Inteligencji [Ethical Data Processing in Artificial Intelligence Systems]. Available online: https://gdpr.pl/etyczne-przetwarzanie-danych-w-systemach-sztucznej-inteligencji (accessed on 6 January 2021).
32. Piano, S.L. Ethical principles in machine learning and artificial intelligence: Cases from the field and possible ways forward. *Humanit. Soc. Sci. Commun.* **2020**, *7*. [CrossRef]
33. Candanedo, I.S.; Nieves, E.H.; González, S.R.; Martín, M.T.S.; Briones, A.G. Machine learning predictive model for Industry 4.0. In *Proceedings of the KMO: International Conference on Knowledge Management in Organizations, Zilina, Slovakia, 6–10 August 2018*; Springer International Publishing: Cham, Switzerland, 2018; pp. 501–510.
34. Lee, I.; Shin, Y.J. Machine learning for enterprises: Applications, algorithm selection, and challenges. *Bus. Horiz.* **2020**, *63*, 157–170. [CrossRef]
35. Cavalcante, A.B. Interpretability of machine learning models: Application for lawsuits prediction in the energy sector. In Proceedings of the 2020 International Conference on Systems, Signals and Image Processing (IWSSIP), Niterói, Brazil, 1–3 July 2020.
36. Alpaydin, E. *Introduction to Machine Learning*; MIT Press: Cambridge, MA, USA, 2020.
37. Bottani, E.; Murino, T.; Schiavo, M.; Akkerman, R. Resilient food supply chain design: Modelling framework and metaheuristic solution approach. *Comput. Ind. Eng.* **2019**, *135*, 177–198. [CrossRef]
38. Tarafdar, M.; Beath, C.M.; Ross, J.W. Enterprise cognitive computing applications: Opportunities and challenges. *IT Prof.* **2017**, *19*, 21–27. [CrossRef]
39. Goodfellow, I.; Bengio, Y.; Courville, A.; Bengio, Y. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016; Volume 1.
40. Trajer, J. Sztuczne sieci neuronowe w modelowaniu procesów z ograniczonym zbiorem danych w inżynierii rolniczej [Artificial neural networks in modeling processes with a limited set of data in agricultural engineering]. *Inżynieria Rol.* **2005**, *9*, 173–180.
41. SAS. Deep Learning, What It Is and Why It Matters. Available online: https://www.sas.com/pl_pl/insights/analytics/deep-learning.html#deepused (accessed on 6 January 2021).
42. Kanagachidambaresan, G.R.; Anand, R.; Balasubramanian, E.; Mahima, V. *Internet of Things for Industry 4.0*; Springer: Cham, Switzerland, 2020.
43. Di Nardo, M. Developing a conceptual framework model of Industry 4.0 for industrial management. *Ind. Eng. Manag. Syst.* **2020**, *19*, 551–560. [CrossRef]
44. Suresh, A.; Udendhran, R.; Balamurugan, M. Integrating IoT and machine learning—The driving force of Industry 4.0. In *Internet of Things for Industry 4.0.*; Springer: Cham, Switzerland, 2019; pp. 219–235.
45. Navarra, A.; Wilson, R.; Parra, R.; Toro, N.; Ross, A.; Nave, J.-C.; Mackey, P.J. Quantitative methods to support data acquisition modernization within copper smelters. *Processes* **2020**, *8*, 1478. [CrossRef]
46. Elbasani, E.; Siriporn, P.; Choi, J.S. A Survey on RFID in Industry 4.0. In *Internet of Things for Industry 4.0.*; Springer: Cham, Switzerland, 2020; pp. 1–16.
47. Ansari, F.; Erol, S.; Sihn, W. Rethinking human-machine learning in Industry 4.0: How does the paradigm shift treat the role of human learning? *Procedia Manuf.* **2018**, *23*, 117–122. [CrossRef]
48. Di Nardo, M.; Clericuzio, M.; Murino, T.; Sepe, C. An economic order quantity stochastic dynamic optimization model in a logistic 4.0 environment. *Sustainability* **2020**, *12*, 4075. [CrossRef]
49. Szum, K.; Nazarko, J. Exploring the determinants of Industry 4.0 development using an extended SWOT analysis: A regional study. *Energies* **2020**, *13*, 5972. [CrossRef]
50. Saabye, H.; Kristensen, T.B.; Wæhrens, B.V. Real-time data utilization barriers to improving production performance: An in-depth case study linking lean management and Industry 4.0 from a learning organization perspective. *Sustainability* **2020**, *12*, 8757. [CrossRef]
51. Baran, M.L. (Ed.) *Mixed Methods Research for Improved Scientific Study*; IGI Global: Hershey, PE, USA, 2016.
52. Kinelski, G. The main factors of successful project management in the aspect of energy enterprises' efficiency in the digital economy environment. *Polityka Energetyczna—Energy Policy J.* **2020**, *23*, 5–20. [CrossRef]
53. Zamasz, K. *Economic Efficiency of a Power Company after the Implementation of the Capacity Market*; Wydawnictwo Naukowe PWN: Warsaw, Poland, 2019; p. 29.
54. Borowski, P.F. Zonal and nodal models of energy market in European Union. *Energies* **2020**, *13*, 4182. [CrossRef]
55. PGE Raport. Kim Jesteśmy. Available online: https://www.gkpge.pl/Relacje-inwestorskie/Grupa (accessed on 6 January 2021).
56. Wysokie Napięcie [High Voltage]. Available online: https://wysokienapiecie.pl/27524-energetyka-w-polsce-w-2019-roku-moc-produkcja-energii-wg-danych-pse/ (accessed on 6 January 2021).
57. Strategia Grupy PGE do 2030 Roku [PGE Group's Strategy until 2030]. Available online: https://www.teraz-srodowisko.pl/media/pdf/aktualnosci/9375-strategia-pge-2030.pdf (accessed on 6 January 2021).
58. Borowski, P.F. Bamboo as an innovative material for many branches of world industry. *Ann. Wars. Univ. Life Sci. SGGW. For. Wood Technol.* **2019**, *107*, 13–18. [CrossRef]
59. Maranesi, C.; De Giovanni, P. Modern circular economy: Corporate strategy, supply chain, and industrial symbiosis. *Sustainability* **2020**, *12*, 9383. [CrossRef]
60. Uliasz-Bochenczyk, A.; Mokrzycki, E. Fly ashes from Polish power plants and combined heat and power plants and conditions of their application for carbon dioxide utilization. *Chem. Eng. Res. Des.* **2006**, *84*, 837–842. [CrossRef]

61. Wojdalski, J.; Grochowicz, J.; Dróżdż, B.; Bartoszewska, K.; Zdanowska, P.; Kupczyk, A.; Ekielski, A.; Florczak, I.; Hasny, A.; Wójcik, G. Energy efficiency of a confectionery plant—Case study. *J. Food Eng.* **2015**, *146*, 182–191. [CrossRef]
62. Luque, A.; Peralta, M.E.; Heras, A.D.L.; Córdoba, A. State of the Industry 4.0 in the Andalusian food sector. *Procedia Manuf.* **2017**, *13*, 1199–1205. [CrossRef]
63. Giacone, E.; Mancò, S. Energy efficiency measurement in industrial processes. *Energy* **2012**, *38*, 331–345. [CrossRef]
64. Wojdalski, J. (Ed.) *Użytkowanie Maszyn i Aparatury w Przetwórstwie Rolno-Spożywczym: Wybrane Zagadnienia [The Use of Machines and Apparatus in Agri-Food Processing: Selected Issues]*; Wydawnictwo SGGW: Warsaw, Poland, 2010.
65. Xiong, J.; Zhang, T.; Shi, S. Machine learning of mechanical properties of steels. *Sci. China Ser. E Technol. Sci.* **2020**, *63*, 1247–1255. [CrossRef]
66. Karim, A.; Bhat, R. Fish gelatin: Properties, challenges, and prospects as an alternative to mammalian gelatins. *Food Hydrocoll.* **2009**, *23*, 564. [CrossRef]
67. Abedinia, A.; Nafchi, A.M.; Sharifi, M.; Ghalambor, P.; Oladzadabbasabadi, N.; Ariffin, F.; Huda, N. Poultry gelatin: Characteristics, developments, challenges, and future outlooks as a sustainable alternative for mammalian gelatin. *Trends Food Sci. Technol.* **2020**, *104*, 14–26. [CrossRef]
68. Ojo, O.O.; Shah, S.; Coutroubis, A.; Jimenez, M.T.; Ocana, Y.M. Potential impact of Industry 4.0 in sustainable food supply chain environment. In Proceedings of the 2018 IEEE International Conference on Technology Management, Operations and Decisions (ICTMOD), Marrakech, Morocco, 21–23 November 2018; pp. 172–177.
69. Industry 4.0. Rzeczywistość Rozszerzona w Przemyśle. Available online: https://przemysl-40.pl/index.php/2017/05/23/rzeczywistosc-rozszerzona-w-przemysle (accessed on 6 January 2021).
70. Akyazi, T.; Goti, A.; Oyarbide, A.; Alberdi, E.; Bayon, F. A guide for the food industry to meet the future skills requirements emerging with Industry 4.0. *Foods* **2020**, *9*, 492. [CrossRef]
71. Mastio, E.; Chew, E.; Dovey, K.A. The learning organization as a context for value co-creation. *Learn. Organ.* **2019**, *27*, 291–303. [CrossRef]
72. Iqbal, Q.; Ahmad, N.H. Sustainable development: The colors of sustainable leadership in learning organization. *Sustain. Dev.* **2021**, *29*, 108–119. [CrossRef]
73. Bełch, P.; Bełch, P. Controlling of logistics in production enterprises with separated processes of logistics in the context of empirical research. *Pr. Nauk. Uniw. Ekon. Wrocławiu* **2020**, *64*, 131–140. [CrossRef]
74. Borowski, P.F. Development strategies for electric utilities. *Acta Energetica* **2016**, *4*, 16–21. [CrossRef]
75. Kupczyk, A.; Mączyńska-Sęczek, J.; Golisz, E.; Borowski, P.F. Renewable energy sources in transport on the example of methyl esters and bioethanol. *Processes* **2020**, *8*, 1610. [CrossRef]
76. Borowski, P.F. Innovation strategy on the example of companies using bamboo. *J. Innov. Entrep.* **2021**, *10*, 3. [CrossRef] [PubMed]
77. Lang, M. *From Industry 4.0 to Energy 4.0. Future Business, Models and Legal Relations*; Digitalisierung in der Energiewirtschaft XX; Jahrestagung Institut für Berg-und Energierecht: Bochum, Germany, 2016.
78. Lan, T.; Jermsittiparsert, K.; T. Alrashood, S.; Rezaei, M.; Al-Ghussain, L.; A. Mohamed, M. An Advanced Machine Learning Based Energy Management of Renewable Microgrids Considering Hybrid Electric Vehicles' Charging Demand. *Energies* **2021**, *14*, 569. [CrossRef]
79. Kościelniak, H.; Puto, A. BIG DATA in Decision Making Processes of Enterprises. *Procedia Comput. Sci.* **2015**, *65*, 1052–1058. [CrossRef]
80. Weiß, P.; Kölmel, B.; Bulander, R. *Digital Service Innovation and Smart Technologies: Developing Digital Strategies Based on Industry 4.0 and Product Service Systems for the Renewal Energy Sector*; University of Naples "Federico II": Napoli, Italy, 2016; pp. 274–291.
81. Goosen, E.; Nikitenko, S.; Kagan, E.; Pakhomova, E. Toward Industry 4.0 in energy sector. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *865*, 012020. [CrossRef]
82. Żelaziński, T.; Ekielski, A.; Siwek, A.; Dardziński, L. Characterisation of corn extrudates with the addition of brewers' spent grain as a raw material for the production of functional batters. *Acta Sci. Pol. Technol. Aliment.* **2017**, *16*, 247–254.
83. Patuk, I.; Borowski, P.F. Computer aided engineering design in the development of agricultural implements: A case study for a DPFA. *J. Phys. Conf. Ser.* **2020**, *1679*, 052005. [CrossRef]
84. McClure, G.; Chang, M.; Lin, F. MAS Controlled NPCs in 3D virtual learning environment. In Proceedings of the 2013 International Conference on Signal-Image Technology & Internet-Based Systems, Kyoto, Japan, 2–5 December 2013; pp. 1026–1033.
85. Xi, M.; Smith, S.P. Supporting path switching for non-player characters in a virtual environment. In Proceedings of the 2016 IEEE Virtual Reality (VR), Greenville, SC, USA, 19–23 March 2016; pp. 315–316. [CrossRef]
86. Kim, J.-H.; Lee, J.; Kim, S.-J. Navigating non-playable characters based on user trajectories with accumulation map and path similarity. *Symmetry* **2020**, *12*, 1592. [CrossRef]