ARTIFICIAL INTELLIGENCE
AS A BASIS FOR THE DEVELOPMENT OF THE DIGITAL ECONOMY

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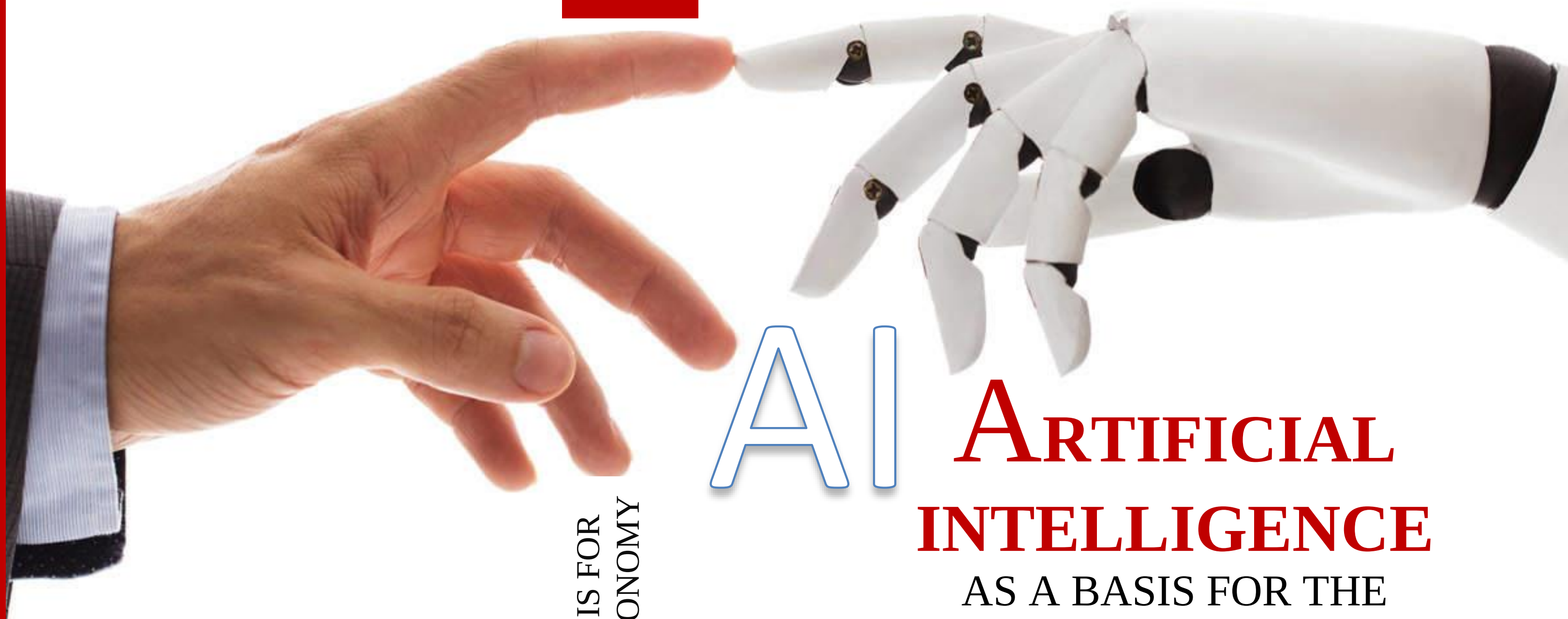

AI

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VI. ARTIFICIAL INTELLIGENCE IN INDUSTRY AND ENERGY

6.1. «Smart» industry

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For centuries, the plant has been considered the epitome of automation, so workers were often judged on the same metrics as machines. Is it any wonder that in industry there was a difficult relationship between people and machines and the worker felt that he was in a losing position. And not without reason. Since 2000, the US industry has lost five million workplaces, with half of them were cut due to increased productivity and automation of production [1].

However, the situation is not as straightforward as it might seem at first glance. As mentioned, the second wave of business transformation focused on automating existing processes, and it was during this period that many people lost the competition to machines. On the contrary, the third wave involves the implementation of completely reimagined adaptive business processes designed to ensure human-machine interaction. At this stage, thanks to artificial intelligence, a human partly returns to production; for example, workplaces on assembly lines have fundamentally changed in the nature and meaning of the operations performed, their number is growing. Artificial intelligence adds value to engineers and managers. Thanks to artificial intelligence, completely new specialties and new opportunities arise for people employed at all stages of production.

In an era of AI-driven business transformation, the irony is that we are seeing a resurgence of human labor in factories and industrial plants. Everyone, from an assembly line worker to a maintenance technician to a robotics engineer and an operations manager, is experiencing how the concept of work is changing under the influence of artificial intelligence. Artificial intelligence frees up time, creativity and resources, preventing humans from doing the work of robots. This means that with the help of artificial intelligence, a human will be able to work more creatively and more efficiently, which will increase productivity and reduce costs. In the long term, it is of paramount importance that companies are rethinking their business processes: completely new professions are opening up for people and new ways of doing business are emerging.

Let's not rush things. Before you start transforming your business processes, job responsibilities and business models, you need to answer the following questions: What tasks do humans do best, and which ones do machines do best? Are there jobs and tasks that will gradually move to robots, since they are better at performing routine operations and processing data than humans? However, the transformation of labor is not unilateral. In this chapter, we will talk about companies that have already solved the problem of integrating man and machine in production, in the operation of equipment. These pioneers recruit both humans and artificial intelligence machines to work, providing them with the jobs that they fit best and thereby benefit from it [2].

In the middle of the 20th century, concepts about the possibility of self-learning of computer programs appeared, including the model of an artificial neural network proposed by the American neurophysiologist Frank Rosenblatt, capable of taking into account previous experience and improving it when solving problems. The enthusiastic expectations, however, quickly gave way to disappointment due to the meager capabilities of the computer technology of that time, which was not capable of complex calculations. And only by the beginning of the XXI century, with the emergence of huge databases and powerful processors capable of processing this data, recent science fiction has become a reality, and artificial intelligence (AI) has quite successfully replaced humans in many industries and areas [3].

How can artificial intelligence benefit manufacturers? The most important opportunity that AI will provide to manufacturers is its ability to correct course based on historical data and make decisions based on the options available. For example, a production line produces a product, but an important quality parameter begins to deviate from the established limits. Nowadays, most processes require some kind of human intervention to make changes to the process. Sometimes this can be done automatically on a single machine, but usually it cannot be done on multiple machines as part of a manufacturing process.

We are used to being alerted to a problem, but we have to use skills and human interaction, and sometimes memory to predict if a problem happens. It relies on someone remembering that event "A" can lead to problem "B", which is theoretically okay if they also remember what solution is required! It is in this context that we need to consider the skills that are best suited to apply this beneficial technological advance [4].

Artificial Intelligence applications in Industry

At manufacturing enterprises AI can be applied at almost all levels [5]:

– at the design level:

a) to improve the efficiency of new product development,

b) to automate the selection and evaluation of suppliers,

c) when analyzing the requirements for spare parts and details.

– at the production level:

a) to improve business processes,

b) in the automation of production lines, to reduce the number of errors, to simplify the production process through the use of image recognition functions and a dialog interface.

– at the logistics level:

a) to improve the planning of vehicle routes,

b) to reduce the delivery time of raw materials,

c) to improve interaction with customers and suppliers through interactive communication,

d) to track items and the delivery process at all stages,

e) in the long term - to predict fluctuations in shipments before they happen.

– at the promotion level:

a) to predict the volume of support and maintenance services,

b) when managing pricing.

Development stages of artificial intelligence

Human-machine interaction is a critical aspect of the transformation process of business and manufacturing processes. The path of this interaction turned out to be thorny. Initially, artificial intelligence was greeted with great enthusiasm, but expectations were not met: disappointment was soon followed by noticeable progress, which led to a second wave of excitement and new disappointments. These two recessions have come to be called the two "winters" of artificial intelligence.

Work on artificial intelligence began in the 1950s, and research progress has been extremely uneven over the following decades. By the 1970s, funding was almost phased out, that period is called the "first winter" of artificial intelligence. Then, for several years in the 1980s, researchers were able to achieve excellent results in the development of so-called expert systems - computer programs capable of analyzing and drawing conclusions. They allowed the machine to make the simplest judgments, and not to work according to a strict, predetermined algorithm. At the same time, the revolution of personal computers was gaining momentum, all attention turned to them, they became more and more accessible to the common man. Funding for artificial intelligence has declined again, and the "second winter" of artificial intelligence has come. This situation persisted until the early 2000s.

The advent of artificial intelligence has contributed to the transformation of assembly lines. Engineers at the Fraunhofer Institute for Logistics (Fraunhofer IML) have been testing inline sensors for a long time to create self-adjusting assembly lines in car factories. In essence, the conveyor itself can modify some operations of the technological process, changing additional modules and equipment to create cars to order. Thus, engineers design not just a conveyor on which one standard model is assembled, but a conveyor that can be reconfigured on its own. Andreas Nettstreter, who coordinates strategic initiatives at IML, notes:

"If one workstation fails or breaks down, its functions can easily be transferred to other stations on the conveyor" [1].

Workers on the assembly line tackle more complex tasks that robots cannot, and process engineers do not need to reconfigure the line with every performance change or breakdown. They can devote time to more creative tasks, such as how to make machines work even more efficiently.

Data monitoring

What starts with smart manipulators spreads throughout the plant and even beyond. Technologies based on artificial intelligence in manufacturing and, more broadly, in industry liberate humans. For example, artificial intelligence has changed the maintenance sphere. Sophisticated AI systems predict an impending breakdown in advance, which means that staff spends less time on routine checks and diagnostics and more time on repairs.

Artificial intelligence for accelerated machine adoption

Sight Machine, a San Francisco-based startup, uses analytics and machine learning to help customers to reduce downtime when new equipment is launched in the workshops. Thus, in one case, it was possible to reduce the downtime inevitable when introducing new robotic systems by 50%. When all fixed assets were put into operation, productivity increased by 25%. Thanks to the new technology, production efficiency has increased, and engineers and maintenance technicians have been able to focus on other, more significant tasks [1]. General Electric monitors the performance of equipment supplied to customers. For this, the Predix platform, equipped with artificial intelligence, is used. It is based on the concept of a “digital twin,” whereby all assets inside and outside the plant — from the bolt to the conveyor belt and to the turbine blade — are simulated and monitored on a computer. Predix collects and analyzes a huge amount of data; this data can be used to rethink business processes in three fundamental ways:

- **Rethinking maintenance**. General Electric collects statistics from all points where its equipment is installed, and uses machine learning technology to predict the timing of failure of certain parts (depending on their current state).

In the past, service technicians have replaced parts according to the manufacturer's recommendations. So, car candles had to be changed after 120,000 kilometers. Now they can be replaced as they wear out. Forecasting based on artificial intelligence saves time and money, while increasing the interest of repairmen in their work [1].

- **Rethinking product development**. Additional data facilitate R&D (НИОКР). General Electric installs sensors on the most stressed turbine parts to track changes in them. In the operating temperature range, the sensors literally burn out, but they manage to collect information about the turbine warming up. This helps to understand better the thermodynamics of the materials used in the manufacture of turbines and to optimize operating conditions. Thanks to the sensors, engineers have at their disposal the most detailed information that sheds light on the operation of certain systems.

- **Rethinking exploitation.** General Electric can create digital twins based on field data collected from operating objects such as jet engines. During virtual flights, the aircraft is exposed to low and high temperatures, dust, rain and even bird attacks. The company monitors tens of thousands of wind turbines, and their digital counterparts make it possible to adjust their work in real time. The analysis of these data allowed us to draw a very important conclusion: depending on the direction of the wind, it makes sense to reduce the rotation speed of the leading turbine in comparison with the calculated one. This example demonstrates that the digital twin model is not only applicable to a single unit, but also optimizes the operation of an entire wind farm. According to General Electric, digital twins can increase wind power production by 20%, which is equivalent to $ 100 million over the life of a 100 megawatt wind farm [1].

Prerequisites and opportunities for the use of artificial intelligence in industry

If a few years ago the topic of artificial intelligence aroused skepticism and mistrust among industrial enterprises, the emergence of new market requirements, the growth of government influence and the development of new technologies radically changed the situation. The question is what exactly can be attributed to the field of artificial intelligence, especially in industry, since the topic is vast, but at the same time controversial from the point of view of applied application.

Today the terms “digitalization”, (“digitalization”), “machine learning”, “artificial intelligence” are pronounced from the tribunes, are actively discussed in the media, are covered on state and commercial channels, and are promoted in the mass consciousness. Since the terminology is not yet fully established, discrepancies often arise, leading to misunderstanding of various sides. Most often this applies to the phrase "artificial intelligence", which is perceived by everyone in their own way, even after trying to appeal to such authorities as Turing, McCarthy or Kurzweil.

The industry is more and more subject to certain standards and completely transparent logic. First, you need to understand that in most cases, artificial intelligence in discrete and continuous production is understood as machine learning - a class of methods for solving problems based on precedents and for searching for patterns in historical data of production systems. And in the modern world, a person should not be responsible for developing recommendations on optimal technological modes and forecasting a resource - supporters of digitalization recommend shifting these tasks onto the shoulders of intelligent systems.

Machine learning in industry. Applications

What urgent tasks can be solved at the stages of development, production and operation using machine learning? Firstly, these are tasks that a human cannot cope with. This can be work in hard-to-reach places, in hazardous chemical production, in permafrost conditions or in increased radiation. Secondly, these are tasks where "natural intelligence" is applicable, but ineffective: predicting critical malfunctions, preventing sudden equipment failure, condition-based maintenance, predicting the remaining equipment resource. These are, in fact, those areas where a human can perform work, but in the conditions of a huge amount of information, this becomes almost impossible. Moreover, a human is not always able to sort correctly data and to resolve contradictions. And the machine can perform these tasks according to predefined algorithms. It is possible to obtain the required amount of data in industry only with an integrated approach: a combination of a system model based on physical processes and machine learning algorithms [5].

Self-learning manipulator

At the Tokyo factory, the third shift begins - and the finest hour of robotic manipulators, which can learn new skills overnight begins. The manipulator is equipped with a video camera and machine learning software, and these rotating limbs can, without assistance, determine the most efficient ways to assemble parts, and then transfer them down the conveyor. Such operations do not require additional programming.

Robotic manipulators are used in factories, for example, for applying hot glue, for installing windshields, for leveling the edges of metal after it has been cut. They are pre-programmed to perform a specific task, and when it changes, the robots have to be reprogrammed. The new robotic arms, developed by Fanuc in partnership with software maker Preferred Networks (both based in Japan), can learn independently using one of the machine learning methods - deep reinforcement learning. Demonstrates a successful result to the robot, and it independently learns to achieve it by trial and error method.

According to Shohei Hido, a senior researcher at Preferred Networks, it takes a robot eight hours to successfully complete a task 90% of the time. Almost the same amount of time would be spent for an engineer to program the robot, and since the robotic arm can learn on its own, the programmer frees up time for more complex tasks, in particular those where it is required to make judgments, evaluate and interpret the results. Having mastered a new skill, the robot can share the acquired knowledge with other robots connected to the network. Thus, eight manipulators working together for an hour can learn the same amount of skills as one manipulator working on a task for eight hours. This process Hideo calls "distributed learning": "You can imagine a thousand factory robots exchanging information."

Now imagine people working side by side with robots. Self-learning industrial robots are excellent at handling routine repetitive operations as well as tough work. But in any enterprise there will always be tasks that are too difficult for robots - for example, connecting numerous small wires or working with moving or inconvenient to grip objects. All this still needs a human.

So, can humans and robots work together successfully? History does not provide a clear answer. Robots, moving quickly and sharply, can be useful and effective, but at the same time dangerous to humans. They are often placed behind protective barriers, but this typical separation of robots and humans promises to disappear over time. So-called cobots from companies like Rethink Robotics, founded by one of the pioneers of robotics and artificial intelligence, Rodney

Brooks, are equipped with sensors that allow them to distinguish objects and avoid collisions with humans. If a robot is relatively nimble, it interacts well with a human. In factories equipped with devices from Rethink Robotics and similar companies, work is often split between humans and robots, working side by side, with tasks selected to suit their capabilities best.

Artificial intelligence in a factory

For a century, factory workshops have been the main training ground for robotization. Here you can find everything - from smart conveyor belts to robotic manipulators and operating systems with elements of artificial intelligence; the plant "grows smarter" day by day. Hitachi uses artificial intelligence to analyze big data and routine tasks of human workers, transmitting this information to robots, which, in their turn, provide instructions to employees to meet changing demand in real time and continually improve the manufacturing process.

As part of a pilot project, the company achieved an eight percent increase in labor productivity in logistics. Siemens uses a group of 3D-printed robots which resemble spiders. Using artificial intelligence, these robots communicate with each other and assemble in a Siemens laboratory in Princeton, NJ. Each robot is equipped with computer vision sensors and laser scanners, all of which are connected to the production chain “on the fly”. In Inertia Switch, robots, thanks to artificial intelligence systems and touch sensors, can work together with humans. The company uses Universal Robotics robots that can learn on the go and switch between tasks flexibly. Thus, they become excellent helpers for human workers in the shop [1].

Artificial intelligence and technical and technological development of robots

While the second winter of artificial intelligence lasted, Rodney Brooks criticized one of the fundamental ideas on which artificial intelligence research has long been based. It is about the comprehension of the surrounding world by robots based on the use of predetermined sets of symbols and the relationships between them [1]. He argued for a much more reliable approach: instead of cataloging the world around us in advance and then representing it in the form of symbols, why not to study the environment using sensors? "The world is the best model of itself," he wrote in a famous 1990 article titled "Elephants Don't Play Chess." Brooks subsequently formed iRobot, which developed the Roomba robot vacuum, and founded Rethink Robotics. iRobot has produced the most autonomous robots in the world to date; more than 10 million were sold between 2002 and 2013.

Today, Brooks's interpretation of artificial intelligence is relevant in both research and manufacturing. Rethink Robotics demonstrated the capabilities of a robotic arm equipped with built-in sensors and motion control algorithms that help the robot “sense” and correct its actions in real time. The manipulator has elastic drives and joints that can return to their original position; thus, it can deflect on contact, extinguishing energy. Therefore, even if it collides with an object (or human), the impact will be noticeably weaker (compared to a conventional robotic arm). What happens when the "iron hands" are able to independently study, as, for example, in Fanuc? Or if the manipulator is more accurate and precise, as in the

Rethink machines? Workers on assembly lines will be able to work together with self-learning robotic arms. Let's say a human is busy assembling a car and needs to fix the dashboard. The robot can lift it and set it up, and the worker will correct its actions and secure the panel without fear of being hit on the head by a bulky machine. Artificial intelligence helps both robots and humans to show their strengths, so that the entire workflow on the assembly line is transformed [6].

Let's look at a few examples of the use of AI in industry

Equipment diagnostics during operation

For industries that traditionally operate equipment (mills, pumps, electric motors, heat exchangers), it is important to have constant feedback from the operating product to assess the behavior of the object in real time, predict possible emergency situations, and prevent sudden equipment failure. In these cases, it is necessary to analyze a large amount of data to extract information from the systematically collected information. But in industry there is often not enough information received from actually operating objects, so the database needs to be supplemented with the results of full-scale and virtual experiments, using engineering analysis technologies based on numerical modeling, carrying out regular calibration to improve the quality of the forecast.

As a result, we get a model based on historical data, supplemented by the results of virtual experiments, so that the information is sufficient for high-quality training. This helps to explain the trends identified during the analysis, as well as to predict the emergence of new aspects and even to classify or segment data based on patterns of behavior, which are almost impossible to identify using traditional "human" methods. Machine learning algorithms in this case can be applied in a variety of ways. For example, in the case of technical diagnostics of equipment, when it is enough to report only the state of the object (serviceable / defective), you can apply the teaching method with a teacher (binary classification: the object is serviceable / the object is defective).

Optimization of operating modes of equipment and technological processes

The reduction of unplanned downtime and an increase in the service life of the equipment and, as a result, an increase in the quality of products and a decrease in the costs of the enterprise as a whole depend on the correctly selected modes of operation of the product. The operator can be helped by a system that selects the most optimal scenarios for technological processes and predicts deviations in equipment operation based on statistical models and engineering analysis. Here you can use a machine learning algorithm based on building a decision tree, where for each level a variable is determined that generates the least entropy. The algorithm unfolds the combinatorial tree and traverses it looking for the best option. The first step is to create a tree containing all possible plans. Then, using intelligent algorithms, those branches are sequentially cut off, which correspond to unrealistic plans or plans that violate decisions or lead to a non-optimal solution.

Also, for optimization problems in industry, you can apply the Stochastic Gradient Descent (SGD) method to minimize the function, taking small steps towards the steepest decrease in the function.

Service as per condition. Predictive maintenance

The transition to maintenance on condition allows to increase the service life of the equipment and its turnaround period, as well as the identification of defects due to data supplied in real time. Information about the current state of components and assemblies and the forecast of the residual life allow us to form recommendations for the maintenance and repair of equipment, to ensure the timely delivery of spare parts. You can determine in advance that something is wrong with the machine and decide on preventive maintenance.

Internal modeling algorithms can be used here: any complex adaptive system is able to create internal environmental models that allow predicting future events and changes for their successful adaptation. Aggregated machine learning methods are also suitable to compensate for the shortcomings of some algorithms with the help of others (Bayesian classifier, support vector machines, decision trees).

Visual recognition of defects. Computer vision

Machine vision is a collection of technologies that allows computers not only to process images as a mass of data, but to perceive and interpret them in a human-like manner. It is becoming more and more popular in the industry, since such methods can automate and significantly improve the process for which visual control is needed.

An example is a moving conveyor with ore, where it is necessary to quickly and accurately detect visual defects during product quality control. The main task is to localize and classify defects using the selected algorithms. One of the key methods in this case is deep learning. To train "deep" networks, properly formed training samples of sufficiently large sizes are required, the quality of which is determined by the completeness and consistency of the input data. At the same time, the implementation of a reproducible process is provided, which makes it possible to obtain stable output data suitable for making a decision on the presence of defects, based on general ideas about the quality of products.

Continuous production

For example, when smelting steel, it is necessary to accumulate history in order to predict the output characteristics based on the current smelting conditions. Or, using machine learning to determine the initial alloy composition and melt parameters to achieve a given quality. This will reduce the cost of raw materials, optimize the composition of elements, predict the quality of the output product, and optimally manage the smelting process. At the same time, you need to understand that there cannot be two identical heats of steel. The challenge of machine learning is to analyze a huge number of parameters in order to optimize the composition and number of input elements and operating parameters to obtain quality according to technical requirements. Here, as in the case of visual defect recognition, neural networks are used.

The machine is given a fairly large set of precedents (objects, situations), each of which is associated with certain scenarios for the development of events. In the information received, the machine finds patterns, thanks to which it subsequently gets the opportunity to predict the consequences of certain events, evaluate various hypothetical scenarios and make optimal decisions after analyzing alternative options.

A neural network should not require manual entry of rules - after training, it behaves like an expert in its subject area. At the same time, intelligent systems need knowledge control tools that can resolve possible contradictions, eliminate redundancy and generalize concepts. To do this, in any case, you need human help.

Flexible energy management. Improving energy efficiency

Machine learning technologies can reduce the operating time of equipment in high-intensity mode, reduce excess inventory, timely predict equipment wear and remaining life, reduce waste, and also reduce energy consumption costs by taking into account the state of the external environment.

Increasingly, soft computing is used to effectively manage energy consumption - this is a set of tools and methods that allow solving problems of high complexity by processing incomplete and inaccurate information: evolutionary algorithms, self-organizing growing neural networks, fuzzy logic. These are the tasks for which the experts were unable to find an optimal solution. Soft computing allows you to quickly find suboptimal, but good enough, solutions to problems of this type.

Equipment and process digital twins

So, industrial production and operation generate a large number of variables, so it becomes clear that there is a huge need for an intelligent system capable of making decisions taking into account all the above factors and on the basis of fuzzy parameters. Experts believe that to create digital twins, it is worth combining technologies such as systems modeling based on physical processes and machine learning. The digital twin is a complex dynamic model that in real time and with high accuracy reproduces the state and operating parameters of equipment and technological processes under existing conditions.

Most companies that have used machine learning to solve production problems are faced with a lack of data. Therefore, there is an urgent need to supplement the information with the results of real or virtual experiments using engineering analysis technologies based on modeling physical processes. At the same time, the model must correspond to real operating conditions and be constantly updated with knowledge about the operating facility. It is important to achieve a high quality forecast for making the right decision. Periodic calibration is performed to ensure that the digital twin matches the real equipment.

Since it is not possible to immediately identify all faults in a working model, it is important to correctly model “ what-if ” conditions to predict and identify the most critical issues from a security and business perspective. The system is focused on a large number of assessments, but it is necessary to choose the best one. On the other hand, a human cannot use all the information about a working product at once - it must be systematized and filtered. The digital twin offers a decision support system and recommendations for operators using machine learning algorithms based on both historical and simulated data.

Experts believe that the factor of success in this case is a combined approach to solving production problems using modern technologies and implementation techniques based on deep industry expertise [7].

Barriers to the use of artificial intelligence in industry and how to eliminate them

Examples of industrial implementations take into account the specifics of a particular industry and its business processes. While technology is still rarely used, companies are looking at AI-powered solutions over the next two years. 70% of global companies have a digital transformation strategy, 80% of companies are already investing in predictive services, 70% are focusing on supply chain optimization and logistics, 81% of US enterprises use real-time equipment monitoring.

Despite serious intentions, heavy industry faces management and decision-making challenges. Companies are often trapped in traditional division of interests. Business management is rarely done with the involvement of the IT department. More often than not, directors and executives focus exclusively on finance. This situation is strikingly different from that which is seen in IT-driven sectors such as retail, finance or internet companies.

Engaging business units in AI projects is critical to generating return on investment. The positive financial results of the project depend not only on the correctly chosen scenarios, but also on the support of the management. The market could grow even faster, even taking into consideration the low base effect. The following aspects will positively influence the growth rate:

- Fashion for digital transformation of industrial companies;
-The presence of niche players with expertise in the field of artificial intelligence and experience in implementing such solutions;
- Positive results of the implementation of pilot projects and proven statistically significant economic effects;
- Initiatives for the full implementation of already completed pilot projects;
- Availability of government programs to support initiatives in this area;
- Professional maturity of personnel and enterprises for digitalization.

As long as the reluctance to change is not reflected in business performance, enterprises also continue to operate at a good pace. Some minor improvements could well be achieved using traditional methods. Full-scale AI adoption is not a one-time event. The lag effect in this process appears slowly, but it will be more difficult to catch up if the lag occurs at the stage of collecting the so-called big data.

Specificity of heavy industry

In most cases, the use of AI in industry boils down to increasing employee productivity, increasing the efficiency of key technological processes, and improving quality control. The most significant potential for using AI is concentrated in highly specialized scenarios: forecasting and making recommendations, creating systems for recognizing patterns in data and identifying anomalies in a technological process and analyzing a video stream.

The scale and complexity of production means that industrialists are focused only on the tasks of their industry. AI requires deep knowledge of both business processes and an understanding of the specifics of industrial AI. This is why industrial companies do not often resort to consulting services in this area, even though there is a shortage of specialists. In addition, insufficiently effective pricing strategies and business models lead to the creation of highly specialized tools, rather than ready-made industrial solutions with the potential to scale.

In manufacturing companies, digital advisors are already able to advise on the optimal process parameters for maximum productivity. Their recommendations are based on historical data and predictive models to eliminate human errors and improve process efficiency. In the future, it is also necessary to take into account the peculiarities of the interaction between human and machine, because production is a place where people and machines are concentrated.

Once the decision has been made to deploy AI applications, a detailed methodology for conducting experiments needs to be developed. An enterprise's sensitivity to cost and the lack of AI experts with the right skills in most enterprises can complicate the implementation process. One proven and viable solution to the problem is working with experienced large IT companies. The lack of the required data can be compensated for by cross-industry data exchange. Companies are wary of sharing information, seeing this as a risk of losing competitive advantage and trying to protect their intellectual property. The industry has yet to realize how large datasets can be useful to everyone involved, while maintaining confidentiality and contractual obligations.

Due to a lack of experience, customers often have overestimated expectations regarding the capabilities of computer vision systems, their cost, and the payback period. Therefore, in order to test approaches and gain experience in implementing such solutions, it is recommended to start implementation with a small project. Education and investment in training is a key part of such projects.

Organizations should start by developing strategies and roadmaps for AI adoption. AI-based digital solutions are an essential part of digital transformation, they must be implemented by the business unit in close collaboration with the IT department, in which it is the business department that determines the desired result. The IT department, in turn, must be responsible for the required approaches and technologies. Usually, the initiative to implement such projects comes from the top down, and there is a need for a strong leader, often in the person of the CEO or digital transformation director, who acts as a link between IT and production within the company and between the optimized processes and the technologies suitable for this. The challenge in implementing AI is to help machine learning models become part of business and production processes [8].

AI in industrial refrigerator production

Industry has traditionally lagged behind the "lighter" areas of business, and so far only a few large projects involving AI are in the manufacturing sector. That is, the corresponding technologies are used here in supporting roles. So far, few decide to integrate AI directly into the production process, primarily because of the price of the issue: the cost of implementation turns out to be very significant, and imperfect technologies can result in serious losses. Therefore, it is often more about remote control of processes, where technology is given only relative independence. For example, recently the American Caterpillar presented a project for remote control of special equipment in mining mines and quarries, where the work of drivers is associated with an increased risk. Instead, operators will monitor the work of bulldozers and trucks, in the future from a distance of up to several thousand kilometers, and in an emergency they will be able to stop the equipment. Although this will already be an extreme case, since the transport is equipped with AI systems that recognize obstacles and allow them to avoid collisions with humans and other equipment.

More confidence in artificial intelligence was demonstrated by the South Korean LG Electronics, which plans to build a kitchen equipment plant worth $ 525 million. It is assumed that all stages of production from manufacturing and purchasing of components to quality control of finished products should be controlled by a single system based on AI and which will also constantly optimize the production process. The plant will occupy an area of 336 thousand square meters and by 2023 it will produce up to 3 million units of products per year. The world leader in the number of implementations of artificial intelligence and machine learning technologies, according to Jet Infosystems and TAdviser, is the USA. They are followed by the UK, which uses AI primarily in large investment banks, and India, which supplies these technologies to foreign customers.

AI in steel making

One of the implemented projects for the use of AI in industry is the introduction of artificial intelligence technologies for steel production in the oxygen converter workshop of the Magnitogorsk Iron and Steel Works. Since the remelted scrap is usually heterogeneous in composition, in order to bring the steel to the required standard, it is necessary to introduce ferroalloys and other special additives into it during the melting process. The service developed by Yandex Data Factory receives data on the initial composition and weight of the charge (the initial mixture of materials loaded into the melting furnace) and, taking into account the target parameters of the finished steel, gives the operator in real time the appropriate instructions on the use of additives. The consumption of the latter in the course of experimental smelting using new technologies decreased by 5%, and taking into account the rather high cost of ferroalloys, metallurgists expect to save up to 23 million rubles per month.

The pioneers are already implementing AI solutions in heavy industry and are conducting many experiments in this area. AI startup in the field of AI is Tulip Interfaces, a spin-off from Massachusetts Institute of Technology, offers an IIoT platform with specific intelligent applications over. Fanuc Corporation, a leading manufacturer of industrial automation equipment, uses artificial intelligence technology to reduce the learning curve for robots. Mining company Freeport-McMoran has successfully tested AI technologies in its smart quarry in Arizona, USA. It plans to increase copper production by 90 kt with minimal capital investment. AI technologies are quite mature, but they continue to actively develop. Data analytics tools help company analysts extract knowledge from a wide variety of information sources. The commitments to using AI launche a flywheel of data accumulation that drives the process of improving enterprise processes.

Examples include products that use predictive analytics in the discrete industry. Analyzing data from computer numerically controlled (CNC) metalworking machines, company Zifra solves the problem of detecting anomalies in the technological parameters of the machine [8]. In addition, possible causes of the anomaly are identified and tool wear on machine tools is predicted to alert users to the optimum time to replace them. Timely identification of anomalies and the need to replace tools allows operators and process engineers in production to quickly make decisions, which reduces the risk of product and equipment rejects, downtime and maintenance costs.

In the oil and gas industry

In the oil and gas industry, several projects with the participation of AI are being implemented at once. One of them, "Cognitive Geologist", involves the creation of a self-learning model of a geological object. The fact is that key decisions on field development have to be made at an early stage of development, and a mistake made at the beginning of the process is almost impossible to correct in the future. Geologists collect data bit by bit in order to get a reliable picture of the structure of the subsoil and to answer the main question: how profitable will production be? It takes a year or two, while the confidence in the correctness of the answer still does not exceed 60%. The Cognitive Geologist will mathematically process the underlying information, evaluate the likelihood of correct answers, and provide recommendations on development methods or the need for additional research. According to the calculations of specialists, the time of interpretation of geological data due to the work of AI will be reduced by six times, and the amount of useful information extracted from them will increase by 30%.

Another project involves the use of AI when drilling complex wells. A typical example: oilmen, based on a geological model, need to get into a reservoir only two to three meters thick at a depth of several kilometers and drill a well along it for a kilometer, promptly responding to changes in the configuration of the productive horizon, which are monitored using sensors installed on the drilling tool. However, the sensors are located 17 meters from the bit, so the specialists who remotely monitor the situation from the GeoNavigator Drilling Control Center learn about the well exit from the productive horizon with a delay of 20-30 minutes. During this time, the drilling trajectory can move away from the three-meter formation by a fair distance [7].

The solution to the problem was found in a trainable model, which in real time will draw conclusions about changes in conditions at the farthest point of the well based on parameters such as load on the drilling tool, resistance, temperature, vibration and ROP. This will allow GeoNavigator specialists to promptly correct the drilling trajectory and refine the geological model of the field, while generating additional data for further training of the “smart” drill. In the future, a mathematical model of drilling will make it possible to proactively predict possible emergency situations using indirect data, to establish optimal operating modes of equipment and even to determine the productivity of a formation in real time, while assessing the economic efficiency of drilling a particular horizon.

Another example is virtual flow metering software solutions - measuring the flow of liquid, gas and steam in industrial systems - based on artificial intelligence in the oil and gas industry and process industries. The disadvantages of measuring devices used today include low sampling frequency and high cost. The virtual flow meter provides an accurate estimate (up to 95%) of the pumping volume of gas and liquid, which significantly increases control over production productivity.

In oil fields, the metering systems in operation today are reliable sources of well production data, but the frequency of measurements using these devices ranges from once a day to once a week, a month or even several months. There are multiphase meters on the market, they can provide real-time production estimates, but their purchase and maintenance is not cost-effective for many fields. The activity of the entire oil production enterprise is directly dependent on production, which makes the use of virtual flow meters with the issuance of production indicators in real time and the subsequent reduction of the material balance especially relevant. For oilmen, the introduction of a virtual flow meter based on artificial intelligence makes it possible to increase oil recovery through the most complete set of production data and update the reservoir model, as well as significantly reduce capital costs for purchasing physical flow meters and operating costs for their maintenance, increase and maintain production through operational identification of shortfalls and losses. At the moment, the cost of a virtual flow meter is ten times lower than hardware counterparts.

AI-based virtual flow meters require a lot of historical data from temperature, pressure and other sensors. As with other AI solutions, regulated, controlled data collection and storage is a key success factor for implementation. The AI learns as new data becomes available to improve the accuracy of virtual flow metering. Examples of successful projects and increased business revenue through the use of AI technologies will be convincing arguments in favor of introducing new projects.

Despite the fact that many projects with AI, especially in industry, are still experimental in nature, analysts are confident in the grandiose prospects of this direction. Jet Infosystems and TAdviser in their materials predict the growth of the market for artificial intelligence and machine learning on a global scale, according to a recent forecast by PwC, the use of AI by 2030 will ensure the growth of world GDP by 14%, or $ 15.7 trillion. And a business that ignores these technologies today risks being simply uncompetitive tomorrow. Moreover, according to the forecasts of individual futurists, in the region of 2030–2050, a breakthrough is expected in the field of creating "strong" artificial intelligence, which is definitely in no way inferior to the human one [8].

Conclusion

The Turing test has not yet been passed. A superintelligence capable of learning as a person, acquiring new knowledge and solving previously unheard-of tasks, which would not be inferior in intelligence to most people, and in many things would even surpass it, has not yet been created. But already the technologies of the fourth industrial revolution are inviting modern enterprises to focus on an integrated approach.

The use of statistical methods in production and at the operational stage is a dead-end branch of development. The symbiosis of machine learning and numerical modeling algorithms is a completely contingent decision. Yes, there are risks, but they can be mitigated with strong industry expertise and best-in-class technologies. The system only generates recommendations - the decision is still left to the human. Perhaps, in a very short time, artificial intelligence will be able to solve new creative problems, but today the technological tandem of man and machine looks the most realistic.

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6.2. European Smart Energy Policy[9]

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The intensive use of artificial intelligence and communication technologies in power systems in the European Union has led to the creation of a concept called the “smart energy”. The development of this concept in power networks leads to optimal network control, optimal use of equipment, increased quality and reliability of power supply, facilitation of the integration of renewable energy sources, optimal planning of the transmission and distribution systems, the development of the use of distributed generation and reduced system’s costs [1]. The role of smart grid in renewable energy sector was actively discussed in the paper [2]. The importance of creating energy hubs based on smart energy concept was declared in the paper [3] and [4]. The scholars mentioned above contributed significantly to the exploration and development of smart energy concept on a global level. In this chapter, we propose to concentrate primarily on the unique smart energy policy of the European countries.

Smart grids. The following statistics represent the projected market value of the global smart grid market in 2017 with a forecast until 2023, broken down by region. In 2023, the European smart grid market is expected to reach 15.4 billion U.S. dollars. It is the second position after the North American smart grid market.

A smart grid is an electricity network that can intelligently integrate the behavior and actions of all its users to ensure a sustainable, economic and secure electricity supply. As a tool that provides much-needed flexibility, smart grids offer potential benefits to the entire electricity value chain (generators, TSOs, DSOs, suppliers and consumers) and to society as a whole. Smart grids will enable DSOs to monitor the electricity flowing within their grids. On the basis of collected data, they will be able to adjust to changing conditions by automatically reconfiguring the network and/or by taking control of connected demand and

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