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Perspective

Artificial Intelligence for Energy Processes and Systems: Applications and Perspectives

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Abstract: In recent years, artificial intelligence has become increasingly popular and is more often used by scientists and entrepreneurs. The rapid development of electronics and computer science is conducive to developing this field of science. Man needs intelligent machines to create and discover new relationships in the world, so AI is beginning to reach various areas of science, such as medicine, economics, management, and the power industry. Artificial intelligence is one of the most exciting directions in the development of computer science, which absorbs a considerable amount of human enthusiasm and the latest achievements in computer technology. This article was dedicated to the practical use of artificial neural networks. The article discusses the development of neural networks in the years 1940–2022, presenting the most important publications from these years and discussing the latest achievements in the use of artificial intelligence. One of the chapters focuses on the use of artificial intelligence in energy processes and systems. The article also discusses the possible directions for the future development of neural networks.

Keywords: artificial intelligence; neural networks; machine learning; deep learning; energy processes and systems

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1. Introduction

Artificial intelligence (AI) is a concept that is difficult to define. There are many definitions of artificial intelligence. However, they all boil down to the fact that AI attempts to model aspects of human reasoning (thinking) using computers or solve problems with computers that would take a human a long time. Furthermore, the cognitive abilities of the human brain to visualize and analyze the hyperdimensional system is limited, thereby AI-based modelling algorithms have a competitive advantage to be utilized for modelling, predictive, and optimization analytics [1].

The term "artificial intelligence" was first proposed and defined in 1955 by John McCarthy. Today, you can find a whole range of different definitions of artificial intelligence. According to Kurzweil [2], artificial intelligence is a field of research that tries to imitate human intelligence. Haugeland [3] believed that artificial intelligence is an attempt to create thinking computers and Schalkoff [4] believed that it is an attempt to explain intelligent behaviour using computational methods.

Intelligence itself is the ability to process information at the level of abstract concepts. It is a certain ability to process information creatively, not just its mechanical processing.

At the end of the last century, this concept was reduced only to having intellectual abilities. The contemporary perception of intelligence is understood as the ability to interact with the abilities created in the emotional, motivational, or human psyche.

The term artificial intelligence also includes neural networks, also known as artificial neural networks (ANNs) or simulated neural networks (SNNs), which are part of the machine learning function and are the basis of deep learning algorithms [5,6]. Their name and structure are based on the human brain and they mimic how biological neurons communicate.

We perceive everything that surrounds us thanks to neurons, e.g., sounds, images, taste, smell, or pain. A neuron is the smallest nervous system element that registers external stimuli and transmits them to a neighbouring neuron until the stimulus reaches the brain. Millions of neuron cells take part in such a process of sending information; the scheme of sending a stimulus to the brain is shown in Figure 1.

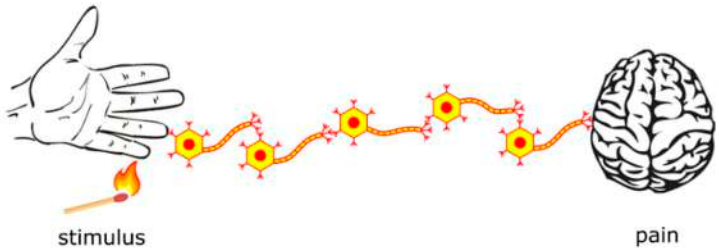

Figure 1. Transmitting and processing information about the stimulus to the brain.

Artificial neurons that are used by the neural networks are equivalent to biological neurons that, together with other neurons, form an artificial neural network.

Artificial neural networks (ANNs) consist of layers with a certain number of neurons. Among the layers of neural networks, we can distinguish: the input layer, one or more hidden layers, and the output layer (Figure 2). The layers are connected to each other through neurons, and these connections are made by weights that can be determined in various ways.

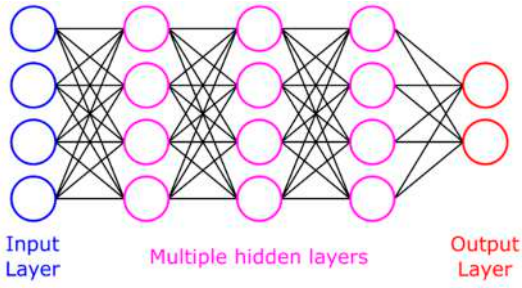

Figure 2. General diagram of neural network.

The neural networks are trained on previously prepared data sets which are divided into training and test data. Training data is used to teach the neural networks to improve their accuracy in predicting results over time. Once they reach the required accuracy, test data which the neural network "has not seen" before is entered into the neural networks to check the correct operation of the neural networks. If the neural network achieves a high prediction rate, it becomes a tool that can be used in various fields of knowledge, such as speech recognition [7] or image recognition [8]. The mathematical expression of the working of ANNs is given as:

$$\hat{Y}_i = f_2\left(\sum W_2\left[f_1\left(\sum X_i W_1 + b_1\right)\right] + b_2\right)$$

Here, X_i is an input vector defined on the number of input variables and i = 1,2,3, . . . , N equal to the number of observations. W_1, W_2 and b_1, b_2 are the weight and bias matrices

compiled at the hidden layer and output layer of the ANN. Similarly, f_1 and f_2 are the activation functions applied at the hidden and output layers of the ANN respectively. The activation function can be tangent sigmoidal, logistic sigmoidal, linear, rectified linear unit, softmax, etc. Various training algorithms are reported in the literature that optimize the parameters such as weights and biases embedded in the architecture of ANNs. Amongst them, the Levenberg–Marquardt algorithm, the scaled conjugate and the Newton method, and the gradient descent method are mostly used [9,10]. The loss function typically considered for the parametric optimization is the mean absolute error, root-mean-squared-error, sum-of-squared-error, etc.

One of the greatest advantages of AI is its ability to solve complex problems that are poorly defined and potentially subject to large errors [11,12]. Traditional algorithms usually do not cope with these type of tasks, or their running time is very long. Artificial intelligence methods do not guarantee a "good" result, but very often they give accurate and fast results that are the best way to solve the problem. The advantage of artificial intelligence is that it is able to capture the patterns in non-linear problems and that it can deal with noise, interference, and incompleteness of input data. Once prepared and taught, the neural network model is able to carry out subsequent simulations and predictions very quickly.

Artificial intelligence can also be used in the power industry for three different types of problems: modeling [13,14], prediction and planning (optimization) [15], and process control [16]. In recent years, there has been an increase in interest in the subject of electricity quality [17,18] or the energy obtained from renewable sources [19,20].

The aim of the article is to present the development of neural networks, their application in the power industry, and the perspectives of using neural networks in energy processes and systems. The use of neural networks in the energy sector has great potential because the human brain's capabilities are limited, which is why artificial intelligence algorithms have an advantage that they can use to predict and optimize selected energy processes.

The Section 2 discusses the development of neural networks from 1940–2000. The Section 3 focuses on the use of artificial intelligence in the years 2000–2022. The Section 4 discusses artificial intelligence methods in the energy sector. The Section 5 discusses the possible future directions for the development of neural networks. The work was finalized with a conclusion.

2. Development of Artificial Intelligence

Most people think that neural networks were created recently, but the truth is a bit different. The 1950s are sometimes called the Middle Ages of neural networks. In 1943, Warren S. McCulloch and Walter Pitts [21] published a paper aimed at understanding how the human brain creates complex patterns using neurons. The authors of this paper compared a neuron to boolean logic (true/false or 0/1). In 1950, Turing [22] proposed a test to determine whether a given program is intelligent. In 1958, Frank Rosenblatt [23] introduced the concept of the perceptron and added weight to neural connections.

The 1960s was a time of heuristic searches, the pioneers of this approach being Newell and Smion [24]. In 1963, the Advanced Research Projects Agency (ARPA) donated a significant amount to the Massachusetts Institute of Technology (MIT) for work in the field of AI. In 1965, work began on the DENDRAL expert system; a year later, ELIZA, a computer psychotherapist was created.

In the next decade, the first expert systems (ES) were created, which, due to heavy criticism from Dreyfus [25,26], led to the cutting of funds for research on artificial intelligence. Dreyfus published, among others, the work "What computers can't do: the limits of artificial intelligence" [25], in which he ridiculed MIT that they built a robot that was supposed to build a tower of blocks, but the robot started building the tower from the top. In the same paper, he touched on the topic of a computer recognizing a cup, which it took

10 min to recognize. Stanford University has also been criticized for its work on how robots move and see—15 min of thinking for one move.

In the 1980s, Paul Werbos [27] raised the subject of backpropagation in his work and applied it to neural networks. Yann LeCun [28] in 1989 published an article on how neural networks can use backpropagation for learning. This study was applied to recognize the digits of a written-by-hand postcode. The above-mentioned scientific works were used to create many different neural networks, which are now widely used and modernized.

In the 1990s, artificial intelligence came full circle as it returned to neural computing. The chess computer (Deep Blue) was created, which faced Garry Kasparov in 1996 and 1997. Kasparov won the first match, but the supercomputer won in the second match.

3. Recent Years in Artificial Intelligence

The directions of work that have recently been observed in AI are very wide. Hybrid intelligent systems [29,30] were created, in which the techniques of fuzzy logic (FL) [31–33], neural calculations [34–36], and genetic algorithms (GA) [37,38], were used to obtain a high machine IQ [39,40].

Systems are also being built to manage exceptional situations in the environment that can cause losses in people and equipment [41,42]. Systems with the support of AI facilitate effective and safe management in crisis situations, e.g., forest fires, floods, or gas leaks from chemical plants. Such systems had their origins in the 1960s, but it was only after the creation of the ARTEMIS project by the European Union in 2004 that they began to develop.

In 2021, a team of machine learning experts and composers managed to finish Beethoven's unfinished Tenth Symphony. For this purpose, the artificial intelligence was given Beethoven's symphonies, piano sonatas, and string quartets for analysis.

In 2022, Jason Allen won the art competition in the Digital Arts/Digitally Manipulated Photography category by presenting the image "Théâtre D'opéra Spatial" generated by artificial intelligence and printed on canvas. Other artists taking part in the competition were indignant because the author did not paint his work himself. In this case, the application of artificial intelligence boils down to the question of whether art generated by artificial intelligence is indeed art?

At the end of 2022, the movie Safe Zone was released, which was the first short film made using artificial intelligence. It was written and directed by artificial intelligence and, more specifically, by ChatGPT. ChatGPT artificial intelligence was used to produce the film by Richard Juan, Aaron Kemmer and Odyssey Flores. They were curious to see if technology was able to direct the actors and camera staff in such a way that the effect resembled a movie created by humans.

As part of a research experiment, scientists from Axios decided to check whether the triumphant ChatGPT could pass the American medical exam. Importantly, before taking the exam, the chatbot was not prepared or trained in any way. The results of the experiment available on the medRxiv portal [43] are still being analyzed by specialists and should soon be published in one of the scientific journals. From what is known currently, ChatGPT has passed all three parts of the US Standard Medical Exam. The authors of the experiment indicated that the answers provided by the algorithm were consistent, thorough, and comprehensive. In 2022, a publication appeared in which artificial intelligence had learned to recognize the race of patients based on X-ray images [44].

Figure 3 shows the number of scientific articles in which the keywords were: neural networks, deep learning, or machine learning. The data in the graph comes from Elsevier's ScienceDirect database. This figure confirms that artificial intelligence is a field that is constantly developing.

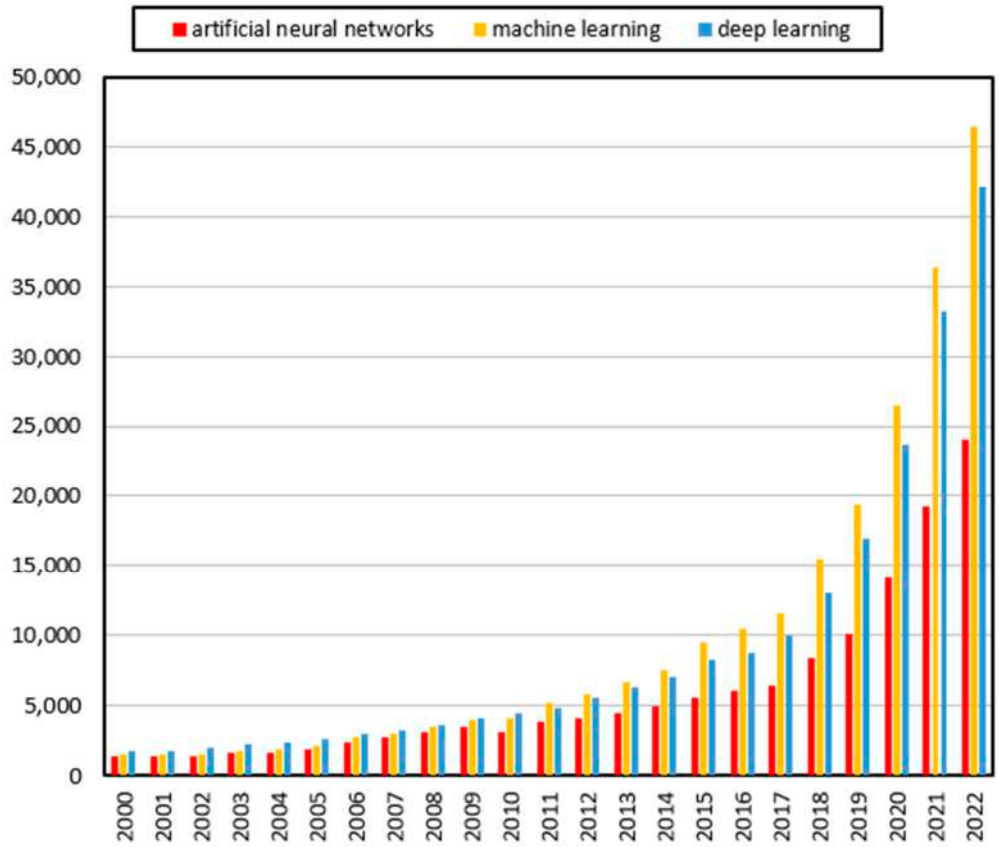

Figure 3. Number of scientific articles related to artificial intelligence in 2000–2022.

4. Artificial Intelligence Methods in the Energy Sector

In today's world, knowledge and time are most valuable. Computer modeling allows the gaining of knowledge about complex energy systems and devices in a relatively short time. This is very important in the context of process optimization when we perform hundreds of calculations for one case. Models of this type are used in every field of energy, starting from the simulation of individual devices, and ending with the entire energy systems for a region or country.

Modeling energy systems is very time-consuming and complicated because their description requires huge systems of differential equations describing the behavior of such a system. An alternative solution is to use an artificial neural network as a substitute model. In this case, there is a possibility of creating an interesting hybrid system: combining a substitute model based on an artificial neural network with a genetic optimization algorithm [45]. It should be noted that the neural network created in this way can be very accurate (giving good optimization results) because most examples from these areas were used in its training.

Most practical applications of artificial intelligence methods in the energy sector that appear in scientific studies concern the possibility of using them for prediction and optimization. Attempts to determine the amount of the electricity demand are very popular. This is because data on the electricity demand is generally available. Electricity consumption depends on many factors, including the day of the week, weather, time of day, and season of the year. This means that the electricity consumption is reduced to a time series that can be used to test various methods, e.g., neural networks [46] and Kohonen networks [47]. Determining the future energy demand is very important from the point of view of Its generation and sale or setting tariff plans. Such forecasting is very important because we cannot effectively store electricity, which means that in a closed system, the energy generated must be balanced with the energy consumed. On the other hand, no power plant is able to continuously adjust the production capacity to the load. For technological

reasons, the amount of energy produced cannot be changed instantly, so a surplus must be maintained. Of course, the smaller the surplus, the greater the savings. As a result, larger consumers have to conclude the contracts for the supply of a certain amount of energy, so it is in their interest to create accurate forecasts of the energy demand.

Artificial intelligence is also used in energy systems based on renewable energy sources [20,48–50]. In such cases, artificial intelligence is designed to predict the weather, especially insolation or wind strength. Another example of the use of neural networks in the energy sector are attempts to predict the energy consumption of buildings [51].

Additionally, neural networks can be used in planning the construction of power systems, selecting the location of transmission network elements, or the use of various renewable sources [52]. Such solutions may use, for example, fuzzy logic [53]. Such a modern and innovative approach to the design of energy systems contributes to the creation of algorithms that can help in the selection of parameters for the considered project [54]. In such projects, expert systems can also be used to support design decision-making.

Artificial intelligence can also be applied to process control systems. The above-mentioned attempts to predict the electricity demand can be used in the control of elements of the energy system or in the algorithm for determining contracts for the purchase of electricity.

Artificial intelligence methods can also be used to read and control environmental parameters, such as temperature and humidity. They make the system able to recognize and react quickly enough to dynamic changes in the environment.

5. Artificial Intelligence Perspectives

According to some researchers, artificial intelligence will remain the most developing technology in the coming years. AI can generate and create virtual worlds that simulate various cataclysms to avoid human losses; for example, such a network can simulate a hurricane or fire over a large area.

In the future, there may also be applications that help design complex devices or computer programs. Such applications should work throughout the project as a team member. They would be aimed at helping in designing, testing, diagnosing, or even finding faults. Programs of this type should increase the capabilities of the project team by increasing its efficiency.

Artificial intelligence can also be equipped with teams of robots that could work in an environment dangerous to humans or as home help. Such robots would have to communicate with each other and decide which obstacles can be moved and which should be avoided. Communication between robots equipped with AI would enable safe and effective work in a human environment. Currently, robots are already equipped with equipment that allows them to move around in a laboratory environment, but they must also be tested in a much more difficult (unknown) environment.

The areas of scientific research important from the point of view of achieving the above objectives are:

- Learning and fine-tuning information;
- Action planning;
- Perception;
- Human–computer communication;
- Obtaining interesting information, transfer learning;
- Acquisition by AI of the ability to evaluate its actions.

One of the promising directions for the development of artificial intelligence methods in the field of energy development is intelligent power systems–such as the Smart Grid [55,56]. The idea of the Smart Grid network is based on the concept of improving the standard power grid. The Smart Grid would ensure communication between all elements of the improved power grid, introducing small energy sources, which would smooth the electricity demand curve. Such an approach would increase the efficiency of energy supply

and reduce the costs, but it would require a comprehensive plan and management and changes in all elements of the network.

Many of the discussed applications of artificial intelligence methods can be used in the design of a modern Smart Grid. Artificial intelligence can also be used on the side of energy consumers. It would be necessary to build a system managed by artificial intelligence to control the charging of devices at home or the office. Devices could be charged at a time when the overall energy demand is low. The demand for different types of services should be taken into account–such patterns could be captured by properly trained neural networks.

Another important research direction in the domain of energy systems operation optimization is the choice of the AI algorithm suitably corresponding to the quantitative and qualitative nature of the problem. Ashraf et al. [57] proposed the classification of the energy system operation into three levels, namely component, system, and strategic. The performance measures corresponding to the component and the system level possess highly nonlinear characteristics, and the output function chosen from these two operational levels is built on hyperdimensional input space. Thus, the input–output variable function space is fairly large and constructing an effective functional map among the variables becomes a challenging task. The ANN is an excellent function approximator algorithm and can build an efficient predictive model, as long as the hyperparameters are optimized and reasonable complexity is embedded in the architecture of the model. The research studies reported in the literature corresponding to the component and system-level problems of the energy system also reveal the competitive advantage of the ANN model over other AI algorithms to build a generalized model [58].

On the other hand, the strategic-level operation problem possesses qualitative features compared to the quantitative nature of the problem associated with the component and system level. The strategic-level problem can be modelled on the system-level operational parameters which are few in number compared with the component-level performance measures (vibration of the pump impeller, temperature, pressure and level of lube oil of bearing, shaft alignment, etc., for pumps, compressors, and other electro-mechanical devices, etc.). Thus, the AI algorithms which were originally proposed for classification problems (like the support vector machine) but their variants (support vector regressor (SVR)) are presented for the regression-based problems can be a suitable choice and may work better than ANNs. The research reported in the literature on the comparative performance analysis of ANNs and SVRs shows better modelling and generalization results of SVRs for the strategic-level problems like thermal efficiency modelling of the power plant [57]. However, in the future, research can be conducted on different energy systems and the comparative performance of the AI models can be investigated corresponding to the quantitative or qualitative nature of problem.

Artificial intelligence, and artificial neural networks in particular, are rapidly evolving fields with many potential avenues for further development. Specifically, here are a few directions that could be promising for the future of AI and ANNs:

- Explainability and interpretability: One of the biggest challenges facing AI is the "black box" problem, where the inner workings of a neural network can be difficult to understand or explain. Developing methods to make AI more transparent and interpretable is a major area of research, as it can help build trust in AI systems and enable humans to better understand how they arrive at their conclusions [59,60].
- Generalization: Another challenge is building ANNs that can generalize well to new situations or data. The current models tend to be highly specialized and can struggle when presented with unexpected inputs. Developing ANNs that can learn more generalizable representations and transfer knowledge between tasks could be an important step towards building more robust AI [61,62].
- Reinforcement learning: Reinforcement learning is a type of machine learning where an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards. This approach has shown great promise in areas like

game-playing and robotics, and could be further developed to tackle a wider range of complex problems [63,64].

- Neural architecture search: Currently, most neural networks are designed by human experts, who handcraft the architecture and hyperparameters. Neural architecture search is an emerging field that uses algorithms to automatically search for the best architecture and hyperparameters for a given task, potentially leading to more efficient and effective models [65,66].
- Hybrid approaches: ANNs are just one approach to building AI, and combining them with other techniques like rule-based systems, expert systems, and symbolic reasoning could lead to more powerful and flexible AI systems [67,68].

Artificial neural networks (ANNs) have shown promise in a variety of applications in the energy field, ranging from forecasting and optimization to fault detection and diagnosis. Here are some examples of how ANNs are being used in energy systems:

- Load forecasting: ANNs have been used to forecast energy demand, which is critical for grid operators to ensure a reliable and efficient power supply. ANNs can take into account a wide range of variables, including the weather, time of day, and previous demand, to predict the future energy demand with a high degree of accuracy [69,70].
- Renewable energy forecasting: ANNs can also be used to forecast the output of renewable energy sources, such as solar and wind power, which can be highly variable and difficult to predict. By accurately forecasting renewable energy output, ANNs can help grid operators integrate these sources into the grid more effectively and efficiently [71,72].
- Energy optimization: ANNs can be used to optimize energy systems, such as determining the optimal scheduling of power plants, distribution of energy resources, or building energy management systems. ANNs can learn from historical data to identify patterns and trends that can inform more efficient and effective energy management [73–75].
- Fault detection and diagnosis: ANNs can be used to detect and diagnose faults in energy systems, such as identifying the source of a power outage or detecting equipment failures. By quickly identifying and diagnosing faults, ANNs can help prevent or mitigate power disruptions, reducing downtime and improving system reliability [76,77].
- Energy trading and pricing: ANNs can be used to model and predict energy prices, allowing energy traders to make more informed decisions about buying and selling energy. ANNs can analyze a wide range of factors that affect energy prices, including supply and demand, weather, and geopolitical events [78,79].
- AI contribution to net zero: The ANN algorithm is an excellent function approximation algorithm and can build an effective model on an ill-defined system. The algorithm has performed well in the predictive analysis for the system under consideration. However, the true potential of ANNs in particular and AI algorithms in general needs to be further explored. A major challenge impeding the incorporation of the ANN model for large-scale industrial applications for modelling, control, and decision support system applications is referred to as the black-box nature of the algorithm. However, the research reported in the literature demonstrates the efficient implementation of the ANN-based findings on the power plant operation [80]. The domain-knowledge supported analysis can be carried out on the developed ANN model; the model-based results are analyzed by the performance engineers and implemented in the live operation of the energy systems. The improvement in the plant-level performance measures like reduction in the emissions discharge, improvement in the energy efficiency, and savings in the cost of operation can be calculated in real-time operation optimization using the ANN model and contribution to the net zero can be reliably made [57].

6. Conclusions

Eighty years is a relatively long time, but for the development of a scientific discipline, it turns out to be too short to say that AI is a field with a fixed scope and methods. We are constantly trying to create a computer that will be as intelligent as a human. We now recognize the human brain as a kind of computer, but most of its functions are still to be explored. In summary:

- Between 1960 and 1980, the field of AI had clearly formulated goals with assumptions regarding when they would be achieved. The main goal was to program the computer to work in an intelligent way. Unfortunately, this approach failed, but each failure can give rise to new hypotheses and directions of development. In contemporary research on artificial intelligence or neural networks, there are no clearly set goals; many researchers treat neural networks as a tool that they add to their work only by increasing the scope of artificial intelligence without their development, without proposing changes in algorithms or creating new algorithms.
- In research on artificial intelligence, the following questions should be answered: whether there is interest in producing products that incorporate artificial intelligence techniques, who is interested in such research, what are the possibilities of such research, and what are the prospects of such research.
- The applications of neural networks are increasing due to their computation time, which can take minutes compared to hours of identification by experts. In recent years, artificial intelligence is starting to work better than humans, which means that there will be better and better algorithms in the future. The progress in the field of AI shows how much a human is able to invent, with which to become unnecessary.

Artificial intelligence offers many solutions that are waiting to be transferred to practical problems. In the constantly developing field of science, which is energy, the use of artificial intelligence seems to be a very good idea.

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