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Energy Security of Photovoltaic Systems in the Context of Artificial Intelligence Development

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Abstract:

Purpose: *This article analyzes the impact of artificial intelligence (AI) advancements on the energy and operational security of photovoltaic (PV) systems. The rapid expansion of solar energy brings numerous benefits but also introduces new challenges, including production instability and operational risks. The paper highlights key AI applications in PV energy forecasting, smart energy management, and advanced fault diagnostics. It also identifies challenges associated with AI deployment, such as data quality, cybersecurity threats, and regulatory issues.*

Design/Methodology/Approach: *The study adopts a mixed-method approach, combining a systematic literature review with case studies of AI applications in photovoltaic systems. Comparative analysis was conducted using data from Poland, the European Union, and other developed countries, allowing for the identification of both common trends and region-specific challenges.*

Findings: *The analysis demonstrates that AI can significantly enhance the reliability and stability of PV energy supply, provided that appropriate technological, organizational, and regulatory frameworks are established.*

Practical implementations: *The findings are illustrated by practical implementations of AI in energy forecasting, predictive maintenance, and intelligent grid management in European and Polish energy companies. Case studies highlight how AI-supported control systems enhance the stability of photovoltaic energy supply by integrating storage facilities and demand-side management.*

Originality/Value: *This article contributes original insights into the role of AI in ensuring both energy security and operational safety of photovoltaic installations under dynamic market and regulatory conditions.*

Keywords: *Photovoltaics, energy security, aArtificial intelligence, machine learning; fault diagnostics, smart energy management, cybersecurity.*

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1. Introduction

The development of renewable energy sources, in particular solar energy, is gaining momentum on a global scale. Photovoltaic (PV) energy has become one of the pillars of the energy transition in many countries, including Poland and the European Union. According to the International Energy Agency, energy security is defined as "the uninterrupted availability of energy sources at an affordable price" (IEA 2025).

In the context of the growing share of PV sources in the energy balance, ensuring energy security means the ability to meet energy demand in a stable manner despite the natural variability of solar production. At the same time, the operational security of photovoltaic systems refers to their reliable, fault-free operation, covering both technical issues (e.g., avoiding damage and failures that could lead to fire or electric shock) and resilience to cyber threats in the era of energy digitalization. In other words, it is necessary to maintain the continuity of energy supply from PV and to protect installations against failures and incidents that could disrupt their operation (Togun, 2025).

Solar energy is playing an increasingly important role in ensuring Europe's energy security, particularly in the face of geopolitical challenges and the need to become independent from fossil fuels. In 2023, the installed capacity of PV installations in the European Union exceeded 260 GW, and the EU plans to increase this figure to 750 GW by 2030, recognizing the development of photovoltaics as critical to the energy security and climate goals of the community (Solar Power Europe, 2023).

Poland has also experienced record growth in PV capacity in recent years, reaching approximately 17.1 GW of installed capacity at the end of 2023, which accounted for over 60% of the country's total renewable energy capacity (IEO, 2024).

However, the intensive development of photovoltaics brings new challenges. The instability of solar production (resulting from the day-night cycle, weather conditions, and seasonality) leads to difficulties in grid management and periodic excess energy in the system (Assareh, 2025).

An example of this is the growing number of cases of curtailment in Poland, i.e., the forced reduction of PV farm generation by system operators during peak production hours to prevent grid overload. These phenomena show that the expansion of PV capacity must go hand in hand with the implementation of smart energy management and storage methods if solar energy is to realistically increase energy security.

Artificial intelligence (AI), including machine learning and deep learning, is seen as a key tool for meeting the above challenges. The use of AI in the energy sector is revolutionizing the way energy is produced, distributed, and managed, increasing the efficiency of systems and their resilience to disruptions (ARTSMART, 2025). Innovative AI-based solutions not only optimize energy efficiency but also address key challenges such as protecting critical infrastructure from failures and cyberattacks. In the photovoltaic sector, AI algorithms are used at many stages of the system life cycle – from site selection and PV farm design, through operation control and generation forecasting, to fault diagnosis and maintenance planning (Lamnatou, 2024).

This makes it possible to reduce the uncertainty, variability, and seasonality associated with photovoltaics, which directly translates into greater stability and reliability of energy supply from these sources. For example, learning algorithms can accurately predict solar energy production based on meteorological data (even taking into account factors such as periodic module soiling), which is crucial for planning the operation of power grids and preventing shortages or overloads (Farmy.pl., 2023).

Equally important is the use of AI for the ongoing optimization and control of distributed PV installations - intelligent energy management systems can dynamically balance production and consumption by activating energy storage facilities during periods of surplus production to ensure continuity of supply during temporary periods of low sunlight. In this way, AI contributes to increasing the flexibility and resilience of the energy system, which is crucial for national energy security (Abbassi, 2025).

Operational safety aspects are no less important. PV systems operate in variable and often harsh environmental conditions, which exposes them to various types of failures and component degradation. Some damage can develop gradually and remain undetected for a long time, leading to serious consequences—for example, local overheating of a module (known as a hotspot) increases the risk of fire (Jathar, 2024).

Traditional monitoring methods often prove insufficient, especially with thousands of dispersed prosumer micro-installations. Artificial intelligence offers groundbreaking possibilities for early anomaly detection and automatic fault diagnosis (Abbassi, 2025).

By analyzing streams of measurement data (e.g., currents, voltages, temperatures) and images from cameras (including thermal imaging and drones), AI algorithms can identify even subtle deviations indicating a developing failure – such as micro cracks in cells, connection degradation or partial shading of modules – before they cause serious failure or performance degradation (Lighthief.com.).

The implementation of such intelligent monitoring systems significantly increases the operational safety of photovoltaic farms and prosumer installations, minimizing the risk of prolonged downtime and potential hazards to people and infrastructure.

An interdisciplinary approach combining engineering and energy policy perspectives is essential to fully exploit the potential of AI in the context of photovoltaic system safety. On the technical side, research and implementation are needed in the areas of advanced control algorithms, energy storage integration, predictive maintenance systems, and cyber security.

At the same time, from a regulatory and organizational perspective, it is necessary to include these new technologies in energy development strategies, both at the EU level (e.g., directives on the digitization and security of energy networks) and at the national level (innovation support policies, grid connection standards, cybersecurity requirements).

1.1 Objective of the Study

This article aims to analyze how the use of artificial intelligence affects the energy security and operational safety of photovoltaic systems. Current research directions and selected examples of commercial implementations of AI in Poland, the European Union, and other developed countries are presented. The analysis is interdisciplinary in nature, combining technical aspects (engineering solutions for PV) with the broader context of energy policy and critical infrastructure security.

1.2 Methods

This paper uses a literature review method and a case study approach. A review of scientific literature was conducted, covering current publications in the field of artificial intelligence applications in solar energy, with particular emphasis on issues related to PV system security. Review and research articles published in journals in the fields of renewable energy, electrical engineering, and applied computer science were analyzed. Selected industry reports and strategic documents were also used to place the issue in the context of energy policy and actual AI technology implementations.

1.3 Research Problem

Particular emphasis was placed on sources presenting experiences from Poland, the European Union, and other developed countries, which enabled comparative analyses and the identification of common trends and specific regional challenges.

The literature review sought answers to the following research questions:

1. *In which areas of the photovoltaic system life cycle is artificial intelligence currently used and what are the benefits from an energy security perspective?* (e.g., improved production forecast accuracy, better integration with the grid and energy storage, dynamic optimization of distributed sources).
2. *How does AI increase the operational safety of PV installations?* (e.g., through early fault detection, failure prevention, predictive maintenance, fire risk reduction, and other operational hazards).

3. *What are the main challenges and risks associated with the implementation of AI in the PV sector from an engineering and regulatory perspective?* (e.g., data and model quality issues, integration of IT systems with energy infrastructure, cybersecurity threats, implementation barriers, need for standards and regulations).

A multidisciplinary approach was adopted – the analysis of the results combined technical facts (e.g., the effectiveness of algorithms in detecting failures) with economic and political conditions (e.g., government initiatives supporting the digitization of the energy sector, EU regulations on network security). In order to obtain a comprehensive overview of the state of knowledge, several dozen publications from 2018-2024 were analyzed, a period during which a rapid increase in interest in AI in solar energy can be observed.

Scientific databases (including Scopus, Web of Science, IEEE Xplore) to search for literature using keywords such as "solar PV," "artificial intelligence," "machine learning," "energy security," and "fault detection." In addition, documents and communications from sectoral institutions (e.g., reports from the nd industry associations, government agencies) describing specific AI implementations in photovoltaic systems were taken into account.

This allowed us to identify examples of commercial implementations and pilot projects, which were described in the results section of the thesis to illustrate the theoretical findings.

The collected source material was critically analyzed, comparing the conclusions of different authors and confronting them with observations from market practice. This triangulation approach increases the reliability of the results obtained and allows for more generalized conclusions to be drawn.

As a result, a synthesis of the current state of knowledge on the impact of artificial intelligence on the security of PV systems was developed, the most important benefits and risks were identified, and research gaps requiring further investigation were identified. It should be emphasized that due to the interdisciplinary nature of the topic, certain issues—e.g., specific algorithmic aspects or detailed legal regulations—have been discussed in general terms, focusing on their significance for energy and operational security in the broad sense.

This approach provides a comprehensive overview of the issue and facilitates understanding of the interrelationships between technology and energy policy.

2. Results

2.1 AI in PV Production Forecasting and Energy Management

One of the key applications of artificial intelligence in solar energy is the forecasting of power generation from photovoltaic installations. High-quality short-term forecasts (hourly, daily) are essential for power system operators to maintain the balance between energy supply and demand in conditions where there is a significant share of non-controllable sources, such as PV.

Traditional forecasting methods based on physical and statistical models are increasingly giving way to AI-based models that can learn from large historical data sets and satellite weather images. The use of neural networks (including advanced architectures such as LSTM and convolutional CNN) and ensemble methods (e.g., gradient boosting) allows for the consideration of nonlinear relationships between weather variables and PV generation and the adaptation of forecasts to local conditions.

As recent reviews indicate, AI-based models are currently among the most widely used forecasting approaches for photovoltaics, demonstrating an advantage over classical models in terms of prediction accuracy. For example, Huang et al. used a combination of the K-means clustering algorithm and LSTM networks with an attention mechanism to categorize historical data and correct weather forecast errors, achieving a significant improvement in the accuracy of short-term PV system power forecasts (Jathar, 2024).

In general, AI makes it possible to reduce solar production forecast error to a few percent, even when taking into account factors that are difficult to model, such as temporary shading or panel contamination (e.g., by dust or snow) (Farmy.pl., 2023). Accurate forecasts translate into increased energy security, as they make it easier for grid operators to plan power reserves and manage load in a way that minimizes the risk of shortages or overloads.

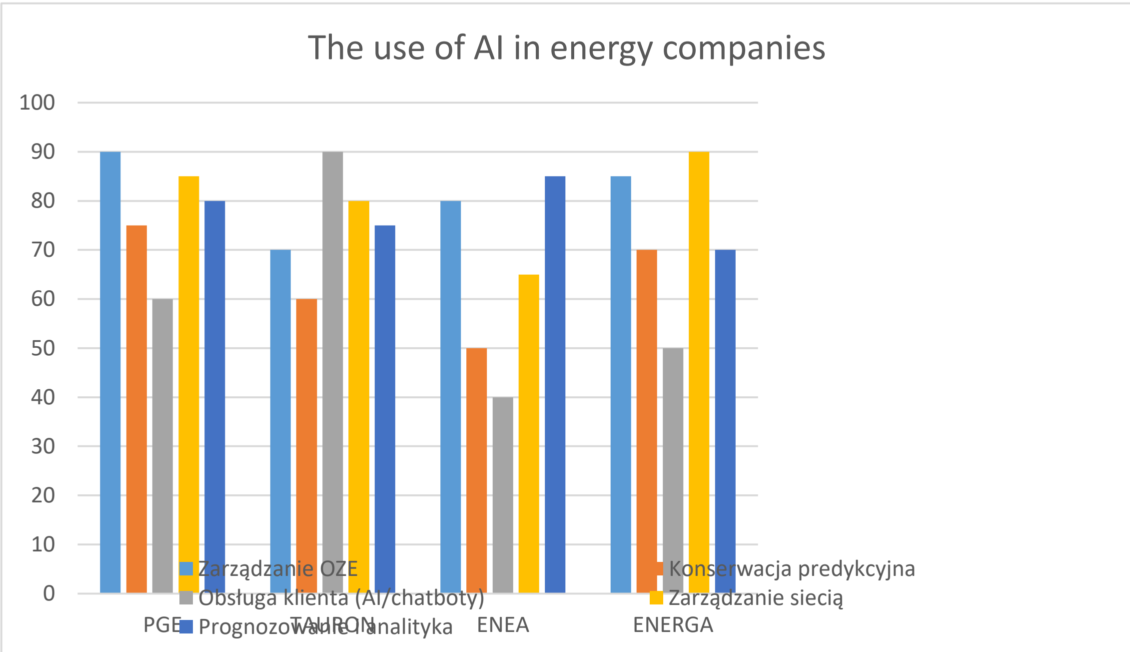
Another important area is intelligent energy flow management and the integration of energy storage in systems with a high share of PV. Artificial intelligence enables the implementation of advanced demand side management (DSM) systems, in which production from solar installations can be dynamically directed to consumers, stored or limited depending on the current needs of the system (Abdel-Basset, 2024).

For example, machine learning algorithms can use historical and current data to optimize the schedule for the use of energy storage facilities so that surplus production is stored during midday hours and stored energy is released during peak demand or after sunset (Liu, 2025). Such solutions are being tested, among others, in microgrids and energy clusters, where local PV resources + storage supported by AI allow power to be maintained to consumers even in the event of interruptions in the main grid.

Commercial example: In Japan, a case study was conducted on a smart PV farm integrated with a multi-stage compressed air energy storage (CAES) system and a gas turbine, where AI algorithms (neural networks and metaheuristics) optimized the operation of the entire system in terms of output power stabilization and peak load reduction (Assareh, 2025).

The results showed that AI achieved a much more uniform generation profile, similar to conventional sources, illustrating the potential of these technologies to increase the predictability of RES. The chart below shows the use of AI in Polish energy companies by area.

***Figure 1**. Application of AI in Polish energy companies by area.*



***Source:** Own study based on: AI in Energy Report, ARTSMART, https://www.inteligentnaenergetyka.pl/enereka/wp-content/uploads/2025/01/Raport_AI-w-energetyce_ARTSMART_31.01.2025.pdf.*

Figure 1 shows the percentage of AI use in Polish energy companies by selected areas:

- PGE leads in RES management and predictive maintenance,
- TAURON is investing heavily in AI in customer service,
- Enea focuses on analytics and investment planning.
- Energa is intensively developing network management using AI.

The modern energy sector, striving for decarbonization and independence from fossil fuels, is increasingly relying on renewable energy sources, particularly photovoltaics. However, the dynamic development of PV micro-installations and their mass connection to the power grid poses challenges related to production instability and difficulties maintaining energy balance.

In Europe, projects are also being implemented to improve the reliability of RES networks through AI – an example is the R-GRID system developed in cooperation between Poland, Ukraine and Finland, which uses artificial intelligence algorithms to prevent power outages in key sectors and has the potential to counteract even widespread network failures (blackouts) (Gramwzielone.pl., 2024).

In the national context, Polish research institutions (NASK and the Institute of Power Engineering) are working on the application of AI to optimize the configuration and operation of power grids with a high share of RES in order to increase their reliability in emergency situations (Jathar, 2024).

The measures being implemented include preparing network operators to recognize threats and automatically respond to disruptions using artificial intelligence algorithms, taking into account new legal requirements (e.g., the EU's NIS2 directive on network security).

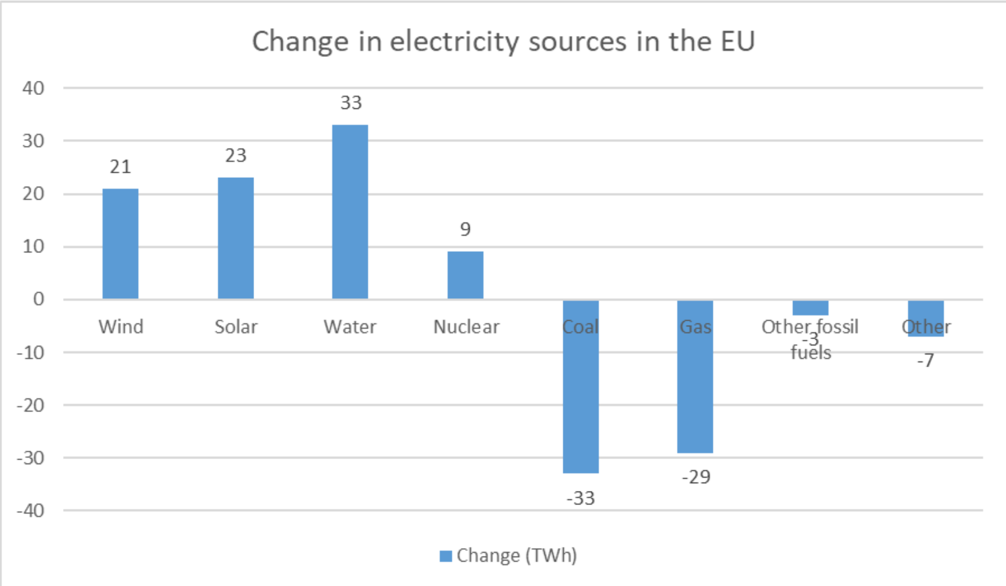
From the point of view of national energy security, smart energy management with PV translates into increased flexibility of the power system. In the first half of 2024, the European Union saw significant changes in the structure of electricity production. The change in electricity sources in the EU is shown in Figure 2.

In the first half of 2024, the European Union saw significant changes in the structure of electricity production. The largest increase was in renewable energy sources, particularly hydroelectric power plants, which generated 33 TWh more than in the same period of 2023. Solar and wind energy production also increased by 23 TWh and 21 TWh, respectively.

A slight increase was also recorded in nuclear energy (+9 TWh). At the same time, energy production from fossil fuels declined. The largest decrease was recorded for coal, down 39 TWh. Production from natural gas decreased by 29 TWh, and from other fossil fuels by 3 TWh. Production from other unclassified sources fell by 7 TWh.

Despite these shifts, total electricity consumption in the EU increased by 9 TWh, marking a rebound after earlier declines caused by, among other things, the energy crisis and industrial savings. The data show a clear direction for the energy transition: an increase in the share of RES while reducing the role of fossil fuels.

Figure 2. *Change in electricity sources in the EU.*



Source: *Wind and solar power overtake coal and gas in EU electricity production, WysokieNapiecie.pl, https://wysokienapiecie.pl/102982-wiatr-i-slonce-wyprzedzily-wegiel-i-gaz-w-produkcji-pradu-w-ue/.*

A system equipped with an AI-based control layer can respond more quickly and effectively to sudden changes, such as a weather breakdown and a drop in solar generation, or conversely, a sharp increase in production on a sunny day with low demand. AI can then automatically send signals to flexible consumers (e.g., industrial farms, EV chargers) to increase surplus energy consumption or activate reserves (storage facilities, backup generators) in case of a shortage before a deficit occurs.

This eliminates or reduces the need for operator intervention in the form of emergency disconnection of PV farms (curtailment) or planned consumer shutdowns. As a result, the stability of energy supply from the end user's point of view is increased and the entire system becomes less susceptible to disruptions.

As analysts emphasize, the skillful combination of various energy sources (solar, wind, storage) using intelligent control platforms creates a synergistic effect that not only ensures stable energy supplies but also protects the environment by maximizing the use of clean sources within a sustainable energy ecosystem (Kanownik, 2023).

It can therefore be concluded that AI acts as a kind of "brain" in modern energy architecture, integrating distributed resources and shaping a new paradigm of energy security based on renewable sources.

2.2 AI in Fault Diagnosis and Maintenance of Photovoltaic Systems

The second fundamental area of AI's impact on PV systems is the improvement of operational safety through advanced methods of monitoring, diagnostics, and maintenance of installations. Photovoltaic systems are prone to a variety of failures and damage resulting from physical factors (material aging, mechanical damage), environmental factors (dirt, shading, weather conditions), and electrical factors (power surges, circuit interruptions).

Table 1 presents the basic categories of typical faults in PV installations, together with their causes and potential effects (Abdel-Basset, 2024).

Table 1. *Classification of the most common faults in photovoltaic systems and their consequences.*

Fault category	Examples and causes	Potential effects
Physical (mechanical)	Microcracks in silicon cells; damage to the laminate and glass of the module (e.g., hail, impact); degradation of adhesives and soldered joints; aging of materials (e.g., cracking of cable insulation).	Decrease in module power due to loss of efficiency of damaged cells; development of hotspots at the site of cracks (risk of overheating); with progressive degradation – module failure or fire in the installation.
Environmental	Panel surface contamination (dust, dirt, soot); organic deposits (bird droppings, leaves); partial shading (growing trees, buildings); corrosion in high humidity conditions.	Reduced power output (incomplete utilization of sunlight); formation of unevenly loaded cells leading to hotspots; in the case of permanent shading of a module section – shutdown of the section by bypass diodes, reduced production.
Electrical	Circuit interruptions (loose MC4 connectors, broken conductive paths); line short circuits (damaged cable insulation, moisture in junction boxes); ground faults; bypass diode damage.	Drop or lack of power generation in part or all of the installation (depending on the location of the interruption/short circuit); risk of sparking and electric arcs (especially in the case of line and ground faults) – fire hazard; uneven operation of modules (in the event of bypass diode failure, increased load on shaded cells).

Source*: Own study.*

As shown in Table 1, many faults – especially physical and environmental ones – are gradual in nature and initially difficult to detect using traditional methods (e.g., periodic output power measurements). For example, microcracks in cells may slightly reduce module efficiency, but over time lead to localized overheating. Similarly, partial shading or soiling can dynamically change the operating point of modules. Artificial intelligence provides tools that enable continuous monitoring of the technical condition of PV installations and detection of subtle anomalies indicating the development of faults.

This involves the use of both electrical data (currents, voltages, power on individual strings or modules) and images – including thermal and visible light images – obtained, for example, from stationary cameras or drones monitoring solar farms.

Modern inverters and SCADA systems for large PV farms already collect data on the performance of individual panel strings as standard. Machine learning algorithms (e.g., random forests, SVM support vectors) can use this data to identify deviations from the expected current-voltage characteristics of the modules, indicating a fault.

For example, ML models trained on historical data can detect a sudden drop in the current of a single string under unchanged irradiation conditions, indicating a break or failure of a module in that string, and generate an alarm about a potential failure (Islam, 2023).

Numerous AI-based fault detection systems are described in the literature: from relatively simple classification methods based on I-V patterns to advanced deep networks that simultaneously analyze multiple inverter operating parameters (ARTSMART, 2025).

Hybrid solutions combining numerical and image analysis are particularly effective (Jathar, 2024). Table 2 presents a conceptual diagram of the steps involved in implementing an AI-based PV fault detection algorithm, from data collection and pre-processing to model training, implementation, and ongoing maintenance of such a system.

Table 2. *Stages of implementing of AI algorithm for fault detection in a PV installation*

Step	**Description**
Data Collection	The first step in applying a fault detection algorithm for photovoltaic (PV) installations is collecting data from the installation. This may include electrical measurements such as current and voltage, as well as data from other sources, e.g., thermal cameras.
Preprocessing and Data Filtering	The collected data may require preprocessing to be ready for analysis by the fault detection algorithm. This may involve cleaning the data

	to remove errors or inconsistencies, as well as transforming the data to make it more suitable for analysis.
Algorithm Training	The next step is to train the fault detection algorithm using the preprocessed data. This may involve providing the algorithm with a set of labeled data indicating the presence or absence of faults, enabling the algorithm to learn from the data.
Algorithm Implementation	Once the fault detection algorithm has been trained, it can be implemented in the photovoltaic (PV) installation.
Monitoring and Maintenance of the Algorithm	It is important to periodically monitor the performance of the fault detection algorithm and apply necessary updates or corrections to ensure that the algorithm continues to accurately detect faults.

Source: *Own study on the basis of Gramwzielone.pl., 2023.*

AI-assisted visual inspection is playing an increasingly important role in the development of automated diagnostics for photovoltaic panels. Thermal cameras mounted on drones or robots can regularly scan fields of modules and provide images showing the temperature distribution on the surface of the panels. These images are then analyzed by deep learning models (e.g., convolutional neural networks) to detect unusual thermal patterns, such as hotspots or inactive fragments of modules.

CNNs trained on hundreds or thousands of images can automatically locate and classify defects – for example, distinguish whether a bright spot on a thermogram is the result of a hotspot, a bypass diode failure, or simply light reflection on the module surface.

Visible and electroluminescent (EL) images are also used for diagnostics – in this case, AI can identify microcracks and structural damage invisible to the naked eye. The use of deep neural networks enables very high defect recognition rates in images – in many studies, it exceeds 90%, which is equal to (and often exceeds) the accuracy of inspections performed by an experienced technician (Gramwzielone.pl., 2023).

It is worth noting that AI also minimizes the number of sensors needed for diagnostics. Ganesan et al. proposed a method for detecting specific types of failures using a minimum number of sensors in an 8×4 module array, using clever voltage analysis – the AI algorithm was able to determine whether the problem was an open circuit or a short circuit between cells, despite limited measurement information (Jathar, 2024).

The benefits of using AI in PV system condition monitoring are multifaceted. First, early fault detection allows for quick service intervention before the fault escalates and causes prolonged downtime or serious damage. This minimizes energy production losses and repair costs (it is usually cheaper to fix a minor fault in advance than to repair a failure that has already damaged multiple modules).

Secondly, intelligent diagnostics increase fire safety by identifying, for example, overheating components that could start a fire in the roof or module field. As mentioned earlier, some defects that are difficult to detect (e.g., local hotspots) significantly increase the risk of materials catching fire; an AI system that alerts to thermal anomalies allows for quick shutdown and inspection of the affected circuit, preventing the worst-case scenario.

Thirdly, AI analysis of device status data facilitates the implementation of predictive maintenance strategies. Instead of a rigid maintenance schedule, devices can be serviced when the algorithm indicates signs of deterioration. This increases the overall availability of the PV system and extends the service life of components, avoiding both emergency downtime and unnecessary interventions.

Commercial AI-based PV monitoring systems are already available on the market, offered by specialized companies. They use cloud platforms to collect data from thousands of distributed installations and machine learning to detect deviations.

For example, there are services that analyze photos from drones monitoring solar farms – after uploading a series of photos from an inspection, the platform automatically generates a report with a list of damaged or suspicious panels, eliminating the tedious work of manually reviewing photos.

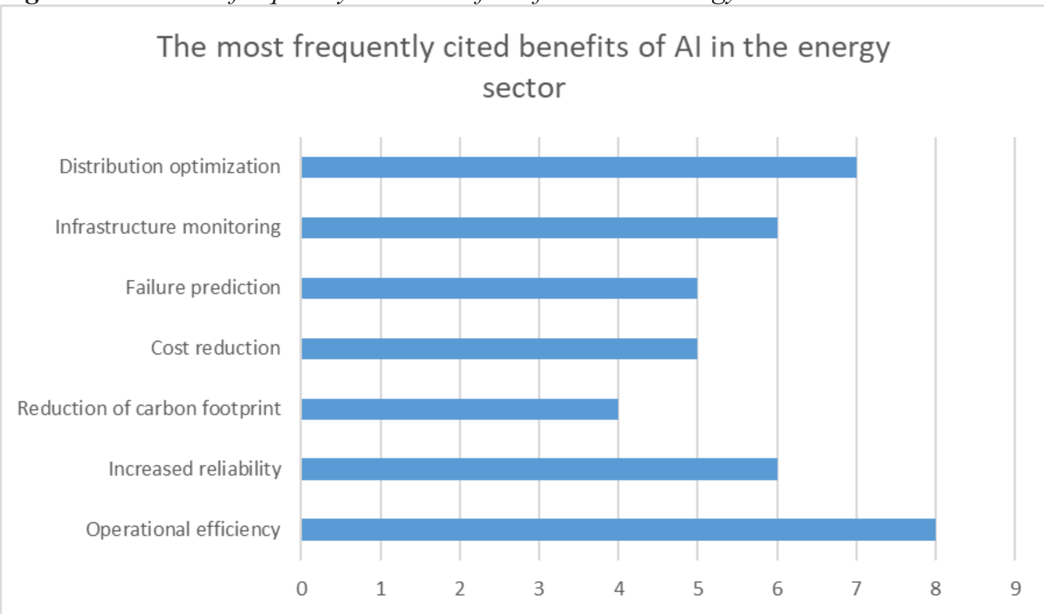
Other solutions integrate with PV farm SCADA systems and report performance anomalies of individual strings in near real time. Such tools are already being used by large PV operators in Europe and the US, delivering measurable results in the form of reduced failure rates and shorter response times to problems. The figure below shows the key areas of application for artificial intelligence in the energy sector.

The report shows which areas, such as demand forecasting and renewable energy management, are considered most important for the sector's transformation.

In summary, artificial intelligence significantly improves the safety standard of photovoltaic systems. It allows traditional reactive operation (actions after a failure occurs) to be transformed into a proactive approach, where potential threats are identified and neutralized before they disrupt the system.

This brings measurable economic benefits (higher energy production, lower service costs) and increases the confidence of consumers and operators in PV technology as a reliable component of the energy mix.

Figure 3. *The most frequently cited benefits of AI in the energy sector.*



Source: *Own study based on: AI in Energy Report, ARTSMART, https://www.inteligentnaenergetyka.pl/enereka/wp-content/uploads/2025/01/Raport_AI-w-energetyce_ARTSMART_31.01.2025.pdf.*

3. Discussion

The results presented clearly indicate that the integration of artificial intelligence with photovoltaic systems can bring significant benefits for both energy security and operational safety. However, it is worth taking a critical look at the conditions necessary to fully exploit this potential and identifying the challenges that need to be addressed through further research or implementation measures.

Ensuring data and model quality. The effectiveness of AI algorithms in forecasting or diagnostics is strongly dependent on the quality and representativeness of the data on which they have been trained. PV systems generate huge volumes of data (measurement, weather, image), which on the one hand is a rich source of information, but on the other hand poses challenges in terms of collection, transmission, and processing.

It is necessary to develop scalable Big Data architectures capable of handling and analyzing data streams from thousands of distributed devices in real time (Islam, 2023). In addition, data from real installations is often incomplete or subject to measurement errors.

The process of pre-processing data (cleaning, filling in gaps, eliminating anomalies unrelated to the system status) therefore becomes a critical step influencing the reliability of the results provided by AI.

The literature emphasizes the need to standardize methods for acquiring and sharing data from PV systems in order to enable effective training of models on a broad base of cases from different regions and operating conditions (Islam, 2023). At the same time, federated learning techniques are being developed that allow AI models to be trained without the need for centralized collection of sensitive data—this is important from the point of view of protecting the privacy of prosumers and operators (e.g., energy production data can reveal household consumption profiles).

These challenges indicate that the implementation of an AI algorithm requires prior investment in IT infrastructure and data management procedures.

Interoperability and integration with existing infrastructure. Another issue is the integration of AI solutions with energy infrastructure and control systems, which are often based on older protocols and devices (e.g., SCADA systems and station security automation). The introduction of AI elements often requires the modernization of the system architecture, e.g., equipping inverters with communication modules and sensors for additional physical quantities (such as module temperature or radiation intensity) needed by AI models to operate.

In the case of large PV farms, the integration of an AI analytics platform with the existing management system may require overcoming compatibility barriers (different data formats, communication protocols). It is therefore important to develop open standards for monitoring and controlling RES installations, which will facilitate the implementation of artificial intelligence algorithms regardless of the equipment supplier.

In recent years, Edge Computing initiatives have been gaining momentum – some of the computing intelligence is being moved to the edge of the network, directly to devices (e.g., PV farm controllers), to reduce latency and make critical functions independent of the cloud connection. However, this approach requires the use of efficient and energy-efficient AI algorithms capable of running on embedded platforms.

Cyber security and AI reliability. Paradoxically, the introduction of advanced IT systems for energy source management creates new risks in the area of cyber security. Every additional access point (inverter communication interface, PV farm connection to the cloud, etc.) can become a potential vector for a hacker attack (Harrou, 2023).

Experts warn that seemingly unrelated topics—green energy and cybersecurity—are in fact closely linked and cannot be treated separately, especially in the context of current geopolitical tensions (Gramwzielone.pl., 2023). 's war in Ukraine has clearly demonstrated the importance of energy independence and the resilience of infrastructure to external interference. In this context, concerns are emerging about the security of the supply chain for renewable energy components (NREL, 2023).

For example, China's dominance in the production of panels and inverters exposes Europe and Poland to the risk of supplies of equipment with potentially built-in backdoors or vulnerabilities. "Buying Chinese components poses a threat to the energy security of the entire Community, as it exposes its members to cyberattacks and supply disruptions," warns the president of the Digital Poland Association, pointing out that smart components for solar power plants manufactured in China could be used to attack installations in EU countries (Kanownik, 2023).

These harsh words are reflected in actions – Poland has launched an educational campaign called "Jasne jak słońce" (Clear as the sun) on cybersecurity in the energy transition process, aimed at raising awareness among PV operators about securing their systems (Kanownik, 2023). Regulations (such as the aforementioned NIS2 directive) are also being implemented at the EU level, imposing cyber protection obligations on the energy sector, which also includes distributed RES sources.

The implementation of AI in PV systems must therefore go hand in hand with the strengthening of the ICT security of these systems. This means encrypting communications, authenticating devices, regularly updating inverter software, and monitoring the tele-IT infrastructure itself using—what else?—AI tools (e.g., machine learning-based intrusion detection systems that detect unusual network traffic patterns that may indicate an attack) (Dou, 2023) (Gramwzielone.pl., 2024).

The introduction of artificial intelligence also raises questions about its resilience and reliability. AI models, especially those based on deep learning, can be as uninterpretable as a "black box." Their decisions—e.g., misclassifying a healthy module as faulty—can be difficult to trace. Therefore, there is growing interest in XAI (explainable AI) methods in the energy sector, which make it possible to explain why an algorithm has made a particular decision (e.g., indicated a failure).

This is important for operators' trust in AI systems – they want to know whether an alarm is actually justified or whether it is a false alarm caused, for example, by an unusual but harmless event. In addition, AI models should be designed with safe failure in mind – in the event of a failure or loss of connectivity, the management system should switch to a safe mode (e.g., disable automatic control and notify the operator). Such procedures must be implemented so that a possible failure in the AI module does not jeopardize the stability or safety of the entire network.

Economic and regulatory aspects. The implementation of the described AI solutions involves costs that must be justified by business or regulatory considerations. Large energy companies are increasingly investing in digitization, seeing it as an opportunity to optimize operating costs (e.g., reducing service calls through remote diagnostics).

However, for small operators or prosumers, the cost of advanced systems can be a barrier. This is where policy comes in – governments and EU institutions can stimulate the market through pilot programs, subsidies for smart meters, data exchange platforms, etc. An example is the Polish grant program for smart energy management systems in clusters, where AI elements are scored as innovation subsidized by public funds.

From a regulatory perspective, it is also important to adapt the legal framework, e.g., regulating the issue of responsibility for decisions made by AI (if an incorrect forecast results in a blackout, is the operator or the algorithm provider liable?), facilitating access to measurement data (privacy vs. public benefit from improved network performance), and ensuring safety standards. It is worth noting that these issues are becoming the subject of broader initiatives, such as the AI Act being processed in the EU, which, although it concerns AI in general, will also have an impact on the energy sector (e.g., requirements for risk assessment of AI systems critical to infrastructure).

Long-term outlook. In the long term, further cooperation between AI and solar energy can be expected. The trend is towards autonomous photovoltaic farms capable of making their own decisions on panel positioning (AI-controlled sun tracking systems can respond to local weather conditions with greater precision than conventional controllers), energy storage management, and grid interaction.

With the development of the Internet of Things (IoT), every device – from panels to meters – will become an intelligent network node, providing data to a global "brain" that optimizes the operation of the entire energy system. This vision is in line with the concept of Smart Grid and distributed energy 4.0. Of course, its implementation requires solving the aforementioned problems of security and trust in AI. Nevertheless, the direction is clear: digitization and automation will continue, and the role of humans will shift from device operators to system supervisors and strategic decision-makers.

From an energy policy perspective, this means that investments in AI should be treated as an integral part of investments in renewable energy infrastructure. Countries that develop their own AI competencies and solutions for the energy sector can gain an advantage by ensuring a more stable, efficient, and secure grid with a high share of renewable sources.

4. Conclusions

Photovoltaic systems are playing an increasingly important role in the energy mix of many countries, making the issue of their security – both in terms of energy supply stability and operational reliability – a matter of strategic importance. The use of artificial intelligence appears to be a key element in meeting the challenges associated with the mass deployment of photovoltaics. The analyses carried out allow the following main conclusions to be drawn:

- **AI as a guarantor of PV generation stability and predictability:** Artificial intelligence algorithms significantly improve the accuracy of solar energy production forecasts, reducing the uncertainty associated with its variability. This enables better planning of the energy system and more efficient use of solar energy, which translates into increased energy security (lower risk of power shortages, lower dependence on conventional reserves). In addition, AI enables dynamic control of energy flows (including storage integration and demand control), allowing a system with a high share of PV to remain stable even under rapidly changing weather conditions or demand.

- **AI as a tool for improving operational reliability and safety:** The implementation of machine learning methods in the monitoring and diagnostics of photovoltaic installations enables early fault detection and failure prevention. Intelligent surveillance systems identify anomalies indicating the development of faults (e.g., overheating modules, performance drops) and generate alarms, allowing operators to intervene quickly. This approach minimizes production losses and reduces the risk of serious incidents, including installation fires and electric shocks. Thus, artificial intelligence contributes to the increased operational safety of PV systems, making them more predictable and maintenance-friendly.

- **An interdisciplinary approach is necessary for the effective integration of AI into the PV sector:** Maximizing the potential of AI requires cooperation between engineers, IT specialists, and decision-makers shaping the regulatory framework. From a technical point of view, it is important to ensure adequate measurement, communication, and computing infrastructure, as well as the quality of data feeding the algorithms. At the same time, from an organizational and legal perspective, standards, guidelines, and incentives are needed to support the digitization of the energy sector—e.g., regulations requiring the monitoring of the status of renewable energy installations, subsidy programs for smart energy management systems, and standardized data exchange protocols for smart grids. Only by combining these perspectives can AI be successfully implemented on a large scale in the PV sector.

- **Challenges to be addressed – cybersecurity and trust in AI:** Despite its numerous benefits, the use of artificial intelligence also carries risks that must be proactively addressed. The most important of these are cyber threats – smart energy infrastructure must be protected against attacks and data manipulation. This requires the implementation of strong IT security mechanisms and continuous auditing of AI system vulnerabilities. The second aspect is ensuring the reliability and explainability of algorithms. In critical applications, such as network control, AI models should undergo rigorous testing and validation, and their decisions should be as transparent as possible to operators. The development of interpretable AI methods and redundancy (backup scenarios in case of AI failure) will be important elements in increasing trust in these solutions.

- **Impact on energy policy and development prospects:** Artificial intelligence is becoming an integral part of modern energy policy. EU countries, including Poland, recognize the need to invest not only in renewable energy capacity, but also in the "smart infrastructure" that accompanies these sources. AI enables a safer increase in the share of photovoltaics in the energy mix and should therefore be given priority in energy innovation strategies. In the future, further autonomization and automation of energy management can be expected, which, with appropriate regulatory oversight, will translate into high resilience of the energy system to both classic threats (technical failures, forecasting errors) and new challenges (cyber attacks, extreme weather events). Artificial intelligence, combined with distributed solar energy, has the potential to become a pillar of energy security in the era of decarbonization.

In summary, the development and implementation of artificial intelligence in the photovoltaic sector is part of the global trend towards smart energy grids. By ensuring more stable energy supplies and safer operation of equipment, AI helps to address the sunny paradox: how to make an unstable source such as the sun the foundation of a secure and reliable energy system.

Experience from Poland, the European Union, and other countries shows that this is possible—but it requires conscious investment, innovative research, and responsible policies that integrate technical and safety aspects into a coherent strategy.

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