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The Use of Artificial Intelligence Technologies in Energy and Climate Security

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ABSTRACT

This study provides a theoretical analysis of the use and application of artificial intelligence (AI) in the energy sector as it relates to climate security. **The object** of the study is energy and climate security as types of economic activity and social activity. **The subject** of the research is artificial intelligence in relation to the object area of research. **The purpose** of the study is to create a sound scientific basis for the use of artificial intelligence in the energy sector, as well as to identify emerging problems in the formation of a science-based approach to climate policy development. The authors' research includes three interrelated research **methodologies:** topic modeling, text mining as part of qualitative analysis and object modeling as part of the systematization of results that are adequate to the subject area of the study and correspond to their reality; in addition, the authors supplemented the quantitative results with a theoretical and heuristic analysis of the scientific results of other researchers. The concept of parametric optimization (PO) is used as an effective method for solving the applied problem of testing the hypothesis of managing energy costs and energy efficiency based on AI in order to achieve optimal performance of the technical system and compliance with the Sustainable Development Goals (SDGs) in the field of climate security. The study's **findings** suggest that AI is becoming fundamental to the development of a modern energy sector based on data and complex relationships and provides tools to improve technical system performance and efficiency in the face of sanctions restrictions. The authors **conclude** that the truth of the hypothesis has been proven: the use of AI as a control feedback loop at a technical facility for purification and energy generation is a more cost-effective and technically optimal alternative to a "live" operator, which will eliminate the human error factor. In this regard, the energy industry, utilities, grid operators and independent power producers must pay special attention to the introduction of AI technologies into existing technical systems.

Keywords: artificial intelligence; energy efficiency; green economics; energy saving; feedback loop; intelligent algorithm; optimization; climate security; energy sector

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Использование технологий искусственного интеллекта в энергетике и климатической безопасности

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АННОТАЦИЯ

Настоящее исследование посвящено теоретическому анализу использования и прикладного применения искусственного интеллекта (ИИ) в энергетическом секторе в приложении к климатической безопасности. **Объектом исследования** выступает энергетика и климатическая безопасность как виды экономической деятельности и общественной активности. **Предметом исследования** является искусственный интеллект применительно к объектной области исследования. **Цель исследования** — создание обоснованных научных оснований для использования искусственного интеллекта в энергетике, а также выявления возникающих проблем в формировании научно обоснованного подхода к разработке климатической политики. Исследование авторов включает три взаимосвязанных **методологии** исследования: тематическое моделирование, интеллектуальный анализ текста в рамках качественного анализа и объектное моделирование в рамках систематизации результатов, адекватных предметной области исследования и соответствия их действительности. Кроме того, авторы дополнили количественные результаты теоретико-эвристическим анализом научных результатов других исследователей. Используется концепция параметрической оптимизации (ПО) в качестве эффективного метода для решения прикладной задачи проверки гипотезы управления энергозатратами и энергоэффективностью на основе ИИ с целью достижения оптимальных показателей работы технической системы и соответствия целям устойчивого развития (ЦУР) в области климатической безопасности. **Результаты исследования** свидетельствуют о том, что ИИ становится основополагающим фактором для развития современного энергетического сектора, основанного на данных и сложных взаимосвязях и предоставляет инструменты для повышения производительности технических систем и эффективности в условиях санкционных ограничений. **Доказана** истинность гипотезы, что использование ИИ в качестве управляющего контура обратной связи на техническом объекте очистки и генерации энергии является более экономически эффективной и технически оптимальной альтернативой «живому» оператору, что позволит исключить человеческий фактор ошибки. В связи с этим энергетическая отрасль, коммунальные предприятия, операторы энергосистем и независимые производители электроэнергии должны уделять особое внимание внедрению технологий ИИ в существующие технические системы.

Ключевые слова: искусственный интеллект; энергоэффективность; зеленая экономика; энергосбережение; контур обратной связи; интеллектуальный алгоритм; оптимизация; климатическая безопасность; энергетический сектор

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Introduction

The energy sector is undergoing fundamental changes due to the adoption of digital technologies, with artificial intelligence (AI) playing a pivotal role. The use of AI enables the integration of energy production, consumption, and renewable sources, allowing for autonomous energy system management through intelligent algorithms that optimize decision-making and operational processes. In the context of rapidly advancing information technologies, AI, and data analytics, regulatory authorities face the challenge of promptly and effectively approving new services and products. This requires informed and adaptive interaction while addressing issues of client safety, confidentiality, and information security. Climate change represents one of the most significant challenges for modern society, yet it often takes a backseat in political agendas, overshadowed by more immediate and pressing issues that align with current political priorities.

This research focuses on three main aspects of energy and climate security:

1. The use of AI in renewable electricity production.
2. The application of AI for managing circular processes in energy supply and energy savings.
3. Recent advancements in AI technologies for utilizing human-generated waste and byproducts to produce clean energy.

This paper presents an overview of the challenges associated with using AI in energy and climate change, emphasizing the applied nature of AI implementation in a technical facility. A scientific hypothesis is proposed: employing AI as a feedback control loop in a technical facility for energy purification and generation is a more cost-effective and technically optimal alternative to a “human” operator, eliminating the human factor.

Theoretical and practical significance of the research lies in the novel applied formulation of the problem of AI usage in the context of energy system design, the use of empirical performance evaluation strategies for parameter search algorithms, the development and assessment of new software implementation algorithms, and the demonstration of AI's application in solving specific design problems in technical and energy systems, contributing to the achievement of sustainable development goals in climate security.

Literature review

At present, extensive applied research on the impact of artificial intelligence (AI) and deep learning (DL) on the process and efficiency of achieving Sustainable Development Goals (SDGs) highlights the significant potential of these technologies across various fields of human activity. These include "environmental safety and sustainability" [1], "using AI to achieve carbon neutrality" [2], "the impact of AI on transformative changes in energy" [3], "quantum artificial intelligence for renewable and sustainable energy" [4], and "AI in the economic evaluation of energy efficiency technologies" [5]. Zhengcheng Fan and co-authors found that "AI can potentially contribute to achieving 134 out of 169 targets across all SDGs…" [6], emphasizing the need for a comprehensive exploration of the subject area.

In Industry 4.0, AI significantly influences various sectors of the economy, transforming activities and states in agriculture, education, and industry, with the emergence of new sectors and types of human activities. For example, "we view BCI (brain-computer interfaces) as a hardware-software communication system that enables humans or animals to interact with the environment without involving peripheral nerves and muscles, using control signals generated by brain activity" [7, p. 2].

The importance of interpretability in DL models is considered a key factor for the effective and optimal use of AI in daily and professional activities: "…due to their overly parameterized 'black-box' nature, it is often challenging to understand the predictive results of deep models. In recent years, numerous interpretability tools have been proposed to explain or uncover how deep models make decisions" [8, p. 3197].

S. Leonelli and H.F. Williamson compellingly argue that AI and DL also hold great promise for environmental sustainability, particularly in applying AI through plant biology systems, defining a new role for AI in achieving SDGs [9].

Research by Ahmad et al. convincingly shows that advancements in AI, such as machine learning, deep learning, the Internet of Things (IoT), and big data analytics, are significantly transforming the energy sector in terms of supply, production, demand, and electricity provision [10].

Numerous scientific studies are devoted to the broad application of AI in clean energy. For instance, researchers N.C. Ohalete et al. recognize the growing role of AI in promoting clean energy sources and its significant impact on improving the efficiency of renewable energy systems [11]. Asif Raihan found that AI and machine learning are actively being implemented in energy research domains, focusing particularly on renewable energy as a key future development direction for AI [12]. He also emphasizes that "future research using advanced sustainability assessment tools such as life cycle assessment, exergy analysis, etc., should further explore the sustainability of biomass-to-bioenergy conversion processes" [13, p. 10].

Researchers Kenji Masio, Mizuki Kasamatsu, and Eisuke Noda raise the critical issue of improving management and safety in nuclear energy. They propose the practical application of AI in disaster management information systems for nuclear power plants under the name DMP (Decision-Making Panel). This enhances the safety and resilience of the nuclear energy sector: "DMP was developed using a human-centered design approach based on international and Japanese human factor design guidelines… and validated through human factors verification (task support verification) to ensure DMP supports decision-making processes" [14, p. 346].

Barbara A. Han et al. explore future prospects for AI and ecology through synergy, emphasizing the need for guided, targeted synergy to expand the understanding of ecological sustainability while improving resilience. They highlight that current AI systems lack state certainty in terms of sustainability, leading to negative consequences in various human experience contexts [15].

Researchers Martin János Mayer, Arthur Silágyi, and Gyula Gróf address critical issues of optimization and efficiency in renewable energy systems, identifying significant differences between ecological and economic optima. At the same time, the proposed multi-objective optimization in applied use has proven effective as a compromise between two conflicting goals of optimization and efficiency [16].

Machelev R. et al. underscore the growing importance of AI in renewable energy and reveal its contribution to achieving sustainable development goals in the energy sector [17]. Researchers Jingze Li, Pei Liu, and Zheng Li examine the challenges of optimal design and management of renewable energy systems [18], while Abdalla et al. investigate the use of AI for optimizing the configuration of renewable energy systems, implementing energy management strategies, and employing energy storage technologies [19].

Connor Sweeney et al. highlight the critical issue of energy consumption forecasting and future energy development in their work [20], while T. Ahmad et al. emphasize and substantiate the fact that AI plays a crucial role in energy consumption prediction, creating a reliable benchmark for future energy initiatives [21].

Despite the extensive study of AI's technological impact on energy, empirical research on its influence on human energy development (HED) is expanding in the scientific field in search of more effective solutions [22]. The effectiveness of AI and DL applications in power systems is evident in the ability to predict optimal power flows by combining deep learning and Lagrangian methods. This improves the accuracy of AC power flow optimization, surpassing traditional power distribution systems [23].

The application of AI and DL in renewable energy, particularly in solar photovoltaic power plants, demonstrates significant success in fault detection and system management. For example, the integration of the solAIR system, which uses AI for automatic fault detection in photovoltaic plants, relies on thermal image analysis using drones and AI to promptly identify anomalies and provide maintenance recommendations [24].

The rapid development of artificial intelligence (AI) and deep learning (DL) in the field of renewable energy has driven numerous studies that foster the emergence of new methodologies and applications. These studies explore energy management systems and energy balance forecasting across various domains of human experience, demonstrating a wide range of approaches and technologies used in both everyday life and professional activities. For instance, the works of Sami Ben Slama and Marwan Mahmoud [25], as well as Zoltan Nagy et al. [26], highlight these advancements.

Vladimir Franki, Darin Majnaric, and Alfredo Viskovic conducted an analysis of the impact of AI on optimizing energy systems and expanding international business. Their findings emphasize the pivotal role of digitalization in unifying business processes and relationships, with a focus on leveraging AI to optimize energy consumption across various industries, including renewable energy [27].

Most of the studies reviewed underscore the importance of applying AI and DL to optimize renewable energy systems. The diversity of methodologies and application directions is notable, with some research focusing on real-time energy trading while others address challenges through comparative analysis of different AI algorithm performances.

In Russia, the applied use of AI in energy has also gained momentum in the scientific domain, expanding as a subject of interest and exploration. For example, Russian researcher L. V. Massel examines critical ethical risks associated with AI use and its prospects in various areas of human experience: "Three types of risks are highlighted: job shortages as machines replace humans; implications for human independence, freedom, and security; and concerns that smarter machines may dominate humans and cause humanity's demise" [28, p. 13]. Domestic researchers E. P. Grabchak and E. L. Loginov explore the implementation of AI-based digital platforms to enhance decision-making efficiency in technologically complex energy systems. They propose the development of an integrated digital platform to address these challenges [29]. Similarly, K. H. Zoido and E. L. Loginov tackle the crucial issue of ensuring reliability and standardization in management decisions within the energy sector using AI [30].

Despite the extensive body of academic research, a significant gap persists between academic studies and industry needs. While the authors have attempted to review applied research, the issue of empirical and practical studies remains relevant. It is crucial to continue research efforts aimed at the practical implementation and scaling of innovative solutions in real-world conditions. Moreover, additional studies addressing the socio-economic and environmental implications of integrating AI and DL into the renewable energy sector have become an urgent necessity.

Materials and methods

Different researchers have varying opinions regarding the advantages and disadvantages of quantitative and qualitative scientific research methods in the context of scientific inquiry and problem-solving. This study incorporates three interconnected research methodologies: thematic modeling, text mining as part of qualitative analysis, and object modeling for the systematization of results relevant to the research subject and their practical applicability. Additionally, the quantitative findings are supplemented with theoretical-heuristic analyses of other researchers' results.

The concept of parametric optimization (PO) is employed as an effective method to address the applied challenge of testing the hypothesis on energy cost management and efficiency using AI to achieve optimal performance of technical systems and alignment with Sustainable Development Goals (SDGs) in climate security. In this research, PO is defined as the process of finding the optimal solution dependent on one or more parameters influencing this solution through feedback loops. AI uses this infinite cycle for continuous regulation, effectively replacing the "human" operator, thereby eliminating the human error factor and improving the efficiency and optimization of the technical energy system.

To test the hypothesis, PID controllers (Proportional-Integral-Derivative controllers) are used as regulation tools. These controllers employ feedback loops and are widely applied in industrial systems for regulation and control, especially where continuous modulated control of an object is required. The PID controller continuously computes the error as the difference between the desired setpoint value (SPSP) and the measured process variable (PVPV). It then applies corrections based on proportional (PP), integral (II), and derivative (DD) components, which are reflected in its name. PID systems provide precise and timely adjustments to control functions.

The initial theoretical and practical application of PID controllers was found in automatic ship steering in the 1920s. Over time, their evolution has seen widespread use in process automation across manufacturing industries, starting with pneumatic controllers and later transitioning to electronic controllers [31]. Today, the PID concept is extensively applied in systems requiring precise and optimized automatic control.

The distinctive feature of PID controllers is their ability to implement three control conditions (proportional, integral, and derivative effects) on the controller's output signal for precise and optimal control. The proportional component (PP) is proportional to the current error between the setpoint and the process variable. Applying a gain coefficient results in a corresponding change in the control output based on the magnitude of the error. However, using proportional control alone may lead to a residual error under steady-state conditions [32].

The integral component considers past error values and integrates them over time to eliminate residual errors resulting from proportional control. The derivative component predicts future error trends and directs the controller to reduce their effect based on the rate of change. Balancing these components is achieved by tuning control loop parameters for optimal performance. The tuning constants must be adapted for each application, depending on the loop and process characteristics.

The direct control action of the controller ensures that a positive error change leads to a corresponding positive change in the control output signal. In some cases, reverse action may be required to apply corrective negative adjustments. AI-driven tuning and training of the control loop optimize the PID controller's operation, ensuring the necessary efficiency and stability in managing technical energy systems.

Application in water treatment and energy systems

The operation of wastewater treatment systems is associated with high energy consumption for technical systems such as pumping equipment, automated management systems, lighting, heating, and ventilation [33]. Special attention is given to sewage treatment facilities (STFs), which use various technical means to move water with specific flow rates and pressures. A critical aspect of STF operations is the backflow of treated water into a water body to ensure environmental safety [34]. Sewer pumping stations (SPS) with pressure dampening wells at the ends of pressurized collectors are often employed to maintain ecological balance in aquatic environments.

This study proposes using the volume of wastewater in the discharge collector to generate energy for STFs through renewable energy sources. The method involves producing clean and renewable electricity for STF needs using specialized installations for generating electricity in pressure-dampening wells, leveraging treated wastewater.

For these purposes, small-scale hydropower plants (HPPs), designed for small rivers or artificial reservoirs, are considered. Continuous water supply is essential for HPPs to avoid downtime. In turn, STFs must operate consistently to ensure a steady wastewater flow to sustain microorganisms in the treatment process. The PowerPal electricity generation unit meets these requirements, ensuring HPP operability [35]. When parameters exceed standard conditions, the unit generates additional power. Under standard conditions, the HPP generates 1250 watts, and the generator weighs 90 kg. PowerPal is easy to operate and maintain, providing long-term, fault-free operation when adhering to the manufacturer's instructions.

HPPs are chosen as a practical example of a technical energy system, prioritizing ecological and climate sustainability. As noted by international researchers, "One strategy is to increase the share of hydropower as a renewable energy source to reduce greenhouse gas emissions. The second strategy is to optimize the operation and management of hydropower to adapt to various climatic conditions" [36]. A subsequent significant study examined energy and climate sustainability and security based on 140 parameters across four categories: "...many researchers have realized the importance of sustainable hydropower development and explained the concept of sustainability from different perspectives" [37].

Results

Preparation stage

1. Selection of a technical device considering the specified parameters.
2. Installation of the technical device in the pressure-dampening well.
3. Development of AI algorithm principles.
4. Assessment of the techno-economic effect of using an alternative electricity source with AI integration.

To test the research hypothesis, a pressure-dampening well located at one of the enterprises in Russia, positioned on the discharge collector to a water body, was selected as the study object.

When designing the sewer pumping station (SPS), located at the highest point of the pressurized collector, the system was divided into two main sections:

1. Pressurized section

This section extends from the starting point to the highest point, where the direction of water movement changes.

2. Gravity-flow section

This section runs from the highest point to the endpoint, where water flows naturally without the use of additional devices.

This design was employed during the planning and operation of the sewer pumping station for discharging wastewater from sewage treatment facilities into a water body at the "N" site. The schematic diagram of this system is presented in *Fig*.

This staged approach allowed for the systematic implementation of AI-driven solutions, optimizing the energy efficiency of the wastewater treatment process while ensuring compliance with environmental safety standards. The results validate the feasibility of integrating renewable energy sources into such systems.

Operational features of the sewer pumping station (SPS)

During the operation of the sewer pumping station (SPS), specific characteristics are observed related to the functionality of submersible sewage pumps. These pumps can transfer wastewater through the centrifugal impeller while the pressurized pipeline operates as a siphon. This behavior is due to the steady-state movement of the liquid, where the product of the average velocity and cross-sectional area remains constant. This characteristic enables energy-saving measures during the transfer of wastewater from sewage treatment facilities to a water body.

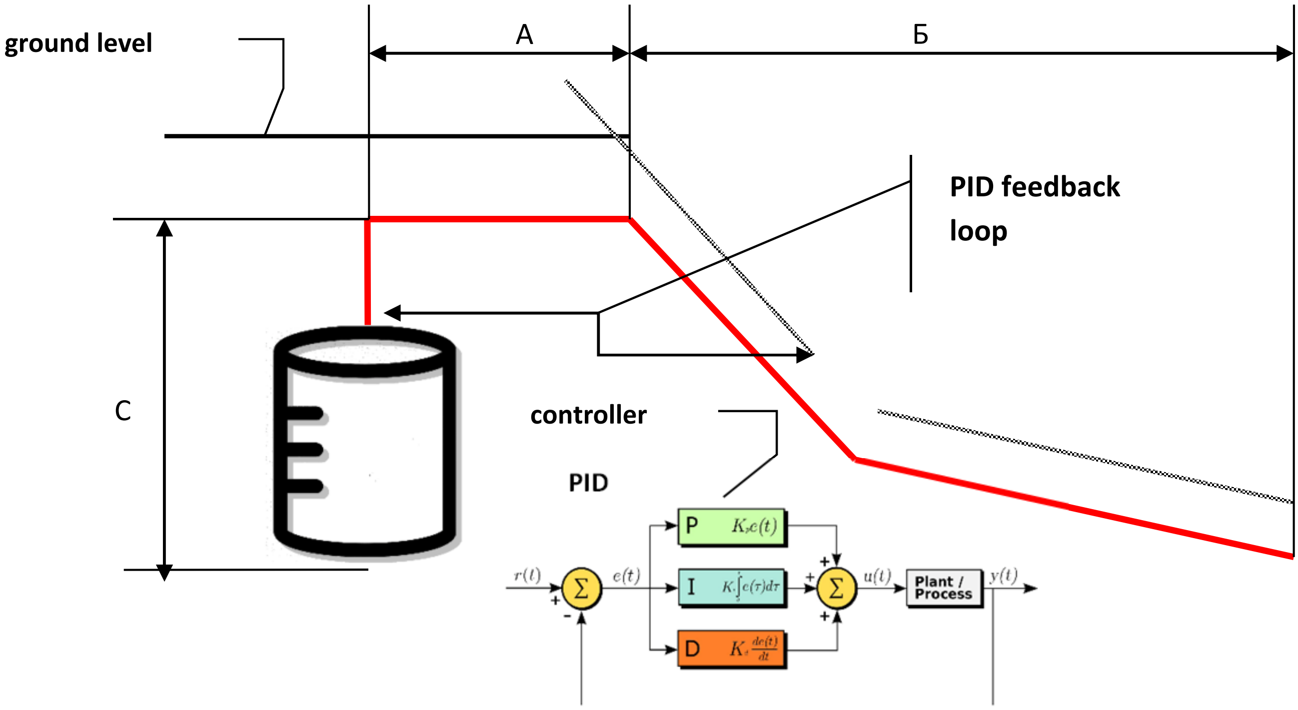

Fig. **Schematic diagram of the SPS device and pipeline system**

Source: Developed by the author.

Using the SIP program to calculate pipeline filling by pumps, it was determined that filling the pipes with water using two pumps takes 44 seconds. Once the pipeline is filled with water, it begins to function as a siphon, while the impeller of the submersible pump continues to pass water through itself.

Field study

A field study was conducted to evaluate the proposed SPS operation method, which included the following steps:

1. Pumping water with active pumps until the reservoir in the SPS reached its minimum level.
2. Employing the siphon method, where the pumps were switched off after the pressurized pipelines were filled with water, and measuring the time taken to empty the SPS reservoir.

Results of the Field study:

- Time for two pumps to operate: 32 minutes.
- Time to fill the pipelines using two pumps: 1 minute.
- Time to drain the water after pump shutdown: 38 minutes.
- Total drainage time: 42 minutes.

PID controller program algorithm and optimization

Steps:

1. Measure wastewater levels and energy consumption.
2. Determine the optimal pump speed using a PID controller (Proportional-Integral-Derivative controller).
3. Adjust the pump speed through an AI feedback loop.

Code for regulating energy generation by submersible sewage pumps

python

```
Copy code
import time
import math
# Parameter setup
setpoint = 50 # Optimal wastewater level (in percentage)
Kp = 0.5 # Proportional coefficient
Ki = 0.01 # Integral coefficient
Kd = 0.001 # Derivative coefficient
# Initialize variables
error_prev = 0
integral = 0
# Infinite loop for constant regulation
while True:
```

```
# Measure wastewater level and energy consumption
level = measure_wastewater_level()
power = measure_energy_consumption()
# Calculate error
error = setpoint — level
# Calculate integral
integral += error * 0.1 # Integral step (0.1 seconds)
# Calculate derivative
derivative = (error — error_prev) / 0.1 # Derivative step (0.1 seconds)
# Update previous error
error_prev = error
# Compute PID controller output
output = Kp * error + Ki * integral + Kd * derivative
# Limit output signal (0–100%)
output = min(100, max(0, output))
# Adjust pump speed
set_pump_speed(output)
# Pause for 0.1 seconds to refresh data
time.sleep(0.1)
```

Explanation of the code step-by-step

1. Define the optimal wastewater level and PID coefficients.
2. Initialize variables for error, integral, and derivative.
3. Measure the wastewater level and energy consumption.
4. Calculate the error between the setpoint and the measured level.
5. Compute the integral of the error.
6. Calculate the derivative of the error.
7. Update the previous error value.
8. Compute the PID controller output.
9. Limit the output within a range of 0–100%.
10. Adjust the pump speed based on the output signal.
11. Pause for 0.1 seconds to refresh the data.

AI logic for pump control

```
python
Copy code
import RPi.GPIO as GPIO # Import GPIO library
import time # Import time library
# Set GPIO numbering mode
GPIO.setmode(GPIO.BCM)
# Configure GPIO pin 18 as output for relay control
GPIO.setup(18, GPIO.OUT)
# Set initial relay state (off)
GPIO.output(18, GPIO.LOW)
# Define regulation interval (e.g., 1 minute)
interval = 60 # seconds
# Infinite loop for continuous regulation
while True:
# Get current time
current_time = time.time()
# Check if the regulation interval has elapsed
if (current_time — start_time) >= interval:
# Toggle relay state (turn pump on/off)
GPIO.output(18, not GPIO.input(18))
# Update last regulation time
start_time = current_time
# Clean up GPIO pins on program exit
GPIO.cleanup()
```

AI operational workflow

1. Import required libraries.
2. Configure GPIO numbering mode (BCM).
3. Set GPIO pin 18 as output for relay control.
4. Initialize the relay to the off state.
5. Define the regulation interval (e.g., 1 minute).
6. Enter an infinite loop for continuous regulation.
7. Retrieve the current time.
8. Check if the regulation interval has elapsed.
9. Toggle the relay state to control the pump.
10. Update the timestamp for the last regulation.
11. Clean up GPIO pins upon program exit.

Testing the scientific hypothesis

The proposed method of energy saving and energy supply primarily allows for the utilization of self-generated energy as a resource. This approach significantly reduces electricity costs and labor expenses, which can be viewed by the owner as income.

To begin, let us determine the difference in automation costs for the sewer pumping station (SPS) before and after implementing the energy-saving method:

1. The power of a single pump transferring wastewater is 7 kW/hour.
2. The daily throughput of the SPS is 530 m^3/day. The monthly throughput of the SPS is calculated as follows: Qmonthly = Qdaily × × 30 = 530 m^3/day × 30 = 15,900 m^3/month

Table 1
Using AI for energy generation: the reduction in operational costs and energy consumption

Parameters	Option with AI	Cost for Pressure Maintenance
Kilowatts per month	14*150.9 = 21,12.6 kW	14*11.04 = 154.6 kW
Monthly electricity cost (rubles)	2,112.6*11 = 23,238.6 rub	154.6*11 = 1,700.2 rub
Annual electricity cost (rubles)	23,238.6*12 = 278,863.2 rub	256.12*12 = 20,402 rub

Source: Developed by the authors.

Qmonthly = Qdaily × 30 = 530 m^3/day × 30 = = 15,900m^3/month.

3. Based on the experimental results, the approximate capacity of two pumps operating together is 105.4 m^3/hour.

4. Calculate the monthly operating time of two pumps transferring wastewater under the first scenario: Toperating time = QmonthlyQcapacity = 15,900 m^3/month105.4 m^3/hour = = 150.9 hours/month. Toperating time = QcapacityQmonthly = 105.4m^3/hour15,900m^3/month = = 150.9hours/month.

5. For the pipeline filling scenario, calculate the time required to fill the pipelines: Tfilling = QfillingQpump rate = 22.08 $m^3$2 × 0.5 m^3/hour = 11.04 hours. Tfilling = Qpump rate Qfilling = 2 × 0.5m^3/hour22.08m^3 = 11.04hours.

6. The electricity tariff at this facility is 11 RUB/kW.

Table 1 presents the results of using AI for energy generation, demonstrating the reduction in operational costs and energy consumption through automation and self-sustained energy production.

Thus, the economic effect is evident: 278,863.2 RUB — 20,402 RUB = 258,461.2 RUB, solely from energy generation and savings, excluding labor costs (as AI eliminates the human factor).

The computational power required to support the growth of AI approximately doubles every 100 days. Consequently, achieving a tenfold increase in AI model efficiency may require a 10,000-fold increase in computational power. The energy consumption needed to execute AI tasks is already exhibiting an accelerated growth rate, increasing annually by 26% to 36%.

The economic impact of AI on the environment manifests at two key stages of its lifecycle: the training phase and the inference phase. During the training phase, models are developed by processing vast volumes of data, after which they move to the inference phase, where they are applied to solve real-world problems. Currently, the environmental footprint is distributed as follows: training accounts for approximately 20%, while inference constitutes the majority — 80%. As AI models are increasingly deployed across various sectors, the demand for inference, along with economies of scale and its environmental impact, will grow. Aligning AI's rapid progress with the need for environmental sustainability requires a carefully designed strategy encompassing immediate and short-term measures while laying the foundation for long-term sustainability.

AI contributes to efforts for transitioning to a climate-neutral and energy-efficient economy in numerous ways. It aids in the development of new materials for clean energy technologies, optimizes the performance of solar and wind power plants, advances energy storage technologies, enhances carbon capture processes, improves the accuracy of climate and weather forecasts for better energy planning, and catalyzes breakthroughs in green energy sources, such as nuclear fusion. Through the strategic application of AI to enhance renewable energy infrastructure, the future of AI promises not only the growth of the green economy but also the creation of more sustainable socio-economic systems for future generations.

In the long term, fostering synergy between AI and emerging quantum technologies is a critical strategy for ensuring sustainable societal development. Unlike traditional computing, where energy consumption grows proportionally to computational power, quantum computing demonstrates a linear relationship between computational power and energy consumption. This potential transformation allows AI to create more compact models, improve training efficiency, and enhance overall functionality, undoubtedly optimizing costs and expenditures for achieving sustainable development goals.

Realizing this potential requires collective efforts, including government support, industry investments, academic research, and public engagement. By uniting these elements, we can ensure a future where progress in AI harmonizes with the preservation of the planet's health.

Discussion

Concerns over data security, ethical dilemmas, and potential technological dependency are key challenges associated with artificial intelligence (AI). It is well known that AI is trained on data provided by owners or regular users, meaning its objectivity directly depends on the quality and objectivity of this data. This raises serious ethical issues related to morality, law, and other aspects of social life. For instance, in the absence of legislation protecting personal data, what would prevent AI from disclosing confidential information? Bias is also inherent in AI algorithms, as their responses are based on the limited datasets used during training. Additionally, AI can generate false information, facilitating propaganda and flooding media spaces with unreliable data.

Generative AI models such as Chat, DALLE-2, Stable Diffusion, and Midjourney rely on vast amounts of data but may still produce incorrect or unethical results. Furthermore, there is no clearly defined entity responsible for the content generated by AI.

The issue of securing data used to train AI is also highly relevant: who will ensure the protection of ordinary users from data breaches? Beyond the risks of data misuse and leaks from AI applications, the technology poses dangers to other services. Generative AI could be used to create fake data capable of bypassing cloud security systems. These generated datasets might launch attacks on systems, manipulate stolen data, or cause other damage, forcing energy companies targeted by AI-powered attacks to improve their security measures. The most effective tool to counter such attacks will likely be another machine learning-based system.

The emergence of modern AI systems has intensified longstanding moral concerns related to artificial intelligence, amplifying issues that have existed for centuries.

Potential long-term negative impacts of AI on environmental and social sustainability:

- **Energy consumption**: Data centers and other infrastructures supporting AI operations consume significant amounts of energy. According to the International Energy Agency (IEA), data centers consumed up to 2% of global electricity in 2023 (excluding cryptocurrency mining).[1] However, advancements in energy efficiency may mean that the computational power required for AI growth will not necessarily result in proportional energy consumption increases. Global data center energy use is expected to grow by only 6% through 2026.
- **Water usage**: Data centers using water-based cooling systems consume less electricity but require large amounts of water. By early 2022, Google's data centers used 16.3 billion liters (4.3 billion gallons) of water. By 2023, this figure rose by 30%, reaching 21.1 billion liters (5.6 billion gallons). Over the same period, Microsoft's water usage increased by 34%, from 4.7 billion liters (1.2 billion gallons) to 6.3 billion liters (1.6 billion gallons) annually.
- **Local utility impact**: AI-based data centers, regardless of their energy generation methods, place significant strain on local utility networks. A typical 100-megawatt data center requires enough electricity to power 80,000 homes.
- **Social bias**: AI systems can exacerbate existing social prejudices, hinder efforts to combat discrimination, and worsen public relations.
- **Fraud**: AI may serve as a tool for creating sophisticated phishing schemes and various forms of forgery used for fraud and deception.
- **Disinformation campaigns**: AI capabilities can be leveraged for targeted disinformation campaigns and public opinion manipulation.

Geopolitical and economic pressures

Rising geopolitical tensions and economic sanctions against Russia hinder technological development, especially in the high-tech sector. Sanctions target areas requiring complex problem-solving, including algorithm design

[1] How Much Energy Is Really Being Consumed by Data Centers? URL: https://thenewstack.io/how-much-energy-is-really-being-consumed-by-data-centers/

Table 2
The Role of AI in ensuring climate security

AI Application	Advantages	Challenges
Climate Condition Forecasting	Improved forecasting accuracy	Requires large, high-quality datasets
Environmental Climate Policy	Data-driven decision-making	Balancing interests of multiple stakeholders
Risk Assessment and Climate Modeling	Comprehensive variable analysis	Integration of diverse data sources

Source: Compiled by the authors.

and the creation of sophisticated software systems. However, AI can partially offset the negative effects of Western sanctions by automating repetitive operations and optimizing complex technological processes. AI is capable of generating innovative solutions based on existing templates and data. It already demonstrates the ability to understand context and adapt to changing conditions and requirements.

Climate risk assessment

Identifying climate risks is fundamental to planning adaptation measures for climate change. The use of machine learning methods significantly enhances this process by simultaneously accounting for numerous variables, leading to a deeper understanding of climate change consequences. *Table 2* provides a detailed analysis of climate risk assessment using AI-based models.

As machine learning technologies advance, their role in analyzing the state of the environment grows. Machine learning aids in predicting climate models and making informed policy decisions. Such AI tools are critically important in efforts to combat climate change.

Conclusion

Further regulation and prospects for AI use in technical and energy systems highlight the effectiveness of parametric optimization methods through AI in addressing complex challenges, especially those related to data instability in renewable energy [38]. Existing developed methods, such as patents for “parametric model generation for high-performance computing systems” [39] and the “universal algorithm for solving parametric optimization problems” [40], form a substantial domestic software foundation.

The authors foresee significant potential for developing software in the renewable energy sector based on artificial intelligence and deep learning, leveraging improvements in training methods and resource management. However, further research and updates to existing approaches are clearly needed to optimize renewable energy sources using advanced machine learning methods.

The study results indicate that AI is becoming a fundamental factor in the development of the modern energy sector, which is increasingly data-driven and characterized by complex interconnections. AI provides tools to enhance the performance of technical systems and improve efficiency under sanction constraints.

The hypothesis has been confirmed: using AI as a feedback control loop in technical facilities for energy purification and generation is a more economically efficient and technically optimal alternative to a “human” operator, eliminating human error. Consequently, the energy industry, utility enterprises, energy system operators, and independent power producers should prioritize the integration of AI technologies into existing technical systems.

REFERENCES

1. Francisco M. Artificial intelligence for environmental security: national, international, human and environmental perspectives. *Current Opinion in Environmental Sustainability*. 2023;61:101250. URL: https://doi.org/10.1016/j.cosust.2022.101250

2. Shang Y. et al. Employing artificial intelligence and enhancing resource efficiency to achieve carbon neutrality. *Resources Policy*. 2024;88:104510. URL: https://doi.org/10.1016/j.resourpol.2023.104510
3. Wang B. et al. How does artificial intelligence affect high-quality energy development? Achieving a clean energy transition society. *Energy Policy*. 2024;186:114010. URL: https://doi.org/10.1016/j.enpol.2024.114010
4. Ajagekar A., You F. Quantum computing and quantum artificial intelligence for renewable and sustainable energy: A emerging prospect towards climate neutrality. *Renewable and Sustainable Energy Reviews*. 2022;165:112493. URL: https://doi.org/10.1016/j.rser.2022.112493
5. Chen C. et al. Artificial intelligence on economic evaluation of energy efficiency and renewable energy technologies. *Sustainable Energy Technologies and Assessments*. 2021;47:101358. URL: https://doi.org/10.1016/j.seta.2021.101358
6. Fan Z., Yan Z., Wen S. Deep learning and artificial intelligence in sustainability: a review of SDGs, renewable energy, and environmental health. *Sustainability*. 2023;15(18):13493. URL: https://doi.org/10.3390/su151813493
7. Hramov A.E., Maksimenko V.A., Pisarchik A.N. Physical principles of brain-computer interfaces and their applications for rehabilitation, robotics and control of human brain states. *Physics Reports*. 2021;918:1–133. URL: https://doi.org/10.1016/j.physrep.2021.03.002
8. Li X. et al. Interpretable deep learning: Interpretation, interpretability, trustworthiness, and beyond. *Knowledge and Information Systems*. 2022;64(12):3197–3234. URL: https://doi.org/10.1007/s10115–022–01756–8
9. Leonelli S., Williamson H.F. Artificial Intelligence in Plant and Agricultural Research. Artificial Intelligence for Science*: A Deep Learning Revolution*. 2023;319–333. URL: https://doi.org/10.1142/9789811265679_0018
10. Ahmad T. et al. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *Journal of Cleaner Production*. 2021;289:125834. URL: https://doi.org/10.1016/j.jclepro.2021.125834
11. Ohalete N.C. et al. AI-driven solutions in renewable energy: A review of data science applications in solar and wind energy optimization. *World Journal of Advanced Research and Reviews*. 2023;20(3):401–417. URL: https://doi.org/10.30574/wjarr.2023.20.3.2433
12. Raihan A.A comprehensive review of artificial intelligence and machine learning applications in the energy sector. *Journal of Technology Innovations and Energy*. 2023;2(4):1–26. URL: https://doi.org/10.56556/jtie.v2i4.608
13. Raihan A.A concise review of technologies for converting forest biomass to bioenergy. *Journal of Technology Innovations and Energy*. 2023;2(3):10–36. URL: https://doi.org/10.56556/jtie.v2i3.592
14. Mashio K., Kasamatsu M., Noda E. Development of Emergency Information System to Support Nuclear Power Plant Management in Severe Accident. *Nuclear Technology*. 2023;209(3):346–353. URL: https://doi.org/10.1080/00295450.2022.2087837
15. Han B.A. et al. A synergistic future for AI and ecology. *Proceedings of the National Academy of Sciences*. 2023;120(38): e2220283120. URL: https://doi.org/10.1073/pnas.2220283120
16. Mayer M.J., Szilágyi A., Gróf G. Environmental and economic multi-objective optimization of a household level hybrid renewable energy system by genetic algorithm. *Applied Energy*. 2020;269:115058. URL: https://doi.org/10.1016/j.apenergy.2020.115058
17. Machlev R. et al. Explainable Artificial Intelligence (XAI) techniques for energy and power systems: Review, challenges and opportunities. *Energy and AI*. 2022;9:100169. URL: https://doi.org/10.1016/j.egyai.2022.100169
18. Li J., Liu P., Li Z. Optimal design and techno-economic analysis of a solar-wind-biomass off-grid hybrid power system for remote rural electrification: A case study of west China. *Energy*. 2020;208:118387. URL: https://doi.org/10.1016/j.energy.2020.118387
19. Abdalla A.N. et al. Integration of energy storage system and renewable energy sources based on artificial intelligence: An overview. *Journal of Energy Storage*. 2021;40:102811. URL: https://doi.org/10.1016/j.est.2021.102811
20. Sweeney C. et al. The future of forecasting for renewable energy. *Wiley Interdisciplinary Reviews: Energy and Environment*. 2020;9(2): e365. URL: https://doi.org/10.1002/wene.365

21. Ahmad T., Zhang H., Yan B. A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. *Sustainable Cities and Society.* 2020;55:102052. URL: https://doi.org/10.1016/j.scs.2020.102052
22. Han Z. et al. Stakeholder engagement in natural resources for energy transitions governance. *Environmental Impact Assessment Review*. 2023;102:107206. URL: https://doi.org/10.1016/j.eiar.2023.107206
23. Yang C. et al. Optimal power flow in distribution network: A review on problem formulation and optimization methods. *Energies*. 2023;16(16):5974. URL: https://doi.org/10.3390/en16165974
24. Balachandran G.B. et al. Comparative investigation of imaging techniques, pre-processing and visual fault diagnosis using artificial intelligence models for solar photovoltaic system — A comprehensive review. *Measurement*. 2024;232:114683. URL: https://doi.org/10.1016/j.measurement.2024.114683
25. Slama S.B., Mahmoud M. A deep learning model for intelligent home energy management system using renewable energy. *Engineering Applications of Artificial Intelligence.* 2023;123:106388. URL: https://doi.org/10.1016/j.engappai.2023.106388
26. Nagy Z. et al. Ten questions concerning reinforcement learning for building energy management. *Building and Environment*. 2023;241:110435. URL: https://doi.org/10.1016/j.buildenv.2023.110435
27. Franki V., Majnarić D., Višković A. A comprehensive review of artificial intelligence (AI) companies in the power sector. *Energies.* 2023;16(3):1077. URL: https://doi.org/10.3390/en16031077
28. Massel L.V. The current stage of development of artificial intelligence (AI) and the application of AI methods and systems in the energy sector. *Information and mathematical technologies in science and management.* 2021;4(24):5–20. DOI 10.38028/ESI.2021.24.4.001
29. Grabchak E.P. Introduction of digital platforms with elements of artificial intelligence to support decision-making in complex technological situations in the Russian energy sector. *Mechatronics, automation and robotics*. 2022;9:93–96. DOI: 10.26160/2541–8637–2022–9–93–96
30. Zoidov K. Kh. Digital authenticity of reality: expanding the boundaries of reliability in management in the Russian energy sector based on the use of elements of artificial intelligence. *Education. The science. Scientific personnel*. 2019;(4):127–130. DOI: 10.24411/2073–3305–2019–10201
31. Ali A., Majhi S. Integral criteria for optimal tuning of PI/PID controllers for integrating processes. *Asian Journal of Control*. 2011;13(2):328–337. URL: https://doi.org/10.1002/asjc.278
32. Lin G. et al. Implementation and test of an automated control hunting fault correction algorithm in a fault detection and diagnostics tool. *Energy and Buildings*. 2023;283:112796. URL: https://doi.org/10.1016/j.enbuild.2023.112796
33. Shaikhislamov A.V., Zentsov V.N., Shaikhislamov V.F., Khairullin V.A. Device for generating electricity from wastewater. Utility model patent No. 158767 U 1 Russian Federation. No. 2015106532/06: application. 02.25.2015: publ. 01.20.2016.
34. Kolpakhchyan P.G. et al. Device for receiving and converting mechanical energy of a fluid flow into electricity. Utility model patent No. 120525 U 1 Russian Federation. No. 2012113352/07: application. 04.06.2012: publ. 09.20.2012.
35. Zentsov V.N., Astashina M.V., Kuznetsova E.V., Khairullin V.A. Solutions for energy saving when changing the design solutions of water supply and sanitation facilities. *Internet Journal of Science*. 2016;3(34):28.
36. Shu J. et al. Impacts of climate change on hydropower development and sustainability: a review. IOP conference series: earth and environmental science. *IOP Publishing*, 2018;163:012126. URL: https://doi.org/10.1016/j.jclepro.2020.121661
37. Zhang Y., Ma H., Zhao S. Sustainability assessment of hydropower: Review and modeling. *Journal of Cleaner Production*. 2021;321:128898. URL: https://doi.org/10.1016/j.jclepro.2021.128898
38. Charny I.A. Underground hydrogasdynamics; Ross. state University of Oil and Gas named after. I.M. Gubkina. Moscow; Izhevsk: Institute of Computer Research, 2006; 414: ill. (Modern oil and gas technologies). 1973. Bibliography: p. 392.
39. Evtushenko G.I. et al Program for parametric generation of a model of a high-performance computing complex and optimization of the model according to a given criterion. Certificate of state registration of a computer program No. 2017614254 Russian Federation. No. 2017611315: application. 02.16.2017: publ. 04.10.2017

40. Koveshnikov V. A. Program for implementing a universal algorithm for solving parametric optimization problems. Certificate of state registration of a computer program No. 2018663352 Russian Federation. No. 2018617155: application. 07.06.2018: publ. 10.25.2018.

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