COMPUTATIONAL PROBLEMS OF ELECTRICAL ENGINEERING

Vol. 15, No. 1, 2025

CLOUD-BASED SMART ENERGY SYSTEMS: SOLUTIONS FOR HYBRID AND VIRTUAL POWER PLANTS

Andrii Andrushko
Lviv Polytechnic National University, Ukraine
andrii.v.andrushko@lpnu.ua

https://doi.org/10.23939/jcpee2025.01.001

Abstract: This paper is devoted to the analysis of modern approaches to the use of cloud technologies in hybrid and virtual power plants, including the assessment of their functional capabilities, advantages, and limitations, as well as practical examples of implementing such solutions in different countries.

Decarbonization and the transition to sustainable energy are becoming increasingly common strategies, with hybrid and virtual power plants emerging as key solutions integrating renewable energy sources, storage systems, and intelligent control technologies. However, the efficient operation of such systems requires a high degree of automation, real-time big data processing, and adaptive management. The paper highlights the advantages of cloud computing, such as centralized access to computing resources, flexible scalability, data storage, and the integration of artificial intelligence. By leveraging cloud platforms, energy companies can forecast generation and consumption, perform real-time load balancing, and efficiently manage distributed energy resources regardless of location.

The study also describes relevant technologies, including both general-purpose infrastructure cloud services (such as AWS, Azure, and Google Cloud) and specialized solutions designed specifically for the needs of energy systems (such as Siemens DEOP, AutoGrid Flex, Next Kraftwerke VPP, and Piclo Flex).

Keywords: cloud technologies, hybrid and virtual power plants, dynamic energy grid.

Introduction

Smart Energy Systems (SES) represent a new paradigm in energy management, combining digital technologies, distributed generation, and intelligent energy flow control. The core of this concept lies in the integrated connection of electrical, thermal, transport, and information subsystems with to improve the efficiency, resilience, and environmental sustainability of energy networks [1]. The traditional power system, based on centralized generation and one-way energy flow, no longer meets the challenges of today's world, which requires the integration of renewable energy sources, demand-response flexibility, and a high degree of automation. Smart Energy Systems address these challenges through the decentralization of energy supply, the active participation of consumers (the prosumer model), and the extensive use of the Internet of Things (IoT), Big Data, Artificial Intelligence (AI), and cloud technologies [2, 5].

Among the key characteristics of Smart Energy Systems there is decentralization, which implies the use of distributed energy resources (DER) integrated into the overall energy network, as well as sector coupling, which integrates electrical, thermal, and transport systems into a unified digital platform [1]. Another important features are forecasting and optimization, based on analytical models for accurate prediction of production and demand [5]. These systems are characterized by automated control implemented through cyber-physical systems, and adaptive control algorithms [3], their technological foundation relying on digital infrastructure, in particular cloud platforms enabling scalability, real-time computing, and large-scale data storage [2, 4].

Potential development directions, driven by the abovementioned challenges, include the improvement of energy supply management, monitoring, analytics, and forecasting systems. A particularly relevant approach is the Energy Internet concept which envisions a flexible, dynamic power grid with decentralized energy exchange between users, coordinated via digital platforms [3]. In such a system, each element – whether a solar panel, battery, electric vehicle, or building – can act simultaneously both as a producer and a consumer of energy, ensuring high adaptability and economic efficiency.

In the energy sector, cloud technologies are crucial in the digital transformation of energy supply management, monitoring, analytics, and forecasting systems. Cloud Computing is a model for providing access to computing resources over the Internet, offering scalability, flexibility, distributed data processing, and cost efficiency.

In the context of cloud technology adoption in the energy sector, it is important to understand the different service models, which differ in the level of control granted to the user and the responsibility borne by the provider, as each model has its own purpose and application area. Existing cloud services are based on the "remote" computing, with implementation depending on user requirements, functionality, and available resources. A summary and description of SaaS, PaaS, and IaaS models are presented in Table 1.

Table 1

Model	Description	Examples of implementation
SaaS (Software as a Service)	A model in which end users access to ready-to-use software solutions via a web interface	Platforms for energy consumption visualization, SCADA applications, and demand management services
PaaS (Platform as a Service)	Provides the environment for developing, testing, and deploying personal software solutions	Creation of energy modules for consumption analytics, DER (distributed energy resources) management, and microgrid optimisation
IaaS (Infrastructure as a Service)	Provides basic computing infrastructure (virtual servers, data storage, network resources)	Storage and processing of large volumes of energy data, support for digital twins, and training prediction models

Cloud technologies in the form of SaaS, PaaS, and IaaS provide the technological foundation for building adaptive, scalable, and cost-efficient Smart Energy Systems, enabling flexible management of hybrid and virtual power plants. The scalability of cloud technologies in the energy sector is a primary advantage, allowing computational resources to be adjusted according to actual needs without significant capital expenditure. Additionally, remote access to data and systems simplifies equipment maintenance, implements new functionalities, and reduces decision-making time [6, 9].

Another type of infrastructure is a cloud-oriented energy system, in which core processes of data collection, transmission, storage, analysis, and energy management are implemented via cloud computing platforms. This approach ensures flexibility, adaptability, and high efficiency in managing energy resources, particularly under the condition of the increasing number of distributed and renewable energy sources [12].

Key functional features of such architecture include a centralized data storage which allows for the identification of global patterns and interregional comparisons; cloud scalability, enabling the processing of increased data flows as the number of devices grows; and the use of AI models for load forecasting, generation prediction, and preventive maintenance [12, 13].

As energy systems belong to critical infrastructure, the architecture of cloud-based energy systems must include multi-level access control (RBAC), data encryption during transmission and storage, secure backup and disaster recovery, and compliance with standards (e.g., ISO/IEC 27001, NIST SP 800-53) [14]. The key components of the architecture are presented in Table 2, which particularly shows the increasing share of distributed and renewable energy sources [12].

Table 2

Key components of architecture	
Peripheral devices (Edge Layer)	This level includes the physical components of the energy system – sensors, smart meters, inverters, batteries, and generators. They provide primary measurement of consumption, generation, voltage, frequency, and other parameters. Part of the data processing (preliminary analysis, filtering, local actions) can be performed directly on site using edge computers
Communication level (Communication Layer)	Includes wired (Ethernet, PLC) and wireless (LTE, LoRaWAN, Zigbee, 5G) channels that transmit information between edge devices and the cloud platform. To ensure data integrity and continuous operation, it is critical to use low-latency and secure transmission protocols (e.g., MQTT, IEC 61850)
Cloud platform (Cloud Layer)	The central component of the architecture that implements: - storage of large amounts of data (Data Lake, NoSQL, Time Series DB), - processing and analysis (Big Data, AI/ML models), - visualisation (analytical dashboards), - decision-making (optimisation modules, control algorithms). This level can be implemented as IaaS, PaaS, or SaaS, depending on the needs of the operator or energy service provider
Control interface (Application & Control Layer)	It contains tools for users, such as operator panels, mobile applications, and APIs for external systems. This level implements monitoring, visualisation, planning, dispatching, forecasting, and response functions

Cloud solutions can be used for real-time monitoring and data collection, in particular through the implementation of SCADA systems in a cloud environment, as well as for forecasting both energy generation and consumption by combining the capabilities of artificial intelligence and cloud platforms, which ensures increased accuracy in consumption forecasts.

Energy generation forecasting uses meteorological data that takes into account weather conditions and climate change, historical data on energy production and consumption volumes, and technical parameters of equipment, including the characteristics of generators or stations. Various machine learning algorithms are used to process and analyse this data, including decision trees, deep neural networks (DNN/LSTM) and combined methods, which ensure high forecast accuracy. The structural components that determine the energy generation forecasting procedure are shown in Fig. 1.

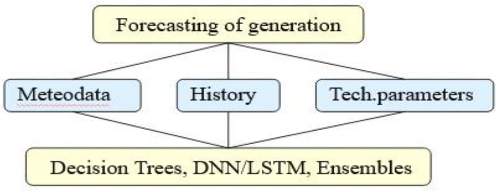

Fig. 1. Structural components of electricity generation forecasting

Energy consumption forecasting is carried out at various levels, covering individual consumers, microgrids and system operators, each of which has its own needs and forecasting horizons. For individual consumers and microgrids, short-term models are usually used allowing for a rapid response to changes in load and optimisation of resource usage. On the other hand, system operators mainly use seasonal or long-term models that allow them to plan the operation of the power system for the future, taking into account changes in demand, seasonal fluctuations, and strategic network development. Energy consumers include individual consumers (domestic, industrial), microgrids, and system operators whose interactions are shown in Fig. 2.

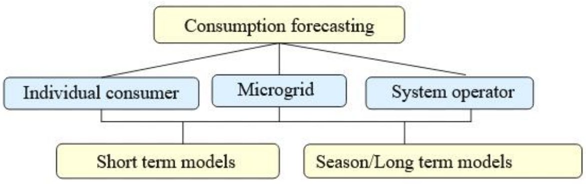

Fig. 2. Energy consumption entities

The integration of cloud computing into energy system management, particularly in the operation of hybrid and virtual power plants, significantly enhances the functionality and scalability of digital infrastructures. However, it simultaneously introduces new challenges in the context of cybersecurity. Since cloud services provide centralized access to critical energy system components, including SCADA, EMS, and forecasting modules, their vulnerability to cyberattacks is considerably increases. These risks may arise from data transmission between field devices and cloud platforms, user authentication, or misuse of the API access.

The challenges are further exacerbated when public cloud services are used without proper resource segmentation and isolation, creating potential risks of unauthorized interference in energy flow management or manipulation of forecasts. In this context, the implementation of protective measures such as **end-to-end encryption, multi-factor authentication, role-based access control, continuous anomaly monitoring, and compliance with industry standards** (e.g., ISO/IEC 27001, NIST CSF) becomes essential for the secure deployment of cloud solutions.

Additionally, it is critical to plan **recovery scenarios after attacks**, maintain a **"cold backup"** for critical services, and regularly test security measures through **simulated attacks**. Robust cybersecurity is not only a technical but also a regulatory challenge: national and transnational frameworks must be established to prevent the exploitation of energy cloud systems for blackmail, sabotage, or political coercion.

Analysis of existing solutions and platforms

The common feature of most platforms is the support for scalable cloud architecture (IaaS, PaaS, or SaaS), the use of artificial intelligence tools for forecasting, and the presence of modules for interfacing with distributed energy resources (DERs). Another notable trend is openness – via APIs and standards such as OpenADR, OCPP, and IEC 61850 which ensures integration with other platforms and energy network operators.

At the same time, some solutions remain isolated, either due to a commercial model (proprietary internal development for a specific corporation) or because of a narrow functional specialization. Table 3 presents analytical tables summarizing a comparative analysis of popular solutions. Market integration, cost and flexibility of integration are presented in Table 4.

Table 3

Platform	Architecture	Forecasting (AI)	Aggregation DER / VPP	Cybersecurity
AWS Energy & Utilities	IaaS / PaaS / SaaS	Yes (Sage Maker)	Partially (through partners)	High (ISO 27001, AWS Shield)
Azure Energy Hub	PaaS / SaaS	Yes (Azure ML, Synapse)	Yes (AutoGrid, Nuvve)	High (Azure Defender)
Google Cloud for Energy	IaaS / PaaS	Yes (Vertex AI)	No	High (BeyondCorp, DLP)
Siemens DEOP	SaaS	Restricted	Yes (own VPP infrastructure)	Average (depends on the customer)
Next Kraft-werke VPP	SaaS (pro-prietary)	Partially	Yes (10 000+ objects)	Average (VPN, API protection)
AutoGrid Flex	SaaS	Yes (deep learning)	Yes (flexible aggregation)	High (API protection, MFA)
Piclo Flex	Web-based	No	Yes (aggre-gation for DSO/TSO)	High (GDPR, Cloudflare)
Iberd-rola AI Hub	Prop-rietary PaaS	Yes (generation from RES)	Partially (within the scope of projects)	Average (internal policies)

Among the presented solutions, AWS, Azure, and Google Cloud demonstrate versatility, flexibility, and scalability, allowing their integration into existing energy infrastructures. They support open standards, provide high performance, offer rich AI/ML analytics toolsets, and comply with leading cybersecurity requirements. For these reasons, these platforms are often used as the foundation for deploying specialized products or as infrastructure for third-party services.

Among the presented solutions, AWS, Azure, and Google Cloud demonstrate versatility, flexibility, and scalability, allowing their integration into existing energy infrastructures. They support open standards, provide high performance, offer rich AI/ML analytics toolsets, and comply with leading cybersecurity requirements. For these reasons, these platforms are often used as the foundation for deploying specialized products or as infrastructure for third-party services.

Table 4

Platform	Market integration	Price of basic configuration	Flexibility regarding integration with other platforms
AWS Energy & Utilities	Yes (API to US/EU markets)	From $0.01/hour per resource	High (modularity, support for open APIs)
Azure Energy Hub	Yes (OpenADR, OCPP)	From $0.02/hour + ML fee	High (integration with SCADA, IoT, DERMS)
Google Cloud for Energy	Restricted	From $0.005/hour per instance	High (BigQuery, IoT Core, third-party APIs)
Siemens DEOP	Yes (via DSO/TSO gateways)	Closed commercial model	Restricted (mainly with Siemens systems)
Next Kraftwerke VPP	Yes (EU flexibility market)	No public tariff	Closed (self-contained ecosystem)
Auto Grid Flex	Yes (through open standards)	Commercial licence	High (OpenADR, OpenFMB, Green Button)
Piclo Flex	Yes (flexibility market)	Free for DSO/TSO	High (adaptive via REST API)
Iberdrola AI Hub	Partially	Closed, for internal use only	Low (based on Iberdrola's own assets)

In contrast, solutions such as Next Kraftwerke VPP, Siemens DEOP, and Iberdrola AI Hub represent isolated or narrowly specialized systems. They have an advantage of high functional density within a specific environment (e.g., VPP optimization within a single country or corporation); however, limited scalability and compatibility with external systems reduce their versatility. Such platforms are suitable for closed infrastructures, internal corporate models, or demonstration projects.

Among specialized solutions, AutoGrid Flex and Piclo Flex stand out, combining the functionality of flexible DER management with open mechanisms for aggregation and energy trading. They can be considered an intermediate category specialized in functionality, yet capable of integration due to support for open standards.

Thus, the choice of platform should be based on the scale of the system, integration requirements, security needs, and regulatory context. Hyper-scale cloud providers are suitable for universal and adaptive solutions, whereas specialized solutions with vertical integration are more appropriate for targeted projects.

An example of the application of cloud technologies in load forecasting: the experience of ISO New England

One practical example of implementing cloud technologies in the energy sector is the project by ISO New England (ISO-NE) aimed at improving short-term load forecasting processes. Load forecasting is a typical engineering task in power systems that extensively utilizes data-driven approaches. This process requires significant computational resources to process large historical datasets and develop highly accurate models. Cloud computing has proven to be an effective solution for providing such resources.

Currently, ISO-NE employs a Short-Term Load Forecasting (STLF) tool integrated into the Energy Management System (EMS). This tool generates load forecasts every five minutes for the next four hours. The forecasting method used is the Similar Day approach, which selects the best historical days based on criteria such as weather conditions, day of the week, season, and actual loads on previous days. However, this method has notable limitations, especially when no days with similar conditions exist, potentially leading to significant forecasting errors.

To enhance this process, ISO-NE implemented a cloud-based solution using Amazon SageMaker being the PaaS platform. This platform significantly simplifies the creation of new machine learning (ML) models, allowing engineers to quickly test various algorithms, including Decision Tree, Random Forest, Support Vector Machine (SVM), and K-means clustering. This enables specialists to focus on applied tasks without spending time on server configuration, dependency installation, or runtime environment setups.

The deployment of the cloud platform substantially reduced the time required for data preparation, model building, training, and validation. The created ML models can be stored in a dedicated format and, if needed, deployed on local infrastructure to ensure compatibility with the EMS and compliance with cybersecurity requirements. Architecturally, the process involves secure transmission of data to the cloud, processing and training models within Amazon SageMaker, storage of training artifacts, and subsequent deployment of the models for integration with the local energy management system.

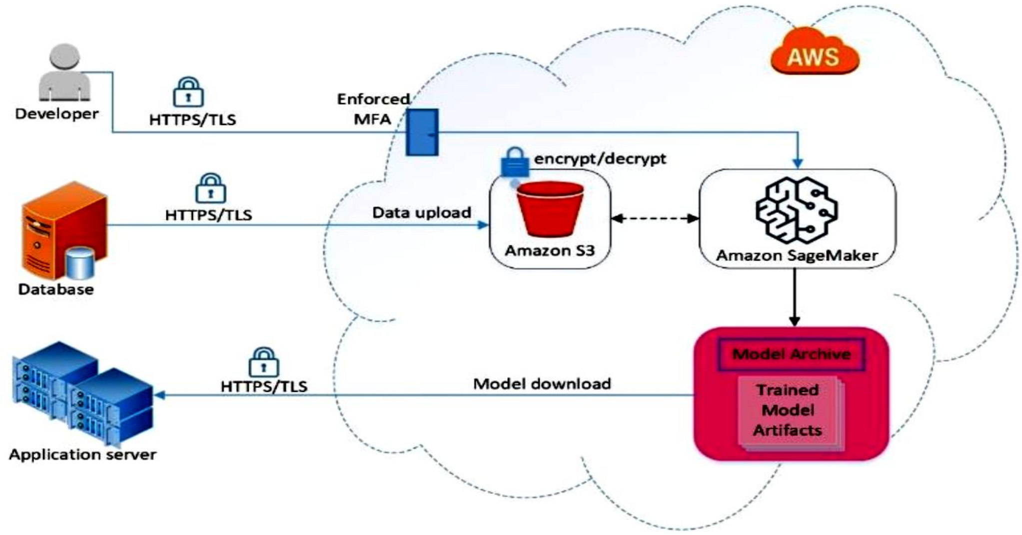

Fig. 3. Schematic diagram of the ML model development process at ISO-NE

Fig. 3 presents a simplified architecture diagram of the process of the ML model development at ISO-NE using cloud services [15]. The diagram illustrates how data are uploaded from databases or by developers to the Amazon S3 service through secure channels (HTTPS/TLS) where it is encrypted to ensure confidentiality. The data are then transferred to the Amazon SageMaker environment for processing, training, and the creation of machine learning models. Trained models are stored in the Model Archive and can be downloaded back to local servers for further use within energy management systems. The system incorporates security measures such as multi-factor authentication (MFA) and encryption, ensuring a high level of data protection.

Conclusion

In the current context of the transformation of the global energy sector, Smart Energy Systems built using cloud technologies represent a strategic development direction for countries with the high share of renewable energy and for regions aiming to enhance energy resilience. It has been established that cloud computing provides a scalable digital infrastructure capable of supporting dynamic management of energy flows under conditions of unstable generation and decentralization. The architecture of cloud-oriented systems is based on the integration of storage, processing, and real-time data analytics services, incorporating SCADA, IoT, and artificial intelligence tools.

Based on the practical capabilities of cloud technologies, including real-time monitoring, generation and demand forecasting, energy flow optimization, and cybersecurity, it is advisable to develop a procedure for combining cloud platforms with AI tools. This approach enables significant improvements in both supply reliability and cost efficiency, as well as better integration with energy markets.

A comparative analysis summarized in analytical tables covering leading cloud solutions from global platforms such as Microsoft Azure, Amazon Web Services, and Google Cloud Platform, to specialized energy platforms like Siemens DEOP, AutoGrid, and Next Kraftwerke showed that while all solutions share a common architectural logic, their functional focus and integration flexibility differ depending on the target market and system scale.

Thus, the review confirmed that cloud technologies not only provide the technological foundation for energy digitalization but also act as a driver for systemic integration of distributed energy resources, the formation of the new market logic, and the strengthening of energy security.

References

[1] H. Lund, P. A. Østergaard, D. Connolly, and B. V. Mathiesen, "Smart energy and smart energy systems", *Energy*, No. 137, pp. 556–565, 2017. https://doi.org/10.1016/j.energy.2017.05.123

[2] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart Grid–The New and Improved Power Grid", *A Survey. IEEE Communications Surveys & Tutorials*, vol. 14, No. 4, pp. 944–980, 2012. https://doi.org/10.1109/SURV.2011.101911.00087

[3] S. Ghosh, A. K. Goswami, and A. Sinha, *Smart Energy Systems: Architecture, Technologies, and Applications*. Springer, 2022.

[4] Y. Simmhan, S. Aman, P. Ravindra, et al. "Cloud-based software platform for big data analytics in smart grids", *Computing in Science & Engineering*, vol. 15, No. 4, pp. 38–47, 2013. https://doi.org/10.1109/MCSE.2013.59

[5] T. Dragicevic, X. Lu, J. C.Vasquez, and J. Guerrero, "DC microgrids – Part II: A review of power

architectures, applications, and standardization issues”, *IEEE Transactions on Power Electronics*, vol. 31, No. 5, pp. 3528–3549, 2016. https://doi.org/10.1109/TPEL.2015.2464277

[6] R. P. Van Leeuwen and R. A. Van der Veen, “Virtual power plants: Definition, applications and barriers to deployment”, *Journal of Energy Storage*, No. 44, p. 103490, 2021. https://doi.org/10.1016/j.est.2021.103490

[7] C. North, et al. “Coordinated operation of virtual power plants in active distribution networks”, *Renewable and Sustainable Energy Reviews*, No. 127, p. 109879, 2020. https://doi.org/10.1016/j.rser.2020.109879

[8] U. S. Department of Energy. *The Role of Virtual Power Plants in a Decarbonized Grid*. Office of Electricity, 2022. https://www.energy.gov/oe/articles/role-virtual-power-plants-decarbonized-grid

[9] Next Kraftwerke. *How virtual power plants balance the grid*, Company Report, 2021. https://www.next-kraftwerke.com/knowledge/virtual-power-plant

[10] Tata Power. *Optimizing microgrid operations using cloud analytics*, Project Case Study, 2022. https://www.tatapower.com

[11] Zhang Song, Pandey Amritanshu, Luo Xiaochuan, Powell Maggy’, Banerji Ranjan, Parchure Abhineet, Fan Lei, and Luzcando Edgardo, “Practical Adoption of Cloud Computing in Power Systems – Drivers, Challenges, Guidance, and Real-World Use Cases”, *IEEE Transactions on Smart Grid*, vol. 13, No. 3, pp. 2390–2411, May 2022, doi: 10.1109/TSG.2022.3148978

[12] E. Baccarelli, M. Scarpiniti, M. Shojafar, and J. Abawajy, “Fog of everything: Energy-efficient networked computing architectures, research challenges, and a case study”, *IEEE Access*, No. 5, pp. 9882–9910, 2017. https://doi.org/10.1109/ACCESS.2017.2704081

[13] V. C. Gungor, D. Sahin, T. Kocak et al. “Smart grid technologies: Communication technologies and standards”, *IEEE Transactions on Industrial Informatics*, vol. 7, No. 4, pp. 529–539, 2011.

[14] C. Candelise, and M. Winskel, “Integrating distributed energy resources using cloud platforms: Benefits and risks”, *Renewable and Sustainable Energy Reviews*, No. 147, p. 111203, 2021. https://doi.org/10.1016/j.rser.2021.111203

[15] *https://www.researchgate.net/figure/Schematic-diagram-of-ISO-NEs-ML-model-development-flow_fig3_353653784*

ХМАРНІ ІНТЕЛЕКТУАЛЬНІ ЕНЕРГЕТИЧНІ СИСТЕМИ: РІШЕННЯ ДЛЯ ГІБРИДНИХ ТА ВІРТУАЛЬНИХ ЕЛЕКТРОСТАНЦІЙ

Андрій Андрушко

Статтю присвячено аналізу сучасних підходів до застосування хмарних технологій у гібридних і віртуальних електростанціях, оцінці їхніх функціональних можливостей, переваг та обмежень, а також практичних прикладів запровадження таких рішень у різних країнах. Декарбонізація та перехід до сталої енергетики стають все популярнішими рішеннями, зокрема гібридні та віртуальні електростанції, які здатні поєднувати відновлювані джерела енергії, накопичувачі та інтелектуальні системи управління. Однак ефективне функціонування таких систем потребує високого рівня автоматизації, опрацювання великих обсягів даних у реальному часі та адаптивного управління. Розглянуто такі переваги хмарних обчислень, як централізований доступ до обчислювальних ресурсів, гнучке масштабування, зберігання даних та інтеграцію штучного інтелекту. Завдяки хмарним платформам енергетичні компанії можуть здійснювати прогнозування виробітку та споживання, оперативне балансування навантажень, а також ефективно управляти розподіленими джерелами енергії незалежно від їх географічного розташування. Описано актуальні технології, такі як універсальні інфраструктурні хмарні сервіси (наприклад, AWS, Azure, Google Cloud), так і спеціалізовані продукти, розроблені з урахуванням особливостей енергетичних систем (наприклад, Siemens DEOP, AutoGrid Flex, Next Kraftwerke VPP, Piclo Flex).

Andrii Andrushko – Master in Engineering, postgraduate student of Lviv Polytechnic National University.

Scientific interests: renewable energy, cloud technologies, hybrid and virtual power plants, digital twins.

Received: 15.09.2025, Accepted: 25.09.2025
ORCID: 0009-0001-1501-011