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DEFINITION OF MICROGRID FEATURES FOR THE CONSTRUCTION OF AN INTELLIGENT CONTROL SYSTEM

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Abstract*—The article addresses the problem of identifying the key features of a MicroGrid as a complex energy system, which is a necessary prerequisite for the development of an intelligent control system. The widespread introduction of distributed generation, renewable energy sources, and energy storage systems necessitates adaptive control methods capable of operating under conditions of uncertainty and variable electrical network modes. Existing approaches to MicroGrid control remain limited due to the lack of a unified and scientifically grounded set of structural, operational, dynamic, and informational features that should be taken into account in intelligent systems. The paper analyzes contemporary scientific approaches to the classification, modeling, and real-time control of microgrids, which makes it possible to identify insufficiently studied aspects related to the formation of feature sets and their influence on decision-making processes. The objective of the study is to systematize and substantiate a comprehensive set of microgrid features that can serve as a basis for the development of intelligent control algorithms. A conceptual approach to structuring microgrid features into the following groups is proposed: architectural, energy-technical, operational, features related to the stability of dynamic operating modes, and data-oriented features. Their significance for forecasting, optimization, state estimation, and autonomous operation of local energy systems is demonstrated. The obtained results form a methodological foundation that enhances the effectiveness of developing intelligent microgrid control systems and contributes to improving the flexibility and reliability of local energy networks.*

Keywords: MicroGrid; intelligent control system; distributed generation; microgrid features; cyber-physical energy systems.

I. INTRODUCTION

The development of the MicroGrid intelligent control system is driven by the need for automated processing of large volumes of heterogeneous data from multiple generation sources, energy storage systems, and consumers in real time. Classic control systems are based on static algorithms and predefined scenarios, which makes it impossible for them to function effectively in conditions of constantly changing generation and consumption balances, sudden changes in weather conditions, emergency situations, or transitions between autonomous and network modes of operation.

The contemporary development of power systems is characterized by a growing share of distributed generation capacity and the widespread deployment of renewable energy sources (RES). This leads to increased variability in power system operating conditions, complicates load forecasting, and creates additional challenges for ensuring system stability [2]. Distributed generation enhances the flexibility and reliability of power supply; however, it simultaneously increases the dynamism and unpredictability of operating regimes, which necessitates new control approaches [8]. The integration of RES and energy storage systems introduces further complexities associated with system stability and synchronization of component operation. Traditional centralized control methods fail to provide sufficient responsiveness and adaptability under complex and highly variable conditions, which limits their effectiveness [3], [4]. This creates a need for the implementation of intelligent systems capable of analyzing data in real time, predicting operating modes, and coordinating the operation of heterogeneous sources and consumers [10], [14].

The MicroGrid concept is considered an effective solution for increasing the autonomy and reliability of local energy systems.

A microgrid combines different types of generation, energy storage systems, and critical loads, ensuring reliable power supply even when the main grid is unavailable [1]. This integration improves energy efficiency, reduces energy losses, and enables the application of intelligent control algorithms [8]. The overall structure of the microgrid and its main functional advantages are shown in Fig. 1.

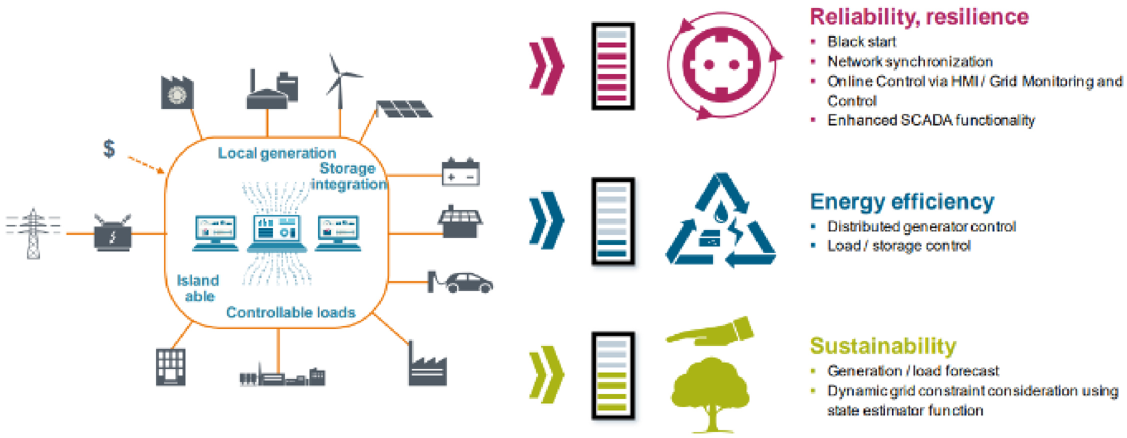

Fig. 1. Comprehensive model of a microgrid system and its key functional advantages (source: author's development)

Recent studies show that the use of artificial intelligence and hybrid control systems significantly increases the efficiency of MicroGrid. Such approaches allow optimizing the system's operation, increasing the accuracy of mode forecasting, improving adaptability, and ensuring the integration of RES and storage devices without reducing network stability [16].

An analysis of the scientific literature indicates certain limitations in existing approaches to systematizing MicroGrid characteristics. The research by Derevianko and Pereguda [1] focuses on aspects of smart monitoring, but does not take into account the complex integration of heterogeneous energy sources and storage devices. Guzov's work [3] proposes modified control systems based on the Internet of Things, but there is no complete formalization of the criteria for evaluating the characteristics of MicroGrid operating modes. Analysis of the ontological models proposed by Mishchenko [4] allows the structure of the system to be formalized, but the dynamic interactions between components are not sufficiently taken into account.

A review of international research complements this picture, demonstrating similar trends and challenges. Razmi and Lu systematized the key issues of distributed energy resource (DER) management in MicroGrid, highlighting the issues of stability, coordination between sources, and integration with intelligent control systems, and outlined the prospects for the development of hybrid approaches and adaptive algorithms [21]. Shahzad et al. focused on the practical possibilities and limitations of MicroGrid, noting that further development of the systems requires careful consideration of economic, technical, and regulatory factors [22]. She et al. considered the prospects of combining model-free reinforcement learning models with MicroGrid management, emphasizing the potential of such methods to increase system autonomy and optimize energy flows without a precise mathematical model description [23].

The definition and systematization of microgrid features constitute a key scientific challenge that precedes the development of intelligent control systems. Its solution makes it possible to increase the adaptability, accuracy, and reliability of control processes and also provides a methodological basis for implementing modern artificial intelligence algorithms in the energy sector. These aspects determine the relevance and scientific significance of this work [5]. **The study aims** to systematize and scientifically substantiate a comprehensive set of microgrid features that form the informational basis for the development of intelligent control algorithms for local energy systems. The study addresses tasks aimed at achieving a comprehensive understanding and optimization of microgrid operation. First, the microgrid architecture is analyzed, and requirements for control systems are defined in the context of the growing share of distributed generation and renewable energy sources. Next, the role of information infrastructure and measurement systems, which provide data for intelligent control systems, is examined. On this basis, a structured system of microgrid features is developed, covering electrical, resource-related, forecasting, topological, communication, and contextual parameters. The final stage is to substantiate the significance of the identified feature categories for forecasting, optimization, and ensuring the stability of microgrid operating modes.

II. MICROGRID ARCHITECTURE AND ITS MODERN CONTROL SYSTEM

The architecture of a microgrid is formed as a multi-level energy system that integrates the physical components of the electrical network, energy conversion devices, and digital control elements. Its structural organization determines the capabilities for autonomous operation, integration with higher-level grids, stability of operating modes, and implementation of intelligent functions [9]. Unlike traditional distribution networks, a microgrid is characterized by high flexibility, the presence of local energy sources, and the ability for decentralized decision-making (Fig. 2).

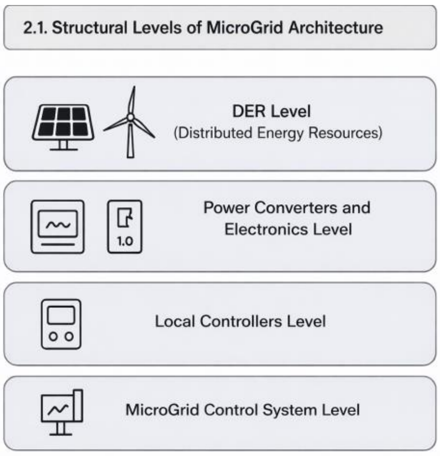

Fig. 2. "Structural levels of MicroGrid architecture" source – author's development

A key element of the architecture is the distributed energy resources (DER) layer, which includes renewable energy sources, storage systems, and controllable loads. The heterogeneity of DERs creates challenges for maintaining stable and predictable operating modes, as generation from solar and wind installations exhibits pronounced stochastic behavior. Coordinated operation relies on power converters and power electronics, which perform energy adaptation between sources and the network [11]. Modern inverters not only convert electrical energy but also implement voltage, frequency, and reactive power regulation, as well as harmonic filtering functions, making them one of the primary tools for controlling microgrid operating modes. An important component of the architecture is the local equipment controllers. They provide real-time control of individual energy modules, perform regulation based on local measurements, and implement primary stabilization mechanisms. However, their action is limited to individual devices, which necessitates the formation of a higher-level microgrid control system [19].

The microgrid control system is built on a hierarchical principle and traditionally comprises three levels. The primary level implements droop control and other fast-acting algorithms responsible for immediate response to load variations. The secondary level restores nominal voltage and frequency parameters after transient processes. The tertiary level ensures power flow optimization, generation planning, coordination with the grid, and the resolution of economic tasks. The tertiary level is particularly suitable for integrating intelligent control methods, as it operates on medium- and long-term data, determines the global behavior of the system, and allows the application of forecasting, optimization, and learning algorithms [20].

The operation of all levels of the microgrid architecture is impossible without an effective communication infrastructure. Data exchange between devices is carried out using digital protocols, SCADA systems, or IoT solutions, which provide real-time data collection, transmission, and processing (Fig. 3). Communication delays, channel availability, and reliability significantly affect control quality, especially when the microgrid operates in islanded mode.

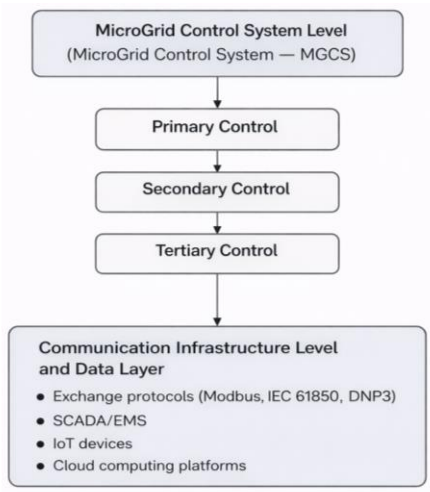

Fig. 3. Microgrid level control systems and communication infrastructure (source: author's development)

The development of microgrids has led to the emergence of various types of control systems.

Traditional centralized systems provide high coordination of operating modes but are limited in terms of scalability and fault tolerance. Decentralized and cooperative structures allow local controllers to make decisions independently, reducing the load on the central node and enhancing system resilience. Hierarchical systems combine the advantages of both approaches and have become the most common control model in modern microgrids. The latest development trend is intelligent control systems, which employ machine learning algorithms, optimization methods, and agent-based approaches to improve adaptability and decision-making accuracy.

Consequently, the microgrid architecture represents a complex network of interconnected physical, digital, and functional components. Its characteristics determine the requirements for the control system, which must account for variable operating conditions, the stochastic nature of renewable sources, and the need for autonomous operation. Understanding the structure of the microgrid and the principles of its modern control is essential for identifying the features used in intelligent systems, which is the focus of the following sections of this article.

Analysis of contemporary microgrid control approaches shows that traditional centralized, decentralized, and hierarchical models no longer fully meet the requirements of power systems with a high share of renewable sources, dynamically changing operating conditions, and increasing data volumes (Table I). In such contexts, intelligent control systems provide the necessary level of adaptability, predictability, and capacity for autonomous decision-making. By integrating machine learning algorithms, optimization techniques, and multi-agent methods, they enable greater efficiency, stability, and flexibility in microgrid operation. This makes the transition to intelligent approaches a logical and strategically important step in the development of local energy systems.

TABLE I. COMPARATIVE CHARACTERISTICS OF CONTROL SYSTEM TYPES (BASED ON MICROGRID) (SOURCE: AUTHOR'S DEVELOPMENT)

Control System Type	Main Operational Concept	Advantages	Disadvantages
Centralized Control System	All decisions are made by a central controller based on data from the entire network.	High mode consistency; simple implementation; convenient monitoring.	Low scalability; single point of failure (dependence on one node); high communication link overhead.
Decentralized Control System	Local controllers make decisions independently and coordinate among themselves.	High fault tolerance; flexibility; rapid local response.	Difficulty in achieving global optimality; potential conflicts between local decisions.
Hierarchical Control System	Functions are divided by levels: primary control is local, while secondary and tertiary levels handle coordination or centralization.	Balanced system operation; combines local speed with global optimization; high scalability.	Architectural complexity; necessity of ensuring data consistency across levels.
Intelligent Control System	Utilizes machine learning algorithms, optimization techniques, multi-agent methods, and self-adaptive decision-making.	Adaptability to changing conditions; high forecasting accuracy; real-time optimization; self-learning and autonomy capabilities.	High computational resource requirements; dependence on data quality; complexity of model development and validation.

III. DESCRIPTION OF THE MEASUREMENT AND DATA TRANSMISSION SYSTEM

The effective operation of a microgrid as a cyber-physical energy system is impossible without a developed infrastructure for data measurement and transmission, which ensures the collection, processing, and delivery of information between all elements of the control system. The quality, speed, and reliability of information flows determine the microgrid's ability to maintain stable operating conditions, adapt to changes in external factors, and implement intelligent control algorithms.

The microgrid measurement system includes a set of sensors, meters, and measurement modules installed at generation sources, load nodes, power converters, and key points in the network. Its components encompass measurements of voltage, current, frequency, active and reactive power, energy storage system charge levels, equipment status, and power quality parameters. The collected data enable local controllers to perform primary regulation and allow the microgrid control system to form a comprehensive digital representation of the energy subsystem state.

An important element is the synchronization of measurement data. Modern microgrids employ PMU/µPMU (phasor measurement units) technology, which provides high accuracy in determining voltage and current phasors. This enables real-time analysis of dynamic processes, detection of unstable operating conditions, and rapid response to disturbances.

Data transmission is carried out via a communication infrastructure combining wired and wireless channels. Various segments of the microgrid use protocols such as Modbus, DNP3, IEC 60870-5-104, and IEC 61850, which ensure a standardized structure for information exchange between devices from different manufacturers (Table II). For high-speed computing tasks and operation of intelligent systems, Ethernet and Wi-Fi networks are employed, along with communication gateways that enable adaptation of protocols to specific equipment requirements.

SCADA and EMS systems play an important role, providing centralized monitoring, data processing, and visualization of MicroGrid operating modes. In modern implementations, IoT platforms and cloud services are added to them, allowing you to store large amounts of data, perform load and generation forecasting, run optimization algorithms, and maintain interaction between the links of the control system.

The reliability of data transmission is critical to the stability of MicroGrid. Delays in communication channels, packet loss, or insufficient bandwidth can lead to incorrect operation of secondary and tertiary control algorithms. Therefore, MicroGrid architecture provides for channel redundancy, the use of secure transmission protocols, and duplication of key elements of the communication network.

Thus, the data measurement and transmission system creates the information foundation for MicroGrid control. It ensures the collection of reliable and synchronized parameters, their stable transmission to all control levels, and supports the use of intelligent analysis and optimization methods, which determines its key role in the construction of modern local power systems.

TABLE II. EXAMPLES OF COMMUNICATION PROTOCOL APPLICATIONS IN MICROGRIDS (SOURCE: AUTHOR'S DEVELOPMENT)

Protocol	Scope / Application Area	Typical Equipment	Example Tasks / Functions
Modbus (RTU/TCP)	Local subsystems, device-to-controller communication.	Inverters, BESS controllers, energy meters, protection automation.	Reading voltage/current metrics; monitoring Battery SOC; issuing charge/discharge commands; equipment configuration.
DNP3	Distribution networks, substations, SCADA systems.	Protective relays, meters, RTUs (Remote Terminal Units), power cells.	Substation telemetry; alarm transmission; remote circuit breaker control; reporting to dispatch centers.
IEC 61850	Digital substations, high-speed protection and automation.	IEDs (Intelligent Electronic Devices), breakers, current/voltage transformers, BCUs.	GOOSE messaging with millisecond latency; protection coordination; synchronized communication between field equipment.
IEC 60870-5-104	Dispatch centers, centralized MicroGrid control.	Substation controllers, RTUs, SCADA servers.	Data transmission to control centers; telemetry collection; switching commands; overall grid status monitoring.
MQTT	IoT solutions, cloud platforms, low-speed sensor networks.	Temperature sensors, smart meters, IoT hubs.	Cloud monitoring; data transmission from numerous sensors; integration with analytics platforms.
OPC UA	Industrial integration, cross-vendor interoperability.	SCADA/EMS services, PLCs, gateways.	Unified data access; standardized interaction between disparate systems; object-oriented data modeling.
Sync/PMU standards (IEEE C37.118)	Phasor measurements, dynamic transient modes.	µPMUs, PMUs (Phasor Measurement Units), high-precision analyzers.	Synchronized measurements (microsecond precision); oscillation monitoring; real-time stability assessment.

IV. Overview of Intelligent Approaches to Microgrid Control

The development of microgrids is accompanied by increasing complexity of energy processes, a growing role of distributed generation and storage devices, and the emergence of new models of electricity consumption and production. Under these conditions, traditional control methods no longer provide sufficient adaptability, responsiveness, or accuracy, driving the transition to intelligent approaches. Artificial intelligence (AI), machine learning, reinforcement learning, heuristic methods, and multi-agent technologies have become the leading tools in modern EMS and tertiary control systems [17].

One of the key tasks in a microgrid is forecasting – both load and renewable generation. Intelligent models account for weather, behavioral, and seasonal factors and can adapt to changing operating conditions. For this purpose, neural networks of various architectures, recurrent models, and hybrid systems combining fuzzy logic and machine learning are employed. These approaches achieve a higher level of forecasting accuracy, which is critical for generation planning and energy storage management [12].

At the level of operational optimization and energy management, reinforcement learning plays a key role, allowing the system to autonomously develop optimal control policies based on accumulated experience. Such methods are effective under uncertainty and variable operating conditions; they are therefore applied to BESS management, power flow optimization, and the formulation of economic strategies in market-based interactions. In addition, evolutionary and heuristic algorithms are used to achieve global optimization of complex tasks, although they require higher computational resources [18].

Multi-agent systems are a distinct area of development in intelligent control. In such models, each energy resource is considered an autonomous agent capable of making decisions and coordinating actions with other microgrid elements [15]. This ensures high fault tolerance, flexibility, and the possibility of decentralized control, which is especially relevant for local systems operating in autonomous or islanded modes. Modern multi-agent systems are combined with reinforcement learning, which allows the system to achieve high levels of coordination and optimization.

Intelligent methods also play an important role in ensuring microgrid stability. Fuzzy controllers, adaptive neural controllers, and model predictive control (MPC) are used to adjust droop parameters, restore nominal operating conditions after disturbances, and enhance system stability under high shares of inverter-based generation. These approaches enable effective operation in environments with frequent transients and significant stochastic fluctuations in generation.

Table III presents a comparison of the main intelligent approaches to microgrid control in terms of their objectives, advantages, and limitations.

TABLE III. COMPARISON OF INTELLIGENT APPROACHES TO MICROGRID CONTROL (SOURCE: AUTHOR'S DEVELOPMENT)

Approach	Key Tasks	Advantages	Limitations
Neural Networks (ANN, LSTM, GRU)	Load and generation forecasting, anomaly detection	High accuracy, ability to model non-linear processes	Require large amounts of data; training complexity
Hybrid Models (ANFIS, NN+Fuzzy)	Forecasting, adaptive control, operational mode correction	Combining the benefits of fuzzy logic and ML; interpretability	Slower performance with large datasets
Reinforcement Learning (RL/DRL)	EMS optimization, BESS management, economic strategies	Autonomy, ability to learn from experience, optimality in dynamic conditions	High computational requirements; difficulty in ensuring stability
Multi-Agent Systems (MAS/MARL)	Decentralized control, coordination of DER (Distributed Energy Resources)	Fault tolerance, scalability, agent autonomy	Complexity of coordination between agents; convergence issues
Evolutionary Algorithms (GA, PSO, DE)	Multi-objective optimization of operational modes	Global search capability, insensitivity to non-linearities	Significant computational complexity; no guarantee of finding the global optimum
Fuzzy Logic (FLC)	Voltage/frequency regulation, droop control	Interpretability, ease of implementation	Limited adaptability, requires expert-defined rules

Despite their significant advantages, the use of intelligent methods is accompanied by several challenges. These include the need for high-quality large datasets, cybersecurity concerns, limited computational capabilities of local controllers, and the complexity of interpreting decisions. Nevertheless, the overall trend in microgrid development indicates that the integration of intelligent methods is becoming a key direction for improving control and enhancing the efficiency of local energy systems.

The experience of using intelligent systems in related fields of managing complex dynamic systems is becoming increasingly important. The effectiveness of neural networks in building adaptive control systems capable of automatically optimizing system behavior under conditions of uncertainty and variable environmental parameters has been demonstrated. Approaches to planning and optimization based on neural network models show high potential for application in the intelligent control of MicroGrids, where such methods can improve forecasting accuracy, response speed, and overall stability of energy processes. Thus, the developed concepts of intelligent controllers in robotic systems provide a relevant methodological foundation for modern EMS and adaptive control of distributed energy resources [6]. It is also important to consider developments in the field of autonomous renewable energy sources, particularly vertical-axis wind turbines. Relevant studies have proposed an algorithm for the automated design of such turbines, aimed at achieving maximum power output with minimal starting torque, which is critically important for regions with weak wind flows. The algorithm is based on an impulse rotor model and allows optimization of the geometric parameters to enhance the efficiency of autonomous power sources. This approach demonstrates the significance of intelligent and optimization methods in the development of local energy systems, consistent with MicroGrid requirements for improved generation efficiency, stability, and autonomy [7].

V. System for Determining Microgrid Characteristics

The development of an intelligent MicroGrid control system requires a formalized approach to describing the state of the energy subsystem. This involves defining a set of features that adequately represent the physical, informational, and functional properties of the MicroGrid across different operating modes. The feature system forms the basis for analytical, optimization, and predictive models, determining the quality of decision-making at the secondary and tertiary control levels. The formation of the feature system takes into account the complexity of the MicroGrid architecture, the dynamic nature of its processes, and the need to ensure scalability. Since the MicroGrid consists of distributed energy resources, storage devices, power converters, loads, and communication infrastructure, the features must reflect the parameters of each component as well as their interactions. Particular attention is given to parameters affecting stability, power quality, and EMS performance.

One of the key feature groups is electrical parameters. These include instantaneous values of voltage, current, frequency, active and reactive power, as well as power quality indicators (harmonics, distortion factor, transient processes, and asymmetry indices). They form the basis for ensuring local stability and generating control signals at the primary level. For intelligent algorithms, these features are essential as input data for neural networks, predictive control models, and adaptive droop parameter correction systems [13].

The second group consists of resource features that describe the status of generation units and storage devices. These include available DER capacity, solar irradiance or wind speed, equipment temperature, state of charge (SOC), state of health (SOH) of batteries, converter efficiency, and available power reserves. These features are particularly important for optimal planning tasks, as they allow the control system to assess available resources and make decisions considering technical constraints.

The third important category includes behavioral and predictive features, which are derived from historical data, forecasting models, and consumer behavior patterns. They encompass load forecasts, expected generation from renewable sources, seasonal variations, statistical characteristics of operating modes, and likely changes in consumption patterns.

Another group is network and topological information, describing the status of network elements: topology configuration, switching modes, line capacity, impedance parameters, power flow balance, and the risk of overloads. Intelligent control systems use these features to model MicroGrid operating scenarios, identify bottlenecks, and enhance reliability.

Communication and informational features characterize the quality of connectivity – delays, bandwidth, channel reliability, and the timing and accuracy of data from sensors and controllers (Table IV). They are critical for systems employing distributed algorithms or multi-agent models, where delays can affect the global behavior of the MicroGrid.

Contextual features include external factors such as electricity market prices, tariffs, weather conditions, demand schedules, and the presence of external constraints or energy import/export requirements. This group enables intelligent systems to make decisions not only from a technical perspective but also from an economic standpoint.

TABLE IV. CLASSES OF FEATURES AND THEIR SPECIFICATION FOR MICROGRIDS (INCLUDING SMGC) (SOURCE – AUTHOR'S DEVELOPMENT)

Feature Category	**Description**	**Specific Features (including SMGC)**
Electrical Operational Parameters	Reflect the physical state of the grid and operational deviations.	• Voltage at coupling points • Frequency • Active/Reactive power • Phase angles • THD (Total Harmonic Distortion) • RoCoF (Rate of Change of Frequency) • Generation–load–storage balance (SMGC)
DER Status Features (Distributed Energy Resources)	Characterize the availability and behavior of generation sources.	• Available DER power • Generation forecasts (day-ahead / intraday, SMGC) • Inverter mode • Generation curtailment/limits • Diesel generator / microturbine status • Generation type (PV/Wind/Diesel)
ESS Features (Energy Storage Systems)	Define energy balancing capabilities and mode stabilization.	• SoC (State of Charge) • SoH (State of Health) • Charge/discharge mode • Power limits (max/min) • Ramp-up / ramp-down limits (SMGC) • ESS Role (PV smoothing, peak-shaving, backup, black-start)
Load Profile Features	Describe the consumption activity of the microgrid.	• Current load • Load forecast (day-ahead, SMGC) • Load types (critical/non-critical) • Daily/weekly/seasonal fluctuations • Share of controllable loads
Communication & Digital Features	Determine the quality of interaction between MicroGrid nodes.	• Protocols (IEC 61850, Modbus, DNP3, MQTT) • Communication channel latency • Bandwidth • Packet loss • Data quality (Data Quality Index) • SCADA/IoT architecture (SMGC)
Economic & Environmental Features	Used for optimization and strategic planning.	• Electricity tariffs • Price forecasts (day-ahead markets, SMGC) • Generation costs • Economic constraints • Emission indicators (CO_2)
Distribution Grid, Protection & Automation Features	Reflect infrastructure status, protection, and emergency processes.	• Circuit breaker status • Protection signals/trips • Line flows and constraints • Emergency scenario parameters (black-start, load shedding, SMGC)

The developed system of features enables the construction of a comprehensive MicroGrid model suitable for operation in an intelligent control system. The correct selection of features determines the accuracy of forecasts, the adequacy of optimization decisions, and the stability of the system to external influences. In the future, these features will be used to build a control model, machine learning algorithms, and a decision-making system in MicroGrid.

VI. Use of a Multiclass Classifier to Support Decision Making

After forming the MicroGrid feature system (classes 1–7), which covers electrical operating parameters, generation characteristics, energy storage system (ESS) behavior, load profile, communication indicators, economic and environmental factors, as well as relay protection and automation (RPA) signals, it becomes possible to build an intelligent decision support mechanism. To do this, it is advisable to use a multi-class classifier based on a neural network, capable of analyzing heterogeneous data and assigning the current state of the MicroGrid to one of the predefined scenario classes. A neural network trained on historical and simulated modes can classify states such as: normal operating mode, line overload, generation deficit, excess renewable energy sources (RES), rapid ESS discharge, the appearance of anomalies in communication channels, or the probability of emergency protection activation. Taking into account the characteristics of the distribution network and relay protection (class 7) allows the classifier not only to detect violations, but also to predict their possible development, which makes it an important element of the MicroGrid self-healing system. After determining the class of the current state, the classifier generates output recommendations for the secondary and tertiary control levels: load correction, change of ESS operating mode, redistribution of power flows, activation of economically optimal scenarios, or initiation of algorithms for localization and isolation of faults.

VII. Review of Possible Multi-Class Classifiers for the Microgrid Automation System

The choice of a specific classification architecture depends on the type of data, their structure, and the requirements for computational speed. Therefore, it is advisable not to rely on a single algorithm, but to consider several promising approaches, each of which is most effective for certain feature classes.

A. Deep Neural Networks (DNN) for tabular features

This approach is appropriate when the data are represented as fixed feature vectors:

- electrical parameters (class 1);
- generation status (class 2);
- ESS parameters (class 3);
- economic features (class 6);
- distribution network features (class 7).

DNNs perform well with a large number of features and allow modeling nonlinear dependencies between them.

B. Recurrent models (LSTM/GRU) for time-series processes

This approach is optimal when time series data are available, in particular:

- load (class 4);
- RES generation (class 2);
- SoC/SoH (class 3);
- frequency and its derivatives (class 1);
- distribution network features (class 7).

LSTM/GRU models can account for the dynamics of changes and reveal hidden temporal patterns, which is critical for forecasting MicroGrid states.

C. Attention-based architectures this approach provides:

- high accuracy when working with heterogeneous features;
- the ability to adaptively assign “weights” to the most important parameters;
- processing of both static and dynamic features.

Attention models perform well in systems where parameters have different contributions to determining the MicroGrid operating state.

D. Hybrid models (CNN + LSTM, DNN + Attention, GraphNN)

Hybrid architectures are particularly promising, as they allow combining different types of features:

- CNN – for structured data or topologies;
- LSTM – for temporal data;
- Graph Neural Networks (GNN) – for describing the network structure of the MicroGrid (classes 1 and 7).

These models provide adaptability and high accuracy in complex operating modes.

E. Lightweight classifiers for real-time tasks

In systems where speed is a priority (e.g., relay protection or inverter control):

- Random Forest;
- Gradient Boosting;
- SVM with multiclass support.

These classifiers provide low latency and can operate on edge devices within the MicroGrid.

Thus, the selection of the architecture for a multi-class classifier in a MicroGrid automation system should be based on a comprehensive analysis of several key factors: the type of features (static tabular data, time series, or network topological structures), real-time requirements (relay protection systems require millisecond-level latency, whereas economic optimization allows for longer computation times), availability of computational resources (centralized servers enable the use of complex deep models, while edge devices require lightweight solutions), and the availability of historical data for training (the volume and quality of the dataset determine the feasibility of applying deep learning).

A properly selected and trained classifier should provide accurate identification of the current state of the MicroGrid (normal operation, line overload, generation deficit, anomalies), forecasting of critical operating modes based on the early detection of disturbances, and support decision-making at the secondary and tertiary control levels by generating recommendations for load correction, ESS management, and power flow redistribution. Additionally, it should ensure seamless integration with the intelligent MicroGrid control system to maintain adaptability, fault tolerance, and economic efficiency of MicroGrid operation under complex and variable conditions.

VIII. Conclusion

The conducted study allows for a comprehensive assessment of the current state of MicroGrid development and substantiates the need for the implementation of intelligent control methods. Analysis of MicroGrid architecture has shown that modern local energy systems are characterized by a high degree of decentralization, stochastic generation, the presence of heterogeneous energy sources and storage devices, as well as complex information infrastructure. Under such conditions, traditional control approaches lose their effectiveness, particularly with the increasing share of renewable energy sources and the need for rapid response to changing operating modes.

The review of existing control systems demonstrated the evolution from centralized to hierarchical and decentralized models, which provide greater flexibility and resilience for MicroGrids. Nevertheless, even these approaches do not fully address the challenges of optimization, forecasting, and operation under uncertainty. This is why intelligent methods are becoming a key direction in the development of modern energy systems.

Intelligent methods, such as neural networks, fuzzy-hybrid systems, reinforcement learning, evolutionary algorithms, and multi-agent approaches, enable the modeling of complex nonlinear processes, adaptation to unpredictable changes, and formulation of optimal decisions in real time. Their integration at the secondary and tertiary control levels enhances the efficiency of DER utilization, supports forecasting tasks, reduces operational costs, and ensures system stability.

A particularly important role in building intelligent control systems is played by the MicroGrid feature system. Its formalization provides a structured approach to assessing the state of energy resources, determining dynamic characteristics, analyzing topology, and modeling system behavior. A well-formed set of features forms the foundation for machine learning algorithms, optimization, and predictive models, determining their accuracy and reliability.

It can be concluded that the use of intelligent methods in MicroGrid control is a logical and necessary response to the increasing complexity of modern energy systems. The combination of accurate measurement data, reliable communication infrastructure, a properly structured feature system, and intelligent models ensures improved efficiency, reliability, and economic performance of MicroGrids. The results of this study confirm the prospects for further research in the integration of artificial intelligence into control systems, as well as the development of algorithms capable of operating in real time and adapting to environmental changes.

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Т. Л. Ногачевський, О. І. Чумаченко. Визначення ознак MicroGrid для побудови інтелектуальної системи керування

У статті розглянуто проблему визначення ключових ознак MicroGrid як складної енергетичної системи, що є необхідною передумовою для побудови інтелектуальної системи керування. Масове впровадження розподіленої генерації, відновлюваних джерел енергії та систем зберігання енергії зумовлює потребу в адаптивних методах керування, здатних працювати в умовах невизначеності та змінних режимів електричних мереж. Існуючі підходи до керування MicroGrid залишаються обмеженими через відсутність уніфікованого та науково обґрунтованого переліку структурних, режимних, динамічних і інформаційних ознак, які мають бути враховані під час роботи інтелектуальних систем.У роботі проведено аналіз сучасних наукових підходів до класифікації, моделювання та оперативного керування MicroGrid, що дозволило виявити недостатньо досліджені аспекти, пов'язані з формуванням набору ознак і їх впливом на процеси прийняття рішень. Мета статті полягає у систематизації й обґрунтуванні комплексної множини ознак MicroGrid, яка може бути використана як основа для розроблення інтелектуальних алгоритмів керування. Запропоновано концептуальний підхід до структурування ознак MicroGrid на групи: архітектурні, енерго-технічні, експлуатаційні, пов'язані зі стійкістю динамічних режимів та орієнтовані на дані. Доведено їх значущість для задач прогнозування, оптимізації, оцінювання стану та автономної роботи локальних енергосистем. Отримані результати формують методологічну базу, що підвищує ефективність розроблення інтелектуальних систем керування MicroGrid та сприяє зміцненню гнучкості й надійності локальних енергетичних мереж.
Ключові слова: MicroGrid; інтелектуальна система керування; розподілена генерація; ознаки MicroGrid; кіберфізичні енергетичні системи.

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