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Optimized control of industrial microgrid energy storage using particle swarm techniques

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Abstract: Renewable energy sources have rapidly developed over the past few years. The stochastic nature of the generated energy in photovoltaic systems (PV) and wind power plants is causing more interest in energy storage systems (ESS). In commercial installations, deterministic methods are used to control the power of the storage, which is not efficient. Developing algorithms that optimize economic and technical aspects is necessary. Methods based on computational intelligence (CI) can be a solution. The paper presents a novel CI algorithm for optimizing power flow in microgrids using the particle swarm optimization (PSO) method. The economic and technical efficiency of control is achieved by combining multiple criteria in the objective function. The solution is universal, scalable, and can be applied to any industrial or residential microgrid. The method uses short-term forecasts of local generation and load and specifications of ESS, ensuring that technological constraints are maintained. Analyses were conducted for a whole year for a real industrial microgrid. The paper presents the selected results of the study. The efficiency of the proposed algorithm is compared with the results obtained by a deterministic algorithm aimed at maximizing autoconsumption. Using the PSO algorithm resulted in an economic effect of €6 635 with 461 full discharge cycles, compared to €2 287 and 110 cycles for the deterministic approach, meaning an increase of more than 2.5 times. However, such storage operation requires more intensive work, affecting its lifetime. Further research can develop objective functions that, without compromising economic effects, support microgrid operation: improving power quality, minimizing voltage fluctuations.

Key words: computational intelligence, control optimization, economic efficiency, energy storage system, microgrid

1. Introduction

In recent years, there has been an increase in the development of renewable energy sources, which has caused problems with their integration into the power system. System stability, voltage and frequency fluctuations, and maintenance of power quality parameters at an appropriate level are some problems that have begun to arise. In response, there is an increased interest in developing energy resources and load control methods to eliminate these problems. Renewable energy sources (RES) and loads are getting connected in microgrids. The importance of energy storage is also increasing [1]. The high number of variables in the optimization problem contributes to an increase in the complexity of the objective function, leading to an interest in new algorithms that use computational intelligence in their operation [2]. The following section presents an analysis of the state of the art in microgrid control methods, application of energy storage systems, and the use of computational intelligence methods in power system optimization problems.

1.1. The state of art

The microgrid management methods can be divided into demand control and energy generation control.

The demand control can be divided into price-based and direct load control. Examples of load control based on energy prices can be found, for instance, in [3]. The publication's authors discuss the case of load control in a residential house. Mainly, interruptible loads and thermostatically controlled loads are controlled. Another example of the application of demand control using energy prices can be found in [4]. The paper presents a case study in Vietnam. Tariffs control the demand. The discussed case is interesting as it does not rely solely on economics; elements such as environment and social satisfaction are also considered for the objective function. The problem under discussion is also presented by [5]. The authors of this paper focused on developing a load control algorithm for a newly built residential neighborhood in China. The paper focuses not only on the case study but also discusses other price-based load control methods already in use in the country. A case study is also presented in [6]; this time, the subject is a pilot network in Cyprus. The analyzed network consists of three hundred prosumers with with photovoltaic (PV) installations. The control of the network is based on tariffs. The work is interesting because the focus is on creating optimal tariffs to meet the objectives. The second method of demand control is direct load control. Thus, to begin with, in [7], the authors focused on the distrust that consumers display toward allowing the distribution system operator to control the load. The study focused on a group of Australian residents. Also, a survey of the society was conducted in [8]. This time, the survey was conducted in Switzerland, and the research object tested consumer preferences on direct load control. This approach allowed the authors to come to interesting conclusions, including that choices are influenced by the type of housing, education, and place of employment. A practical application of direct load control is presented in [9], where the scheduling of a unit of air conditioners in a region of China is discussed. Another practical application is the case shown in [10]. The object was a military microgrid, and the purpose of the load control was to flatten the demand curve. Another application, this time in a civilian application, can be seen in [11]. Here, the object was a smart building. The model made it possible not only to control devices in the building but also to disconnect them from the grid. The goal of the control was to minimize costs. In the paper [12], on the other hand, the authors implemented technical objectives, such as frequency regulation and reducing oscillations in the power grid. The model was tested on a 39-bus IEEE system.

Also, the management of generated power can be divided further. The main division is between grids with renewable energy sources and grids with conventional energy sources. If the latter is the case, a further distinction can be made between unit commitment (UC), i.e. controlling energy sources to meet the established technical and economic objectives while covering the demand, and economic dispatch (ED), i.e. covering the demand to the lowest cost of the project.

The UC approach can be encountered in [13], where the system that contains wind turbines is addressed. The authors attempted to solve the problem of forecasting generation. The authors of [14] also discussed wind turbines; here, the solved problem was the sizing of wind turbines and their location in the system. Similarly, in [15], the author's interest was a network with wind turbines. Here, however, the problem was to control the power flow considering the uncertainties presented by the generation forecast. Not only wind power plants, but RES in general present dangers associated with the stochastic nature of the generated power. In [16], the authors link the UC problem to demand control to balance the uncertainties associated with generation. Optimization objectives can also be related to optimizing the sources' operation, and such an approach is seen in [17]. The authors' goal is to maximize the use of the generator, which is a hydroelectric power plant.

On the other hand, the ED approach is found, for example, in the publication [18]. The object of the study is a microgrid, and air conditioners are controlled. The goal is to reduce operating costs. On the other hand, the paper [19] addresses the cost optimization problem related to line capacity in the power grid. Another example of solving the ED problem is the publication [20]. Here, the author's primary object of interest was water resource recovery facilities (WRRF) as potential energy generation units. The goal of the optimization was to reduce costs. Another example of solving the ED problem is the article [21]. The publication combined the economic dispatch problem with demand control, and artificial neural networks were used for optimization. Since the object of consideration was a microgrid in island operation mode, the optimization goal was to maintain the stability of such a system.

Directly related to the UC and ED problems are energy storage systems, which allow storing energy when an excess is produced and giving the energy back when there is a shortage. For example, in [22], the authors solve the UC problem by scheduling an energy storage system (ESS) in a grid with a wind turbine to enable more efficient scheduling of generation units and improve the power system's stability. The studied networks can be complicated; in [23], a grid containing photovoltaic installations, fuel cells, an energy storage system, and wind power plants is examined. The goal of controlling such a network was to minimize operating costs and reduce emissions. An interesting approach is taken by the authors of the publication [24], where the energy storage system is a hydropower plant. The publication analyzes the problem of scheduling the operation of a hydropower plant to reduce costs. Energy storage systems support not only economic goals but also technical ones. In [25], the authors use ESS to maintain the frequency at an appropriate level in the network where wind power plants are located. Another example of achieving technical goals is published in [26]. Here, the goal of reducing emissions is realized by supporting grid operation with an energy storage system.

Intelligent control of a microgrid involves the application of not a single method but a combination of multiple ways to efficiently meet technical and economic objectives. This makes the resulting objective functions characterized by high complexity and many local extremes at which traditional optimization algorithms fail. To address this problem, algorithms using computational intelligence (CI) are used. A well-publicized algorithm is particle swarm optimization (PSO).

For example, in [27], the authors use a modified version of the PSO to solve the UC problem in a grid with hydropower plants, wind turbines, and thermal units. The problem is the uncertainty in the forecast of the energy produced by the wind power plant. Also, concerning wind turbines, the paper [28] uses a variant of the PSO algorithm, the crow search algorithm (CSA). There, the operation of CSA is supported by the JAYA algorithm and is used to solve the problem of maximizing the use of wind turbines in the analyzed system. Another optimization problems are environmental objectives, for example in [29]. The variant of the PSO algorithm used is Niching Penalized Chimp Optimization (NPChOA). An extension of the environmental variant to include cost balancing is presented in [30]. In this case, the PSO variant used is the mayfly algorithm (MA). A well-developed and proven method that uses CI is artificial neural networks. Their application can be seen in the publication [31]. The optimization problem considered by the authors is transmission line losses.

1.2. Research gaps and contribution of the work

The literature review indicates that the answer to microgrid control problems is not to use a single optimization method but multiple, properly combined planning strategies. However, the experiments show that this approach results in multi-criteria optimization, contributing to the optimization process's complexity. Hence, the answer to this problem is to solve the optimization problem using algorithms based on computational intelligence.

Therefore, in this paper, the authors propose a new algorithm for controlling the operation of a microgrid energy storage system. The algorithm uses a deterministic and CI approach, which employs the PSO method. The objective function combines technical and economic objectives and is scalable to any system. Load and generation forecasts were used in the calculations. The algorithm allows the implementation of any time intervals. Representative operation of the ESS is provided by experimentally determining the charging and discharging characteristics of the energy storage system. The operation of the control algorithm is tested for six cases.

1.3. Nomenclature

The article uses the abbreviations and symbols listed in Table 1.

Table 1. Nomenclature

Parameter	Description	Unit
T	Time step (e.g. 1 hour)	h
N	Number of control steps	–
PO	Power load (forecast)	kW
PG	Power PV (forecast)	kW
PS	Power grid	kW
PM	Power ESS	kW
PZ	Assigned power of energy exchange with the grid	kW
PX	Max. power of ESS (nominal)	kW

Continued on next page

Table 1 – *Continued from previous page*

Parameter	Description	Unit
EX	Max. energy of ESS (capacity)	kWh
SOCX	Min. SOC of ESS (e.g. 20%)	%
SOC	State of charge	%
B23	Energy purchase tariff	€ /kWh
RCE	Energy sales tariff (energy market price)	€ /kWh
PLC	Charging power by ESS characteristics	kW
PLO	Charging power by ESS capacity limit	kW
PRC	Discharging power by ESS characteristics	kW
PRO	Discharging power by ESS capacity limits	kW
f_{ECO}	The objective function in the economic aspect	–
f_{PZ0}	The objective function in the technical aspect (fit with PZ)	
f_{SOC}	The objective function in the technical aspect (SOC optimization)	–
f_{LCR}	The objective function in the technical aspect (minimize the number of discharge cycles)	–
w_x	Weights of objective function criteria	–

2. The microgrid and ESS models, description of the algorithm

2.1. The microgrid model

The research was based on data from a metallurgical company located in Bialystok, Poland (Podlaskie voivodeship). The company produces high-grade stainless steel automotive accessories and metal laser processing. In connection with the ERA-NET MESH4U project, the company has become an industrial partner for the multi-energy storage hub system demonstrator. The research aims to propose the optimal operation of an ESS in an industrial microgrid system to reduce energy consumption costs and maximize energy use from a local PV installation while improving power quality.

The company is powered by a 20 kV distribution network. Power demand is 510 kW during the winter (December-April) and 330 kW during the rest of the year. The energy purchase price is related to the three-zone energy tariff B23. The factory's annual energy consumption has grown steadily in recent years, from 0.531 MWh in 2018 to 1.190 MWh in 2021. The breakdown of energy consumption parameters for production by daily time zones is as follows: morning peak (7 a.m.–1 p.m.) – about 31%, afternoon peak about 12%, and other hours – about 55%. An investment in a 317 kWp PV installation was made to reduce energy demand. The PV installation began generating energy at the end of 2021. The second stage of the plant's grid modernization was the installation of an ESS to act as a UPS for sensitive laser processing equipment and to minimize energy consumption costs. Due to limited resources, the ESS has a capacity of 150 kWh (EX) and a maximum power of 150 kW (PX). In contrast, the capacity to which the equipment can be discharged is 20% of the maximum storage capacity (SOCX). The storage unit was commissioned in early 2023, and analyses of its actual work are underway.

The calculations developed for the microgrid model relate to an industrial facility's existing low-voltage network. The parameters of the modeled devices correspond to actual data, making it possible to verify the methods under conditions of actual microgrid operation after the implementation of ESS control algorithms.

Figure 1 shows a simplified diagram of a microgrid, which is used in power flow calculations. The grid consists of an energy storage system, a photovoltaic power plant, and a load. The microgrid is connected to the distribution grid via a transformer.

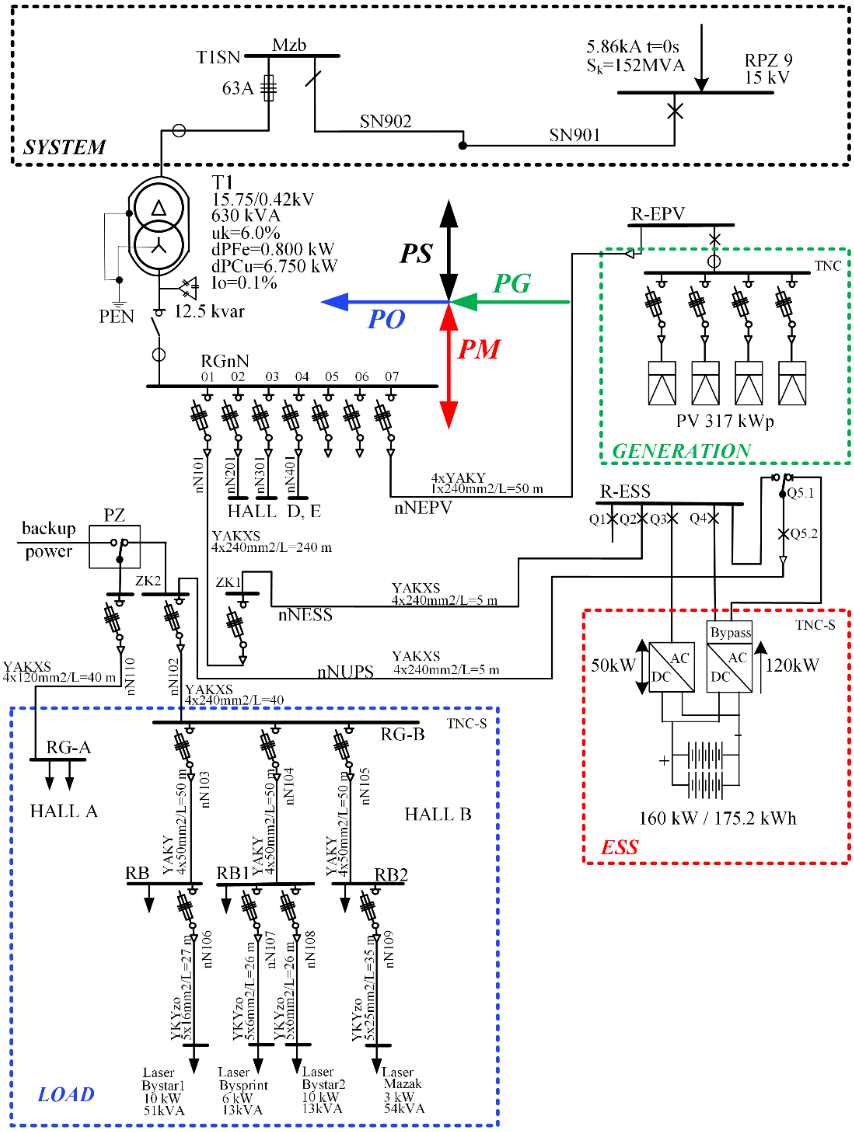

Fig. 1. A diagram of the analyzed industrial microgrid

2.2. The energy storage system model

The energy storage system model used for the calculations is based on its charging and discharging characteristics. The ESS characteristics determine its technical limitations and are usually specified by the manufacturer. The shape of the ESS characteristics results from the storage technology and the battery management system's (BMS) algorithms that manage the operation of the cells, responding to changes in temperature, voltage, current levels, state of charge, level of cell degradation, etc. The characteristics shown in Fig. 2 reflect the physical energy storage system; the characteristics were determined experimentally. The authors described how they were defined in [32]. In addition, the system operator can use appropriate shaping of characteristics to control optimization.

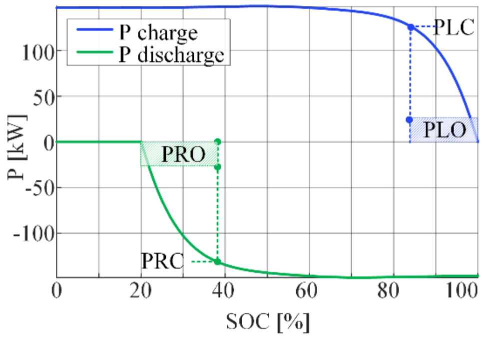

Fig. 2. ESS charging and discharging characteristics, P = char(SOC)

2.3. Description of the proposed algorithm

The algorithm uses a method of particle swarm optimization and a deterministic algorithm to match the power exchanged with the power system to the desired optimal profile. The algorithm results in an ESS control plan (PM) to manage the excess energy generated by local microgrid sources or the energy shortage to supply local loads, thus making it possible to control a microgrid due to economic and technical aspects. The algorithm also allows the combination of multiple aspects. Suppose only the economic factor is considered; the objective function is modified so that the algorithm will minimize the cost of energy purchase and maximize profits from energy sales. The pseudo-code of the energy storage system control algorithm CI is as follows:

Algorithm CI PM[1..N] = **function**(PG [1..N], PO[1..N], T, EX, PX, SOCX, SOC0)

```
Initialization for each particle PZ[1..N]
repeat for each particle until a termination criterion is met (start PSO)
SOC = SOC0 initial value of SOC
    for k = 1:N
    PLO(k) = EX*(1-SOC)/T                  charging power based on available ESS energy
    PRO(k) = EX*(SOCX-SOC)/T               discharging power based on available ESS energy
    [PLC(k), PRC(k)] = char(EX, PX, SOC)   charging, discharging power based on ESS characteristics
        if PG(k) + PO(k) + PZ(k) >
           PM(k) = min(–(PG(k) + PO(k) + PZ(k)), PLO(k), PLC(k))   limitation of charging ESS
        else
           PM(k) = max(–(PG(k) + PO(k) + PZ(k)), PRO(k), PRC(k))   limitation of discharging ESS
        end
```

```
        PS(k) = microgrid_model (PG(k), PO(k),PM(k))          power flow calculations
        SOC = (EX * SOC + PM(k) * T)/EX
        SOC(k) = SOC;
    end
  objective function f calculation
  check the criterion for termination PSO
  end  (stop PSO)
  result best PM[1..N]     optimal schedule of ESS control
```

If the technical aspect is considered, the algorithm works based on a preset condition of the best match between the preset energy exchange curve and the system, resulting from the microgrid's ESS constraints and power balance. Other technical aspects relate to minimizing the number of discharge cycles or maintaining the state of charge (SOC) at the required level. Combining economic and technical aspects is done by modifying the objective function. Depending on the weights of each criterion of the objective function, the algorithm will search for a compromise between optimizing costs and profits and matching technical constraints.

The algorithm uses the generation and demand forecast and the characteristics of the energy storage's available charging and discharging power, depending on the state of charge. These elements can directly affect the effectiveness of the control algorithm. However, obtaining the actual storage characteristics through intentional testing or in-use can improve the algorithm's reliability. The collection of historical data can enhance the effectiveness of the forecasting method.

As input data, the algorithm uses a generation power forecast matrix (PG), a load power forecast matrix (PO) of size N, a given time step (T), the maximum capacity of the energy storage system (EX), the maximum power of the ESS (PX), the minimum SOC of the ESS (SOCX). At the beginning of each control algorithm calculation step, the ESS's output state of charge is also set (SOC0). Limiting the values in the PZ matrix ensures that only the excess of locally generated energy or its local deficit is managed.

The ESS characteristic P = char(SOC) defines the permitted charging (PLC) and discharging (PRC) power of the energy storage system, depending on the SOC. The algorithm calculates the permitted power of the storage under extreme charging and discharging conditions (PLO, PRO), which depend on the available energy of the ESS. The algorithm's operation begins with generating a random PZ profile in the PSO loop. In the first step of loop "k", the initial state of charge of the storage (SOC0) is determined. For each consecutive value of the matrices PZ(k), PG(k), and PO(k), the permitted values of the charging and discharging power of the ESS are calculated according to the set characteristics of the storage. The algorithm in the deterministic part calculates in each step "k" the excess of generated power or its deficiency and, depending on this, decides to charge or discharge the ESS. For the charging decision, the power in the storage operation plan PM(k) is the minimum value of the storage power resulting from the comparison of three values: the power of excess generation [(PG(k) + PO(k) + PZ(k)], the power resulting from the storage characteristics PLC = char(SOC), and the power for the available charging energy PLO. In the case of the discharge decision, the power in the PM(k) matrix is the maximum value of the storage power obtained by comparing three powers: the power of generation deficiency [PG(k) + PO(k) + PZ(k)], the power resulting from the characteristic PRC = char(SOC), and the power for the available discharge energy PRO. The microgrid model is then used to calculate the power flow, resulting in a matrix of power values for power exchange with the distribution system PS(k) and a matrix of the state of charge SOC(k). The loop is executed until the entire control plan PM(k) matrix is filled. The heuristic algorithm then evaluates the solution according to the given objective function. Suppose the result of the search for the optimum is satisfied, the algorithm terminates (e.g. reaching the set number of iterations or no changes in the value of the objective function according to the set tolerance), and if not, a new value of PZ(k) is calculated in the PSO loop and the evaluation process repeats. The result of the algorithm is the matrix PM(k), which is the work plan of the ESS.

The proposed algorithm's advantage is its high flexibility and scalability. The method can be successfully used in larger, more complex systems by increasing the number of dimensions in the search space (e.g., more storage units, longer time horizon) and implementing techniques such as multi-swarm PSO, which enable parallel optimization in distributed systems. This allows the algorithm to be applied to industrial microgrids and residential or commercial systems with multiple RES and ESS units.

The algorithm operates on metering data, energy production, and demand prediction data. The usual interval is 1 h to 15 minutes, and planning captures 24 hours. Implementing PSO modifications for larger-scale systems in such a time regime should not significantly affect the solution's performance. Section 2.4 on PSO characteristics provides more details.

2.4. PSO algorithm

The particle swarm optimization algorithm is a heuristic optimization algorithm inspired by the behavior of animal packs. In PSO, potential solutions are represented as particles moving through the search space. The particles cooperate, adjusting their position according to local and global best solutions [33]. This collective approach allows the algorithm to efficiently explore and exploit the search space, which can lead to finding better solutions compared to classical optimization algorithms. Figure 3 shows a simplified diagram of how the PSO algorithm works.

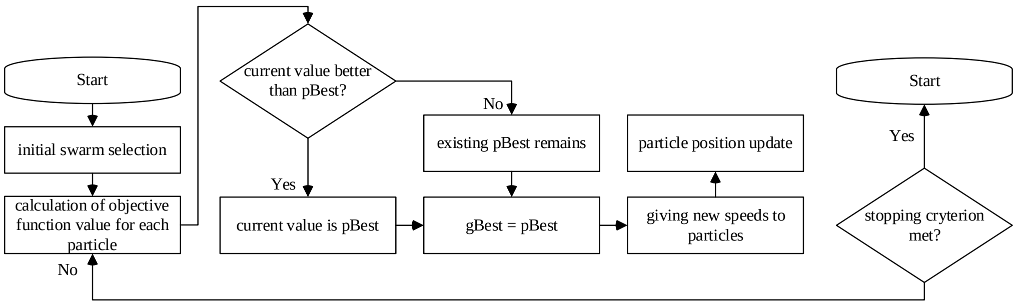

Fig. 3. A block diagram of the PSO algorithm

PSO is especially effective in high-dimensional spaces where traditional methods can encounter difficulties, especially when solving multi-criteria microgrid optimization problems, as shown in [34, 35]. Its ability to simultaneously search and exploit contributes to efficiently finding global optima, making it an attractive tool in optimization.

The literature compares many CI techniques. The article [36] compares the performance of genetic algorithms, memetic algorithms, particle swarm, ant colony systems, and shuffled frog leaping. Comparative benchmarks between the algorithms are presented for continuous and discrete optimization problems regarding processing time, convergence speed, and results quality. The authors demonstrate that PSO performs better than the other algorithms studied in terms of success rate and solution quality, while being the second best (after ant colony) in processing time.

The method's main advantages are its simplicity, rapid convergence to the global optimum solution, scalability, and ability to work efficiently in multidimensional spaces. The proposed approach, which has not been used before in this type of problem, deals with optimization in high-dimensional space, where each planned value of ESS power in the control schedule is the coordinates of the position of the swarm particle in the search space. In the daily analysis at 1h resolution, the dimension of the space is 24. The large dimension of the search space and the nature of the objective function, which is discontinuous and contains many local minima, require appropriate methods. The PSO algorithm was used because classical optimization methods are helpless in such cases, and other CI algorithms achieve barely correct results with much more computation time.

The economic and technical criteria are expected to affect the results equally in the examples shown. In the algorithm, normalization of the criteria was applied through the weights. Their different values are because the criteria have different units and change ranges. The economic component unit is much larger than the technical component, which was considered when calibrating the weights. The average daily energy cost is €2 000, the maximum daily number of discharge cycles is 4, the maximum SOC change is 0.8, and the average daily energy exchange power with the host system is 3 200 kW. The weights used for the various criteria are shown in Table 2, while a description of the objective function for the same criteria can be found in Section 2.5, and the calculation of weights is in Section 2.6. Table 2 also shows the parameters used for the PSO algorithm in the simulation calculations.

For the values shown in Table 2, i.e. 24-hour optimization with a resolution of 1 h (search space of 24 dimensions), 72 particles, and a maximum of 100 iterations, the average optimization time was less than 10 seconds. Each time, ten PSO runs were performed for different random starting positions of the swarm particles on an i7-class computer (3.4 GHz, 16 GB RAM). This approach aims to select a schedule that guarantees the objective function's minimum and repeatable value.

Compared to other algorithms based on CI, such as genetic algorithms or neural networks, the PSO method has a favorable balance between solution quality and processing time, which has also been confirmed in the literature [36]. For larger decision spaces (e.g., longer time horizon, more ESS), the computational cost increases proportionally, but parallel methods or adaptive versions of PSO can reduce it.

2.5. The objective functions

In technical terms, ESS applications for cooperation with the power grid can have various purposes. These include maintaining the required power quality parameters through load compensation, reducing load peaks, shifting load and generation peaks, reducing overload losses of transmission devices by reducing power flows, voltage level control, voltage asymmetry reduction, emergency power supply, and interaction with renewable energy sources.

Table 2. PSO parameters

Symbol	**Description**	**Parameter value**
N	Size of search space	24 (number of forecast steps)
S	Swarm size	72
MaxIter	Maximum iterations	100
C1	Self-adjustment weight	1.49
C2	Social adjustment weight	1.49
Inertia	Inertia range	[0.1–1.1]
Tol	Function tolerance	10e-4
Lb	Lower bound	unlimited[1] max(PO + PG) limited[2] $\max(PO_k + PG_k)$
Ub	Upper bound	unlimited[1] min(PO + PG) limited[2] $\min(PO_k + PG_k)$
w_{ECO}; w_{PZ0}	Weights for f_{EPZ0}	0.6160; 0.3840
w_{ECO}; w_{SOC}	Weights for f_{ESOC}	0.0002; 0.9998
w_{ECO}; w_{LCR}	Weights for f_{ELCR}	0.0020; 0.9980

[1] The maximum and minimum values (PO + PG) over the total control range were taken as a boundary.
[2] The maximum and minimum values ($PO_k + PG_k$) for each control step were taken as a boundary.

The optimization objective function (1) in the technical aspect (f_{PZ0}) is to best match the power curve of energy exchange with the distribution system (PS) and the calculated power curve (PZ) for the entire forecast interval. For a one-day forecast with a resolution of one hour, N is 24. The achievement of PZ depends mainly on the parameters of the ESS, namely its maximum capacity (EX) and rated power (PX), as well as the waveform of charging and discharging characteristics, and the state of charge and power balance in the microgrid.

$$f_{PZ0} = \sum_{k=1}^{N} \sqrt{(PS_k - PZ_k)^2}. \tag{1}$$

The economic optimization uses prices for energy purchases according to the B23 tariff. This is a three-zone tariff designed for companies supplied from the medium-voltage grid whose contracted power exceeds 40 kW. In the B23 tariff on business days (Monday–Friday), zones are as follows:
- morning peak,
- afternoon peak (the most expensive zone),
- remaining hours of the day (the cheapest zone).

The hours of each zone depend on the month. On weekends and public holidays, one zone applies. Figure 4 shows an example of the distribution of prices in each zone of the B23 tariff for a weekday in the summer month (June 1, 2021). The morning peak applies from 7 a.m. to 1 p.m., and the afternoon peak applies from 7 p.m. to 10 p.m. Figure 4 also shows the energy sales rates published on the day-ahead energy price market.

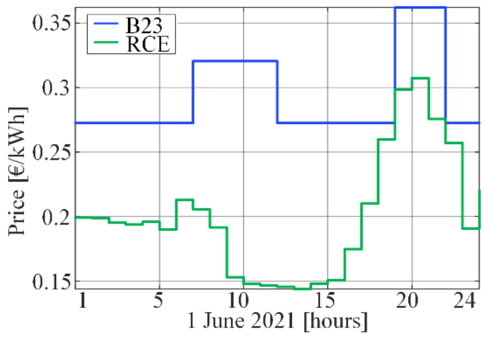

Fig. 4. Energy prices for the B23 tariff and the energy market RCE on June 1, 2021

An hourly storage operation schedule can be created based on the energy purchase tariff (B23) and the energy sales prices in the market (RCE). The economic analysis is based on energy purchase prices and energy sales prices. CI algorithms mainly use this information to decide how the ESS will work.

The optimization objective function (2) in the economic aspect (f_{ECO}) is to minimize the cost of energy purchase and maximize the profits of energy sales. The power exchange curve (PS) is split into a part with positive values (PS_k^+) by replacing negative values with zeros in the PS vector and a part with negative values (PS_k^-) by replacing positive values with zeros in the PS. The new vector PS_k^+ is the power resulting from energy purchased at B23 tariff prices, and PS_k^- is the power resulting from energy sold at the forecast energy price market (RCE). The difference between costs and profits forms the objective function, the minimization of which provides the best economic effect.

$$f_{\mathrm{ECO}} = T \cdot \sum_{\mathrm{k}=1}^{N} \left(\mathrm{PS}_\mathrm{k}^+ \cdot B23_\mathrm{k}\right) - \sum_{\mathrm{k}=1}^{N} \left(\mathrm{PS}_\mathrm{k}^- \cdot \mathrm{RCE}_\mathrm{k}\right), \tag{2}$$

where T is the time step.

Having the objective functions (1) and (2), the two criteria can be combined with appropriate weights, w_{ECO} and w_{PZ0}, using the Weighted Objectives Method. Multi-criteria optimization is then reduced to a single criterion by introducing a substitute criterion. The choice of the values of the criteria weights depends on the preference for economic or technical effects and can be carried out experimentally by simulation.

$$f_{\mathrm{EPZ0}} = w_{\mathrm{ECO}} \cdot f_{\mathrm{ECO}} + w_{\mathrm{PZ0}} \cdot f_{\mathrm{PZ0}}. \tag{3}$$

An example of another objective function implementing a technical aspect is (4), which is related to maintaining the SOC at the end of the control period (SOC_N) at an average level. That is, in the case presented here, at the end of each day. Such a function ensures that the ESS at the beginning of each new forecasting period is not entirely discharged or charged. The calculations assumed a sample SOC value of 60% as the target at the end of the control period.

$$f_{\mathrm{SOC}} = |0.6 - \mathrm{SOC}_N| \,. \tag{4}$$

As before, the criteria are combined in (5) with appropriate weights.

$$f_{\mathrm{ESOC}} = w_{\mathrm{ECO}} \cdot f_{\mathrm{ECO}} + w_{\mathrm{SOC}} \cdot f_{\mathrm{SOC}}. \tag{5}$$

An important technical criterion relating to the lifetime of an EES operating in a microgrid is minimizing the number of ESS discharging cycles. The objective function that calculates the discharging cycles in the considered control interval is described by (6).

$$f_{\mathrm{LCR}} = \frac{1}{2} \cdot \sum_{\mathrm{k}=1}^{N-1} |\mathrm{SOC_k} - \mathrm{SOC_{k-1}}| \,. \tag{6}$$

Similarly to (3), an economic criterion was combined with a technical one.

$$f_{\mathrm{ELCR}} = w_{\mathrm{ECO}} \cdot f_{\mathrm{ECO}} + w_{\mathrm{LCR}} \cdot f_{\mathrm{LCR}}. \tag{7}$$

Now, the minimization of energy purchase costs is being realized, with consideration given to the life of the ESS. The used weights may prefer the economic or technical aspect. An important engineering problem is to select the weights so as to achieve a significant reduction in discharging cycles with minimal change in the economic balance. The adopted weights are designed to normalize the criteria. This ensures that each criterion of the objective function has a similar impact on the optimization result.

2.6. Calculating weights in the objective function

To calculate the individual weights, the weighted objective function method was used. In this method, technical and economic criteria are combined into a single optimization function. Since these criteria have different units and ranges (e.g., euros, kW, number of cycles), it was necessary to normalize them in advance and then calibrate the weights objectively.

The objective function f is the sum of L normalized criteria f_{in}

$$f = \sum_{i=1}^{L} f_{in} = \sum_{i=1}^{L} \frac{f_i}{f_{is}}, \tag{8}$$

where f_{is} is the normative value of the criterion f_i.

The objective function as a sum of weighted criteria has the form

$$f = \sum_{i=1}^{L} w_i \cdot f_i. \tag{9}$$

Hence, the weights w_i of the f_i criteria are:

$$w_i = \frac{\frac{1}{f_{is}}}{\sum_{i=1}^{L} \frac{1}{f_{is}}}. \tag{10}$$

The sum of the weights equals one. This normalization method ensures that each criterion has a comparable impact on the optimization result, regardless of units or scale. The weights given in Table 2 are calculated according to (8–10) for the adopted normative values of the criteria described in Section 2.4. The weights presented are specific to the analyzed case and depend on the structure of the objective function and the technical and economic data of the system in question. For other microgrids (e.g., residential) or other market conditions (e.g., other energy tariffs), the weights would have to be redetermined according to the procedure presented.

3. Performance analysis

All analyses presented in the paper were performed for an industrial metallurgical plant. The plant has a photovoltaic installation and energy storage. Figure 5 shows generation and load forecasts for June 1, 2021.

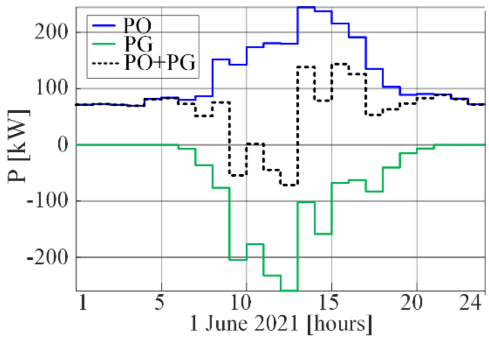

Fig. 5. Load PO and generation PG forecasts on June 1, 2021

The authors analyzed the microgrid operation for five cases of different objective functions of the proposed CI algorithm. To compare the obtained results, a case of control using a deterministic algorithm (DE) was also considered.

3.1. Deterministic algorithm, balancing exchange power to zero (DE)

The DE algorithms aim to limit the power exchanged with the distribution system to a preset level (PZ). In this case, the most common situation was considered: an attempt to reduce to zero the power taken from the distribution system and given back to the system, the value of this PZ level throughout the entire interval is zero, i.e. island operation of the microgrid is enforced. The discussed case considers only the technical aspect and is usually proposed by companies offering integrated photovoltaic installations with energy storage systems.

Applying this type of algorithm could allow a profit of €2 287. In addition, the number of full discharge cycles would amount to 110.

The rest of the cases involve the CI algorithm and use heuristic methods. Each deals only with economic goals or combined economic and technical criteria. The algorithm aims to achieve the economic objective of minimizing costs and maximizing profits.

3.2. CI algorithm, economic criterion with constraint (E-LIM)

In the second case (E-LIM), charging ESS from the distribution system is prohibited. The energy storage system can only be charged with surplus power from the photovoltaic plant and discharged when there is a deficit of energy to meet demand – in other words, implementing the economic objective with the limitation of ESS cooperation with the distribution grid. The algorithm is focused on minimizing the cost of purchasing energy and maximizing the profits of energy sales. In this case, there is no preset level of exchange power PZ, so the algorithm worked only based on prices determined from the tariff and prices in the energy market.

Adopting this approach for a whole year could gain the studied facility € 3 070, an increase over the previous approach. In addition, the number of full discharge cycles was also reduced by two to 108.

3.3. CI algorithm, economic criterion with global constraint (E-NO-LIM)

In the third case (E-NO-LIM), ESS charging from the grid is allowed by introducing a fixed power limit. This level was set as the maximum and minimum PO+PG (the sum of load and generation power) for the entire day. The economic criterion remained unchanged. The algorithm's goal is to minimize costs and maximize profits.

The analysis was performed for June 1, 2021. Analyzing the waveforms, particularly the intensive work of the ESS, can be seen, especially if we compare the changes in SOC to previous cases. Without technical limitations, the algorithm took advantage of every opportunity to save money. This resulted in charging and discharging the energy storage system whenever it was economically viable.

Compared to the previous two, this algorithm involves intensive energy storage system operation, as can be seen in the dynamic changes of the SOC. It makes the most of saving opportunities by making every economically advantageous decision, and is not technically limited. As a result, charging and discharging of the ESS occur whenever it is profitable, which translates into effective cost optimization. In this case, the annual profit reaches as much as € 6710. However, the annual number of full discharge cycles increases greatly, reaching 745.

3.4. CI algorithm, both technical and economic aspects, balancing to PZ (E-PZ0)

In the fourth case (E-PZ0), the algorithm combines the economic and technical goal of compensating the power exchanged with the system. The objective function contains two criteria: the technical aspect, with a weight of 0.384, and the economic aspect, with a weight of 0.616.

It can be noted that in this case, too, the ESS worked very intensively. The energy storage system charged and discharged more frequently than in the previous case. The ESS worked practically every hour, allowing an annual profit of € 6 689, with an annual number of full discharge cycles of 930. In summary, with similar gains, a much higher number of full discharge cycles came out.

3.5. CI algorithm, both technical and economic aspects, conditions for SOC (E-SOC)

In the fifth case (E-SOC), an economic and technical criterion regarding the state of charge of the energy storage system is combined. The algorithm will aim for the SOC to be the same at the beginning and end of the day. This time, the weights of the components were 0.0002 and

0.9998 for the economic and technical criteria, respectively. Analyzing the obtained results, it is noticed that the ESS operates at a lower frequency than in the case of E-PZ0. The operation of the energy storage system is similar to that of E-NO-LIM. The profit reached € 6 697, while annual full discharge cycles equal 706.

3.6. CI algorithm, both technical and economic aspects, limitation of the number of discharging cycles of ESS (E-LCR)

In the sixth case (E-LCR), the number of ESS discharging cycles is minimized in addition to achieving the optimal economic goal. The weights for the individual components of the objective function were 0.002 and 0.998 for the economic and technical criteria, respectively.

It can be seen that adding the number of discharging cycles to the objective function significantly reduced the ESS's activity. The energy storage system operates less frequently than in previous cases. Its activity is comparable to the case in which the economic aspect was analyzed while reducing the ESS's cooperation with the grid (E-LIM), which means in this case, reaching the annual number of full discharge cycles of 461 cycles.

Next, the economic effect of such control was checked. The obtained waveform is similar to the E-NO-LIM and E-PZ0 cases. In this case, the annual gain reached € 6 635.

As it was one of the most interesting cases the authors decided to show the power flow and state of charge curves June 1, 2021. In Fig. 6, it can be seen that despite the restriction of ESS operation for part of the day, it manages to reduce the power taken from the distribution system, for example, the hours between 7 and 9 p.m. It can also be noted that there are hours when the algorithm decides to charge the ESS from the system, for example, between 4 and 7; this is due to the part of the objective function responsible for the economic effect. A load and generation forecast is given to the algorithm's input, so the ESS operation is scheduled to receive the best value of the objective function throughout the entire day.

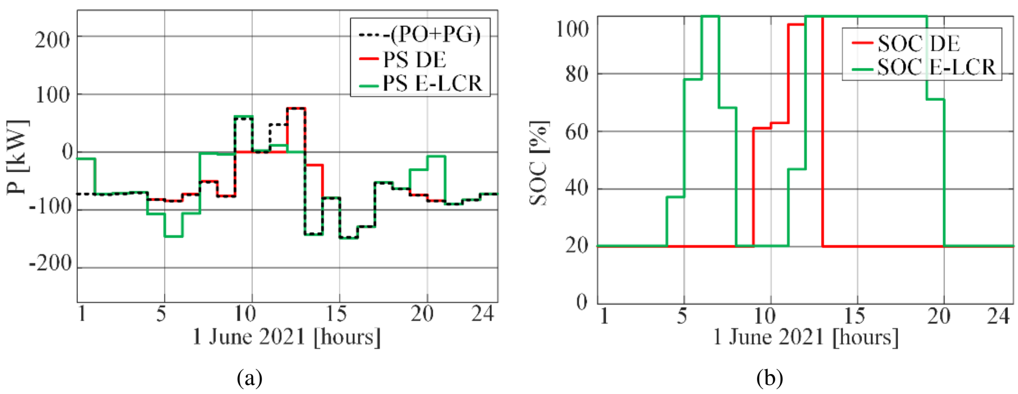

Fig. 6. Power flow (a) and state of charge (b) curves, June 1, 2021. PO – load power, PG – generation power, PS – distribution system power for DE and E-LCR algorithm

4. Summary of conducted analyses

The final stage of the analysis was to compare all the cases considered with each other. It should be noted that the economic analysis of the control method was carried out and referred to the effects obtained in a microgrid without ESS. The calculations are based on energy purchase and sale tariffs. Only net electricity prices were considered, deliberately omitting distribution charges, fixed charges, and taxes. The study omits investment costs and energy losses in the ESS and transmission lines, which have no significant impact on the comparative analysis since the comparison of all control methods involves the same microgrid system and equipment with the same parameters. A graphical illustration of the summary is shown in Fig. 7.

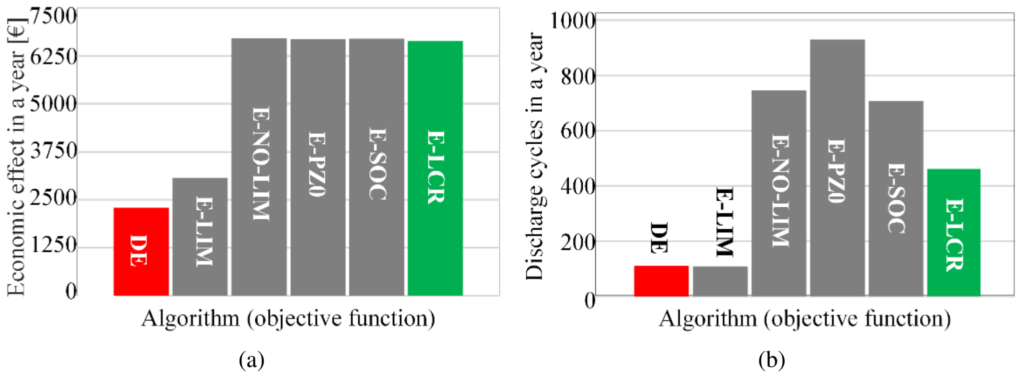

Fig. 7. Comparison of the total annual economic effect for all considered cases (a) and the total annual number of complete discharging cycles for all considered cases (b)

Analyzing the data, it can be seen that the best economic effect was obtained with E-NO-LIM control. Still, CI algorithms with technical constraints, such as E-PZ0, E-SOC, and E-LCR, are only slightly behind the best solution in economic terms.

The annual cost of energy in 2021 required to cover the loads of the studied industrial plant is € 352 281. After installing a 317 kWp PV system, the cost decreased to € 265 036, or 24.77%. Installing an ESS in a microgrid and using the E-LCR algorithm reduces the cost to € 258 401, or 26.65%. This means the difference between an installation without ESS and one with ESS is 1.88% (€6 635). The result depends mainly on the parameters of the energy storage system. In the studied case, the small capacity of the ESS significantly reduced the control ability.

In contrast, a comparison with the DE algorithm shows an increase in the annual economic efficiency of more than 280%. On the other hand, the yearly number of discharging cycles favors the DE algorithms. It reached 110 cycles for the DE. From the group of CI algorithms, the smallest value of discharging cycles was obtained in the case of E-LIM, i.e., where the algorithm preferred the economic effect, while reducing cooperation with the grid. However, the economic effect is much lower in this case than in the other CI cases.

A general conclusion can be drawn that with a small number of discharging cycles, the economic effect will be low, so to maximize the profits of using an ESS, a shorter life of the ESS resulting from its more intensive operation must be taken into account.

Assuming that the lifetime of modern ESS based on lithium-ion cells is about 3 000 cycles, it is possible to plot an analysis of the lifetime of ESS for each scenario (Fig. 8).

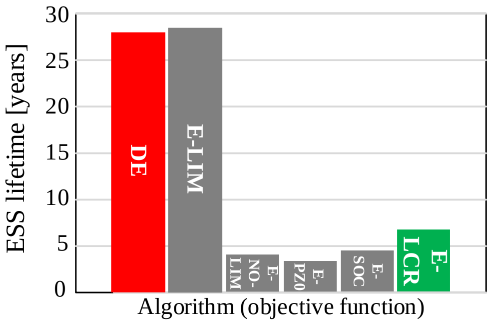

Fig. 8. Estimated energy storage system (ESS) life for different control strategies, assuming 3000 full discharge cycles as reference life

Analysis of the results leads to the conclusion that there is a compromise between profit maximization and ESS lifespan. The scenarios with the highest profit, such as E-NO-LIM and E-PZ0 (€ 6 710 and €6 689), result in fast degradation of the ESS (745 and 930 full discharge cycles per year). On the other hand, strategies such as E-LCR or E-SOC allow a significant reduction in the number of cycles, to 461 and 706 per year, respectively, while maintaining high profits: € 6 635 and € 6 697. With E-LCR, the gain is only 1.1% lower than with E-NO-LIM, and the number of cycles is more than 38% lower.

Assuming a typical lithium-ion battery life of about 3 000 full cycles, these differences translate into significantly different system lifetimes: from about 3.2 years (for E-PZ0) to more than 6.5 years (for E-LCR). This shows that optimizing ESS control should take into account not only short-term gains but also the lifetime and potential need for storage replacement.

5. Conclusions

Optimal control of a microgrid energy storage system requires consideration of many technical and economic components. This contributes to the complexity of the objective function, which must consider many elements. This results in deterministic optimization methods not always successfully finding the global minimum. Therefore, the paper uses deterministic and heuristic methods to present a CI control algorithm for a microgrid energy storage system.

The authors used the proposed algorithm to control the operation of the ESS in five cases of different objective functions and constraints. One case of deterministic control is also presented as a background to compare the achieved results. The deterministic algorithm typically aims to balance the power exchanged with the distribution grid to zero.

The following five cases combined economic objectives and various technical constraints. In case two, the ESS was only permitted to charge using excess power from the photovoltaic system. In case three, ESS charging from the distribution system was allowed. In case four, an economic criterion was combined with a technical criterion concerning the compensation of power exchanged with the distribution system. In case five, the technical constraint was the state of charge of the ESS. The SOC at the beginning and end of the day was to be the same, at the average level of ESS capacity. The last case was a limitation on the number of full discharging cycles of the energy storage system.

Choosing the optimal control strategy is not straightforward and results from a compromise between technical and economic aspects. The E-LIM method had the smallest number of complete discharging cycles of 108 among PSO-based methods. It was also characterized by the smallest annual profit of € 3 070. Compared to deterministic methods, the economic effects are not much better. Still, in this case, a significant flattening of the power curve of energy exchange with the system is achieved, which should be considered a great advantage of the method. On the other hand, the strategies with the highest profit were characterized by the highest number of complete discharging cycles. The economic profits varied from €6 735 to € 6 710. On the other hand, the number of full discharging cycles was between 461 and 930 cycles. The best strategy, in terms of the compromise achieved between economic profit and the annual number of full discharging cycles, was the last tested strategy, E-LCR. With this control, the annual profit was € 6 635 with 461 discharging cycles. Compared to the effects obtained by a deterministic algorithm, the improvement in economic efficiency is significant, reaching the level of 280% in the present case. The profits result from the active operation of the ESS, which reduces the device's lifetime. In the currently preferred prosumer billing systems, such control seems optimal, maximizing the ESS's life with a minimum annual economic gain. As the presented research shows, artificial intelligence methods allow adjusting the objective function to find the optimal balance of economic and technical effects.

Despite the positive results obtained, the proposed approach also has some limitations. The algorithm relies on short-term demand and generation forecasts, the accuracy of which directly affects control efficiency. In the current version of the work, no formal analysis of robustness to forecast errors has been carried out, which we plan to address in future studies. In addition, the algorithm's behavior has not yet been analyzed for larger, more complex systems, which can significantly affect the computation time and convergence of the algorithm. Finally, the current objective functions focus on economic and basic technical aspects – in the future, the authors plan to expand them to include qualitative criteria, such as improving power quality, minimizing voltage fluctuations at microgrid nodes, load symmetrization, extending storage lifetime, etc. To achieve this, the objective function will require parameters calculated in an adequately developed electrical grid distribution model, taking into account the exact electrical parameters of devices and transmission lines, as well as the structure of the microgrid. In addition, the authors plan to research using multi-criteria optimization algorithms in the Pareto-optimal sense combined with MCDA. In addition, the algorithm is ready to consider other energy storage technologies. However, this requires future mapping of electricity dispatch characteristics depending on the characteristics of the stored energy, such as heat and temperature, compressed air pressure, etc. In addition, the method can be called multiple times during the day, introducing an element of self-correction of storage scheduling due to current measurements from the system or other information. The final result of the system with plan autocorrection requires sensitivity and performance testing. Further possibilities for developing the solution also involve replacing the weighting system in constructing the objective function with multi-criteria optimization. It is then possible to transfer not only techno-economic factors, but also environmental indicators or elements of social factors to the objective function.

The authors hope that the research and results presented are steps to develop smart systems that integrate RES and ESS in microgrids.

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