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Optimal Grid Connection Capacity of a Hybrid Renewable Microgrid: An Energy Management and Economic Optimisation Model

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Abstract. The paper presents a developed model for determining the optimal power of connection to the electric grid, which limits the possibility of introducing additional electric energy from the general grid (import) and withdrawing excess electric energy (export) in order to minimise the levelized cost of the microgrid. The model takes into account the daily cost of producing electric energy at generating plants, the daily cost of storing energy at a battery energy storage system (BESS), the daily cash flow, which includes the daily costs of purchasing electric energy from the grid to the microgrid, income from selling electric energy from the microgrid to the grid, purchasing fuel for a backup generating plant, the daily costs of paying for lost load for consumers in the form of penalties, and the daily costs of connecting to electric grids. The optimisation model proposes an economic algorithm to determine the priority power source's output (backup gas generator or import) based on an operational comparison between the market price "day in advance" and the backup generator's production cost. For a hybrid network, the structure of which includes a solar power plant (PV) with a power of 60 kW, a wind power plant (WPP) of 20 kW, a reserve power generator (RES) of 40 kW, a four-hour BESS with a nominal power

of 50 kW and a nominal capacity of 200 kWh, with different loads of critical and non-critical consumers ranging from 40 to 240 kW across six scenarios, the optimal power of connection to the electrical network is determined, which, while ensuring the balance of electrical energy, allows reducing the cost of the microgrid to 2.8%.

Keywords: optimisation model; hybrid microgrid; photovoltaic plant; wind power plant; battery energy storage plant; reserve power generator; energy not served; self-sufficiency ratio.

1. Introduction

1.1. Motivation

Consumers connected to and receiving electricity from the smart grid network, unlike those receiving electricity from the general power system, have several advantages, particularly increased supply reliability and cost optimisation through reduced electricity purchase costs. At the same time, smart grids are accompanied by significant digitalisation, which positively affects consumer awareness of the operational status of electricity supply and the costs of electricity and fuel resources, thereby stimulating the development of demand management measures. In modern development conditions, with the availability of variable renewable energy (VRE) and BESS, smart grids enable more efficient use of network infrastructure, reducing electricity losses during transmission [1].

The generally accepted structure of a microgrid may include combined electric and thermal energy production systems, renewable energy sources, energy storage systems, backup generators, consumer loads of various types, and interconnected communication with the external network, power transmission lines, and communication for monitoring and control of microgrid elements. When microgrid elements are not constructed simultaneously, the most common connection scheme is on the AC side, which allows use of the existing network infrastructure [2].

Network infrastructure capacity is a costly and limited resource. At the bulk power system level, this capacity is the subject of expansion planning. In [3], the

problem of coordinated generation and transmission expansion planning with high-voltage direct-current (HVDC) links and reactive power management of the AC and DC stations was solved with a metaheuristic algorithm, and in [4] it was formulated as a bi-level stochastic problem solved by Benders decomposition. In both studies, the economic and operating indices of the network improved by 10-40% relative to a conventional power-flow study, and in [3] the HVDC option reduced the total annual planning cost by 5.8-8.2% at higher load levels. In [5], reliability-constrained transmission expansion planning with simultaneous forecasting of loads and renewable generation was proposed, taking into account N-1 contingency constraints; in [6], a bi-level robust formulation of composite generation and transmission expansion under uncertain load growth, fuel cost, and wind output was given. These studies show that energy management capabilities and network capacity sizing are closely related: every kilowatt of transfer capacity reserved for a user must be built and maintained by the network operator, and its cost is passed on to the user through the connection charge. For a microgrid, the same trade-off exists at the point of connection, where the contracted connection power determines both the connection cost and the admissible import and export power.

The technological composition of microgrids has broadened over the last decade. In addition to PV and WPP, present-day microgrids include electrochemical and hydrogen storage, fuel-cell units, controllable backup generating sets and flexible demand. A comparative review of fuel-cell technologies for sustainable microgrid systems [7] classifies six chemistries by electrical efficiency and unit rating. Alkaline units are rated at 5-150 kW and proton-exchange-membrane units at 5-250 kW, with an efficiency of 0.40 to 0.65. Phosphoric-acid units cover 50 kW to 11 MW, and molten-carbonate units cover 0.1 to 2 MW; their efficiency reaches 0.85 in cogeneration mode. The rated power of these technologies matches the scale typical of distributed microgrids, which operate in grid-integrated, grid-parallel, stand-alone, and backup modes. Generating and storage assets within a single microgrid therefore differ in rated power and in the cost of the energy they produce or store. For this

reason, economic criteria are decisive when selecting the operating mode for each asset.

When hydrogen and thermal carriers are integrated, the microgrid becomes a multi-energy system. In [8], the flexible scheduling of a smart distribution network with renewable units, electric-vehicle charging stations and hydrogen refuelling stations was studied, where the hydrogen storage unit stores electricity and, at the same time, supplies hydrogen to end users; the proposed scheme reduced the power losses by 32.8 %, the voltage deviations by 24.4%, and the peak load by 38.3% relative to a load-flow study. In [9], energy hubs with hydrogen and thermal storage improved the voltage profile by 47-56 % and the temperature profile by 38-40 % in coupled electrical and heating networks. In [10], a multi-objective scheme for heat and electrical microgrids with heat pumps was proposed, which simultaneously reduces the operating cost, the emissions and the voltage and temperature deviations by means of fuzzy decision-making, and in [11] the joint minimisation of the operation and energy-loss costs of renewable hubs in coupled electrical and thermal microgrids lowered the economic cost by approximately 48.8 %. In [12], hydrogen refuelling stations are treated as prosumers in an isolated multi-energy microgrid with mobile storage systems, and in [13] as elements of interconnected power and gas networks with vehicle-to-infrastructure technology, where the daily cost of the coupled 33-bus electrical and 14-node gas network amounted to \$760.37. At the company level, in [14], portfolio-wide coordination of participation in the electricity, hydrogen, and green-certificate markets across geographically distributed assets reduced daily operating costs by 9.4%. The more heterogeneous the asset mix, the stronger the total cost's dependence on the operating mode selected for each asset and on exchange conditions with the external grid.

Research on microgrid energy management has grown rapidly, and optimisation-based approaches dominate the field. In a bibliometric review of Scopus, Web of Science, and LENS records published from 2019 onward [15], unique sources on energy management systems (EMSs) for microgrids and microgrid systems were identified. The reviewed sources were classified into six strategy

families: classical optimisation methods account for 47% of the total, artificial-intelligence methods for 16%, and the remainder is covered by stochastic methods, multi-agent systems, decision-making methods, and game-theoretic approaches.

The value a microgrid delivers to its customers is determined by supply continuity. This continuity is probabilistic because both primary energy availability and equipment condition are uncertain. A reliability assessment of a fully renewable standalone microgrid was carried out in [16] over a 25-year horizon, which corresponds to 219600 hourly steps. The authors propagated uncertainty in solar irradiance, wind speed, ambient temperature, demand, and equipment-failure timing using a non-sequential Monte Carlo simulation and evaluated the loss-of-load probability (LOLP) and loss-of-load frequency (LOLF) across 125 scenarios. The results showed that the representation of input data uncertainty materially affects the outcome. Sampling of the empirical cumulative distribution function spanned a solar-irradiance range of 629-904 W/m², whereas sampling within a confidence interval spanned only 761-864 W/m². Undersupplied energy should therefore be treated as a quantity with an expected value and, consequently, an economic cost comparable to the cost of the equipment installed to avoid it.

Based on these observations, the motivation of the present study can be defined. A grid-connected microgrid with VRE faces three interrelated problems: the variability of generation, which requires the use of storage, a dispatchable backup unit or import of electricity; the hourly volatility of the market prices, which changes the cheapest source of balancing energy during the day; and the cost of the connection to the external grid, which has to be paid irrespective of how much of the contracted power is actually used. If the connection is oversized, the microgrid's fixed cost increases; if it is undersized, import and export are restricted, which may lead to undersupply for consumers. Therefore, choosing the connection power is an economic optimisation problem with direct practical implications for both microgrid owners, who contract the connection, and distribution system operators, who must reserve the corresponding network capacity.

1.2. Literature review

Microgrid optimisation is carried out in the following directions: technical to improve electricity quality, economic to reduce electricity costs, and environmental to reduce harmful emissions. Technical optimisation, in particular, aims to plan and apply the most effective operating modes of electrical installations using forecasting and to develop new laws for controlling electrical energy flows. Optimising the microgrid according to the economic criterion, using modelling results, enables selection of the structure of electrical installations at the design stage before construction. In the future, optimising the microgrid according to economic criteria allows minimal electrical energy costs by using economic models to minimise the cost of imbalances [17].

Several studies focus on ensuring electrical energy quality and appropriate voltage levels in networks, particularly by building monitoring systems or optimising the location of renewable energy sources [18], [19].

The growing share of PV and WPP in microgrid electricity production increases the need for effective models to predict solar insolation and WPP. At the same time, the electricity market's shift to shorter time horizons increases the need for fast data processing, including economic indicators such as electricity cost. Thus, in the study of microgrid control algorithms [20], the structure of which includes a PV with a power of 195 kW, a WPP with a power of 150 kW, a four-hour BESS with a power of 200 kW and a capacity of 800 kWh and a diesel generator with a power of 200 kW, it was proven that the smallest error for the imbalance of electricity is achieved when using methods based on artificial neural networks for forecasting.

As shown in [21], artificial intelligence enables advances in machine learning, which is necessary for processing large datasets on solar insolation, air temperature, and wind speed to predict the output of solar and wind power plants.

Forecast information becomes economically useful when it is embedded in the control law that dispatches a microgrid's assets. In [22], the energy management of a group of grid-connected microgrids was formulated as a mixed-integer quadratically constrained problem. The decision variables are the active and reactive power of the wind, photovoltaic, and microturbine units; the charging and discharging power and

the state of charge of the BESS; the curtailment ratio of the renewable sources; and the power exchanged between the microgrids and the external grid. The constraints cover the power balance, voltage stability, thermal line limits and storage dynamics. The problem was solved in a receding-horizon scheme with a six-hour prediction horizon and a one-hour control horizon. The predictive formulation reduced total operating cost by 19.23% relative to a non-predictive baseline and reduced average external grid resource consumption by 46.18%. Work [23] presented a control-oriented model of a standalone microgrid with a hybrid storage system that combines a lithium-ion battery with a hydrogen electrolyser and fuel-cell chain. The same receding-horizon logic was applied over a 24-hour horizon, keeping the battery state of charge within 20-88.52% and the hydrogen tank level within 10-90 % across four weather and demand scenarios, while renewable generation was fully utilised and the load was fully satisfied. Both works show that the optimisation horizon and the technical bounds imposed on the storage unit affect the attainable economic result as strongly as forecast accuracy.

In the optimisation model for operating a microgrid with PV and BESS, the objective function is to minimise the cost of purchasing electricity on the retail market. The model accounts for electricity prices, penalties to limit undesirable BESS operating modes, and penalties for excess electricity from the solar power plant. The hourly balance of this microgrid's operation accounts for electricity consumption volumes, production volumes, and electricity restrictions at the solar power plant, as well as BESS charging and discharging. Optimisation modelling results showed changes in BESS operating modes as the market buy-and-sell electricity price changed one day in advance [24].

In the study [25], an optimisation model for determining the minimum cost of electricity is presented by identifying the optimal operation of the BESS, taking into account the microgrid's power balance and predicted electricity costs. The hourly balance of this microgrid operation accounts for generation from solar, wind, and diesel plants, the BESS, and electricity imports from the grid. Calculations of microgrid operation under different modes show the importance of accurate

modelling of the energy storage plant's charging and discharging processes, which enables the microgrid to achieve balance by prioritising the use of electricity generated from renewable energy sources.

When the microgrid composition is itself the decision variable, the sizing and dispatch problems are solved jointly, most often using mixed-integer linear programming (MILP). A MILP model of a grid-connected photovoltaic and battery system for the education sector was developed in [26]. The objective function minimises the differential net present value over a 25-year lifetime. The number of photovoltaic modules and the battery capacity are design variables, while hourly grid imports and exports, charging and discharging power, state of charge, photovoltaic output, and curtailment are operating variables. The constraint set combines the hourly energy balance, the storage dynamics with a round-trip efficiency of 90%, C-rate limits, a state-of-charge band of 10 to 90%, a cyclic condition that equates the end-of-year and the start-of-year state of charge, binary logic that prohibits simultaneous charging and discharging, a temperature-dependent photovoltaic efficiency and time-varying tariffs. The unconstrained optimum installed 3.19 MWp of photovoltaic capacity, together with 12.3 MWh of storage, and delivered 78.9% self-sufficiency. When capital expenditure was restricted to 2.0 M€, the optimum fell to 0.99 MWp and 1.68 MWh; self-sufficiency dropped to 32.0%; the net present value was 4.46 M€, and the payback period was 3.9 years. These results show that the optimal microgrid structure depends on the constraints imposed on the system boundary.

In sizing problems, the cost function is often non-convex because fuel consumption depends nonlinearly on the backup generator's loading, battery degradation depends on the depth of discharge, and converter efficiency depends on the operating point. For such problems, metaheuristic algorithms are the prevailing solution technique, and the levelised cost of energy is the prevailing objective. Grey-wolf optimisation was applied in [27] to size a grid-connected multi-microgrid with photovoltaic, wind, fuel-cell, and battery assets on an IEEE 14-bus network. The net present cost and the levelised cost of energy were minimised under stochastic

representations of load, weather and price. The resulting net present cost is \$428.832 M, and the levelised cost of energy is \$0.267/kWh, outperforming the particle-swarm and JAYA algorithms on both indicators. The pelican optimisation algorithm was applied in [28] to a grid-connected photovoltaic, wind and diesel microgrid with electric-vehicle charging. The cost of energy was minimised over 8760 hours subject to hourly supply adequacy and a restricted charging window. The optimum comprises 304.2 kW of PV and 230 kW of WPP. It lowered the cost of energy from 11.74 to 5.20 INR/kWh, raised the renewable factor to 90.42 % and reduced annual emissions from 650 to 114 t of CO₂, while 5042 kWh per year of charging demand remained unserved. A techno-economic study of an island microgrid [29] minimised the net present cost across candidate photovoltaic, wind, diesel, battery, and converter capacities under full demand coverage.

How widely this approach is used can be seen from a comprehensive review of grey wolf optimiser applications in energy systems [30], which covers the problems of energy production, conversion, transmission and distribution, storage and consumption; the popularity of this algorithm is explained there by its balance between exploration and exploitation, its fast convergence and the simplicity of its coding. In cases where a single algorithm converges slowly, hybrid metaheuristics are used instead: a combination of the ant lion optimiser with the artificial bee colony algorithm in [11], and a combination of the grey wolf optimiser with a training-and-learning-based algorithm in [5], both of which give solutions with a low standard deviation.

A prerequisite for a microgrid's self-sufficiency in isolated mode of operation is balancing electrical energy production and consumption during each iteration period, accounting for BESS charging and discharging and network losses. In addition, achieving a daily electricity balance while ensuring supply stability is important [31].

Optimisation models are nonlinear, particularly because fuel consumption depends nonlinearly on the backup generator's power [32].

Microgrid balance must be maintained under uncertainty in both primary energy and prices, and deterministic formulations are therefore increasingly being replaced

by stochastic ones. Work [33] proposed a multi-stage stochastic MILP framework for dispatching a microgrid with a high share of renewables. The objective function minimises expected operating cost, comprising fuel, start-up, storage degradation, grid exchange, and unserved energy, over a scenario tree of photovoltaic, wind, and load realisations. The decision variables are unit commitment, dispatchable output, charging and discharging power, state of charge, curtailment, and grid exchange, and the constraints cover power balance, ramping, state of charge, and non-anticipativity. The multi-stage recourse structure absorbed renewable variability at a lower expected cost than the deterministic and two-stage benchmarks. In [34], the optimal design of a photovoltaic-based microgrid was formulated as minimising the expected levelised cost of energy over the lifetime, subject to a chance constraint on the annual total loss of power supply. The decision variables are the number of photovoltaic modules, the inverter rating, the number of batteries, the number of generating sets and their rated power. Uncertainty in the timing and duration of grid blackouts was described with a kernel density estimator, irradiance with a beta distribution, and temperature with a Gaussian distribution; all three were propagated via Monte Carlo simulation. Accounting for blackout uncertainty altered the optimal battery-bank size and improved the accuracy of the levelised-cost estimate relative to a deterministic design. The reliability of the external grid thus enters the microgrid design problem as an economic parameter.

If probability distributions are unavailable, or if the decision-maker is risk-averse, robust and risk-based formulations are used instead. In [35], adaptive robust optimisation was applied to a flexible renewable integrated energy system with four objectives, namely the operating cost, the emissions, the total harmonic distortion of voltage and the voltage stability index; at an uncertainty level of 45%, the proposed scheme reduced the operating cost by 55.2%, the emissions by 49.3%, and the energy losses by 45.4%. In [12], a two-layer hybrid model treats electricity prices robustly at each hydrogen refuelling station and wind power stochastically at the microgrid operator level. In [36], the conditional value at risk was embedded in a bi-level

bidding system of interconnected microgrids in the day-ahead market, and it was shown that accepting higher financial risk lowers the market-clearing price.

A separate group of models places undersupplied energy directly in the objective function. Paper [37] introduced the concept of a cost-effective reliability level, balancing investment cost against the cost of energy not served for a fully renewable, standalone microgrid. The method combines 25-year Monte Carlo simulation, regression modelling and mixed-integer linear programming. The minimum total cost was at a reliability level of 98.71%. Above this level, each additional unit of avoided undersupply costs more than the damage that it prevents. Demand-side management provides a complementary mechanism. In [38], the loads of an isolated solar microgrid are dynamically classified into user-defined priority tiers, and day-ahead generation forecasts are allocated among these tiers using particle swarm optimisation. The essential tier maintained uninterrupted supply under generation deviations of $\pm 20\%$, and overall load satisfaction increased from 83% to 96%. These works justify a formulation in which interrupting a non-critical consumer is an admissible model decision and is priced with a penalty rate.

The economic outcome of a grid-connected microgrid depends on the price signal it responds to. Work [39] assessed battery profitability in the day-ahead and intraday markets. The charging and discharging schedule was embedded in a market-equilibrium model calibrated to historical bid curves, so the BESS bids shift the clearing price. Four operating strategies were compared, including perfect foresight with and without internalisation of the own-price effect. Most profit accrues in the intraday market, and profitability declines as installed capacity grows because historical price patterns lose predictive value once traded volume approaches the market's depth. Paper [40] proposed a multi-objective formulation of microgrid energy management. The authors aggregated seven components using the global-criterion method: the cost of purchasing from the main grid, the fuel and start-up costs of the controllable units, the cost of renewable generation, emission penalties, demand-response incentive payments, the cost of losses, and voltage regulation. The decision variables are the outputs of the photovoltaic, wind, diesel, microturbine, and

fuel-cell units; the battery charging and discharging power and state of charge; the grid exchange; the unit-commitment binaries; and the shifted or curtailed demand-response load. Real-time pricing reduced operating cost by 3.49%, emissions by 4.18%, and losses by 3.7% against a baseline of \$269.8 per day without demand response. A microgrid connected to a market with hourly and, prospectively, quarter-hourly price resolution should therefore compare the price of imported energy with the marginal cost of its own dispatchable sources at every settlement interval.

In a growing number of works, the microgrid is considered not as a price-taker but as a participant in local energy and flexibility markets. In [41], a four-level hierarchical model driven by the distribution system operator (DSO) is used to integrate energy communities with peer-to-peer exchange into a local electricity market, while the privacy of the agents is preserved; on a 594-node network in Victoria, Australia, the day-ahead contracts are kept within the network security constraints, and the members' electricity bills are lowered by 7.5 %. In [42], a three-stage Stackelberg model harnesses the flexibility of IoT-enabled appliances and smart charging systems in smart homes, reducing the upstream network's share in the local flexibility market by 56.86% and the DSO's balancing cost by 22.36%. In [43], the flexibility provision by industrial parks was cleared through a bi-level game-based local market with curtailable, interruptible and deferrable loads, and in [44] jointly with internet data centres, through a proxy-driven mechanism based on the alternating direction method of multipliers (ADMM); the latter converges 74.52 % faster than the standard ADMM and lowers the congestion management cost by 35.27 %. In [45], an adaptive ADMM algorithm for decentralised coordination of community microgrids reduced the flexibility market cost by 49.67% and network losses by 24.1%. In [46], cooperative and competitive schemes of collective storage in energy communities with an internal market were compared, and the cooperative scheme was found to reduce prosumers' bills more, but to be more sensitive to storage and community size. In these market-oriented studies, the connection capacity to the upstream network is taken as a given parameter, and the DSO enforces network constraints instead of pricing them to the microgrid.

In a separate group of studies, researchers address the capacity of the connection to the external grid. An iterative sizing procedure developed for a grid-connected prosumer [47] treated the maximum injection power as a parametric constraint. Without an injection limit, the configuration that maximised self-sufficiency comprised 7 kW of PV and 6 kWh of BESS, providing 65% self-sufficiency and 51% self-consumption. When injection was prohibited altogether, the optimum was reduced to 4 kW and 4 kWh; self-sufficiency fell to 52%, and self-consumption rose to 98%. The same study quantified the influence of the energy balance's time resolution. Self-sufficiency was 56% at a five-minute resolution, 57% at a fifteen-minute resolution, and 61% at an hourly resolution, which defines the accuracy attainable by an hourly model. At the utility-scale, the connection capacity was analysed under cable-pooling conditions in [48], where photovoltaic, wind, and battery capacities were optimised subject to a fixed injection limit of 100 MW. Three alternative financial objectives were considered: the ratio of net present value to capital expenditure, the net present value subject to a lower bound relative to capital expenditure, and the net present value subject to a cap on capital expenditure. The investor's financial objective and revenue stream governed the resulting renewable mix and the extent of generation curtailment. In [49], the interconnection capacity was an explicit decision variable in a capacity-expansion model and was co-optimised with the siting and sizing of wind, solar, and storage power. This reduced the required grid connection and transmission expansion by approximately 10% at a moderate storage penetration and increased the value of co-located storage by 43-45% relative to standalone storage. In all of these formulations, the connection capacity is either fixed exogenously or optimised at the level of a transmission-connected generating plant. Such a plant has no consumers of differing criticality, no penalty for undersupplied energy, and no dispatchable backup unit that competes economically with imported energy; therefore, the levelised cost of the microgrid as a whole is not the quantity being minimised.

1.3. Research gap

The reviewed studies can be divided into the following groups. In the system-level planning studies [3]-[6], the network capacity is optimised from the network operator's perspective. In the multi-energy and hydrogen-oriented studies [8]-[14], [35], as well as in the market-oriented studies [36], [41]-[46], the operation of distributed resources is optimised behind a fixed connection capacity. Studies that address connection capacity explicitly [47]-[49] do so only for a prosumer or a transmission-connected plant, without consumers of different criticality. None of these groups treats the microgrid's connection power as a decision variable with its own cost.

Based on the review of studies on the functioning of microgrids, it can be noted that among the existing models there are no models that simultaneously cover different sources of electricity generation (renewable energy sources, backup gas generator, charging of a BESS, possibility of import), and sources of electricity output (availability of consumers of various types, discharging of a BESS, possibility of export or curtailment of electricity generation from renewable energy sources), taking into account the cost of production and storage for each of the power plants, and electricity prices when importing or exporting, and the cost of undersupply of electricity.

In existing models, the power of microgrid elements is set manually based on input assumptions, and the power of the connection to the grid is not considered as a parameter to be optimised. From the perspective of ensuring electricity balance in the microgrid, introducing electricity imports from an external network may be equivalent to producing electricity from a backup generator. At the same time, to minimise electricity costs and achieve an economic effect, it is advisable to conduct an economic comparison of electricity import prices, taking into account hourly and, in the future, 15-minute changes in electricity prices.

In addition, existing models do not account for grid-connection costs, which limits the possibility of importing or exporting electricity between the microgrid and the grid. At the same time, the undersupply of electricity to consumers should also be assessed in terms of economic losses, taking into account applicable penalties.

1.4. Objective and contributions

The purpose of this work is to develop an optimisation model to determine the grid-connection power level that affects the possibility of importing and exporting electricity, thereby ensuring the lowest levelised cost of the microgrid while accounting for the actual power of the electricity supply and withdrawal sources.

The main contributions of the paper are as follows:

1) The levelised cost of microgrid (LCOM) is proposed as a single objective function, which combines the daily cost of electricity production at the generating plants, the daily cost of energy storage at the BESS, the daily cash flow from import, export and fuel purchase, the penalties for the energy not served and the daily cost of connection to the grid.

2) The power of connection to the external grid is introduced as a decision variable, which limits both the import and the export, and the cost of the connection is taken into account in the objective function. In this way, the proposed model differs from the formulations in which the connection is set exogenously or is not considered at all.

3) An economic algorithm for selecting the priority power source is proposed: at each hour, the day-ahead market price is compared with the cost of electricity production at the backup gas generator, so that the import and the own dispatchable generation compete with each other by cost.

4) The consumers are divided into critical and non-critical ones, and the energy not served to each of these groups is included in the objective function with a differentiated penalty rate, so that the reliability is assessed in the same monetary terms as the equipment and connection costs.

5) For a hybrid microgrid with a 60 kW PV, a 20 kW WPP, a 40 kW backup generator and a 50 kW / 200 kWh BESS, the optimal connection power was determined for the maximum consumer loads from 40 to 240 kW. It was found to rise from 17.9 kW to a maximum of 170 kW, and the LCOM is reduced by up to 2.8% compared with a connection sized for the maximum theoretical export.

Together, these elements integrate the technical operation of the microgrid and the economic valuation of its grid connection within a single optimisation model, which existing approaches address only partially or in isolation.

The remainder of the paper is organised in the following way. Section 2 presents the research methodology and the optimisation model, Section 3 describes the input data used for modelling, Section 4 reports the simulation results, and Section 5 concludes the paper.

2. Research methodology

A grid-connected microgrid with VRE, a BESS, and a backup generator requires a single, fixed grid-connection power to be contracted before construction, which then limits hourly import and export throughout operation. Existing formulations either fix this connection power exogenously or omit it from the objective entirely, so its cost is never traded off against other microgrid costs. This study addresses this by formulating the connection power P as a decision variable in an optimisation model that minimises the microgrid's levelized cost, $LCOM(P)$, evaluated over the hourly balance, storage, and dispatch constraints presented below. Unlike the reviewed studies, this work combines connection cost, priority-source dispatch, and the penalty for unserved energy into a single objective function, yielding the optimal connection power and its economic effect across a range of consumer loads.

The objective function of the optimization model is to minimize the levelized cost of the microgrid (Levelized Cost of Microgrid, $LCOM$), which takes into account the daily cost of electricity production at generating plants, the daily cost of energy storage at the BESS, the daily cash flow, which includes the daily costs of purchasing electricity from the grid to the microgrid, income from selling electricity from the microgrid to the grid and purchasing fuel for the RES (conditionally variable fuel component), the daily costs of paying for lost load for consumers in the form of penalties and the daily costs of connecting to the grid:

$$LCOM_d(P) = \frac{C_d^{PV} + C_d^{WIND} + C_d^{BESS} + C_d^{RES}(P) + CF_d(P) + ENS_d(P) + C_d^{CONN}(P)}{W_d^{SERVED}(P)} \rightarrow \min, \quad (1)$$

where $LCOM_d(P)$ is the levelized cost of the microgrid per day d , \$/kWh; P is the technical limit of the power of the microgrid connection to the grid, or the power of connection to the electric grids, kW; C_d^{PV} is the daily cost of electricity production at a PV, \$; C_d^{WIND} is the daily cost of electricity production at a WPP, \$; C_d^{BESS} is the daily cost of storing electricity at a BESS, \$; $C_d^{RES}(P)$ is the daily cost of electricity production at a backup power source, \$; $CF_d(P)$ is the daily cash flow, which includes the daily costs of purchasing electricity from the grid to the microgrid, income from selling electricity from the microgrid to the grid and purchasing fuel for the backup generating plant (conditionally variable fuel component), \$; $ENS_d(P)$ is the daily costs of paying for lost load for consumers in the form of penalties, \$; $C_d^{CONN}(P)$ is the reduced daily costs of connecting to the grid, \$; $W_d^{SERVED}(P)$ is the actual amount of electricity received by consumers per day, kWh.

The model constraints apply to the technical limit of the microgrid connection power to the grid, which sets the maximum possible power of input of electricity from the grid to the microgrid (import) and the maximum possible power of output of electricity from the microgrid to the grid:

$$P = P_{\max}^{IMP} = P_{\max}^{EXP}, \quad 0 \leq P \leq P_{\max}^{CONN}, \quad (2)$$

where $P_{\max}^{IMP}$ is the maximum possible power of input of electric energy from the network to the microgrid, kW; $P_{\max}^{EXP}$ is the maximum possible power of output of electric energy from the microgrid to the grid, kW; $P_{\max}^{CONN}$ is the maximum possible power of connection to the grid, kW.

The daily cost of production of electric energy on the RES is determined [50]:

$$C_d^{RES}(P) = \sum_{t=1}^{24} P_t^{RES}(P) \cdot LCOE^{RES} / 1000, \quad (3)$$

where $P_t^{RES}(P)$ is the hourly power of the RES, kW; $LCOE^{RES}$ is the cost of producing electricity on the RES (levelized cost of energy, LCOE; without the fuel component), \$/MWh.

The daily cost of storing electricity in a BESS is determined based on the average hourly charging and discharging power and the specific cost of storage (levelized cost of storage, LCOS) [51]:

$$C_d^{BESS}(P) = \sum_{t=1}^{24} \frac{P_t^{CHRG} + P_t^{DISCH}}{2} \cdot LCOS^{BESS} / 1000, \quad (4)$$

where P_t^{CHRG} is the charging power of the BESS during hour t , kW; P_t^{DISCH} is the discharging power of the BESS during hour t , kW; $LCOS^{BESS}$ is the cost of storing energy in the BESS, \$/MWh.

The daily cash flow, which includes the daily costs of purchasing electrical energy from the grid to the microgrid, the income from selling electrical energy from the microgrid to the grid, and the purchase of fuel for the backup generating unit (conditionally variable fuel component), is determined [52]:

$$CF_d(P) = \sum_{t=1}^{24} (P_t^{IMP}(P) \cdot p_t^{DAM} - P_t^{EXP}(P) \cdot p_t^{DAM} + P_t^{RES}(P) \cdot p_t^{FUEL}) / 1000, \quad (5)$$

where $P_t^{IMP}(P)$ is the power of input of electric energy from the grid to the microgrid, kW; p_t^{DAM} is the hourly price of purchase and sale of electric energy on

the day-ahead market (DAM), \$/MWh; $P_t^{EXP}(P)$ is the power of supply of electric energy from the microgrid to the grid, kW; P_t^{FUEL} is the specific fuel cost of the reserve source, \$/MWh.

Daily costs of payment of lost load for consumers (energy not served, ENS) in the form of penalties are determined [53]:

$$ENS_d(P) = \sum_{t=1}^{24} \left(P_t^{ENS-CR}(P) \cdot c^{ENS-CR} + P_t^{ENS-NCR}(P) \cdot c^{ENS-NCR} \right), \quad (6)$$

where $P_t^{ENS-CR}(P)$ is the hourly underdelivered power of the critical load, kW; c^{ENS-CR} is the specific cost of the penalty for underdelivered power of the critical load, \$/kWh; $P_t^{ENS-NCR}(P)$ is the hourly underdelivered power of the non-critical load, kW; $c^{ENS-NCR}$ is the specific cost of the penalty for underdelivered power of the non-critical load, \$/kWh.

The daily costs for connecting to the electric grids are determined by:

$$C_d^{CONN}(P) = 24 \cdot C_t^{CONN} = \frac{(c^{CAP} \cdot P + c^{LEN} \cdot L) \cdot CRF}{k^{VAT} \cdot 365}, \quad \forall t \in \{0, \dots, 23\}, \quad (7)$$

where C_t^{CONN} is the cost of connecting to the grid for one hour t , \$; c^{CAP} is the specific fee for the power of connecting to the grid, \$/kW; c^{LEN} is the specific fee for the linear component of connecting to the grid, \$/meter; L is the length of the line connecting to the grid, meters; k^{VAT} is the VAT payment coefficient; CRF is the capital recovery factor (CRF).

The capital recovery factor is determined by a well-known formula that accounts for the discount rate and the term of commercial operation of electrical equipment $CRF = r / 1 - (1 + r)^{-n}$. At the same time, it is taken into account that the discount rate

is calculated using the weighted average cost of capital (WACC), which has been repeatedly used to reduce total costs to daily costs [54], [55].

The daily cost of electricity production at a PV and WPP is determined similarly to the daily cost of electricity production at a backup power source based on the hourly power of these sources and the cost of electricity production on them, but without taking into account the dependence on the power of connecting to the grid (P).

In the presence of load distribution into critical and non-critical, the actual amount of electricity received by consumers per day is determined as the difference between the total demand for undersupplied electricity:

$$W_d^{SERVED}(P) = W_d^{CR} + W_d^{NCR} - W_d^{ENS}(P), \quad (8)$$

where W_d^{CR} is the daily volume of critical load, kWh; W_d^{NCR} is the daily volume of non-critical load, kWh; $W_d^{ENS}(P)$ is the daily volume of undersupplied electricity that could not be supplied to any consumer (neither critical nor non-critical) due to the shortage of power of all sources together (generating plants, energy storage plants and imports), kWh.

For each hour of operation of the microgrid, a total electricity balance is achieved, which, on the one hand, takes into account the generation power of VRE (PV and WPP), the backup generator power, import power, discharge of BESS, ENS, and, on the other hand, the consumption power (critical and non-critical), charging of BESS, the power of electricity export from the microgrid to the grid, the power of curtailment on VRE. The hourly balance is determined by the formula [56]:

$$P_t^{PV} + P_t^{WIND} + P_t^{RES}(P) + P_t^{IMP}(P) + P_t^{DISCH} + P_t^{ENS-CR}(P) + P_t^{ENS-NCR}(P) - P_t^{CR} - P_t^{NCR} - P_t^{CHRG} - P_t^{EXP}(P) - P_t^{CURT}(P) = 0, \quad (9)$$

where P_t^{PV} is the generation power of the PV during hour t , kW; P_t^{WIND} is the generation power of the WPP during hour t , kW; $P_t^{RES}(P)$ is the generation power of the RES during hour t , kW; $P_t^{IMP}(P)$ is the import power during hour t , kW; $P_t^{ENS-CR}(P)$ is the ENS for critical consumers during hour t , kW; $P_t^{ENS-NCR}(P)$ is the ENS for non-critical consumers during hour t , kW; P_t^{CR} is the power of critical consumers during hour t , kW; P_t^{NCR} is the power of non-critical consumers during hour t , kW; $P_t^{EXP}(P)$ is the export power during hour t , kW; $P_t^{CURT}(P)$ is the power of curtailment on VRE during hour t , kW.

The current state of charge of the BESS is defined by [57]:

$$SOC_t = SOC_{t-1} + \frac{P_t^{CHRG} \cdot \eta}{E^{BESS}} - \frac{P_t^{DISCH}}{\eta \cdot E^{BESS}}, \quad (10)$$

where SOC_t is the residual charge capacity in the BESS at hour t , a.u.; SOC_{t-1} is the residual charge capacity in the BESS at the previous hour $t-1$, a.u.; η is the efficiency of the BESS, a.u.; E^{BESS} is the nominal capacity of the BESS, kWh.

For dispatching the BESS, the established approach is to cover the load deficit with the BESS, followed by a transition to other sources [58]. The actual charging power of the BESS is determined based on the available surplus of electrical energy generated from VRE:

$$P_t^{CHRG} = \min \left\{ P_{\max}^{CHRG}; \frac{(SOC^{\max} - SOC_{t-1}) \cdot E^{BESS}}{\eta}; \max \left\{ 0; P_t^{PV} + P_t^{WIND} - P_t^{CR} - P_t^{NCR} \right\} \right\}, \quad (11)$$

where $P_{\max}^{CHRG}$ is the technical limit of the charging power of the BESS, kW; $SOC^{\max}$ is the maximum permissible state of charge of the BESS, a.u.

The actual discharging power of the BESS, which is necessary to cover the needs of consumers in the presence of a deficit of electrical energy generated from VRE, is determined by:

$$P_t^{DISCH} = \min \left\{ P_{\max}^{DISCH}; (SOC_{t-1} - SOC^{\min}) \cdot E^{BESS} \cdot \eta; \max \{ 0; P_t^{CR} + P_t^{NCR} - P_t^{PV} - P_t^{WIND} \} \right\}, \quad (12)$$

where $P_{\max}^{DISCH}$ is the technical limit of the discharge power of the BESS, kW; $SOC^{\min}$ is the minimum permissible discharge state of the energy storage device, a.u.

The residual power deficit after the discharge of the energy storage device is determined by:

$$P_t^{BESSdef} = \max \{ 0; P_t^{CR} + P_t^{NCR} - P_t^{PV} - P_t^{WIND} - P_t^{DISCH} \}. \quad (13)$$

The generation power of the backup source is determined by comparing the current cost of electricity production from the RES (fuel component only) and the cost of purchasing electricity on the DAM, implemented according to the principle:

$$X_t = \begin{cases} RES, & p_t^{FUEL} < p_t^{DAM} \\ IMP, & p_t^{FUEL} \geq p_t^{DAM} \end{cases}. \quad (14)$$

After definition (14), the priority source becomes the generator or import, which ensures coverage of the residual power deficit after discharging the BESS based on its maximum power:

$$Q_t^{PRI}(P) = \min \{ P_t^{BESSdef}; P_{\max}^{X_t} \}, \quad (15)$$

where $Q_t^{PRI}(P)$ is the power that the priority source delivers at hour t to cover the residual power deficit after the discharge of the BESS, kW; $P_{\max}^{X_t}$ is the technical power limit of the source selected as the priority one according to (14) (equal to P for import or the installed power of the backup source for the generator).

In the case where the priority source is electricity imports, its maximum power is limited by the grid connection capacity, which is a variable in the optimisation model. After the available power range of the priority source is exhausted in the presence of an electricity deficit, the second source, determined according to (14) as non-priority, provides coverage, taking into account the power already delivered by the priority source. In this case, for this non-priority power source, the maximum power limitation is also taken into account:

$$Q_t^{ALT}(P) = \min \left\{ P_t^{BESSdef} - Q_t^{PRI}(P); \overline{P_{\max}^{X_t}} \right\}, \quad (16)$$

where $Q_t^{ALT}(P)$ is the power produced by the non-priority (backup source) at hour t if the priority source selected in formula (14) did not have time to completely close the deficit, kW; $\overline{P_{\max}^{X_t}}$ is the technical limit of the power of the alternative (non-priority) source, kW.

Thus, the actual power of the import and backup generator:

$$(P_t^{IMP}(P), P_t^{RES}(P)) = \begin{cases} Q_t^{ALT}(P); Q_t^{PRI}(P), & X_t = RES \\ Q_t^{PRI}(P); Q_t^{ALT}(P), & X_t = IMP \end{cases}. \quad (17)$$

The established approach of distributing the undersupplied power between critical and non-critical loads [59] is applied. The undersupplied power is defined as:

$$P_t^{ENS}(P) = \max \left\{ 0; P^{BESSdef} - P_t^{IMP}(P) - P_t^{RES}(P) \right\}. \quad (18)$$

Undersupplied power for non-critical consumption is determined by:

$$P_t^{ENS_NCR}(P) = \min \{ P_t^{NCR}; P_t^{ENS}(P) \}. \quad (19)$$

The undersupplied power for critical consumption is determined by:

$$P_t^{ENS_CR}(P) = \max \{ 0; P_t^{ENS}(P) - P_t^{ENS_NCR}(P) \}. \quad (20)$$

Export power is determined by:

$$P_t^{EXP}(P) = \min \{ P_t^{BESSprof}; P \}, \quad (21)$$

where $P_t^{BESSprof}$ is the power surplus after charging the BESS, determined by

$$P_t^{BESSprof} = \max \{ 0; \max \{ 0; P_t^{PV} + P_t^{WIND} - (P_t^{CR} + P_t^{NCR}) \} \}. \quad (22)$$

The curtailment power on VRE is determined by:

$$P_t^{CURT}(P) = P_t^{BESSprof} - P_t^{EXP}(P). \quad (23)$$

For the technical assessment of the microgrid, well-known coefficients were used, namely the self-sufficiency coefficient (self-sufficiency ratio, SSR), which shows what percentage of the load is covered by self-generation sources, taking into account the charging and discharging of the BESS, without involving the import of electricity from the external network into the microgrid, which is determined [60]:

$$SSR(P) = 1 - \frac{W_d^{IMP}(P)}{W_d^{SERVED}(P)}, \quad W_d^{IMP}(P) = \sum_{t=1}^{24} P_t^{IMP}(P), \quad (24)$$

where $SSR(P)$ is the self-sufficiency coefficient, which depends on the power of connection to the grid; $W_d^{IMP}(P)$ is the daily volume of electricity import from the external grid to the microgrid, kWh.

The optimisation model was implemented in Microsoft Excel, with the daily balance, storage dynamics and dispatch logic computed on an hourly basis for each of the six load scenarios. For each scenario, the optimal connection power P was found using the Excel Solver add-in, which automatically searched over the feasible range $0 \leq P \leq P_{\max}^{CONN}$ to minimise the levelized cost of the microgrid, $LCOM(P)$, subject to the power-balance and storage constraints of the model.

3. Input data for modeling

Description of the main elements of the microgrid

A hybrid microgrid consisting of a PV, WPP, RES, BESS, consumers and an existing connection to the grid was adopted for modelling [61]. PV and WPP are the main sources of energy for consumers, which are divided into critical (20%) and non-critical loads (80%). The installed power of the PV and WPP is given as input data, while it is assumed that their total power is equal to the maximum consumption power of critical and non-critical consumers. Thus, with proper PV and WPP, the consumption demand can be fully covered by the electricity generated at its own power plants from VRE.

To balance the demand and supply in the microgrid, a four-hour BESS is installed. For modeling, its parameters are given as input data. To increase the generation supply in the event of insufficient PV and WPP, an RES (gas generator) is used.

In general, the operation of the microgrid is based on a synchronous mode with the external network. The possible power for exporting (exporting) electricity from

the microgrid to the grid and for importing (importing) electricity from the external network to the microgrid is limited by the power of the connection to the grid, which is a variable of the optimization model.

Description of the process of exporting electricity and limiting generation

If PV and WPP generation exceeds the consumer load, the energy storage system charges. Subsequently, when the energy storage system reaches its maximum capacity, the microgrid exports electricity to the grid. The export possibility is limited by the grid connection power, which is a variable in the optimisation model. In the future, if it is not possible to charge the energy storage system and export electrical energy, the production of electrical energy at PV and WPP is limited as a last resort.

Description of the process of importing electricity and the operation of the backup power source

When PV and WPP generation falls short, the BESS discharges accumulated energy. When the energy storage system is discharged to a critical level to cover current consumption, a priority power source (backup generator or electricity import) is started up. To determine the priority power source, the system compares the operational economic cost of producing electricity on the backup power source (fuel component only) with the cost of purchasing electricity on the DAM. Depending on which value is smaller, that source is prioritised to cover the existing electricity consumption deficit in the microgrid.

If one source is exhausted, for example, reaching the limit of electricity production power on the backup power source, or reaching the limit of electricity import power, which is limited by the power of connection to the grid, which is a variable of the optimisation model, or changing the result of the economic comparison, the priority power source is changed. When the balance of electrical energy returns to its original state, with an increase in the power of electrical energy production at own power plants from renewable energy sources or a reduction in the

load (critical and non-critical consumers), the power of the priority power source (backup generator or electricity import) is reduced until it reaches zero.

Description of consumption and generation profiles

To model the optimal power for connecting a hybrid microgrid to the electricity grid, we used the arithmetic mean price of buying and selling electricity on the DAM in the Integrated Energy System of Ukraine, based on actual data for July 2026 from the JSC "Market Operator" website [62]. Because data on the operation of the Integrated Energy System of Ukraine for use in conducting the study from the end of February 2022 are limited, we used available data on the actual operation of the Integrated Energy System of Ukraine for 2019 to determine typical profiles of consumption, PV, and WPP generation. We converted the price of buying and selling electricity from hryvnias to US dollars for modelling at a rate of 45.0.

Because the DAM data for the Integrated Energy System of Ukraine were taken as actual for July, we analysed all July days and identified the day with the highest electricity consumption across all consumers. This day was July 29. For this day, the average actual consumption across all hours, relative to the maximum electricity consumption in the power system throughout the year, is normalised to about 24.5 GW (January 28). For a solar power plant, the average actual generation power across all hours of the day on July 29, relative to the installed power of solar power plants in the Integrated Energy System of Ukraine, is normalised to about 2.2 GW, with a total annual capacity factor of 14.4%. For a WPP, the averaged actual generation power for all hours of the day on July 29, relative to the installed power of WPPs in the Integrated Energy System of Ukraine, is normalised at about 0.6 GW, with a total annual capacity factor of 33.7%.

Fig. 1 shows the electricity purchase and sale prices on the DAM, typical electricity production profiles at PV and WPP, and typical profiles of critical and non-critical consumption.

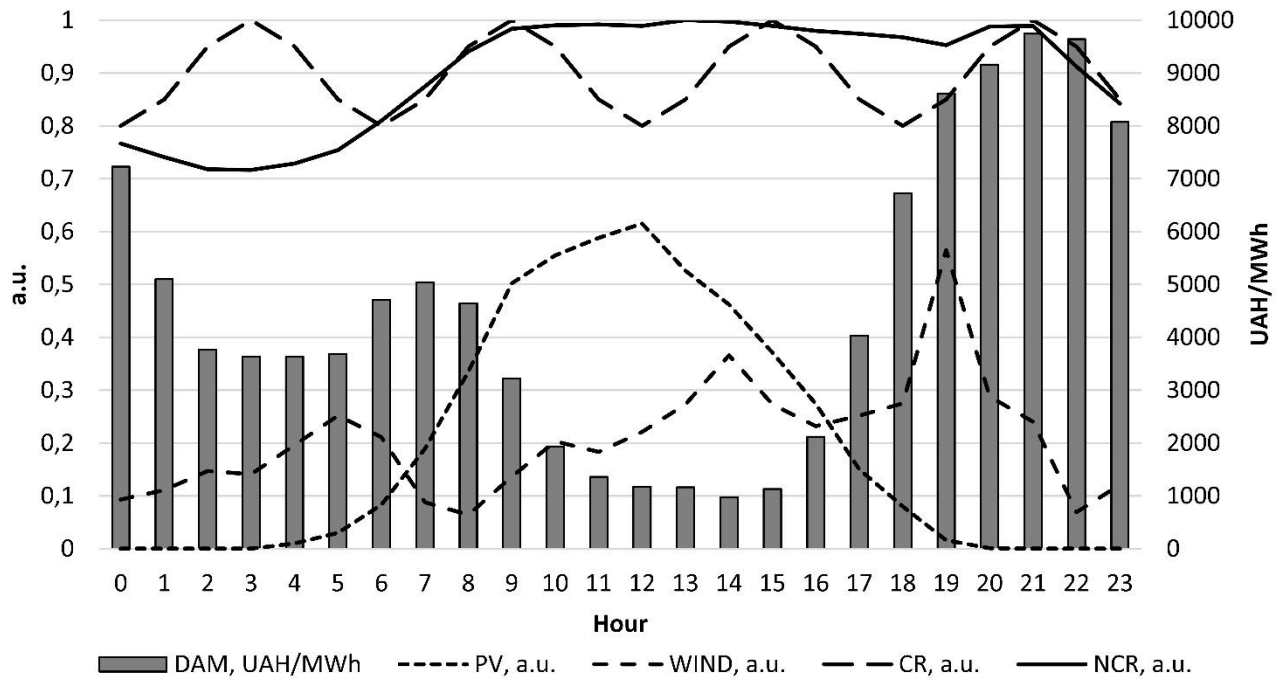


Figure 1. Typical profiles of electricity production at PV and WPP, critical and non-critical consumption, and prices on the DAM

As shown in Fig. 1, the DAM price is highest in the late evening and lowest around midday, while PV generation follows the opposite pattern, peaking at midday and falling to zero overnight. Non-critical consumption rises toward the evening, coinciding with the highest DAM price and the lowest renewable output. This coincidence of low renewable output and high DAM prices in the evening triggers the hourly comparison between the DAM price and the backup generator's fuel cost described above.

To model the optimal microgrid connection power to the electrical grid, we used the input technical and economic indicators in Table 1.

Table 1. Input technical and economic indicators

Name	Indicator
Installed power of PV (AC), kW	60.0 [63]
Installed power of WPP, kW	20.0 [63]
Installed power of RES, kW	40.0

Critical load share, %	20.0
Non-critical load share, %	80.0
Nominal capacity of BESS, kWh	200.0 [63]
Nominal power of BESS, kW	50.0 [63]
Round-trip efficiency, %	90.3
Minimum state of charge of BESS (SOC_min), a.u	0.3 [63]
Maximum state of charge of BESS (SOC_max), a.u	0.8 [63]
State of charge of BESS at the beginning of the day (average between SOC_min and SOC_max), a.u	0.55
Cost of lost load for critical consumers, \$/kWh	1.0
Cost of lost load for non-critical consumers, \$/kWh	0.2
Average daily cost of electricity on the DAM, \$/MWh	102.3
LCOE for PV, \$/MWh	69.0 [64]
LCOE for WPP, \$/MWh	68.0 [64]
LCOE (without fuel component) for RES, \$/MWh	157.9 [64]
LCOE (fuel component) for RES, \$/MWh	52.6 [64]
LCOS for BESS, \$/MWh	251.0 [64]
Cost of connection to the grid (power fee), \$/kW	62.2
Cost of connection to the grid (linear component), \$/meter	69.6
Length of connection to the grid, meters	50.0

When determining the WACC, the National Bank of Ukraine discount rate of 15.5% was used, established in accordance with the decision on monetary policy from 31.07.2026 [65]. The share of borrowed funds was assumed to be 70%, the share of own funds 30%, the income tax rate 25%, and the cost of equity 12%. Thus, the WACC-derived discount rate is 11.7%, and the capital recovery factor (CRF) for 20 years of commercial operation of hybrid microgrid electrical installations is 13.2%.

4. Simulation results

The simulation to determine the optimal power for connecting the microgrid to the grid was carried out for different options for maximum consumer load from 40 to 240 kW, with a step of 40 kW.

The maximum possible power of connection to the electrical grid, for the application of the optimisation model constraint (2) for all simulation options, is taken at 170 kW, which corresponds to the maximum possible theoretical power of supply (export) of electrical energy, which is equal to the sum of the power of all generating installations (PV, WPP and RES) and the discharge power of the BESS. To determine the percentage reduction in LCOM, the connection power to the electrical grid at 170 kW is taken as the base value. Table 2 presents the simulation results.

Table 2. Simulation results

Name/variant	1	2	3	4	5	6
Maximum consumer load, kW	40.0	80.0	120.0	160.0	200.0	240.0
Optimal grid connection power, kW	17.9	56.8	95.8	134.7	170.0	170.0
Undersupplied energy for consumers per day, kWh	0	0	0	0	0	64.0
Cost of undersupplied energy for consumers per day, \$	0	0	0	0	0	13.1
LCOM (before optimisation), \$/ MWh	142.3	135.1	124.4	118.7	115.4	121.7
LCOM (after optimisation), \$/ MWh	138.3	133.7	123.8	118.5	115.4	121.7
LCOM decrease, %	2.8	1.1	0.5	0.2	0.0	0.0

According to the modelling results, for all options, the daily capacity factor, as the ratio of actual to maximum possible volumes of electricity production per day,

was determined for the solar power plant at 19.9%; for the WPP – 20.8%, confirming that the assumed generation profile is representative and independent of the connection-power outcome.

It was established that at a maximum consumer load of 200 kW, the optimal power of connection to the power grid already reaches the model limit of 170 kW, since this value equals the sum of the installed power of all generating units and the BESS discharge power. With a further increase in maximum consumption to 240 kW, the system has undersupplied energy volumes. Figure 2 shows the LCOM (after optimisation) and the self-sufficiency coefficient.

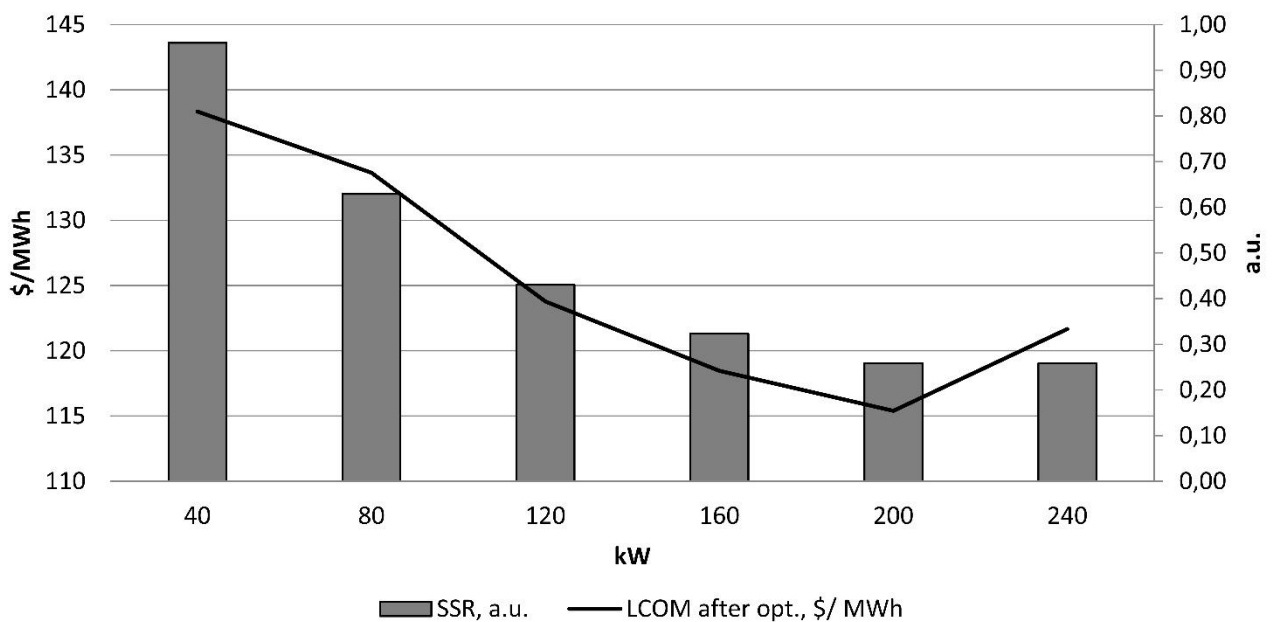
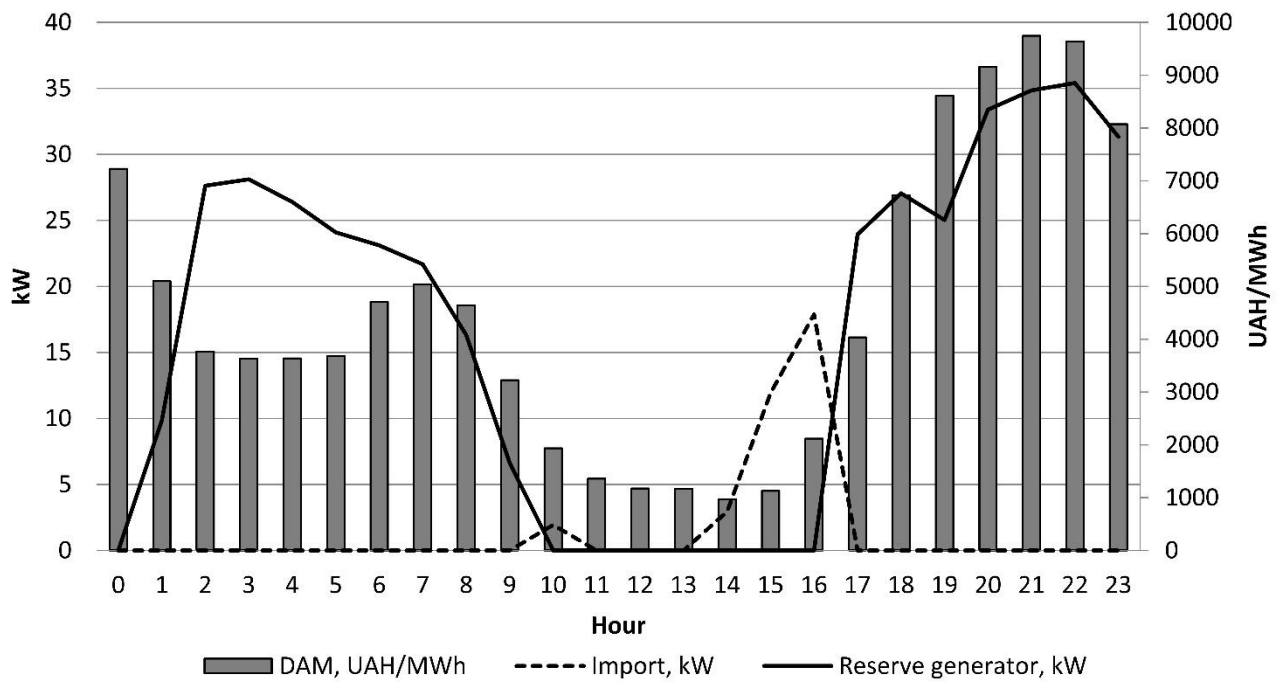
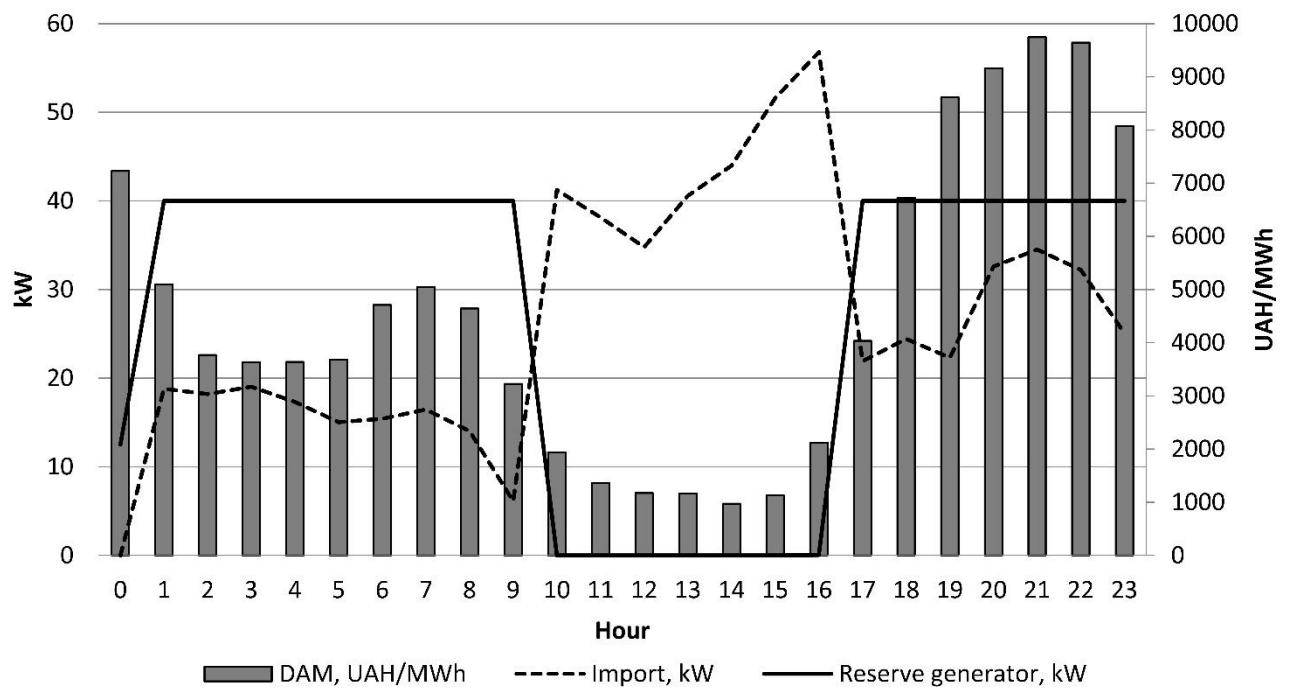


Figure 2. LCOM (after optimisation) and self-sufficiency ratio at different maximum consumer load options

For the simulation options with maximum consumer loads of 40 kW and 80 kW, Figure 3 shows the daily schedule of import power and backup generator power, depending on the price of purchasing electricity on the DAM.



a)



b)

Figure 3. Daily schedule of import and backup generator power depending on the purchase price of electricity on the DAM at maximum consumer load of 40 kW (a) and 80 kW (b)

Figure 3 clearly shows how the proposed algorithm determines the priority power source. Thus, at a maximum consumer load of 40 kW, it is clear that almost the entire deficit of electricity remaining after the discharge of the energy storage system is covered by the power of the backup generator, and electricity is imported only for several hours per day during periods when the purchase price of electricity on the DAM is lower than the cost of electricity production on the backup power source, which, given the accepted input data, is 52.6 \$/MWh (2368 thousand UAH/MWh).

At a maximum consumer load of 80 kW, it is clear that for most hours the backup generator's 40 kW limit is reached, and electricity is imported in parallel to cover the remaining deficit. At the same time, during hours when DAM electricity prices decrease, the backup generator power is reduced in favour of increasing electricity imports. The import process will subsequently be limited by the power of connection to the electrical grids, which is a variable of the optimisation model.

Figure 4 shows the daily balance at a maximum consumer load of 40 kW.

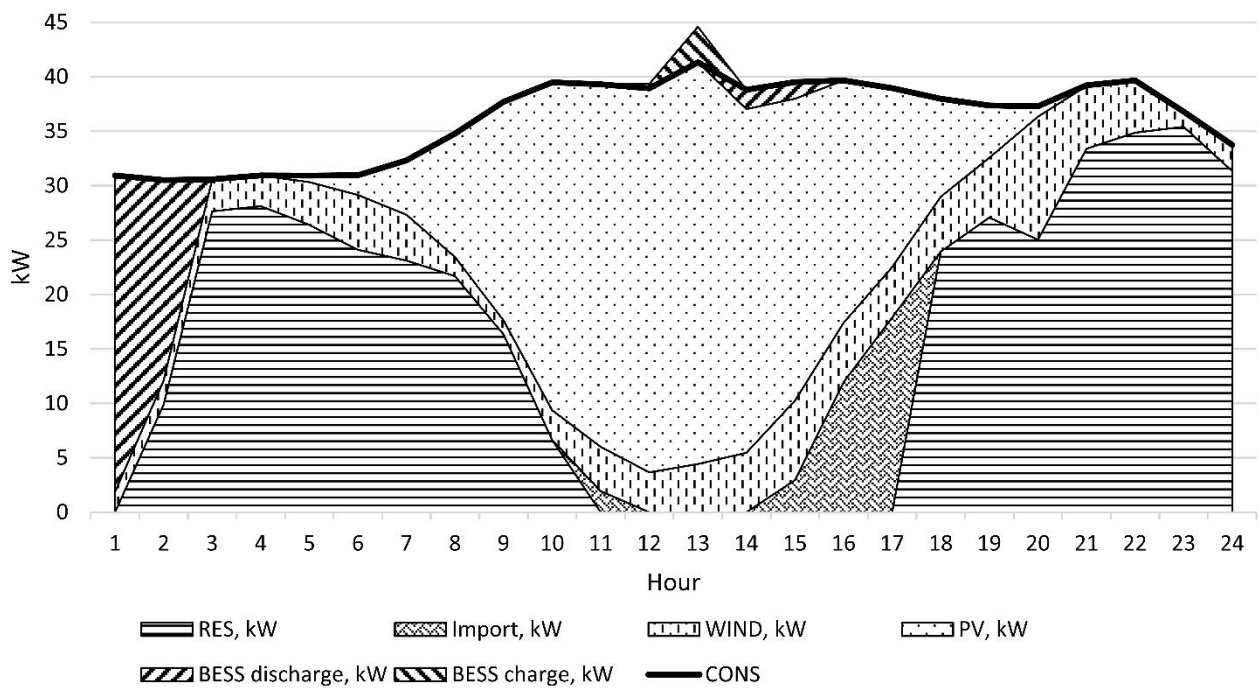


Figure 4. Daily balance at maximum consumer load at 40 kW

For this typical daily profile with the given parameters and input data, there is no undersupply to consumers, no export of electricity, and no restrictions on renewable energy sources. The consumption of critical and non-critical consumers during the day is covered by 46% of the electricity generated by the backup power source, 33% by solar energy, 11% by wind energy, 4% by importing electricity into the microgrid from the external network and 6% by discharging the BESS, together accounting for the full daily demand. At the beginning of the day, the BESS discharges previously accumulated energy, and at the peak of solar generation, it charges with excess electricity.

At the same time, the BESS charging volumes show that the accumulated electricity from excess renewable energy sources is not enough to support a similar discharge at the beginning of the next day. This is because, based on the input data, excess electricity from renewable sources during the current day is insufficient to fill the BESS to the target charge state by the end of the day. Thus, the developed model can be improved, in particular in determining the priority of charging or discharging the BESS, based on the prices of buying and selling electricity from the external network and the need to ensure a given state of accumulated energy capacity at the beginning of the next day.

5. Conclusions

Existing methods for determining the levelized cost of electricity production and storage do not account for grid-connection costs. These costs depend on grid-connection capacity, which can limit the amount of electricity the microgrid can export to the grid. The ability to import, along with the availability of a backup generator, is a key factor in ensuring reliable electricity supply in a microgrid, where renewable energy sources form the basis for meeting consumer loads.

Accordingly, a model to determine the optimal connection power to the electrical network was developed based on the criterion of minimising the microgrid's daily cost. In addition to generally accepted capital and operating costs, the model accounts for grid connection costs and penalties for lost load. The model also uses an

economic algorithm to determine the power of the priority power source (backup gas generator or import), based on an operational comparison between the price of purchasing electricity "day in advance" and the current cost of producing electricity on the backup generator.

For fixed indicators of the installed power of generating units and nominal parameters of the BESS, for each of the six values of the maximum load of consumers (from 40 kW to 240 kW), modelling was carried out, and the optimal power of connection to the grid was determined, which will ensure the minimum value of the daily cost of the microgrid. The results show that the optimal grid connection power increases almost proportionally with the maximum consumer load, up to the limit equal to the total power of the generating units and BESS (170 kW). At the same time, the economic effect of optimising the power of connection to the grid decreases nonlinearly, from 2.8% at a maximum load of 40 kW to 1.1% at 80 kW, 0.5% at 120 kW and 0.2% at 160 kW, and generally disappears when the value of the maximum load of consumers is at the level of the set limit.

The study, based on the developed model, confirmed the importance of accounting for grid connection costs, which, unlike existing methods that consider only generally accepted capital and operating costs, allows reducing microgrid costs by up to 2.8%. Beyond the 170 kW technical limit, undersupplied energy emerges (64 kWh per day at a maximum load of 240 kW), indicating the boundary of the proposed model's applicability under the given configuration.

The proposed model has a limitation that outlines a direction for future research: the dispatch of the BESS is governed by an hourly rule that does not reserve charge for anticipated low-price hours or guarantee a target state of charge at the start of the next day, as observed in the case study for the 40 kW load scenario. Extending the model with a predictive or optimisation-based charge/discharge strategy that accounts for the forecasted price profile and a target end-of-day state of charge is considered as future work.

Abbreviations

BESS	Battery Energy Storage System
DAM	Day-Ahead Market
ENS	Energy Not Served
LCOE	Levelized Cost of Energy
LCOM	Levelized Cost of Microgrid
LCOS	Levelized Cost of Storage
PV	Photovoltaic
RES	Reserve Power Generator
VRE	Variable Renewable Energy
WACC	Weighted Average Cost of Capital
WPP	Wind Power Plant

Author Contributions: Conceptualization, I.B; methodology, I.B; software, I.B; investigation, I.B; writing – original draft preparation, I.B. and A.B.; writing – review and editing I.B., A.B. and A.Z.; visualization, I.B.; supervision, A.Z.; project administration, A.Z.; funding acquisition, A.Z. All authors have read and agreed to the published version of the manuscript.

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Ethics declarations

Ethics approval and consent to participate: Not applicable. This study does not involve human participants, animals, or biological samples.

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