Optimization of Operating Modes of an Industrial Enterprise Photovoltaic Plant with a Battery Energy Storage System

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Abstract – The paper compares rule-based and day-ahead linear-programming control of a 400 kWh battery storage operating with a 298 kW photovoltaic plant at a machine-building enterprise. Simulation in MATLAB/Simulink for three seasons shows that optimal scheduling reduces daily electricity costs by 20.9–25.7 % and cuts winter contracted-capacity exceedance 26-fold.

Keywords **–** photovoltaic plant, battery energy storage system, energy management, peak shaving, linear programming, rule-based control, industrial enterprise, MATLAB/Simulink

I. Introduction

Industrial enterprises remain the largest electricity consumers in Ukraine and bear the main burden of rising tariffs and supply interruptions. After massive attacks on the energy infrastructure in 2022–2025, capacity deficits and consumption limits during peak hours have become routine for industry [3]. Under these conditions on-site generation has turned from an image issue into a tool of business resilience. Rooftop and ground-mounted photovoltaic (PV) plants are the most accessible option, since module prices have fallen several-fold over the last decade and a plant of several hundred kilowatts can be built within weeks [1], [2].

However, the PV generation profile does not match the consumption profile: the output peaks at noon, whereas the most expensive electricity and the highest loads occur in the morning and in the evening. Lithium-ion battery energy storage systems (BESS), whose pack prices dropped to a record 115 USD/kWh in 2024 [4], can align these profiles. Yet the mere presence of a storage unit does not guarantee an economic effect – the result is largely determined by the algorithm that charges and discharges it.

Most studies of PV–BESS scheduling deal with residential and commercial buildings [5], whereas industrial plants are characterized by higher power, pronounced peaks during working hours and a contracted capacity whose exceedance entails financial penalties. Known control methods range from simple rule-based logic embedded in commercial hybrid inverters to mathematical programming and model predictive control [6]-[8].

The aim of this work is to reduce the electricity costs and peak loads of an industrial enterprise by optimizing the operating modes of a PV plant with a BESS. The novelty lies in coupling a daily power-balance model of the energy complex with an electrochemical battery model for verifying optimal schedules, and in a quantitative comparison of rule-based control and optimal scheduling for three characteristic seasons with regard to the contracted capacity of the enterprise.

II. Modelling of the Energy Complex

The object of study is a medium-sized machine-building plant working in two shifts (7:00–15:30 and 15:30–23:00), whose main consumers are CNC machine tools, a compressor station, welding equipment and ventilation. The PV plant, the BESS and the utility grid (via a 10/0.4 kV transformer) are connected to the common 0.4 kV bus of the plant (Fig. 1). The energy

management controller receives power measurements, the state of charge (SOC) of the storage, prices and forecasts, and generates the power set-point of the BESS converter.

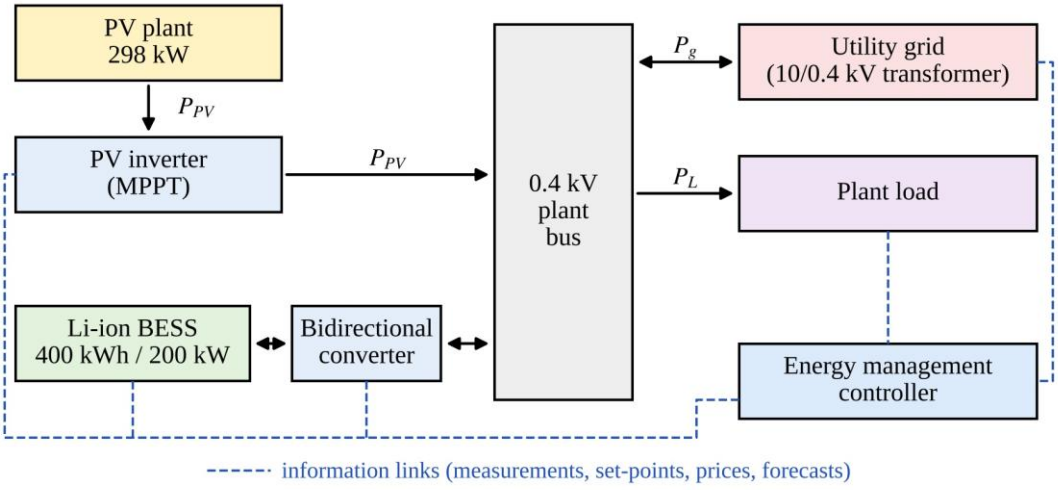

Fig. 1. Structure of the enterprise energy complex

The PV array of 1400 polycrystalline 213 W modules (20 modules in series × 70 strings) was modelled in MATLAB/Simulink by the Simscape Electrical "PV Array" block, which implements the single-diode equivalent circuit [9]. The simulated I–V curves give a maximum power of 298.1 kW under standard test conditions at about 580 V; the maximum power point voltage stays within 575–586 V for 200–1000 W/m², while the power at 65 °C is 16.8 % lower and at 0 °C 9.8 % higher than at 25 °C. The resulting temperature coefficient of –0.41 %/°C agrees well with datasheet values. The string length matches the MPP voltage to the range of a 0.4 kV grid inverter, and the rated power was chosen below the minimum daytime load on working days, so that the PV energy is consumed on site. For daily simulations with a one-minute step, a simplified model is used:

$$P_{\mathrm{PV}} = P_{\mathrm{STC}} \cdot \frac{G}{G_{\mathrm{ref}}} \cdot [1 + \gamma_{\mathrm{P}}(T_{\mathrm{c}} - T_{\mathrm{ref}})] \cdot \eta_{\mathrm{inv}} \cdot k_{\mathrm{loss}}, \tag{1}$$

$$T_{\mathrm{c}} = T_{\mathrm{a}} + \frac{\mathrm{NOCT} - 20}{800} \cdot G, \tag{2}$$

where G is the plane-of-array irradiance, W/m²; T_{a} is the air temperature, °C; γ_{P} = –0.41 %/°C; η_{inv} = 0.97 is the inverter efficiency; k_{loss} = 0.97 accounts for cable, soiling and mismatch losses; NOCT = 45 °C. The error of model (1) with respect to the detailed model does not exceed 1.5 %. Input data are the average daily irradiance and temperature profiles from PVGIS [10] for Lviv (49.84° N, 24.03° E; south orientation, 35° tilt) for January, April and July. The daily PV yield amounts to 1484 kWh in July, 1350 kWh in April and only 444 kWh in January, i.e. 3.3 times less than in summer.

A 400 kWh / 200 kW lithium-ion BESS (two-hour discharge at rated power) is considered. Its electrochemical behaviour is described by the Tremblay–Dessaint model [11] implemented in the Simscape "Battery" block (700 V, 600 Ah), which is used to verify the schedules, while daily calculations use the energy model

$$E_{k+1} = E_k + \left(\eta_{\mathrm{c}} P_{\mathrm{ch},k} - \frac{P_{\mathrm{dis},k}}{\eta_{\mathrm{d}}}\right)\Delta t, \tag{3}$$

where $\eta_{\mathrm{c}} = \eta_{\mathrm{d}}$ = 0.95 are the charge and discharge efficiencies (round-trip efficiency 0.90); the SOC is kept within 0.10–0.95 to extend the battery lifetime. Simulated discharge curves at

0.25C, 0.5C and 1C show a long flat region of 720–760 V; at 50 % SOC the voltage equals 749.7, 745.4 and 736.8 V, respectively, and within the working SOC range it varies by no more than 12 %, which ensures stable operation of the bidirectional converter.

The daily load profile of the enterprise was formed as a sum of a 110 kW base load, a 300 kW shift component, technological peaks at 9:30, 14:30 and 19:00, a lunch-break dip and a smoothed random component; in winter, additional lighting and heating loads were added. The hourly electricity price reproduces the structure of the Ukrainian day-ahead market [12] including network tariffs: from 4.3 UAH/kWh at night and at midday to 9.9 UAH/kWh in the evening (18:00–21:00); the export price is 50 % of the purchase price. The main parameters are summarized in Table 1.

Table 1

Main parameters of the energy complex

Parameter	Value
Rated PV plant power (STC)	298.1 kW
BESS capacity / converter power	400 kWh / 200 kW
Charge / discharge efficiency	0.95 / 0.95
Allowed SOC range; initial SOC	0.10–0.95; 0.50
Peak load, July / January	533.1 / 568.1 kW
Daily consumption, July / January	8173 / 9044 kWh
Load factor, July / January	0.64 / 0.66
Contracted capacity	470 kW
Penalty for exceedance	20 UAH/kWh
Simulation / optimization step	1 min / 15 min

Without additional measures the contracted capacity is exceeded for 6.5 h per day in summer and for 11.4 h in winter. Since the load exceeds 300 kW from 7:00 to 23:00, the whole PV output on working days is consumed on site. Hence, the storage is needed not for saving PV surplus but for shifting grid purchases from expensive to cheap hours and for peak shaving. The grid power is determined from the active power balance on the plant bus:

$$P_{\mathrm{g}} = P_{\mathrm{L}} - P_{\mathrm{PV}} - P_{\mathrm{dis}} + P_{\mathrm{ch}}. \tag{4}$$

III. Control Algorithms

Economic, technical and environmental criteria are largely consistent for the considered system: shifting consumption from evening to night hours reduces both costs and the load on the power system, and peak shaving reduces both penalties and grid loading. Therefore, a single criterion – the minimum of daily costs – is adopted, technical requirements being included as constraints or penalty terms:

$$J = \sum_{k=1}^{N} \left[c_k P_{\mathrm{imp},k} - c_k^{\mathrm{e}} P_{\mathrm{exp},k} + c_{\mathrm{ov}} P_{\mathrm{ov},k} + c_{\mathrm{deg}} \left(P_{\mathrm{ch},k} + P_{\mathrm{dis},k} \right) \right] \Delta t \rightarrow \min, \tag{5}$$

where c_{k} and $c^{\mathrm{e}}_{\mathrm{k}}$ are the purchase and export prices; c_{ov} = 20 UAH/kWh (about twice the maximum price) forces the optimizer to shave peaks first; c_{deg} = 0.01 UAH/kWh prevents physically meaningless simultaneous charging and discharging. Criterion (5) is linear in the control variables, which reduces the task to linear programming (LP) with a guaranteed global optimum [13].

The first, rule-based algorithm requires neither forecasts nor optimization and can be embedded directly into a hybrid inverter controller. At every one-minute step it checks the

conditions in order of priority: 1) PV surplus charges the BESS; 2) if the price is not lower than 8 UAH/kWh, the BESS covers the net load; 3) if the net load exceeds 400 kW, the BESS discharges by the difference; 4) if the price does not exceed 4.6 UAH/kWh and SOC < 0.9, the BESS is charged from the grid with at most 100 kW without exceeding the contracted capacity; 5) otherwise it stays idle. Its drawbacks are fixed thresholds for all seasons and the lack of foresight.

The second approach forms the optimal day-ahead BESS schedule. The day is divided into $N = 96$ intervals of 15 min, with six variables per interval (P_{ch}, P_{dis}, P_{imp}, P_{exp}, E, P_{ov}), i.e. 576 variables in total. Besides balance (4) and dynamics (3), the constraints are

$$0 \le P_{\mathrm{ch},k}, P_{\mathrm{dis},k} \le 200\ \mathrm{kW},\ \ s_{\min} E_{\mathrm{n}} \le E_k \le s_{\max} E_{\mathrm{n}}, \tag{6}$$

$$E_N \ge E_0,\ \ P_{\mathrm{imp},k} - P_{\mathrm{ov},k} \le P_{\mathrm{con}}, \tag{7}$$

where $P_{con} = 470$ kW is the contracted capacity; condition $E_N \ge E_0$ ensures a fair comparison of algorithms. The problem is solved by the linprog function (dual simplex) in less than 0.1 s, which allows its repetition every 15 min in a receding-horizon (model predictive) mode [8]. Ideal forecasts are assumed, so the results estimate the upper limit of the optimization potential. Since the penalty exceeds any price spread, the optimizer first reserves storage energy for the hours of exceedance and then uses the remainder for price arbitrage, which is profitable only when the price ratio exceeds $1/0.9 \approx 1.11$.

IV. Simulation Results

Four scenarios were simulated for each season: 1) grid only; 2) PV only; 3) PV and BESS with rule-based control; 4) PV and BESS executing the optimal schedule. The results are given in Table 2 and Fig. 2; costs of scenario 3 are corrected by the cost of restoring the initial SOC at the night price.

Table 2

Daily results of the energy complex operation

Season / scenario	Cost, UAH	Peak grid power, kW	Exceedance, kWh	Grid purchase, kWh
July, grid only	57 977	533.1	193.4	8173
July, PV only	45 367	454.6	0	6689
July, rule-based	43 916	446.7	0	6563
July, optimization	43 079	477.6	1.9	6758
April, grid only	58 144	534.9	198.5	8180
April, PV only	46 462	467.9	0	6830
April, rule-based	44 936	460.1	0	6708
April, optimization	44 187	482.5	2.5	6900
January, grid only	76 572	568.1	604.4	9044
January, PV only	68 915	568.1	354.1	8601
January, rule-based	67 529	568.1	332.6	8465
January, optimization	60 552	502.6	23.3	8663

The PV plant alone provides the largest contribution, reducing costs by 21.7 % in July, 20.1 % in April and only 10.0 % in January. In summer it also eliminates the exceedance of the contracted capacity (the peak drops from 533 to 455 kW), since daytime load peaks coincide with high generation. The BESS with optimal control gives an additional cost reduction of 5.0,

4.9 and 12.1 % with respect to the PV-only case, i.e. the storage is most effective in winter, when the PV plant is least efficient. In total, optimal control reduces costs compared with the base case by 25.7 % in summer, 24.0 % in the transitional season and 20.9 % in winter.

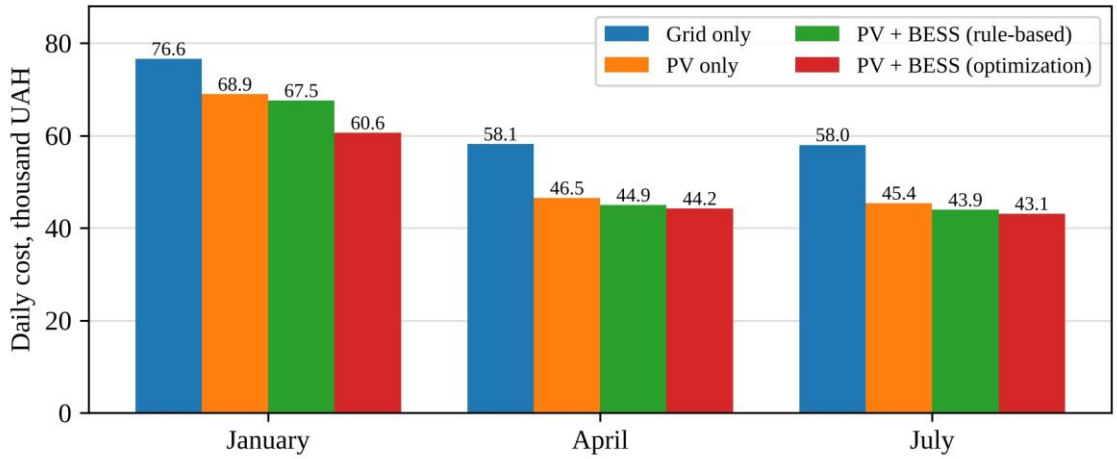

Fig. 2. Daily electricity costs by scenarios and seasons

In July the optimal schedule charges the BESS at night (2:00–4:00) and at midday (12:00–14:00), when the price is minimal (4.3–4.4 UAH/kWh), choosing the midday charging power so that grid consumption just reaches the contracted capacity. Discharge takes place during the morning price rise (7:30–9:00) and at full power in the evening peak (18:00–20:00); after 23:00 the battery is recharged with cheap night energy, so the next day starts in the same state.

The rule-based algorithm gives only 2.0–3.3 % of additional savings and is inferior to optimal scheduling in all seasons: by 1.9 % in July, 1.7 % in April and as much as 10.3 % in January. In July it starts discharging at 17:00, when the price exceeds the 8 UAH/kWh threshold, reaches the minimum SOC by 18:30 and leaves the most expensive hours (19:00–21:00, 9.6–9.9 UAH/kWh) uncovered. In January higher midday prices prevent recharging, so the battery stays empty after the morning peak; the peak is not reduced and the exceedance decreases by only 6 %. The optimal schedule, in contrast, keeps the grid power at the contracted level, discharging exactly by the amount of exceedance: the winter peak drops to 502.6 kW, the exceedance falls from 604.4 to 23.3 kWh (26 times), and the load factor of grid consumption rises from 0.66 to 0.72. The remaining exceedance is caused by short load spikes within the 15-min optimization intervals.

The higher summer peak of the optimal schedule is not a drawback: the optimizer deliberately charges the BESS at the cheapest midday hours up to, but not above, the contracted capacity. Grid purchases grow by 69–70 kWh per day due to cycle losses, yet this energy is bought at lower prices. The daily BESS throughput of 582–646 kWh corresponds to 1.5–1.6 equivalent full cycles, i.e. about 10 years of service at 6000 cycles. Verification of the July schedule on the electrochemical model showed a maximum SOC deviation of 5.7 percentage points (46.3 % vs. 49.7 % at the end of the day) and a battery current not exceeding 303 A (0.53C); thus, the schedule is physically feasible, and a small SOC margin is sufficient to compensate for the discrepancy.

V. Conclusion

A MATLAB/Simulink model of an industrial energy complex comprising a 298 kW PV plant, a 400 kWh / 200 kW BESS, the grid and a two-shift machine-building load has been developed, and rule-based control has been compared with day-ahead LP scheduling. Optimal

scheduling reduces daily electricity costs by 20.9–25.7 % compared with the grid-only supply and by 4.9–12.1 % compared with the PV plant alone, and cuts the winter exceedance of the contracted capacity 26-fold. A rule-based controller with fixed thresholds is acceptable in summer but loses 10.3 % in winter, when peak shaving is most critical. The LP problem is solved in less than 0.1 s, which makes it suitable for receding-horizon implementation in an energy management controller.

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