Battery Energy Storage Schedule Optimization Considering Different Forecast Scenarios

Vladislav Lazić[1], Aleksandar Janjić[1], Bratislav Trojić[1], Uroš Ilić[1]

[1]Faculty of Electronic Engineering, University of Niš

Abstract

This paper deals with the optimization of battery energy storage in a microgrid with renewable energy sources and a connection to the utility grid with an option to buy or sell electrical energy. Due to the intermittency of renewable sources, battery energy storage is an integral part of microgrids, not just to provide energy continuously in times when renewables don't deliver energy, but also to lower the costs of purchasing energy from the utility. In the paper, a model for optimization of battery storage scheduling is derived using the software package MATLAB. Since model parameters such as wind speed, solar irradiance, load, and electricity prices are subject to significant forecast errors, five different scenarios are created to assess possible changes in optimal results.

Introduction

Many of the most challenging problems humanity is facing in 21st century are related to energy generation and its use. Renewable energy generations and some new concepts such as microgrids provide part of the solution to these problems. One of the major issues concerning renewable energy is the intermittency and the unpredictability of its sources. For this reason, an optimal battery energy storage scheduling needs to be derived to get the most out of the microgrid, taking into consideration forecasted parameters. However, quantities such as solar irradiance, wind speed, load, and electricity price are susceptible to errors in forecasting. In order to asses these uncertainties, in this paper five different scenarios were generated. An optimal battery schedule was found for each of the scenarios, and these schedules were then used crosswise in other scenarios. After that, it was analyzed how results change when all scenarios are taken into account for optimization. Also, it was assessed what the effects of using the probability of scenario occurrence are.

Model of the microgrid

In order to perform this analysis, mathematical models of microgrid elements had to be derived. Solar and wind generation power output, P_{pv} and P_w, heavily depend on weather conditions, specifically solar irradiance G and wind speed v. These dependences are expressed in the following equations.

$$P_{pv} = P_{stc}\left[1 + k\left(T_c - T_{ref}\right)\right]\frac{G_t}{G_{stc}}$$

$$P_w = \begin{cases} 0, 0 \le v \le v_r \\ P_{rated}\dfrac{\left(v^3 - {v_{ci}}^3\right)}{\left({v_r}^3 - {v_{co}}^3\right)}, v_{ci} \le v \le v_r \\ P_{rated}, v_r \le v \le v_{co} \end{cases}$$

where P_{stc} is the output power of PV cells in standard test conditions ($G_t = G_{stc} = 1000\frac{W}{m^2}$, $T_c = T_{ref} = 25$ °C), G_t is the light intensity incident on a PV panel. Coefficient k is equal to $-0.47\frac{\%}{K}$, while T_c is the working temperature of solar panels and it depends on ambient temperature and G is solar radiation inflicted on a horizontal panel. P_{rated} is wind turbine rated power, while v is the measured wind speed, v_r, v_{ci}, and v_{co} are rated speed, cut-in-speed and cut-off-speed of the wind turbine, respectively.

Apart from the benefits gained using a battery as often as possible, its use also brings additional costs. Every time the battery is used, it loses a fraction of its remaining useful life, so the costs of a battery depreciation should also form part of the optimization target function. One of the crucial parameters for battery modeling is a state of charge (SOC). It shows the battery's remaining capacity. Next equation shows how SOC is updated after each charging/discharging cycle.

$$SOC(i+1) = SOC(i) - \frac{P_{bat}(i)}{C_{bat}}\Delta t$$

where $P_{bat}(i)$ is the battery power during i-th hour of the day and lasts for a period $\Delta t = 1\ h$ and C_{bat} is the battery capacity. Equivalent cost of charging/discharging cycle is calculated using following equation:

$$c_{storage} = \frac{c_{init}}{a_1 e^{a_2 D_n} + a_3 e^{a_4 D_n}}$$

where the denominator represents equivalent cycle number when the depth of the discharge is D_n. The correlation coefficient factors a_1, a_2, a_3, and a_4 are equal to -16.27, 2.679, 4110 and -1.85, respectively

Problem formulation

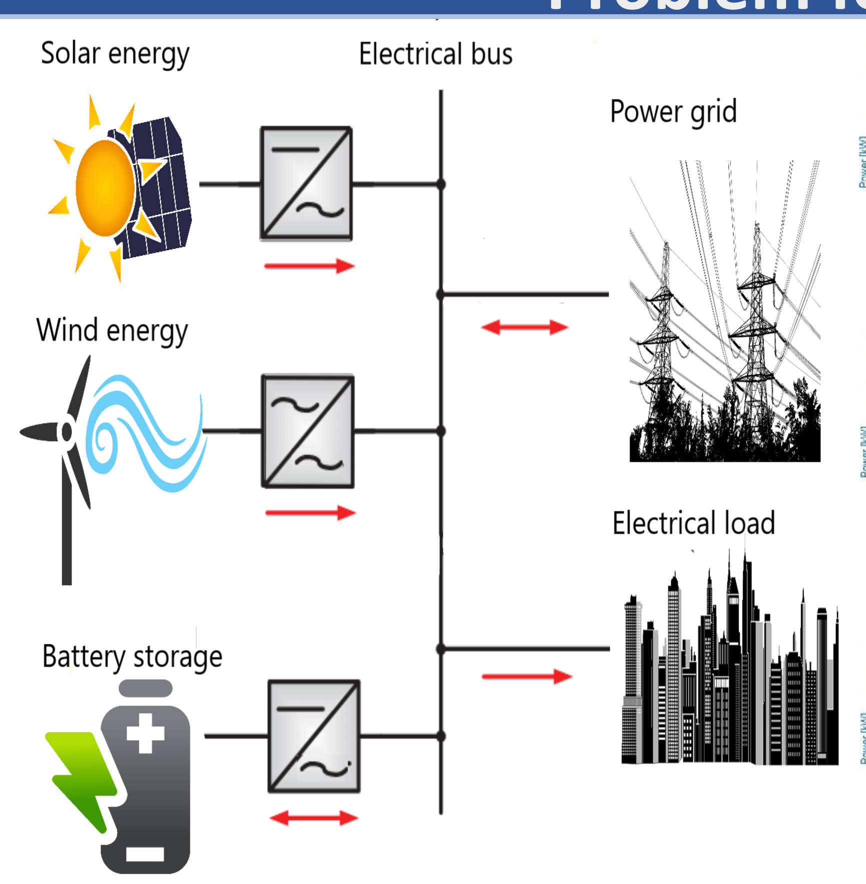

Figure 1. Microgrid diagram.

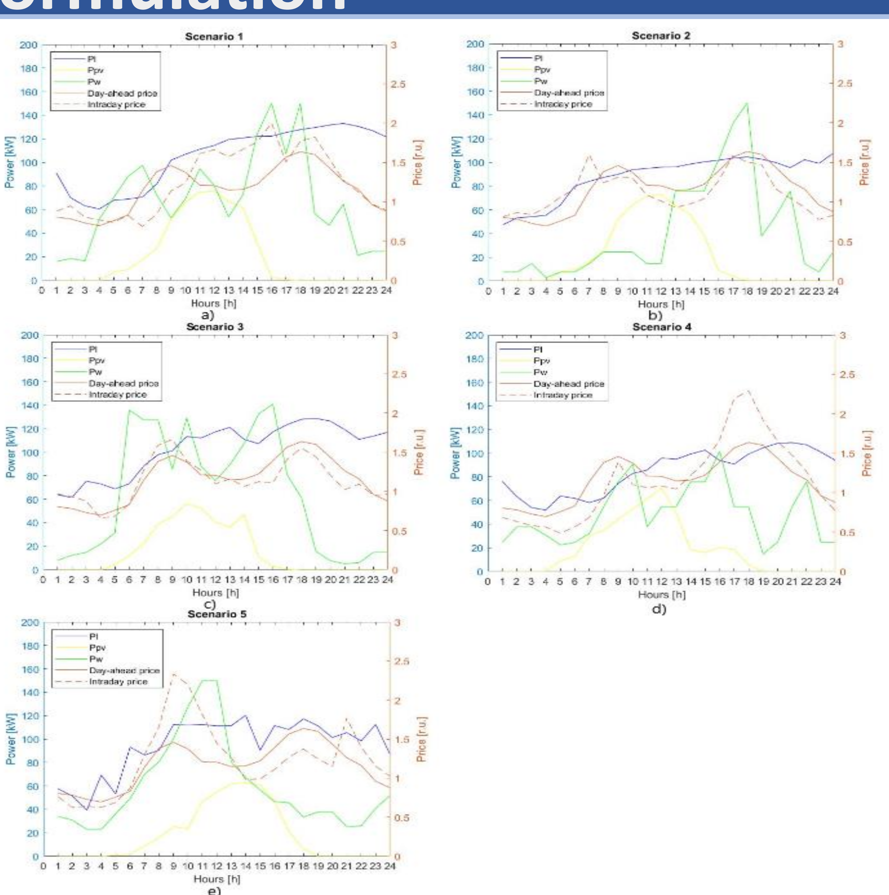

Figure 2. Forecast scenarios.

Fig 1. presents the diagram of the microgrid used in this paper. Rated powers of PV and wind power generation were 100 kW and 150 kW, respectively, while battery capacity was 100 kWh. The goal is to forecast weather, load, and prices condition, which would subsequently be used for battery schedule optimization in order to get the lowest operating costs of a microgrid. The energy is bought on the day-ahead market based on forecasted parameters, but if, due to errors in forecasting, the power balance condition isn't satisfied, the energy difference would be bought or sold on the intraday market, where prices are bigger and more volatile.

As an input to the model, forecasted 24-hour vectors of solar irradiance, wind speed, load, and electricity prices were inserted. However, as was mentioned before, all four parameters are highly susceptible to errors in forecasting, which are almost impossible to avoid. To assess the effects of uncertainty in input parameters on battery schedule optimization, five different scenarios were generated (Fig. 2). Weather forecast changes in several consecutive days for a fixed location were used as a basis for different scenarios. After that, scenarios have been moderately altered to insert occasional spikes and drops that would be a consequence of unexpected weather changes. The biggest changes were made to the intraday market prices profile compared to the day-ahead prices profile, which was fixed in this problem.

Objective function

The goal of the optimization algorithm in this paper was to minimize the operating costs of the microgrid for the day ahead.

$$f^k = P_{grid}^k \pi_{d,a} + \left(P_{grid}^k - P_{grid}^{bs}\right)\pi_{i,d}^k + c_{storage}^k \qquad f = \sum_{k=1}^{n} f^k \qquad f = \rho f^{bs} + \frac{1-\rho}{n}\sum_{k=2}^{n} f^k$$

a) b) c)

Three objective functions were evaluated in this paper, considering number of constraints. Function a) takes into account only one scenario and it was evaluated for each scenario individually. f^k is the objective function value of scenario k, $\pi_{d,a}$ is the 24 h vector of day-ahead energy prices which is the same for all scenarios, $\pi_{i,d}^k$ is the 24 h vector of intraday prices for scenario k, the difference $P_{grid}^k - P_{grid}^{bs}$ is the amount of energy needed to buy on the intraday market for each scenario, while $c_{storage}^k$ is the price of the storage for the optimal solution in the scenario k. Function b) takes into account all scenarios equally. By this mean, the risk of the occurrence of each of the scenarios other than baseline scenario would be mitigated. In function c) the coefficient ρ which represents the probability of the baseline scenario occurrence was introduced to assess the importance of the forecast quality. All other scenarios have the same probability of happening.

Simulation results

The optimal battery schedule for one scenario doesn't provide the best solution for other scenarios. This is where it can be seen how important the accuracy of the forecast is. Even though big errors are possible, solar energy, wind energy, and load have profiles that are usually stable. The electricity price profile has the biggest impact on the difference in optimal results across scenarios. To analyze the difference between the results in different scenarios, the optimization was performed for all scenarios individually. Then the optimal battery schedule x_{opt}^k of one scenario S^k is then applied to the costs function of other scenarios. The results showed differences in costs function output depending on which scenario's optimal battery schedule was used. After that, the optimization function considering all scenarios was evaluated and the resulting schedule x_{opt}^{1-5} was obtained. The results are presented in Table 1.

Fig. 3 depicts how the optimal battery energy storage scheduling output gives the smaller operating costs when the probability of baseline scenario occurrence is higher, which is expected as in this case all scenarios were worse than the baseline scenario in terms of needed operating costs. Fig. 3 actually represents how much we have to give up on baseline optimal solution in order to lower the risk of bigger costs.

Table 1. Optimal output across different scenarios.

x_{opt}^k	Costs $[r.u.]$				
	s^1	s^2	s^3	s^4	s^5
x_{opt}^1	**1100.28**	1701.94	1596.16	2051.31	1744.38
x_{opt}^2	1143.98	**1670.62**	1574.48	2049.37	1707.66
x_{opt}^3	1145.76	1680.02	**1559.62**	2044.15	1689.69
x_{opt}^4	1118.51	1683.99	1572.25	**2030.90**	1712.52
x_{opt}^5	1177.70	1714.56	1590.32	2103.00	**1667.10**
x_{opt}^{1-5}	1125.77	1677.00	1565.77	2035.94	1690.03

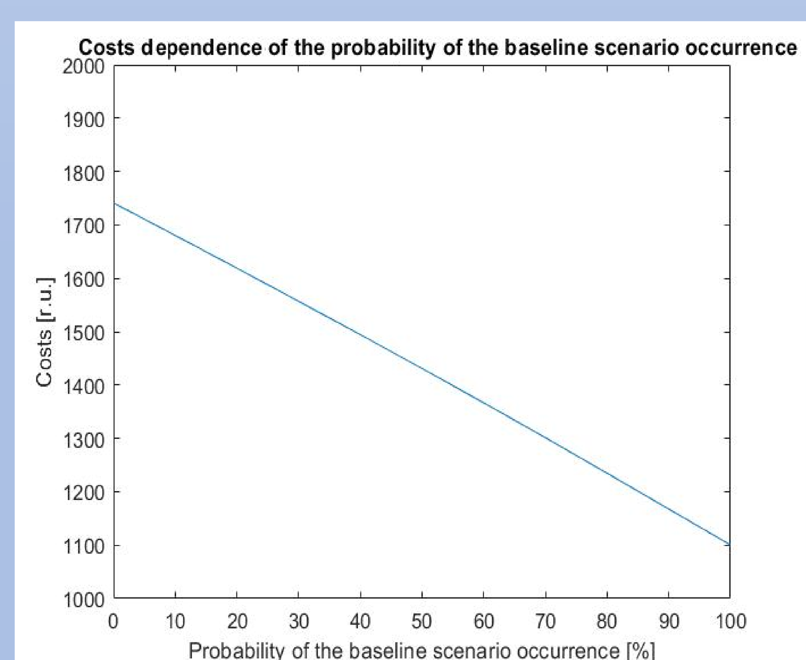

Figure 3. Costs dependence of the probability of the baseline scenario occurrence.

Conclusion

This paper assesses the battery energy storage schedule optimal results in a microgrid across different forecast scenarios. It shows how differences in input parameters, such as solar, wind, load, and electricity prices, which are susceptible to forecasting errors, may invoke changes in the optimal schedule and higher costs than expected. To minimize the risk of the worst-case scenario occurrence, more scenarios have to be taken into account when finding the optimal scheduling output. This can either be done by just adding all scenarios and finding the optimal solution across all of them, or use the probability of the scenario occurrence if it is available.

For future work, a more comprehensive model that encompasses more of the significant factors and gives a closer representation of the grid can be built. Also, more elements of modern microgrids can be included, especially electric vehicles that are becoming more and more important.