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A Study on Nonlinear Optimization of Home Energy Trading Digital Twin

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홈 에너지 거래 디지털 트윈의 비선형 최적화에 관한 연구

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Abstract

This study explains a nonlinear optimization problem in home digital twin energy trading. By considering battery degradation costs, the objective function is to minimize energy trading costs with power balance constraint. This paper simulated the optimization problem across five different scenarios of using batteries or solar panels for prosumers. The results show that the use of batteries can provide benefits to prosumers compared to without batteries. Installation using large batteries or with large solar panels is a better scenario because it makes the total cost lower. Although self-power consumption is larger when using high batteries, prosumers get the larger revenue in these scenarios by more actively taking part in energy trading.

I. Introduction

Home energy trading digital twin is a virtual model that replicates a physical energy trading system of house [1], usually implements Artificial Intelligence (AI) to optimize energy trading operations [2]. Home energy management system (HEMS) optimizes energy consumption of individual houses and reduces electricity costs in the energy trading process [3]. This study implements optimization to get optimal energy cost values and apply to five scenarios.

II. Method

A home energy trading digital twin would use non-linear optimization to balance energy generation, consumption, storage, and trading with the grid. The goal is to minimize the total cost (or maximize profit) over a planning horizon T.

$$\min \sum_{t=1}^{T} [C_{grid}(t)P_{buy}(t) - R_{grid}(t)P_{sell}(t) + C_{deg}(P_{batt}(t), SoC_{batt}(t))] \quad (1)$$

$C_{grid}(t)$ represents the time-varying grid electricity price for buying and $R_{grid}(t)$ is the time-varying feed-in tariff for selling. $P_{buy}(t)$ express power purchased from the grid and $P_{sell}(t)$ is power sold to the grid. C_{deg} captures the battery degradation costs function based on power rates $P_{batt}(t)$ and state of charge $SoC_{batt}(t)$ of battery.

$$P_{gen}(t) + P_{buy}(t) + P_{discharge}(t) = P_{load}(t) + P_{sell}(t) + P_{charge}(t) \quad (2)$$

The power balanced constraint in (2) maintains the physical law of energy conservation, ensures that the total energy supply equals the total energy demand at every time step in the system. Battery degradation formula captures the battery degradation costs [4], expressed in (3) using degradation model parameters α_1 through α_4.

$$C_{deg}(P_{batt}(t), SoC_{batt}(t)) = \alpha_1 |P_{batt}(t)| + \alpha_2 P_{batt}(t)^2 + \alpha_3 e^{-\alpha_4 SoC(t)} \quad (3)$$

Ⅲ. Result and Analysis

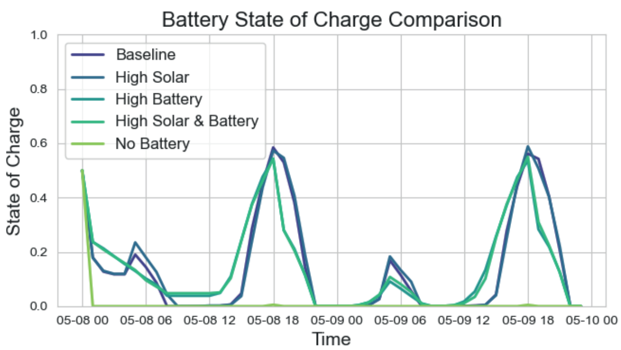

Fig 1. Battery state of charge in one day (24 hours).

Using the Python code and based on one year energy data provided by Grida Energy's digital twin simulator [5], this paper conducted a simulation following the objective function and constraints. The simulation defines five scenarios, and SoC batteries in one day described in Fig.1.

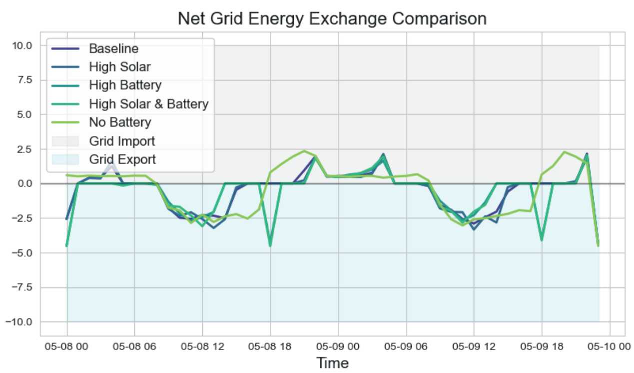

Fig 2. Selling and buying process of energy trading.

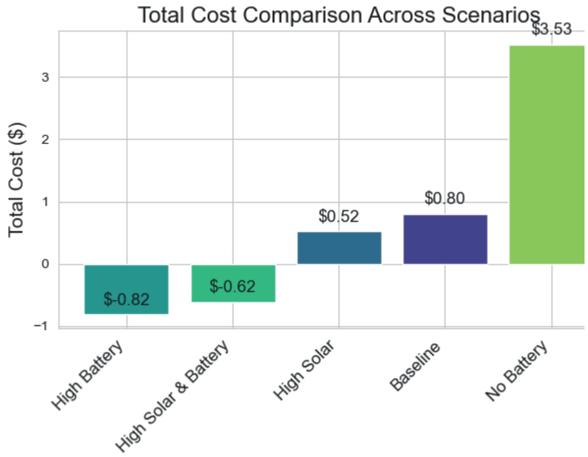

Fig 3. Total cost comparison based on (1) for all scenarios.

All scenarios join the energy trading and doing import or export energy from grid as shown in Fig.2. Based on power generation or consumption, the total cost calculation from (1) gives the simulation result in Fig. 3. No battery scenario has the highest cost. The negative value of total cost means the prosumer has the benefit of selling energy from higher batteries or with higher solar panels.

Table 1. The simulation summary for each scenario.

Scenario	Solar (kW)	Battery (kWh)	Total Cost ($)	Consumption for self (%)
Baseline	5	5	0.80	69.55
High solar	10	5	0.52	73.97
High battery	5	10	-0.82	78.86
High solar + high battery	10	10	-0.62	77.76
No Battery	5	0.01	3.53	43.87

The result summary of simulations is in Table 1, showing the highest self-power consumption is a high battery scenario. Negative total cost (gain a benefit) only achieved by installing the battery as shown in Fig.4, which only uses high solar without battery, still gains the cost for the prosumer.

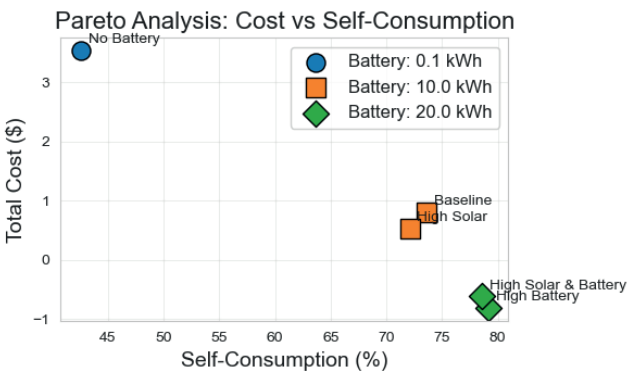

Fig 4. Pareto analysis comparison across scenarios.

The radar chart in Figure 5 also displays the simulation summary for all scenarios. The larger polygon area means better configuration performance in energy trading. More active in energy trading means more participation in export or import energy at load peak time in the power grid. Even self-consumption is higher, the best scenario, which is using high battery or adding high solar panels, can give the better cost saving or gain the higher revenue.

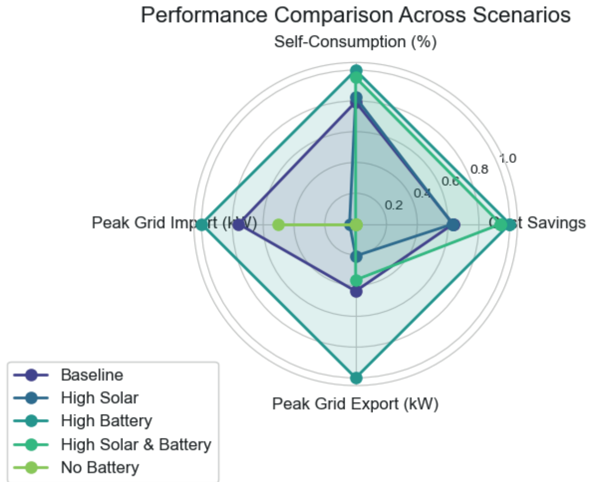

Fig 5. Performance results for all scenarios.

IV. Conclusion

The total cost formula expresses nonlinear optimization as the objective function by considering battery degradation cost and power balance constraint. This paper presents a simulation of a nonlinear optimization problem, encompassing five different scenarios where prosumers use either batteries or solar panels. No battery scenario shows the highest total cost in simulation results with the lowest self-power consumption. Using a high battery is the best scenario because the total cost is the lowest even though the self-power consumption is the highest. Solar energy generation by prosumers can provide a revenue stream and lead to a reduction in home electricity costs.

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