

# Optimal Participation of PEV charging stations integrated with Smart Buildings in the Wholesale Energy and Reserve Markets

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**Abstract**—The emerging nano-Grids (n-Grids), which we designated as commercial or residential buildings hosting electric vehicle charging stations, a fixed battery storage and photovoltaic panels integrated with the building’s load, all being interfaced to the grid through a bidirectional energy exchange framework may provide substantial advantages to the power grid and n-Grid owner. The n-Grids, because of their substantial energy storage capacity and ramp rate, have an added capability, if aggregated can provide ancillary services, reserve in particular, for the wholesale market. In this paper, the optimal framework for their aggregated participation in the day-ahead energy and reserve markets is developed. In the developed bi-level optimization, at a centralized level the aggregator attempts to maximize its profitability by offering optimal energy and reserve prices to the n-Grids. At the decentralized level, the n-Grid optimizer, based on the prices offered by its aggregator, while assuring its own flexibility and dependability, runs the scheduling of its resources to maximize their profit from energy and reserve product procurement. The simulation results demonstrate that the n-Grids are able to provide significant flexibility and resilience to the system by leveraging their high ramp and storage capacity, and as a consequence, provide financial profit to their owners.

**Index Terms**—Ancillary services, Battery storage, electricity market, PEV charging station, nano-Grid

## I. INTRODUCTION

The ever increasing interest in reducing environmental pollution, producing clean and resilient energy, as well as having smarter power systems has led to an increased engagement of customers by owning distributed energy resources (DERs) and making the buildings smart [1]-[3]. Various ways of facilitating customer engagement is through installing PV generation, battery storage, utilizing plug-in electric vehicles (PEVs) for controlling demand response, etc. [4]. This engagement brings about a variety of advantages for both the grid and the customer. From the grid perspective, the increment in reliability, security, resilience and flexibility levels are worth pursuing [5], [6]. For the customer, less expensive

electricity, opportunity of financial profitability and less probability of its load supply loss are of a high significance [7], [8].

The focus of this paper are smart customers that own an n-Grids. As Fig. 1 depicts, an n-Grid may be in located a commercial/residential building which has implemented (rooftop) photovoltaic panels (PVs), a fixed battery energy storage system (BESS) integrated with PEV charging stations (CSs) allowing charging/discharging of PEV’s mobile battery storage. Installing a BESS makes the n-Grid capable of handling uncertainties of load, PV generation and PEV charging/discharging forecasts, and may increase the profitability of n-Grid owner, if and only if proper scheduling framework and incentives are developed.

In order to provide the opportunity of profitability for n-Grid owners, an aggregator aggregates their resources and participates in the wholesale market on their behalf. Various schemes of aggregators’ participation in the wholesale market are discussed in [9]-[17]. The authors in [9] proposed the optimal electricity market bidding strategy for energy storage aggregators, [10], [11] for demand response aggregators, [12] for DER aggregators, [13]-[16] for PEV aggregators and [17] for a combination thereof. A comprehensive framework for PEV and DER participation in the wholesale market is developed in [17]. In the proposed bi-level optimization algorithm, the aggregator maximizes its profits in the upper level and the PEV parking lot owners maximizes their profit in the lower level. However, the authors do not consider the interactions of a PEV parking lot chargers with a smart building. Reference [18] discusses the PEV and BESS scheduling for a number of n-Grids connected to each other and proposes hourly and sub-hourly optimal commitment of the resources. The interaction with the aggregator as well as n-Grid’s ability to provide reserve product in the wholesale market is neglected.

Our paper covers the missing part not covered in the literature, which is the participation of n-Grids in the electricity market. We demonstrate how the n-Grids are able to provide

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This material is based upon work supported by the Department of Energy, Office of International Affairs and Office of Electricity under Award Number DE-IA0000025.

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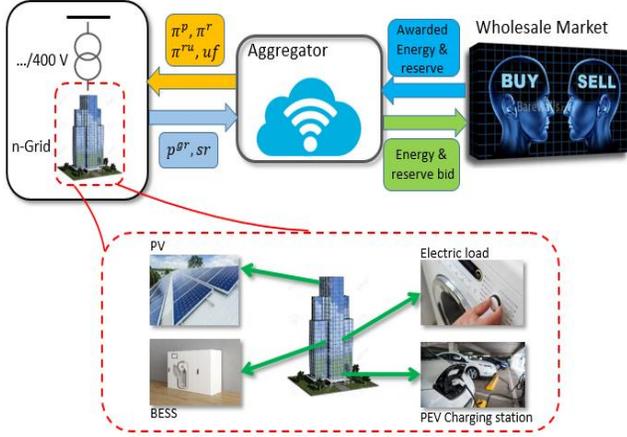


Figure 2. A typical nano-Grid and its interaction with the aggregator.

the reserve product from the combination of BESS and PEVs energy storage capacities creating a profit for its owner. A novel optimization framework for the participation of n-Grids in the day-ahead energy and reserve ancillary service products based on the aggregator pricing is proposed in our paper. In the proposed bi-level optimization, an aggregator at the centralized level aims at maximizing its profit from participation in the wholesale energy and reserve markets, on behalf of its agents. The n-Grids offer energy and reserve prices to the agents. Then, at the decentralized level, the n-Grids aim at maximizing their profit based on the received prices from the aggregator.

The rest of the paper is organized as follows: the proposed framework, the interaction among the wholesale market, aggregator and n-Grids is elaborated in Section II. Section III is devoted to the mathematical optimization formulation and a case study. Simulation results are presented in Section IV. Lastly, the concluding remarks are discussed in section V. References are given at the end.

## II. N-GRID PARTICIPATION IN THE WHOLESALE MARKET

Each aggregator and its agents, n-Grids in this case, attempts to maximize its own profit. The aggregator offers a set of energy, reserve prices and reserve utilization factor to the agents. This is done based on its forecast of the wholesale prices, the wholesale market factor (the portion of reserve expected to be employed for energy generation) and its agents' behavior (see Fig. 2). The n-Grids, based on the forecast of their PV generation, load, PEV arrival/departure and initial state of charge (SOC), and the inputs received from the aggregator, run their own optimization. The aforementioned forecasts are done using historical data and/or mathematical models [18]-[19]. Afterwards, the n-Grid sends its desired energy and reserve levels to the aggregator. The optimization process is run iteratively until the optimal results are achieved. Finally, the aggregator submits its offers to the wholesale market and the awarded energy and reserve amounts would be binding. The mathematical formulation of the optimization is discussed next.

## III. MATHEMATICAL FORMULATION

### A. The Centralized Level Optimization (Aggregator)

The objective function the aggregator attempts to maximize in the day-ahead market is as follows:

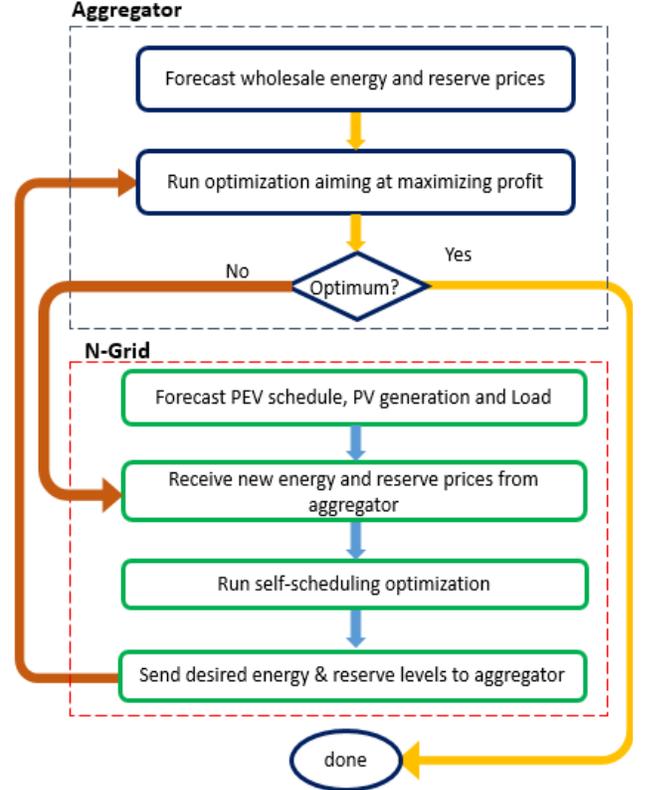


Figure 1. The flowchart of aggregator and n-Grids' interaction.

$$C = \max \sum_t \left( (\lambda_t^p - \pi_t^p) \sum_a (p_t^a + sr_t^a \cdot uf_t) + (\lambda_t^r - \pi_t^r) \sum_a sr_t^a \right). \quad (1)$$

For  $\forall t$  S.T.:

$$\underline{\pi}^p \leq \pi_t^p \leq \bar{\pi}^p \quad (2)$$

$$\underline{\pi}^r \leq \pi_t^r \leq \bar{\pi}^r. \quad (3)$$

Where  $\lambda_t^p$  and  $\lambda_t^r$  are, respectively, the predicted prices of energy and reserve in the wholesale market. Variables  $\pi_t^p$ ,  $\pi_t^r$  stand for the offered energy and reserve prices to the agents. The offered energy, reserve, and reserve utilization factor are given by  $p_t^a$ ,  $sr_t^a$  and  $uf_t$ . Also, index  $t$  indicates time-intervals and  $a$  stands for the agents.

### B. The Decentralized Level Optimization (n-Grid)

Based on the received prices from the aggregator, the n-Grid seeks to maximize the following objective function:

$$C = \max \sum_t \left( \pi_t^p p_t^{gr} + \pi_t^r sr_t + \pi_t^p psr_t - \theta^b \bar{E}^b - \sum_{k_t} [\phi_t^{dis} (p_{k_t,t}^{ev,dis} + psr_{k_t,t}^{ev}) - \phi_t^{ch} p_{k_t,t}^{ev,ch}] - \sum_l lc_{l,t} \Omega_l^d \right). \quad (4)$$

Where  $p_t^{gr}$ ,  $sr_t$  and  $psr_t$  are the power output of n-Grid to the main grid, reserve and energy under reserve service.  $\theta^b$ ,  $\bar{E}^b$  are the BESS degradation cost and maximum SOC. Parameters  $\phi_t^{dis}$  and  $\phi_t^{ch}$  are the discharging reward and charging price of PEVs. Also,  $p_{k_t,t}^{ev,dis}$ ,  $p_{k_t,t}^{ev,ch}$  and  $psr_{k_t,t}^{ev}$  indicate the discharging and charging power and reserve utilization of PEVs. The load loss and the associated prices are shown by  $lc_{l,t}$  and  $\Omega_l^d$ . Index  $l$  indicates type of load and  $k_t$  indicates the number of PEVs predicted to be connected to the charging station at time  $t$ .

The n-Grid is compensated for the procured energy, reserve and energy under reserve service, based on the offered energy and reserve prices by the aggregator, i.e.,  $\pi_t^p$  and  $\pi_t^r$ . Also, it is assumed that the n-Grid owners negotiated with the PEV owners the charging price and discharging rewards. To generalize the model, in the case that the owner of PEVs and n-Grid is the same, e.g. household n-Grids, the contract prices needs to be set to 0 ( $\phi_t^{dis}, \phi_t^{ch} = 0$ ) that the PEV charging/discharging does not impose any costs except the energy cost. Regarding reserve procurement, the PEVs are only compensated for the part of their procured reserve called up for energy production. The PEVs do not impose any penalties, if they cannot provide energy under the reserve product. Also they are free to arrive and depart at their convenience, hence, there is no necessity to compensate them for providing reserve, and they only are compensated for energy production.

For  $\forall t$ , (4) is subject to the following constraints:

$$p_t^{pv} + p_t^b + \sum_{k_t} (p_{k_t,t}^{ev,dis} - p_{k_t,t}^{ev,ch}) = p_t^{gr} + psr_t + \sum_l ds_{l,t}. \quad (5)$$

Where  $p_t^{pv}$ ,  $p_t^b$  and  $ds_{l,t}$  stand for the PV power, BESS power and supplied load. In (5), the power flow equality constraint is enforced. The power output of PV is not controllable and is defined as a variable generation source. The BESS power is positive in discharge mode and negative in charging mode.

The constraints associated with the total procured reserve product of the n-Grid are given below:

$$\bar{sr}_t = sr_t^b + \sum_{k_t} sr_{k_t,t}^{ev} \quad (6)$$

$$sr_t \leq \bar{sr}_t - \left[ (p_t^{pv} - \underline{p}_t^{pv}) - \left( \sum_l (d_{l,t} - \bar{d}_{l,t}) \right) \right] \quad (7)$$

$$sr_t uf_t = psr_t = psr_t^b + \sum_{k_t} psr_{k_t,t}^{ev}. \quad (8)$$

Variable  $\bar{sr}_t$  represents for the maximum available reserve capacity. Parameters  $\underline{p}_t^{pv}$  and  $\bar{d}_{l,t}$  lower limit of PV power and upper limit of load forecasts.

According to (6), the maximum available reserve capacity equals the BESS and PEVs reserve capacities. Hence, a portion of reserve capacity should be withheld from other commitments to be able to respond the uncertainties in the PV power generation and load forecast to enhance the robustness of the proposed framework which leads to (7). Based on (8), the portion of total reserve which is expected for energy generation

( $psr_t$ ) is provided by the BESS and PEVs. It is assumed that there is no constraint for the BESS or PEVs to supply only their own part of  $psr_t$ , and that they are also able cover the  $psr_t$  of each other. The precision of the framework is highly dependent upon  $uf_t$ . In fact, the aggregator should estimate the reserve utilization in the wholesale market very precisely and send this signal to its agents for self-scheduling.

Equation (9) limits the power supplied/injected from/to the grid, based on voltage and line capacity limits.

$$\underline{p}^{gr} \leq p_t^{gr} \leq \bar{p}^{gr}. \quad (9)$$

The load constraints are provided below:

$$0 \leq lc_{l,t} = d_{l,t} - ds_{l,t} \quad l \in (1, L-1) \quad (10)$$

$$0 \leq lc_L = d_L - \sum_t ds_{L,t}. \quad (11)$$

$$p_t^{pv} + (e_t^b - \underline{E}^b) + \sum_{k_t} (e_{k_t,t}^{ev} - \underline{E}_{k_t}^{ev}) \geq \sum_{n=t}^{t+t'-1} \left( \sum_{l=1}^i d_{l,n} + ldp_n d_{L-1,n} \right). \quad (12)$$

Where  $d_{l,t}$ ,  $lc_{l,t}$  and  $ds_{l,t}$  are the load, load loss and supplied load. Also,  $ldp$  represents the lower limit of power controllable load. Index  $i$  indicates the inflexible loads needed to be supplied during main grid faults. The duration of fault in the main grid is shown by  $t'$ .

Based on (10) and (11), the total load is divided to different loads, based on their characteristics. A portion of it is the deferrable load ( $d_L$ ) which can be postponed to the later hours, e.g. laundry machine—see (11). A portion of it is the power adjustable load ( $d_{L-1,t}$ ), such as the air conditioner, which in extreme situations can be lowered to a preset limit to meet the constraints. Also, the inflexible loads can be sorted into different categories according to their importance. Equation (12) assures that in case of grid failure, the n-Grid is capable to supply its important loads, determined by the owner identified by index  $i$ , and the lower level of power adjustable load during a fault occurring at  $t$  and lasting for  $t'$ . In case the n-Grid is called to provide the energy for reserve product and there is not sufficient energy stored, this constraint may be released.

The power output, reserve and SOC constraints of the BESS are set by (13)-(16):

$$\bar{P}^{b,ch} \leq p_t^b + sr_t^b \leq \bar{P}^{b,dis} \quad (13)$$

$$e_{t+1}^b - e_t^b = -p_t^b - psr_t^b \quad (14)$$

$$\underline{E}^b \leq e_t^b \leq \bar{E}^b \quad (15)$$

$$sr_t^b \geq 0. \quad (16)$$

Where  $e_t^b$  stands for the SOC of BESS. In (13), the available reserve capacity of the battery is limited to the difference of its power level and maximum power limit in the charging mode ( $\bar{P}^{b,ch}$ ). Note that  $\bar{P}^{b,ch}$  is a negative parameter. The change in SOC of the BESS is determined by (14), the SOC limits are set in (15) and positivity of the BESS reserve is enforced in (16).

Similar constraints are used for PEV power and SOC requirements in (17)-(21), that is, for  $\forall k_t, \forall t \in T_k^{in}, T_k^{fn}$ :

$$\overline{P}_{k_t}^{ev,ch} \leq p_{k_t,t}^{ev,dis} - p_{k_t,t}^{ev,ch} + \overline{sr}_{k_t,t}^{ev} \leq \overline{P}_{k_t}^{ev,dis} \quad (17)$$

$$sr_{k_t,t}^{ev} \leq av_t \overline{sr}_{k_t,t}^{ev} \quad (18)$$

$$p_{k_t,t}^{ev,dis}, p_{k_t,t}^{ev,ch}, sr_{k_t,t}^{ev} \geq 0 \quad (19)$$

$$e_{k_t,t+1}^{ev} - e_{k_t,t}^{ev} = -p_{k_t,t}^{ev,dis} + p_{k_t,t}^{ev,ch} - psr_{k_t,t}^{ev} \quad (20)$$

$$\begin{cases} \underline{E}_{k_t}^{ev} \leq e_{k_t,t}^{ev} \leq \overline{E}_{k_t}^{ev} & t = T_k^{in}, \dots, T_k^{fn} - 1 \\ \underline{E}_{dep}^{ev} \leq e_{k_t,t}^{ev} \leq \overline{E}_{k_t}^{ev} & t = T_k^{fn} \end{cases} \quad (21)$$

Where,  $T^{in}$  and  $T^{fn}$  are Arrival and departure times of PEVs. Also,  $av_t$  is the availability factor of PEV and  $\overline{sr}_{k_t,t}^{ev}$  is the maximum reserve the PEV can provide. The maximum reserve capacity of each PEV is given by (17) where  $\overline{P}_{k_t}^{ev,ch}$  is negative. In order to increase the robustness of provided reserve capacity by PEVs, in (18), it is assumed that their reserve capacity is limited by their availability factor at the time. Equation (19), assures the positivity of power output and reserve. Lastly, the PEV SOC constraints are fixed by (20) and (21). In addition, in (21), it is assumed that the PEV owner can set a minimum departure SOC and hour of departure ( $\underline{E}_{dep}^{ev}$ ), in case they need more stored energy in PEV for long distance travels.

#### IV. CASE STUDY

##### A. Core Assumptions

The n-Grid under study is a large commercial building at work and is considered to have 20 PEV chargers with the maximum charging/discharging rate of 7.2 kW/h. 100 PEVs are assumed to have charging/discharging contract with the building. To model the mobility of PEVs, the arrival/departure and initial SOC distribution functions developed in [19] are used. The BESS is assumed to have maximum energy capacity of 113.4 kWh with the maximum power output rate of 70.875 kW [18] whose operational cost is provided in [20]. The PV generation data are given in [21] and its forecast error is assumed to follow a normal distribution function with standard deviation given in [22]. Load is modeled based on [18] with normal error distribution function given in [23]. The load and PV data are depicted in Fig. 3. The confidence level of PV generation and load forecast errors coverage in (4) is set to 95%.

The wholesale market under study is the California ISO (CAISO) market. The aggregator attempts to participate in the day-ahead market whose energy and reserve prices are taken from the day-ahead prices on 07/10/2019 [24]. Based on the CAISO regulations, an aggregator in order to be eligible to participate in the market needs to offer a combination of energy and reserve higher than 0.5 MWh at each hour. To meet this criterion and emphasize the core role of BESS and PEVs in n-

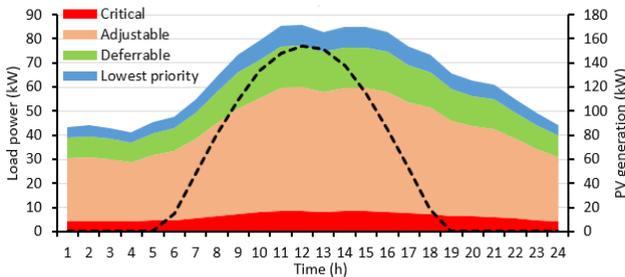


Figure 3. The n-Grid's different load type and PV power data.

Grids, it is assumed that the aggregator participates in the market on behalf of 30 agents with the following characteristics:

- 10 n-Grids with the given data (nGI)
- 10 n-Grids without BESS (nGII)
- 10 n-Grids without PEV charging station (nGIII).

##### B. Simulation Results

Since the objective functions of the aggregator and agents conflict each other, the bi-level optimization is run iteratively until it reaches a settling point in which both the objective function are reach an optimum. In order to find the optimum solution, genetic algorithm (GA) is adopted to search in the feasible solution space. The energy and reserve prices offered by the aggregator to its agents, as well as its forecasted market prices are depicted in Fig. 4. By comparing Fig. 3 and Fig. 4, it is observed that during the intervals in which the net power (PV power minus load) of n-Grids is positive, the aggregator tries to offer energy prices lower than the market price, and offer higher energy prices, otherwise. The reserve prices offered by aggregator are mostly lower than the market reserve prices.

The aggregator's expected profit in detail is given in Table I. It can be seen that the main part of aggregator's total profit comes from energy trade. The aggregator can gain higher profits out of nGII and nGIII demonstrating the fact that nGI, due to its higher storage capacity, is more capable to manage its power consumption/generation in response to the aggregator's prices. The aggregator's reserve profitability is much lower than energy and mostly comes from nGI, as well due to its higher storage capacity.

TABLE I. AGGREGATOR'S EXPECTED PROFIT

n-Grid type	Expected energy profit (\$)	Expected reserve profit (\$)	Expected reserve util. (\$)	Total profit (\$)
nGI	118	13	-16	115
nGII	168	0	0	168
nGIII	200	03	-4	198
Aggregated	486	16	-20	481

Each n-Grid's expected profit is provided in detail in Table II. The procured reserve by nGII is almost zero. In nGII, the only available energy storage capacity is PEV battery. Hence, if it procures reserve product and is called for energy under

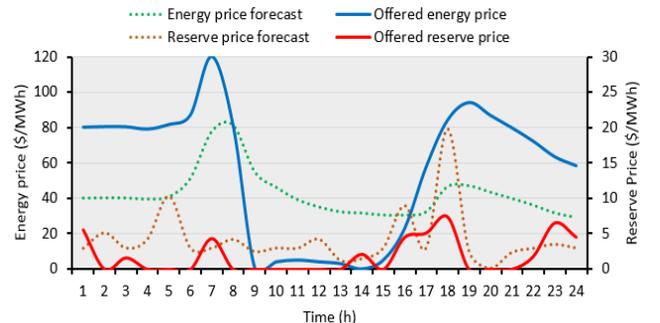


Figure 4. The aggregator's energy and reserve prices forecasts, and the corresponding prices offered to its agents.

reserve, it should use the stored energy of PEVs and needs to compensate the PEVs based on their contract which is much higher than the energy price. The nGIII because of using BESS storage which is almost free, can provide a notable amount of reserve product. The nGI, on the other hand, is able to procure much higher reserve product since (i) it benefits from both BESS and PEV storage capacities (ii) for energy under reserve, it can use the BESS stored energy. The total cost of operating the n-Grid for nGI is significantly lower than the others, since unlike nGII it can make profit from PEVs storage capacity, and unlike nGIII it can make profit from its charging station. Lastly, the charging station profit for nGI is higher than nGII since it benefits from their storage capacity for reserve procurement.

TABLE II. EXPECTED PROFIT/COST OF EACH NANO-GRID

Case	Total reserve (kWh)	Expected reserve profit (\$)	Expected energy cost (\$)	Total cost (\$)	CS profit (\$)
nGI	1730	13.4	36.8	8.7	22.7
nGII	0	0	38.2	20.8	17.4
nGIII	696	4.8	29.5	24.7	0

## V. CONCLUSION

An n-Grid comprised of a PEV charging station integrated with a smart building have a potential of customer profitability by participating in reserve ancillary service product for the grid. In this paper, a bi-level optimization algorithm for the optimal participation model of an n-Grid in the wholesale energy and reserve markets is developed, the following features are demonstrated through simulation:

- The aggregator's profitability mainly comes from energy trade between wholesale market and its agents. In this study, the expected energy profit is \$486 while its reserve profit is \$16.
- The n-Grids without BESS (nGII), are reluctant to participate in reserve market since the compensation of PEVs for energy under ancillary services is higher than energy price.
- The total available reserve capacity for the entire day for nGIII, is 696 kWh which increases to 1730 kWh in the presence of BESS demonstrating the key role of the combination of fixed BESS and PEV charging station in reserve procurement.
- The total operating cost of nGI is lower than the others, as well, emphasizing the core value of BESS and PEV charging station for leveraging n-Grid profitability.

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