"Ovidius" University Annals, Economic Sciences Series
Volume XXIV, Issue 2 /2024

Optimizing Energy Storage Systems. A Dynamic Framework For Capacity Allocation And profit Maximization In Electricity Markets

Adela Bâra
Simona-Vasilica Oprea
Bucharest University of Economic Studies,
Department of Economic Informatics and Cybernetics, Romania
bara.adela@ie.ase.ro
simona.oprea@csie.ase.ro

Abstract

This paper presents an algorithmic approach for optimizing energy storage system (ESS) capacity allocation across multiple electricity markets to maximize profits. The methodology involves collecting real-time and historical data on market prices, renewable energy forecasts and grid demand. Predictive analytics, including machine learning models, forecast future market conditions, while optimization techniques such as mixed-integer linear programming (MILP) determine the optimal schedule for charging and discharging. Reinforcement learning (RL) is integrated into the framework to enable dynamic, adaptive decision-making, allowing the ESS to continuously refine its market strategies. Key constraints such as storage capacity, charge/discharge rates and market regulations are incorporated into the model. A feedback loop ensures real-time adjustments based on market fluctuations, improving profitability over time. Revenue stacking across day-ahead, intra-day, ancillary and balancing markets further enhances the financial viability of ESS investments.

Key words: energy storage systems, energy transition, operation strategy, algorithmic approach, optimization
J.E.L. classification: O13, P18, G14

1. Introduction

Energy storage systems (ESS) have an important role in electricity markets, enabling flexible grid management and enhanced renewable energy sources (RES). As electricity markets become more decentralized and RES proliferate, ESS have emerged as essential assets for balancing supply and demand, ensuring grid stability and providing ancillary services. However, effectively managing ESS across various markets requires a decision-making process to maximize profitability while adhering to operational and regulatory constraints. Participants can access a range of opportunities, including day-ahead markets (DAM), intra-day markets (IDM), ancillary services markets (ASM) and balancing markets (BM). Each market offers unique benefits and risks, driven by factors such as price volatility, market liquidity and grid demands. The challenge lies in efficiently allocating ESS capacity to the most profitable markets. This paper addresses this challenge by developing an algorithm that combines predictive analytics, optimization techniques and real-time data processing to dynamically allocate ESS capacity across these markets.

The methodology proposed involves several steps, starting with data collection, where real-time market prices, RES forecasts and grid demand data are gathered. Predictive analytics, powered by machine learning (ML) models, generate forecasts of future market conditions. These predictions inform an optimization model that calculates the most profitable allocation of ESS resources, subject to constraints like ESS capacity, charge/discharge rates and market regulations. The optimization is formulated as a mixed-integer linear programming (MILP) problem, ensuring that the ESS operates within its technical limits while maximizing profit.

In addition to optimization, reinforcement learning (RL) is integrated into the algorithm to allow the ESS to continuously learn and adapt to market conditions. The RL framework ensures that the ESS respond to real-time fluctuations in market prices, grid demand and other variables, improving decision-making over time. By learning from its interactions with the market, the RL agent refines its strategy to achieve higher long-term profitability.

The concept of revenue stacking is also explored, where ESS operators participate in multiple markets simultaneously or sequentially, optimizing their operations to capture value across different market segments. This strategy enhances financial returns by using the flexibility of the ESS to provide services such as frequency regulation, voltage control and energy arbitrage.

This paper provides a comprehensive framework for ESS capacity allocation, using both traditional optimization techniques and advanced machine learning models. The proposed approach maximizes profits and also ensures that ESS are utilized efficiently, contributing to grid stability and RES integration.

2. Literature review

The integration of ESS into electricity markets has garnered significant attention in recent years, driven by the increasing penetration of RES. The literature surrounding ESS optimization primarily focuses on three key areas: energy market participation strategies, optimization techniques for capacity allocation, and the use of ML and RL for adaptive decision-making.

ESS have become critical in managing the intermittency of RES, such as wind and solar, by storing excess energy during periods of low demand and releasing it during high demand. Several studies have explored how ESS participate in various electricity markets to enhance profitability. In these markets, ESS operators may capitalize on price fluctuations and provide critical services like frequency regulation, voltage support and demand response. ESS engage in energy arbitrage in the DAM and IDM by charging during off-peak hours and discharging during peak demand, thereby exploiting price differences (Wu et al., 2022). However, the importance of accurate price forecasting in maximizing profits is expanded by subsequent research. Moreover, (Wang, Liu and Wen, 2024) explored the potential of ESS for providing ancillary services. The research emphasized that ESS generate higher revenues through such services compared to energy arbitrage alone, particularly when revenue stacking across multiple markets is permitted. The concept of optimizing ESS operations was also introduced to simultaneously participate in several market segments, a strategy that maximizes revenue but introduces complexity in the decision-making process.

Optimizing the allocation of ESS capacity across different markets has been a central focus of many studies, with several methodologies proposed. MILP has been widely used for formulating and solving the ESS scheduling problem. In their research, MILP models were further proposed for determining the optimal charging and discharging schedules for ESS in the DAM and BM, accounting for ESS constraints such as storage capacity, charge/discharge rates and efficiency losses (Muschick et al., 2022). In addition to linear programming methods, metaheuristic approaches like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been applied to solve the ESS optimization problem in complex, nonlinear market environments. (Kim et al., 2020) combined MILP with PSO for ESS capacity allocation in electricity markets. Also, (Li et al., 2023) combined MILP and PSO to provide an optimal schedule. PSO provides faster convergence and better adaptability in highly volatile market conditions. While MILP is highly effective for deterministic scenarios, PSO and other heuristic methods are better suited for environments with uncertainty and stochastic variables. Stochastic programming has also gained traction as a method to account for the inherent uncertainty in electricity markets, such as volatile prices and unpredictable RES output (Bhattacharya, Kharoufeh and Zeng, 2018).

As electricity markets become more dynamic, the integration of ML and RL into ESS management has been increasingly studied. ML models, particularly those based on time series forecasting, have been employed to predict market prices and grid demand with a high degree of accuracy. (Zhao, Zhang and Peng, 2022) illustrated the use of deep learning models, such as Long Short-Term Memory (LSTM) networks, to forecast power fluctuations caused by RES. Their results demonstrated the superiority of LSTM over traditional time series models.

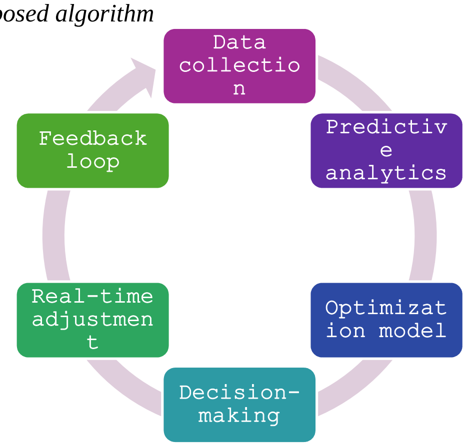
RL has emerged as a powerful tool for managing ESS. An RL-based framework was developed that controls ESS (Abedi, Yoon and Kwon, 2022). These models employed Q-learning to maximize profits while minimizing wear and tear on the ESS. Advanced RL techniques, such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), have also been applied to ESS management.

Recent research has also focused on hybrid models that combine ML, RL and traditional optimization methods. The hybrid approach may demonstrate superior performance in both profitability and adaptability compared to single-method models. Multi-objective optimization has become increasingly relevant as ESS operators seek to balance conflicting goals, such as maximizing profits and minimizing system degradation. (Song et al., 2023) developed a multi-objective optimization framework to optimize the charge/discharge schedule in each battery.

3. Research methodology

Developing an algorithm to allocate ESS capacity to various electricity markets to maximize profits involves creating a decision-making framework that dynamically adapts to changing market conditions and price signals. An outline of how such an algorithm might be structured, using predictive analytics, optimization techniques and real-time data processing is provided.

Figure no. 1. Steps of the proposed algorithm



Source: Authors' contribution

The algorithm starts by gathering real-time and historical data on electricity prices across different markets (DAM, IDM, ASM, BM), weather forecasts (to predict RES supply fluctuations) and grid demand forecasts. Using historical data, the algorithm employs ML models to forecast future price trends and demand patterns in each market. Techniques like time series analysis, regression models, or more complex neural networks can be used. The core of the algorithm is an optimization model that calculates the most profitable allocation of ESS capacity across different markets. This model considers: price forecasts obtaining predicted prices in each market; storage constraints such as ESS capacity, charge/discharge rates and efficiency; risk preferences settings that allow the operator to manage risk versus return preferences. The optimization model uses a MILP to determine the optimal schedule for charging and discharging operations. The goal is to maximize profit while adhering to operational and regulatory constraints. The algorithm adjusts its operations based on real-time market data and unexpected changes in the grid (e.g., outages, sudden demand spikes). This involves recalculating the optimization problem to reflect new conditions and potentially shifting storage resources to more profitable or necessary uses. The outcomes of the algorithm's decisions are continuously monitored and the results are fed back into the system to refine the predictive models and optimization framework, improving accuracy and profitability over time.

Pseudocode no. 1. Implementation

```
def optimize_ESS_allocation(prices, demand, capacity, charge_rate, discharge_rate):
    # Initialize optimization model
    model = OptimizationModel()
    # Define constraints
    model.add_constraint('capacity_limits', capacity)
    model.add_constraint('charge_limits', charge_rate)
    model.add_constraint('discharge_limits', discharge_rate)
    # Set objective to maximize profits
    model.set_objective('maximize', prices x (discharge_rate - charge_rate))
    # Solve the model
    optimal_schedule = model.solve()
    return optimal_schedule
# Run the algorithm every hour to update the ESS schedule
while True:
    current_prices = fetch_market_prices()
    current_demand = fetch_grid_demand()
    optimal_schedule = optimize_ESS_allocation(current_prices, current_demand, ESS_capacity, max_charge,
max_discharge)
    execute_schedule(optimal_schedule)
# Wait an hour before recalculating
    wait(1 hour)
```

Source: Authors' contribution

RL is a type of ML where an agent learns to make decisions by interacting with an environment. In the context of ESS, the "agent" is the algorithm that manages the ESS and the "environment" includes the various electricity markets, price signals, grid demands and regulatory constraints. The goal of the agent is to maximize a reward function, which in this case is the profits from buying and selling energy at optimal times. The agent receives feedback in the form of rewards or penalties based on the actions it takes (e.g., charging or discharging the ESS at certain times), which it uses to improve its decision-making process. RL algorithms adapt to changes in market conditions without needing reprogramming or human intervention. This is essential in electricity markets where price signals and grid requirements can change rapidly. RL manages multiple objectives simultaneously, such as maximizing profits while minimizing wear and tear on the ESS. RL develops a strategy, that dictates the best action to take in a given market scenario. RL incorporates forecasts (like price, demand and RES supply) into its decision-making process, allowing it to make strategic decisions that account for expected future conditions.

In an RL model for ESS, the state includes all relevant information about the current market conditions, state of the ESS (e.g., current charge level) and any other pertinent information like weather forecasts. Actions are the possible decisions the agent makes at any time, such as how much power to charge or discharge and when to engage in each electricity market. The reward function is related to profit to ensure that the RL agent's goals align with the business objectives. The RL agent uses historical data and ongoing experience to develop and refine its policy for market participation. Over time, it identifies the best actions (strategies) to take in various situations to maximize cumulative rewards. To construct a mathematical model for maximizing profit from the allocation of storage capacity across various electricity markets, a range of variables are considered, including prices, capacity, charge and discharge rates and time constraints. Let us consider the following variables:
C_t = charge amount (in MWh) at time *t*
D_t = discharge amount (in MWh) at time *t*
S_t = state of charge of the ESS at time *t*
P_t^b = price of buying electricity at time *t*
P_t^s= price of selling electricity at time *t*
η_c = charging efficiency of the ESS
η_d = discharging efficiency of the ESS
CAP = total ESS capacity (in MWh)

r_c = maximum charging rate (in MW)
r_d = maximum discharging rate (in MW)

The objective is to maximize total profit, which is the revenue from selling electricity minus the cost of buying electricity, integrated over the operational horizon *T*:

$$Maximize \sum_{t=1}^{T} \left(P_t^s \times D_t - P_t^b \times C_t \right) \tag{1}$$

The main constraints are:

(1) ESS capacity constraints:

$$0 \leq S_t \leq CAP \tag{2}$$

(2) State of charge dynamics:

$$S_{t+1} = S_t + \eta_c \times C_t - \eta_d \times D_t \tag{3}$$

(3) Charging and discharging rate constraints:

$$0 \leq C_t \leq r_c \text{ and } 0 \leq D_t \leq r_d \tag{4}$$

(4) Non-simultaneous charging and discharging:

$$C_t \times D_t = 0 \tag{5}$$

Initial and final state of charge: S_1 is given and S_{T+1}may be set to a specific value or left free. The time increment *t* can be chosen based on the market intervals, typically hourly for many markets. Charging and discharging efficiencies (η_c, η_d) reflect energy losses during these processes. Prices (P_t^s, P_t^b) require estimation.

Enhancing the mathematical model for ESS capacity allocation with RL involves incorporating an RL algorithm to dynamically adapt the ESS operation based on learned strategies from market interactions. In an RL framework, the objective is to learn a strategy π that dictates the optimal actions to take in various states of the environment to maximize cumulative future rewards (profits in this case). This is achieved through interactions with the environment, which in this context consists of the electricity markets and ESS dynamics. Reward function *R* is defined as the profit from selling electricity minus the cost of buying electricity.

RL algorithm starts with a random strategy π or a baseline strategy for initializing C_t, D_t. At each time step *t*, observe the current state which includes S_t, P_t^s, P_t^b. Based on the strategy, RL agent determines the action a_t (either C_t *or* D_t, ensuring that charging and discharging do not occur simultaneously). Then, it calculates the immediate reward R_t from the action taken and the reward and the new state are used to update the policy using an RL method like Q-learning, Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO), depending on the complexity and requirements. This process is continued, refining the strategy over time to maximize the expected cumulative reward.

Stacking revenue streams from various electricity markets is a strategy for investors using ESS as a flexible tool. This approach involves participating in multiple market segments simultaneously or sequentially, maximizing the financial returns from the ESS's operational capabilities. Thus, an ESS might be able to provide ancillary services while also engaging in arbitrage between the day-ahead and intra-day markets. For instance, an ESS could be contracted for frequency regulation while still retaining some capacity for charging and discharging based on price signals from the DAM and IDM. In markets where simultaneous participation is not allowed or feasible, ESS can shift between markets based on seasonal, weekly or daily variations in market conditions. For example, during periods of high RES output, an ESS might focus on energy arbitrage due to significant price volatility, while in periods of grid stress, it might prioritize ancillary services.

The revenue stacking strategy involves scheduling ESS operations to take advantage of the economic opportunities in these markets, sometimes participating in multiple markets within the same operational timeframe. It consists of (a) identifying overlapping opportunities where participation in one market does not preclude or undermine opportunities in another; (b) optimizing charging and discharging cycles to maximize revenue across different markets. For example, charge the ESS during off-peak hours using low-cost energy from the DAM and use the stored energy to provide frequency regulation in the ASM during peak hours; (c) monitoring real-time market signals and adjust operations dynamically. If prices spike unexpectedly in the real-time market, it might be more profitable to sell energy there rather than providing ancillary services; (d) optimizing for net metering and other incentives that might be available for using ESS to store and dispatch RES.

For instance, an ESS starts the day by charging during early morning hours when wind energy production is high, but demand is low, taking advantage of cheap electricity prices in the wholesale market. During the morning peak hours, it switches to providing frequency regulation services, earning premium payments. In the afternoon, it discharges to meet spikes in local demand, selling power at higher prices in the real-time market. Later, it may participate in the capacity market, ensuring availability during the highest demand periods of the day. Diversification across multiple revenue streams reduces financial risk as each market presents unique risks that may affect the profitability and operational strategy of ESS investments. A closer look at the risks associated with different markets and how these can be integrated into a mathematical model reveals that prices may fluctuate significantly due to unexpected changes in demand or supply conditions on DAM. Moreover, misestimations of DAM prices may also lead to suboptimal charge/discharge decisions. IDM are generally less liquid than DAM, which makes it more difficult to execute large trades without affecting prices. Prices may be more volatile within the day, impacted by real-time variations in demand and supply. Participating in ASM might lock the ESS into certain operational modes that preclude other potentially profitable activities. ESS might be reserved for peak demand periods, potentially underutilizing their capabilities at other times. On the other hand, high demands on ESS responsiveness and cycling may increase wear and tear on BM. Balancing responsibilities and compensation can vary, affecting predictability of returns.

To factor these risks into a mathematical model, we use a risk-adjusted return approach that modifies expected revenue based on the risk profile of each market using the following variables: P_t^m probability of successful trading in market *m* at time *t*; R_t^m potential revenue from market *m* at time *t*; γ_m risk adjustment factor for market *m*, reflecting the unique risks of each market. We modify the objective function to incorporate these risks by adjusting the expected revenue using a risk factor that penalizes or rewards based on the risk characteristics of each market:

$$Maximize\ E\left[\sum_{m\in M}\sum_{t=1}^{T}(P_t^m \times R_t^m \times \gamma_m)\right] \tag{6}$$

Where *M* is the set of all markets. The risk adjustment factor γ_m decreases the contribution of higher-risk markets to the objective function, thereby incentivizing safer, more predictable operations. Next, we add constraints that ensure compliance with operational and regulatory requirements for each market:

$$\sum_{t=1}^{T}(P_t^m) \geq Min\ threshould\ of\ probability, \forall\ m \in M \tag{7}$$

Then, we define γ_m based on historical data and predictive modelling of market risks. For example: DAM and IDM might have lower γ values during periods of high price volatility, whereas ASM might have higher γ values during stable regulatory periods.

4. Findings

Average prices in electricity markets can vary significantly depending on a variety of factors including geographic location, time of day, season, market demand, supply conditions and the penetration of RES. In the DAM, electricity prices are determined one day before the actual delivery. Prices in these markets vary widely based on anticipated demand and supply conditions for the next day. Generally, prices might range from \$20 to \$60 per MWh, but during periods of high demand or supply shortages, prices can spike much higher, sometimes exceeding \$100 per MWh. IDM allow for trading electricity on the same day of delivery, providing a mechanism to adjust positions taken in the DAM. These markets are typically more volatile. Similar to the DAM but can exhibit greater fluctuations. Prices might briefly peak at even higher rates during unexpected supply shortfalls or sudden demand spikes. ASM involves services that support the transmission of electricity from generators to consumers and help maintain grid reliability. Services include frequency regulation, voltage control and spinning reserve. The pricing is often premium due to the necessity and urgency of these services. Prices can be significantly higher than energy-only markets, sometimes several times the average DAM price depending on the urgency and the scarcity of available resources. Capacity markets are designed to ensure that there is enough power supply available to meet peak demand. Participants are paid simply for being available to supply power, regardless of whether they actually generate electricity. Average payments range from $5,000 to $75,000 per MW per year, varying greatly by region and the reliability requirements of the grid (https://www.energy-storage.news/evolution-of-business-models-for-energy-storage-systems-in-europe/). BM manage the real-time variability in electricity supply and demand, ensuring that the grid remains stable. Prices in the BM can be highly variable. They range from negative values (when there is excess supply) to several times the average DAM rate during times of tight supply.

Estimating the potential annual revenue for an investor with a 10 MW installed ESS capacity requires some assumptions and calculations to provide an approximate estimate for different market scenarios. We assume its participation in DAM, IDM, ASM and capacity markets, and the following prices: for DAM, average price of $40/MWh; for IDM, average price similar to DAM but with higher volatility; for ASM, premium services might offer prices ranging from $50 to $300/MWh depending on the service and urgency; and for capacity market, an average payment of $20,000/MW per year.

We model the annual revenue from each type of market participation based on typical market operation scenarios: DAM and IDM-assume an average operational strategy where the ESS charges and discharges once per day (full cycle), with average price $40/MWh for buying or selling, energy cycled daily 10 MW x 1 cycle/day = 10 MWh/day. Let's assume 250 effective operational days/year (accounting for lower price days and maintenance), the revenue is 10 MWh/day x $40/MWh x 250 days = $100,000/year.

For ASM, assume participation in frequency regulation, priced higher due to its necessity, average price $100/MWh (conservative estimate for premium services), daily participation: Assume 4 hours of service per day at full capacity, effective days 300 days/year (high demand for grid stability services), the revenue is 10 MW x $100/MWh x 4 hours/day x 300 days = $1,200,000/year.

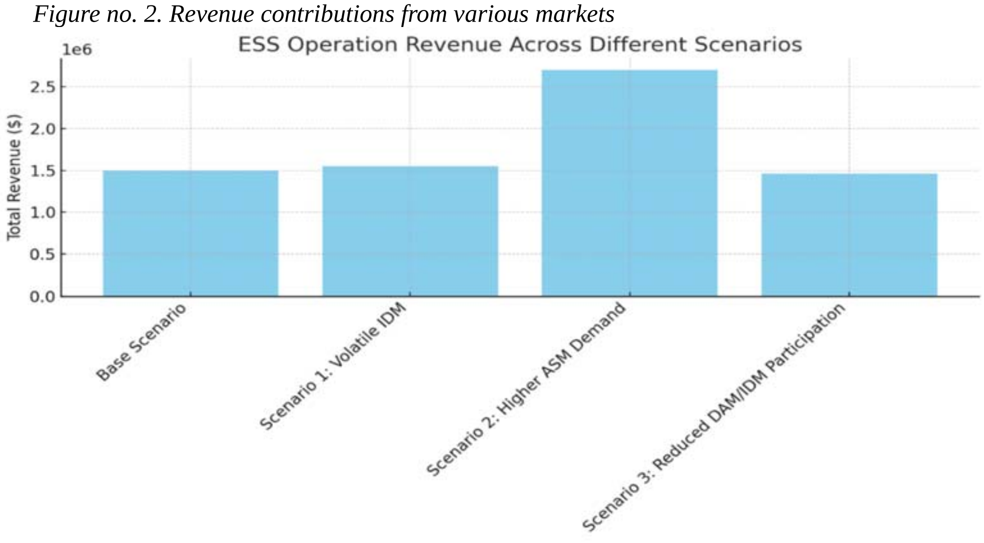
For capacity market, the annual payment rate: $20,000/MW and the revenue is 10 MW x $20,000/MW = $200,000/year. Total estimated annual revenue is from DAM and IDM ($100,000) + ASM ($1,200,000) + Capacity Market ($200,000). The total is $1,500,000/year. These costs need to be subtracted from the gross revenue to obtain net profits.

Three alternative scenarios are envisioned for a 10 MW ESS operation:

1. Scenario 1. Volatile IDM-Higher prices in the IDM lead to increased revenue from the DAM & IDM market.
2. Scenario 2. Higher ASM demand-A significant increase in ASM prices results in the highest total revenue.
3. Scenario 3. Reduced DAM/IDM participation-Reduced effective operational days for DAM & IDM lead to lower revenue from those markets.

Figure 2 breaks down the revenue contributions from DAM & IDM, ASM and the capacity market.

Figure no. 2. Revenue contributions from various markets



Source: Authors' contribution

Table 1 summarizes the revenue from different markets under each scenario, along with the assumptions driving those changes.

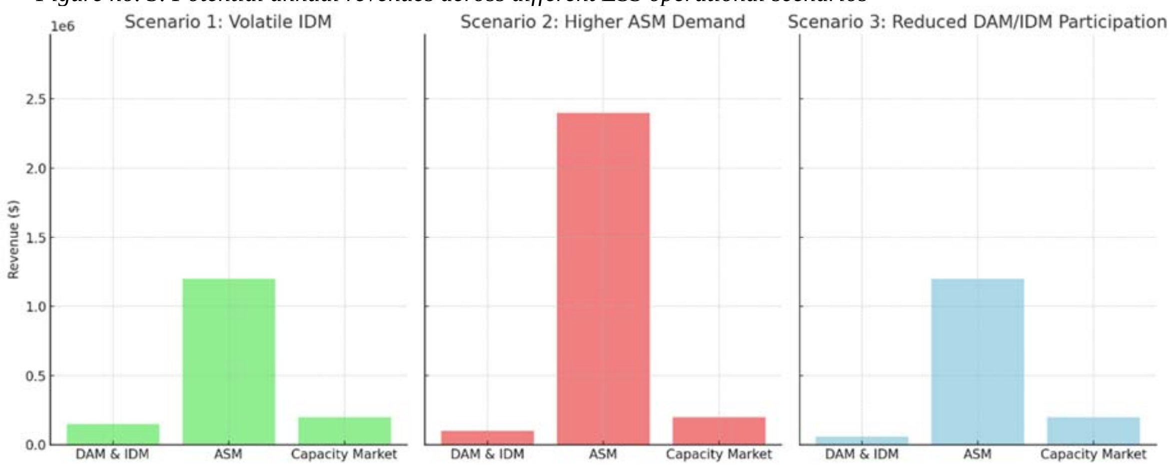
Table no. 1 Assumptions for each scenario and revenues

Scenario	Assumptions	Revenue from DAM & IDM ($)	Revenue from ASM ($)	Revenue from Capacity Market ($)	Total Revenue ($)
Base Scenario	- ESS Capacity: 10 MW - DAM & IDM Price: $40/MWh - 250 Operational Days for DAM/IDM - ASM Price: $100/MWh - ASM Participation: 4 hours/day, 300 days/year - Capacity market payment: $20,000/MW/year	100,000	1,200,000	200,000	1,500,000
Scenario 1. Volatile IDM	- IDM price increases to $60/MWh - All other assumptions remain the same	150,000	1,200,000	200,000	1,550,000
Scenario 2. Higher ASM demand	- ASM price increases to $200/MWh - All other assumptions remain the same	100,000	2,400,000	200,000	2,700,000
Scenario 3. Reduced DAM/IDM participation	- Only 150 operational days for DAM/IDM - All other assumptions remain the same	60,000	1,200,000	200,000	1,460,000

Source: Authors’ contribution

A comparison of potential annual revenues across different ESS operational scenarios is provided in Figure 3.

Figure no. 3. Potential annual revenues across different ESS operational scenarios



Source: Authors’ contribution

5. Conclusions

The analysis of alternative scenarios for energy storage system (ESS) operation provides several important insights. First, it is clear that revenue diversification significantly enhances the profitability of ESS operations. The ability to participate in multiple markets, including the DAM, IDM, ASM and the capacity market, offers strong financial advantages. This diversification buffers against market fluctuations and ensures a more consistent stream of income, even under varying conditions such as volatile IDM prices or reduced DAM/IDM participation. In the scenario where IDM prices increase due to market volatility, the total revenue sees a modest increase. This demonstrates that price fluctuations in the IDM may positively affect revenues, particularly if the ESS capitalize on the volatility by adjusting its operations. However, while beneficial, the impact of volatile IDM prices on total revenue is relatively modest when compared to the changes observed in ASM conditions.

The analysis further shows that higher prices in the ASM have a profound effect on total revenue. When ASM prices increase, the total revenue jumps significantly, illustrating that ancillary services play a crucial role in revenue generation. ASM-related services such as frequency regulation can provide much higher returns than traditional energy arbitrage in DAM or IDM. Thus, ESS operators should prioritize participation in ancillary services to maximize profitability.

On the other hand, when DAM/IDM participation is reduced due to fewer operational days, the total revenue declines. However, ASM and capacity market revenues help to stabilize overall earnings. Across all scenarios, ASM consistently generates the highest revenue compared to DAM/IDM and the capacity market. Even in the base scenario, the contribution from ASM dominates, highlighting its importance as a revenue driver for ESS operators. The capacity market, while offering lower returns compared to ASM, provides stable and predictable income. This revenue stream helps cover fixed costs and serves as a hedge against the volatility of other markets. In conclusion, stacking revenue streams from multiple markets and adopting flexible, dynamic strategies are important for maximizing financial returns.

6. Acknowledgement

This work was supported by a grant of the Ministry of Research, Innovation and Digitization, CNCS/CCCDI - UEFISCDI, project number COFUND-CETP-SMART-LEM-1, within PNCDI IV.

7. References

- Abedi, S., Yoon, S.W. and Kwon, S., 2022. Battery energy storage control using a reinforcement learning approach with cyclic time-dependent Markov process. *International Journal of Electrical Power and Energy Systems*. https://doi.org/10.1016/j.ijepes.2021.107368.
- Bhattacharya, A., Kharoufeh, J.P. and Zeng, B., 2018. Managing energy storage in microgrids: A multistage stochastic programming approach. *IEEE Transactions on Smart Grid*. https://doi.org/10.1109/TSG.2016.2618621.
- Kim, R.K., Glick, M.B., Olson, K.R. and Kim, Y.S., 2020. MILP-PSO combined optimization algorithm for an islanded microgrid scheduling with detailed battery ESS efficiency model and policy considerations. *Energies*. https://doi.org/10.3390/en13081898.
- Li, Q., Xiao, X., Pu, Y., Luo, S., Liu, H. and Chen, W., 2023. Hierarchical optimal scheduling method for regional integrated energy systems considering electricity-hydrogen shared energy. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2023.121670.
- Muschick, D., Zlabinger, S., Moser, A., Lichtenegger, K. and Gölles, M., 2022. A multi-layer model of stratified thermal storage for MILP-based energy management systems. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2022.118890.
- Song, H., Gu, M., Liu, C., Amani, A.M., Jalili, M., Meegahapola, L., Yu, X. and Dickeson, G., 2023. Multi-objective battery energy storage optimization for virtual power plant applications. *Applied Energy*. https://doi.org/10.1016/j.apenergy.2023.121860.
- Wang, X., Liu, J. and Wen, F., 2024. Optimal allocation of bi-level energy storage based on the dynamic ancillary service price. *Electric Power Systems Research*. https://doi.org/10.1016/j.epsr.2023.109953.

- Wu, D., Qi, T., Wei, W., Liu, J., Chen, L. and Mei, S., 2022. An Efficient Decomposition Method for Bilevel Energy Storage Arbitrage Problem. *CSEE Journal of Power and Energy Systems*. https://doi.org/10.17775/CSEEJPES.2021.02790.
- Zhao, L., Zhang, X. and Peng, X., 2022. Power fluctuation mitigation strategy for microgrids based on an LSTM-based power forecasting method. *Applied Soft Computing*. https://doi.org/10.1016/j.asoc.2022.109370.