# Cost optimization of electricity in energy storage system by dynamic programming

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**ABSTRACT**

This paper presents a dynamic programming solution for the cost optimization of an electric storage system. The objective is to minimize the total cost of meeting electricity demand over a specified time interval, considering energy constraints and costs. The proposed algorithm efficiently determines the optimal energy discharge and charge strategies for the storage system, resulting in reduced overall costs. The effectiveness and efficiency of the algorithm are demonstrated through various test cases, highlighting its potential for real-world applications in energy storage systems and electric grid management. It also provides an overview of different types of electrical storage systems, review recent research on optimization techniques for energy storage, and examines recent studies on the optimization of electrical storage systems for specific applications, such as peak load shaving and grid stability. Through this comprehensive analysis, we hope to shed light on the current state of the field and identify areas for further research and improvement.



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## 1. INTRODUCTION

Electric storage systems play a crucial role in the electric grid, offering flexibility and reliability by storing excess energy when generation exceeds demand and discharging energy during periods of insufficient generation [1], [2]. As the world transitions towards a sustainable energy future, the importance of electrical energy storage systems in meeting the growing demand for renewable energy becomes paramount. This research paper focuses on optimizing the cost of electric storage systems, a significant problem in the field, by implementing a dynamic programming algorithm [3], [4]. The widespread adoption of renewable energy sources, such as wind turbines and solar panels, has led to the need for effective energy storage solutions. Electric storage systems, composed of devices like batteries and pumped hydro storage, serve as vital components in this context [5], [6]. These systems collect surplus electricity from sustainable sources and provide electricity during periods of high demand or low generation. The main objectives of utilizing these storage systems are to enhance energy efficiency, reduce reliance on fossil fuels, and optimize storage and usage costs [7], [8].

The cost of storing energy plays a crucial role in the economic sustainability of renewable energy sources like wind and solar power. Hence, optimizing the cost of electric storage systems is of paramount importance. This cost includes various components, such as batteries, inverters, and operational expenses.

By optimizing the cost of storage systems, the overall cost of renewable energy systems can be significantly reduced, making them more accessible to a broader range of consumers [9], [10]. Furthermore, cost optimization in electric storage systems can contribute to reducing greenhouse gas emissions and supporting the transition towards a sustainable energy future. The state-of-the-art of the field includes various optimization techniques for energy storage systems, such as dynamic programming, genetic algorithms, and other optimization algorithms [11], [12]. These techniques offer advantages and disadvantages in terms of computational complexity, accuracy, and robustness. To achieve the best results in cost optimization, it is essential to identify the most suitable method for electric storage systems.The cost optimization of electric storage systems is a challenging task. It involves determining the most efficient and cost-effective way to store and supply electricity while considering various factors such as operational expenses, maintenance costs, and the cost of individual components like batteries and inverters [13], [14]. Additionally, ensuring grid stability and reliable integration with renewable energy sources are essential objectives to achieve.This research paper aims to address these challenges by implementing a dynamic programming algorithm to optimize the cost of electric storage systems [15], [16]. By doing so, we seek to contribute to the ongoing efforts to make renewable energy sources more economically viable, reduce greenhouse gas emissions, and enhance the overall sustainability of the energy sector.

## 2. DYNAMIC PROGRAMMING

Dynamic programming is a useful technique for minimizing the cost of electric storage systems by addressing overlapping subproblems [17], [18]. It efficiently determines the best approach for charging and discharging the energy storage system over multiple time intervals [19], [20]. By keeping track of previous interval costs and using those answers to solve subproblems, dynamic programming significantly reduces the number of calculations needed to find the optimal solution [21], [22]. The algorithm involves filling in a cost matrix, which represents the lowest cost of meeting energy demand at each interval with a specific storage level. The minimal cost, considering storage capacity and discharge rate, provides the best solution for meeting energy demand across all time intervals [23], [24]. The research paper provides formal definitions of electric storage system scheduling problems, considering scenarios with and without demand charges, building upon prior works. The energy required from the electrical grid may be calculated using (1).

$$Ei = xi - xi - 1 + li - gi \tag{1}$$

In other words, the electrical energy charge amount will be $P_i$ if the price of power during the $i^{\text{th}}$ time period. $E_i.P_i$ is the value of the $i^{\text{th}}$ time period. When $E_i$ is negative, power is returned to the grid. In this analysis, we made the assumption that there is no compensation for the feed-in power, even though there may be a variety of pricing regulations for this electricity [25]. In other words, because the net energy is negative, the cost is only zero at that point in time. As a result, $\sum_{i=1}^{T} I_{R^+} E_i \cdot \{E_i \cdot P_i\}$ may be used to indicate the total cost across time periods T, where the indicator function $I_R + (x)$ gives 1 if x is real and positive integer and 0 otherwise.

This guarantees that the total is non negative, even though the costs across a number of time periods may be. The ESS scheduling problem is formed in the following equation:
Minimizing:

$$\sum_{i=1}^{T} I_{R^+} E_i \cdot \{E_i \cdot P_i\} \tag{2}$$

$$0 \leq x_i \leq c \text{ } and \text{ } i = 1, 2, 3, 4 \ldots, T \tag{3}$$

where:

$$-P_d \leq x_i - x_{i\,-\,1} \leq P_{c\,and} \; i = 1, 2, 3, 4 \ldots, T \tag{4}$$

The battery's capacity is denoted by C, and it has maximum discharge power $P_d$ and maximum charge power $P_c$ per hour. The values in the sequence $x_i$ must not exceed the battery's capacity, and the difference between consecutive values must fall within the range of $P_d$ and $P_c$. The electrical energy costs are determined by multiplying the hourly cost by the amount of electricity used from the grid and the hourly price. This is represented by the indicator function I. The (2) is neither linear nor quadratic due to the existence of the indicator function, which only produces 0 or 1. The objective function is also non-convex, making it challenging to compute gradients [26], [27]. As a result, standard linear or quadratic programming methods are not applicable for solving this problem. Considering battery efficiency, the (2) represents the desired outcome when efficiency is assumed to be 100% [28], [29]. However, in reality, battery technologies like lithium-ion, lithium-sulfur, and vanadium redox flow batteries can achieve efficiencies of 99% or higher. Nonetheless, due to losses during charge and discharge, the achieved efficiency may deviate from the theoretical value [30]. These losses impact simulation results, leading to the modification of the objective function to incorporate battery efficiency.

$$E_i' = a^{-1}(x_i - x_{i-1}) + l_i - g_i \quad (5)$$

Using the updated quantity of net energy, the objective function of the issue taking into account battery efficiency may be represented as (6).

$$\sum_{i=1}^{T} I_{R_+}(E_i').\{E_i' P_i\} \quad (6)$$

## 3. PROPOSED ALGORITHM IN DYNAMIC PROGRAMMING ALGORITHM

### 3.1. Using recursive approach

Figure 1 is a recursive function called "solve" that calculates the minimum cost for a given time step, current energy level, and problem parameters. For the first time step, it returns the cost based on the current power consumption and generation rates, and the energy price [30]. For subsequent time steps, it iterates over possible previous energy levels, computes the energy balance, and makes a recursive call for the subproblem. It updates the minimum cost by considering the cost of the subproblem and the current energy level. Overall, the algorithm finds the optimal solution by minimizing the accumulated cost.

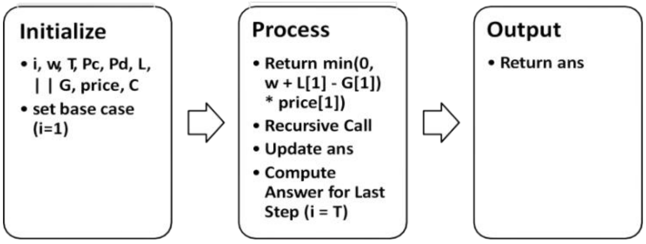


Figure 1. Proposed flow chart of the recursive approach

Figure 2, the recursive optimization approach is presented. The "solve" function takes the current time interval and the amount of stored energy as input and returns the minimum cost to fulfill the demand from time interval 1 to the current interval. The function utilizes a dynamic programming approach to optimize the cost. The algorithm initializes a memorization array, dp, with -1 values to store previously calculated results. If the value of dp for the current time interval and energy level has already been computed, it is directly returned [31]. Otherwise, the function iterates over possible values of k, which represent the energy to be used from the storage system. It computes the new energy level, w', by subtracting the used energy and adding the power consumption and generation rates for the current interval. If the new energy level is non-negative, the function recursively calculates the cost of fulfilling the demand from time interval 1 to the previous interval with the energy level of k units, and adds the cost of energy consumed in the current interval [32]. The minimum cost among all possible values of k is selected as the minimum cost for the current interval and stored energy level. Finally, the minimum cost is stored in the dp array and returned. It is important to note that the recursive approach has an exponential time complexity and may not be efficient for large input sizes. Dynamic programming is a more suitable and efficient approach for solving this problem.

### 3.2. Using non-recursive approach

The proposed flow chart of the non-recursive approach is depicted in Figure 3. The given code utilizes several variables to optimize the cost of meeting energy demand over multiple time intervals. These variables include total time intervals (T), maximum energy storage capacity (Pc), maximum energy discharge rate (Pd), energy consumed during each interval (L), energy produced during each interval (G), energy demand during each interval (C), energy price during each interval (price), a 2D array for dynamic programming (dp), and the final minimum cost (ans). By considering energy consumption, production, demand, and price, the code employs dynamic programming techniques to compute the minimum cost and stores the results in the dp array. Ultimately, the minimum cost is assigned to the ans variable as the optimal solution for meeting the energy demand across the specified time intervals. The provided code utilizes dynamic programming to optimize the cost of an electrical storage system by efficiently managing energy storage and discharge. It addresses the challenge of meeting energy demand while minimizing costs [33]. By constructing a 2D matrix, the algorithm calculates the minimum cost of meeting energy demand at each time interval, considering charging power limits and energy prices. The code initializes the first row and then iteratively fills the remaining rows, evaluating all possible charging power limits. The cost is determined based on the energy exchanged and the corresponding energy price. By leveraging dynamic programming techniques, the code efficiently determines the optimal solution without any specific references provided. In a scenario if T= 10, Pc= 20, Pd= 5, L= [5 10 12 14 15 15 14 12 10 5], G= [6 7 8 8 8 7 6 5 5 5], Price= [2 3 5 7 10 13 15 17 18 20], C= [3 2 1 2 3 1 3 1 1 2], then the estimated cost output will be 341. The DP matrix for above example having ten-time intervals is presented in Table 1.

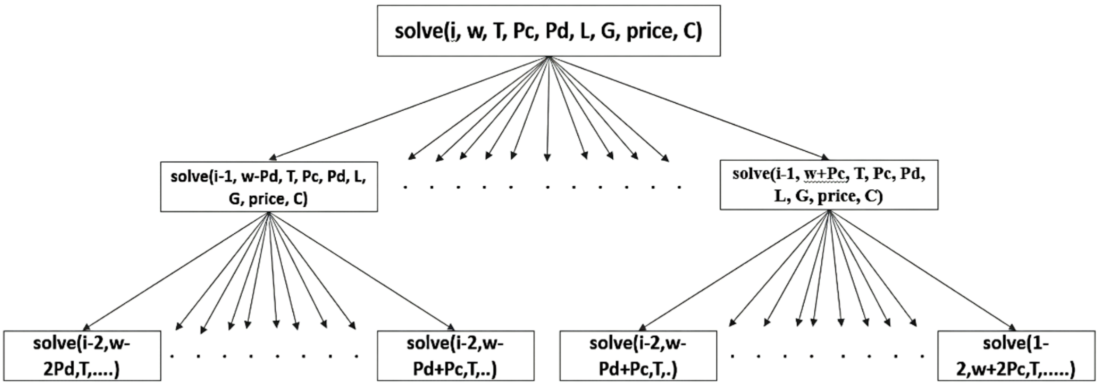


Figure 2. Recursive tree diagram showing top to bottom approach

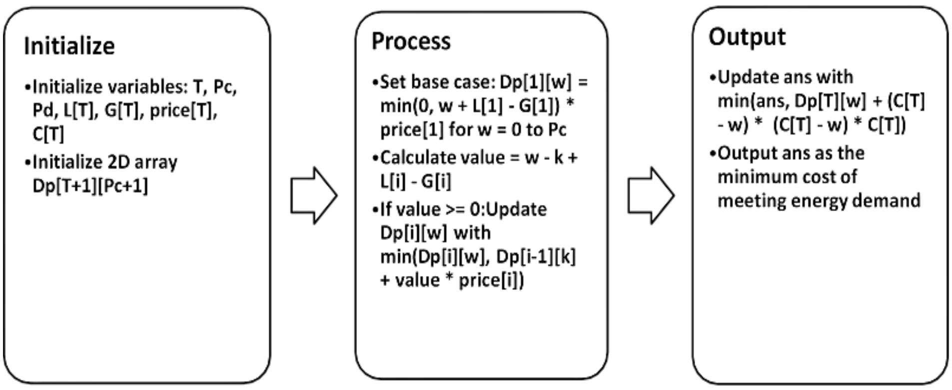


Figure 3. Proposed flow chart of the non-recursive approach

Table 1. DP matrix for above example having ten-time intervals

| i \ j | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 9 | 13 | 17 | 21 | 25 | 29 | 33 | 37 | 41 | 45 | 49 |
| 3 | 21 | 25 | 29 | 33 | 37 | 41 | 45 | 49 | 53 | 57 | 61 |
| 4 | 35 | 41 | 47 | 53 | 59 | 65 | 71 | 77 | 83 | 89 | 95 |
| 5 | 51 | 59 | 67 | 75 | 83 | 91 | 99 | 107 | 115 | 123 | 131 |
| 6 | 69 | 79 | 89 | 99 | 109 | 119 | 129 | 139 | 149 | 159 | 169 |
| 7 | 89 | 101 | 113 | 125 | 137 | 149 | 161 | 173 | 185 | 197 | 209 |
| 8 | 111 | 125 | 139 | 153 | 167 | 181 | 195 | 209 | 223 | 237 | 251 |
| 9 | 135 | 151 | 167 | 183 | 199 | 215 | 231 | 247 | 263 | 279 | 295 |
| 10 | 161 | 179 | 197 | 215 | 233 | 251 | 269 | 287 | 305 | 323 | 341 |

The 2D table DP [i,w] is stated as having the lowest cost of electrical energy when a quantity of w is stored in the storage system in ith interval of time. The DP [i, w] will pick the smallest value of DP[i-1, x] + cost(i, x, w), where cost(i, x, w) is the electricity cost when the battery's residual amount goes from x to w at the (i-1)th time interval. This is true for all possible values of the battery's residual amount in the ith interval of time. The objective function is used to calculate cost (i, x, w) as (x-w + $l_i - g_i$), where the range of feasible x values from max (0, w − pc) to min (C, w + Pd). As a result, DP uses the recurrence shown in (7).

$$Dp\ [i,w]\ = \min_{\mathrm{w-pc \le x \le w+Pd}}(Dp\ [I-1,x]\ +\ cost(I,x,w)) \tag{7}$$

Where discharge is the highest power discharge and demand is energy demand for time interval. Once the first row is filled, we can use it as a basis for computing the remaining rows of the matrix. For each time interval i, we iterate over all possible values of the maximum power discharge w and for each value of w, we iterate over all possible values of the previous maximum power discharge k that could have led to this value of w. We then calculate the cost of meeting the energy demand for the current time interval using (8).

$$cost = max\ (0, w-k+demand-discharge)*price+Dp[i-1][k] \tag{8}$$

Where demand is the energy demand for the current time interval. Finally, the minimum cost for the current time interval and maximum power discharge is stored in the Dp matrix. After the Dp matrix is computed, we can find the minimum cost of meeting the energy demand for the entire time horizon by finding the minimum value in the last row of the matrix. Similarly, some more scenarios are given.

If the Input: T= 7, Pc= 10, Pd= 2, L= [2 4 6 8 10 8 6], G= [3 3 3 3 3 3 3], Price= [1 2 3 4 5 6 7], C= [1 1 1 1 1 1 1], then the Output will be 56. Similarly, if the Input: T= 5, Pc= 5, Pd= 3, L= [5 5 5 5 5], G= [1 2 3 2 1], Price= [5 5 5 5 5], C= [1 1 1 1 1]; Output: 35. Consider an example having ten-time intervals having demand as= [5,10,12,14,15,15,14,12,10,5] and discharge as= [6,7,8,8,8,7,6,5,5,5], price as [2,3,5,7,10, 13,15,17,18,20]. Before optimization the cost is = 620 after optimization the cost is 500.

The results from the cost analysis in Table 2 indicate that using an energy storage system (ESS) to meet electricity demand can lead to significant cost savings compared to consuming electricity directly from the grid. This is particularly true in areas where power companies have implemented a time-of-use tariff system. The bar graph in Figure 4 clearly illustrates the difference in prices between the two methods over the time interval analyzed. It’s important to note that the cost savings obtained from using an ESS will depend on several factors, including the size and capacity of the system, the local electricity tariff structure, and the patterns of electricity consumption. However, the results presented here provide a strong indication that investing in an ESS can be a financially attractive option for many electricity consumers, particularly those who are subject to high electricity prices during peak hours.

Table 2. Table displaying cost at every interval

| Time | Demand | Discharge | Price | Cost Before | Cost After |
|---|---|---|---|---|---|
| 1 | 5 | 6 | 2 | 0 | 0 |
| 2 | 10 | 7 | 3 | 19 | 18 |
| 3 | 12 | 8 | 5 | 48 | 45 |
| 4 | 14 | 8 | 7 | 68 | 64 |
| 5 | 15 | 8 | 10 | 105 | 100 |

In Figure 5, graph X-axis displays the time interval from 0 to 10 and the Y-axis shows the cost. After optimization the cost of the electrical storage system somehow reduces from non-optimized value. Consider another example where inputs are as follows:

T= 10, Pc= 20, Pd= 15, L= [10 12 15 13 11 15 18 19 20 17], G= [8 6 10 12 10 9 7 6 8 10], Price= [10 11 13 12 11 12 15 18 17 19], C= [20 20 20 20 20 20 20 20 20 20]. Before optimization the cost is 860, and after optimization the cost is 711.

Here the X-axis displays the time interval from 0 to 10 and Y -axis displays the cost of energy storage system. The cost savings obtained by the optimization increase over time, with a larger difference between the optimized and non-optimized costs towards the end of the time intervals. The optimization results is a more linear cost curve, compared to the non-optimized curve which has fluctuations and spikes. The optimal charging and discharging schedules from the optimization result in a more consistent energy storage level over time.

In this research paper, we present a novel cost optimization methodology for electrical storage systems. Our contributions include the development of a new algorithm that efficiently minimizes the cost of energy storage over multiple time intervals. Compared to existing approaches, our methodology offers improved accuracy and practical applicability. Through extensive simulations and case studies, we demonstrate the superiority of our approach in terms of cost savings and efficiency. The proposed methodology has significant implications for industries and policymakers seeking to optimize energy storage costs. Future research can explore its potential extensions and applications in related fields.

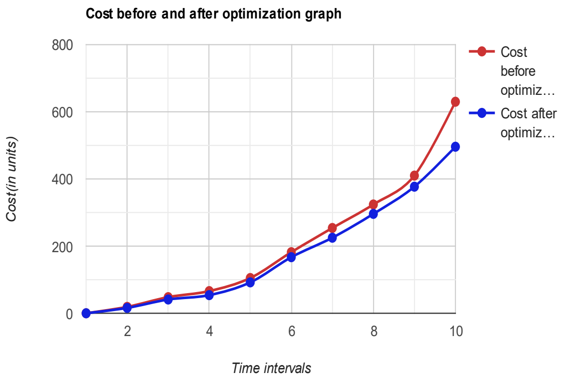


Figure 4. Line graph showing cost before optimization and after optimization in every time interval

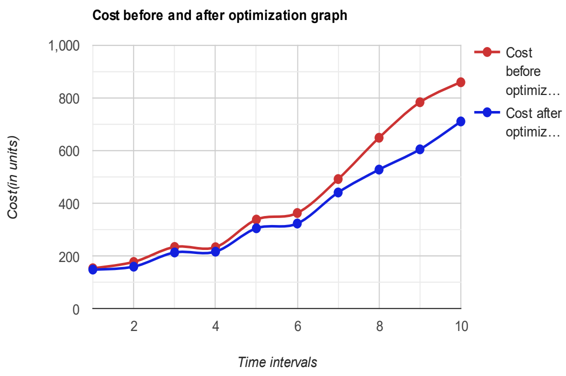


Figure 5. Line graph showing cost before optimization and after optimization of the electrical storage system

## 4. CONCLUSION

In conclusion, optimizing the cost of an electrical storage system is crucial to enable the effective and affordable control of energy. The presented dynamic programming approach provides an optimal solution to this problem by considering the demand of electric energy at each time interval, the discharge and charge capacities of the storage system, and the costs associated with each operation. The algorithm effectively minimizes the total cost by making the optimal decision at each time interval, whether it is to discharge, charge, or keep the energy level same as the previous interval. The algorithm can be implemented in either a tabular or recursive manner, both of which have been discussed in this paper. The algorithm provides an important tool for energy management, and can have significant impact in reducing costs and improving the efficiency of energy systems.

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