Optimal Design for Hybrid Energy Storage Systems Considering System Aging and Costs

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***Abstract*—Some challenges of high penetration of renewable energy sources (RES), such as frequency variation and voltage deviation, can be minimized using an energy storage system (ESS). Some ESS have complementary features that make them desirable to use in a hybrid mode. While hybridizing different ESS, their power-sharing control plays a crucial role in exploiting the supportive characteristics of each other. Among various control strategies, a low pass filter is widely used to separate the low and high-frequency signals in a Hybrid Energy Storage System (HESS). This paper proposes a Multi-Objective optimization model for a battery and flywheel HESS based on two variables of total cost and the life loss costs of the battery. The cost function is obtained by the different costs of the power and energy for the battery and the flywheel. In contrast, the life loss cost of the battery is obtained by cycle counting of the battery's energy profile using the rainflow cycle counting (RFC) algorithm. To solve the optimization model, a genetic algorithm is employed to obtain the Pareto front. VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique is applied to select the optimal solution from Pareto solutions.**

***Index Terms*—hybrid energy storage, filter, multi-objective, optimization, battery, flywheel, Pareto, VIKOR, rainflow**

I. Introduction

Climate change is often addressed as the most critical concern in the 21st century. Among available solutions to mitigate this issue, using renewable energy systems (RES) is widely accepted as the best substitute for conventional energy resources based on fossil fuels. However, using RES brings up some challenges due to their low inertia and unpredictability as voltage instability, frequency fluctuation, poor power quality, and load-following [1]. These challenges can be alleviated using energy storage systems (ESS) [2]. Several countries have already started investing in ESS technologies. As an example, Germany expects a considerable deployment of ESS as a result of lower costs of batteries in the near future [3]. Thanks to the advancement in ESS technologies, there are a variety of these systems, like compressed air energy storage (CAES), supercapacitors (SC), superconducting magnetic energy storage (SMES), flywheels, pumped hydro storage, hydrogen tanks, and different batteries to facilitate the stable operation of the grid. Although there are various ESS in the market, every ESS has limitations restricting its range of applications. For instance, each ESS is limited by its power or energy density, while an ideal application simultaneously demands both features. Therefore, it makes sense to build a system with a combination of two ESS that can overcome the disadvantages of a single one by combining the advantages of both [4]. By hybridization, more benefits can be obtained. However, the importance of controlling the functionality of both systems working together is inevitable in this case. Due to the complexity of a HESS, some challenges such as estimating the internal state of the system accurately, extending the battery life, and realizing the coordinated and optimized control of power and energy in the system have been addressed in various research from the fields of materials, information, energy, control, and artificial intelligence [5].

Among widely used storage systems, Lithium-ion (Li-ion) batteries have been the most predominant source in different scales, from phones and laptops to electric vehicles and grid-energy storage [6], [7]. However, if Li-ion batteries are used in a fast transient with a large power force, the degradation of the battery would be faster, and the life of the battery decreases [8]. On the other hand, fast-dynamic ESSs such as a Flywheel Energy Storage System (FESS) can quickly react to power changes without any visible impact on their lifetime [9]. Thus the combination of these two systems is worth to be studied for HESS applications. The structure of a HESS in the power system with solar energy as RES and battery and flywheel as storage systems can be seen in Fig. 1. The connection of the single ESS units can occur either on the AC side or at the DC level. In this work, the DC connection is preferred due to the simpler control approach and the higher efficiency of the system.

Various strategies to control a HESS are mostly categorized into three big groups. Rule-based controllers (RBCs), filtration-based controllers (FBCs), and optimization-based controllers. FBCs, such as a Low-Pass Filter (LPF), are the most frequently used controllers for HESS, mainly separating the power demand into high and low-frequency components. This benefits the batteries by reducing their power and energy variations [10]. Choosing the cut-off frequency while designing the LPF directly affects the sizing of the HESS. On the other hand, the project's cost, which includes the total capital

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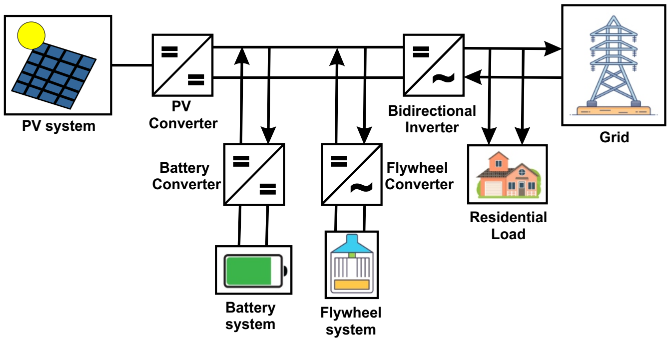

Fig. 1. Separating Signals in a Hybrid Energy Storage Systems Using a Low-Pass Filter

cost, replacement cost, operation, and maintenance (O&M) cost, can be reduced significantly by optimizing the sizing and the lifespan of ES [11], [12]. Thus, it is essential to optimize the cut-off frequency of the LPF while considering the battery's life and the HESS's cost.

This paper analyzes the effect of different cut-off frequencies on the HESS cost and life loss of the battery based on its number of cycles. More precisely, this study helps to optimally size the HESS by finding the optimal cut-off frequency of the LPF, considering costs and the life of the battery. The optimal cut-off frequency for the LPF is obtained by solving a multi-objective optimization using Pareto analysis and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR).

Section II of this paper describes the HESS model using an LPF. In section III, the two different optimization functions based on the total cost of the HESS and the battery's degradation cost are defined. The Pareto analysis and obtaining the optimal value using VIKOR for a study case is explained in IV. In the last section V, the work of this paper is concluded.

II. Model: Hybrid Energy Storage Using a Filter

Figure 2 shows the power control approach implemented in this work. A LPF is used to dispatch the power between the battery and the flywheel, splitting the low and the high-frequency signals based on (1).

$$Filter = \frac{1}{1 + Ts\cdot} \tag{1}$$

with $T = \frac{1}{w_f}$ where w_f is the cut-off frequency of the filter. With this approach, the fast power variations are destined for the flywheel, while the battery can focus on slower but more energy-needed power swings.

However, it must be noted that the filter's cut-off frequency determines how much each ESS contributes to compensating for the input power. Thus, this value is an important factor in how large (and expensive) the whole system is going to be and how much the battery is going to be involved in high-frequency power compensation.

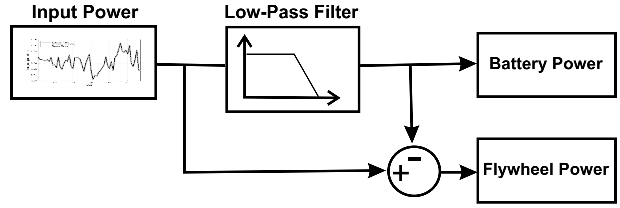

Fig. 2. Separating Signals in a Hybrid Energy Storage Systems Using a Low-Pass Filter

III. Optimal Cut-Off Frequency under Different Objective Functions

A. Cost Objective Function

Since the two ESS are responsible for either the high energy or high power signals, it makes sense to allocate a different cost for their energy and power. Therefore, the first objective of the defined hybrid system is the total cost reduction as below:

$$Cost\ Objective\ Function = Total\ costs \tag{2}$$

Where:

$$Total\ costs = Battery\ costs + Flywheel\ costs \tag{3}$$

$$Battery\ costs = a \cdot P_{n_{battery}} + b \cdot E_{n_{Battery}} \tag{4}$$

$$Flywheel\ costs = c \cdot P_{n_{Flywheel}} + d \cdot E_{n_{Flywheel}} \tag{5}$$

Weighting Coefficients a, b, c and d are based on the costs obtained from [18], [19] presented in the table I.

TABLE I
Cost of Battery and Flywheel Energy and Power

Cost E (\$/kWh)		Cost P (\$/kW)	
b-Battery	d-Flywheel	a-Battery	c-Flywheel
350	1800	1400	120

The nominal power P_n is calculated by applying the one-way efficiency η of the ESS while considering both charging and discharging modes by the sgn function. The nominal energy E_n is estimated by integrating over the power profile as well [13].

The corresponding equations are shown in (6) and (7).

$$P_n = \max|R(t)| \quad \text{where} \quad R(t) = \eta^{sgn(P(t))}P(t) \tag{6}$$

$$E_n = \frac{maxE(t) - minE(t)}{SOC_{max} - SOC_{min}} \quad \text{where} \qquad E(t) = \eta^{sgn(P(t))}\int_0^t P(\tau)d\tau \tag{7}$$

As a result of the optimization, the cut-off frequency of the filter determines the ESS power and energy ratings, respectively. Thus, the HESS cost is affected by changing this value. This impact can be seen in Fig. 3, where the HESS costs are plotted under different filter's cut-off frequencies. A higher cut-off frequency means the battery is responsible for more part of the power compensation. Due to the higher cost of the flywheel energy density, a higher cut-off frequency shows a lower price.

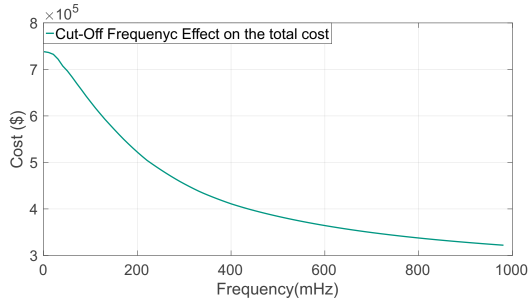

Fig. 3. The effect of different cut-off frequency on the cost of HESS

B. Life Loss Cost of the Battery Using Rainflow Algorithm

One of the primary reasons to use a HESS is to maintain the battery's health for a longer period. To consider this factor, the second objective function is defined based on the life loss of the battery, which is related to the number and depth of the cycles.

1) Rainflow Cycle Counting Algorithm: The Rainflow Cycle Counting (RFC) method is widely used in literature to estimate the degradation modeling of the battery in the form of cycle identification [14], [15]. The cycle counting using RFC in this paper is based on [16] where the energy profile of the battery is taken as input, the local extreme points are identified. Then the depth of all cycles is counted based on local extreme sequences. Moreover, the life loss cost is defined based on [17] where the cycle aging of electrochemical battery cells is evaluated based on stress cycles and the battery degradation cost is modeled based on the RFC method. The algorithm is explained in the steps below:

Step 1: The energy profile of the battery is used as an input.

Step 2: The profile is plotted vertically downward and the lines connecting the profile peaks are referred as to a series of pagoda roofs. Half cycles are counted between the most positive maximum and the most negative minimum based on some rules:

- Half cycles are counted between the most positive maximum and the most negative minimum occurring before it in history and between this minimum and the most positive maximum occurring before it.
- After the most negative minimum in history, half cycles are counted which terminate at the most positive maximum occurring subsequently in history, the most negative minimum occurring after this maximum.

This process continues till the beginning or the end of the time history of the input profile depending on the extrema. The flowchart of the first iteration of the process of choosing the half cycle is shown in Fig. 4.

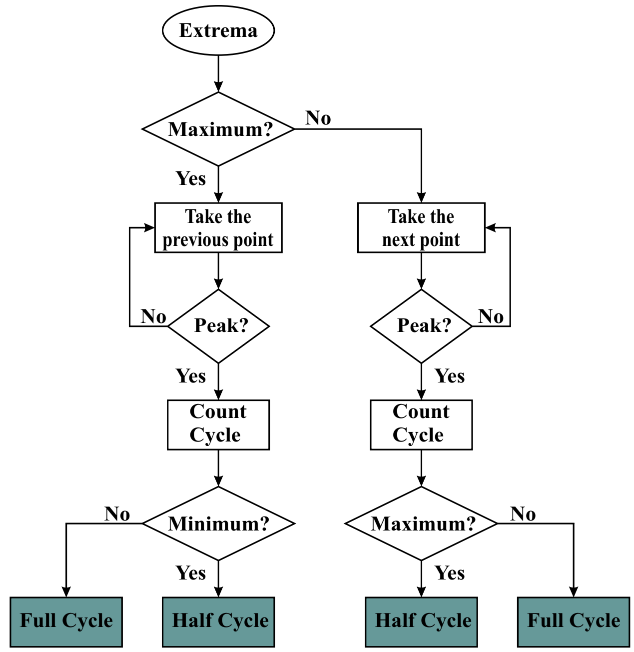

Fig. 4. Flowchart of counting the cycles based on rainflow algorithm

Step 3: The rest are counted as full cycles.

Step 4: The depth of the cycle is obtained from its range.

The total number of cycles is counted by summing the full cycles and considering two half cycles as one cycle. Figure. 5 shows how the number of cycles by RFC changes by changing the cut-off frequency.

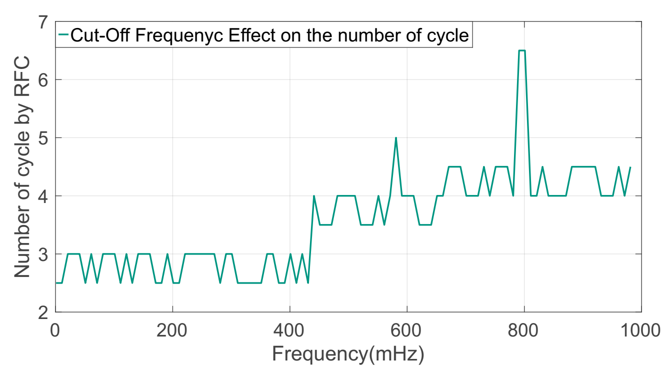

Fig. 5. Effect of cut-off frequency on the number of cycles by RFC

2) Battery Degradation Cost: with $u = [u_1, u_2, ...u_N]$ as a cycle depth vector and $X = [x_1, x_2, .., x_T]$ as the battery energy profile of length T, we can define:

$$u = \mathit{Rainflow}(X) \tag{8}$$

The life loss of the battery is modeled after counting the cycles with a cycle depth stress function $Q(u)$, which is obtained by the depth of each cycle in the rainflow algorithm.

Cycle aging is a cumulative fatigue process. Thus, total life loss (ΔL) is defined as the sum of the life loss from all cycles as below:

$$\Delta L(X) = \begin{cases} \frac{Q(u_i)}{2} & u_i \text{ is a half cycle} \\ Q(u_i) & u_i \text{ is a full cycle} \end{cases} \tag{9}$$

For optimizing the size of the battery, the life loss function is converted to a cost function by considering the cost of energy in the battery as shown in (10):

$$\textit{Life Loss Cost Function} = \Delta L \cdot b \cdot E_{n_{Battery}} \tag{10}$$

Where b and $E_{n_{Battery}}$ are obtained as in subsection III-A.

IV. Case Study

The optimal cut-off frequency of the optimization analyses in this work is used to size a HESS for a power profile obtained from [10]. The power profile is obtained from an improved motif discovery algorithm to find the most recurring daily consumption patterns within the time series of interest. The input data was recorded in South Germany over the summer of 2018 at four different 10/0.4 kV substations.

A. Pareto Analysis of Genetic Algorithm

Two objective functions are solved by a genetic algorithm using Matlab. Pareto analysis is used for obtaining multi-objective optimization since this work aims to simultaneously minimize the total cost of the HESS and battery degradation. VlseKriterijumska Optimizacija I Kompromisno ResenjeEV electric vehicle (VIKOR) Method is used to obtain the optimal cut-off frequency of the filter, which is explained in detail in IV-B.

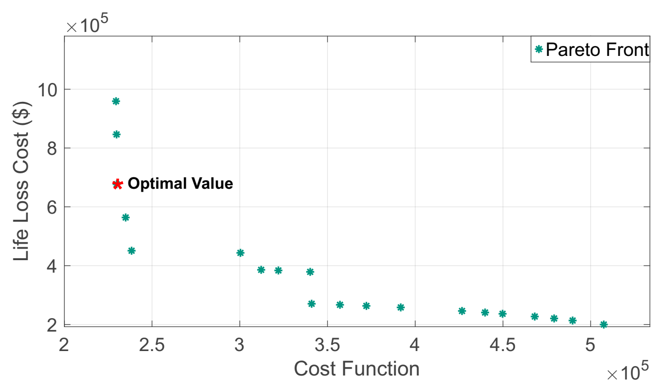

Fig. 6. Pareto front analysis of the total cost of the system and life loss cost of the battery

B. VlseKriterijumska Optimizacija I Kompromisno ResenjeEV Electric Vehicle (VIKOR) Method

The decision-making is inspired by [13] a multi-criteria decision-making method that can choose the optimal solution based on the distance concerning the ideal solution for each objective. The steps to find the most optimal value are as follows:

Step 1: Establish a matrix of criteria and alternatives. For N_{pop} being the population size and N_{obj} being the number of objectives, the values can be defined as:

$$r_{ij} \quad \text{where} \quad i = 1, .., N_{pop}; j, .., N_{obj} \tag{11}$$

Step 2: Determine the best and the worst values:

$$r_i^+ = max(r_{ij}) \quad \text{and} \quad r_i^- = min(r_{ij}) \tag{12}$$

Step 3: With w_i being the weight of the corresponding objective, compute the values of S_j and R_j as bellow:

$$S_j = \sum \left[\frac{w_i(r_i^+ - r_{ij})}{r_i^+ - r_i^-} \right] \tag{13}$$

$$R_j = max \left[\frac{w_i(r_i^+ - r_{ij})}{r_i^+ - r_i^-} \right] \tag{14}$$

Step 4: Compute Q_j for utility function:

$$Q_j = v \frac{S_j - S^+}{S^- - S^+} + (1 - v) \frac{R_j - R^+}{R^- - R^+} \tag{15}$$

Where :

$$S^+ = max(S_j) \quad \text{and} \quad S^- = min(S_j) \tag{16}$$

$$R^+ = max(R_j) \quad \text{and} \quad R^- = min(R_j) \tag{17}$$

And v is the group utility maximization coefficient which is considered 0.5 for the balance in evaluating the alternatives.

Step 5: Rank alternatives by sorting Q_j to obtain the most optimal value.

Figure 6 depicts the Pareto front analysis of the two objective functions of the total cost and the life loss cost based on the number of cycles gained by the rainflow counting method. The optimal frequency, where both objective functions are minimized, gained by the VIKOR analysis is also shown in this figure. The VIKOR analysis resulted in the optimal frequency of $88.4mHz$.

The filter uses the cut-off frequency to obtain each ESS's power profile. The result of this power contribution is shown in Fig. 7. The comparison between the cost, number of cycles,

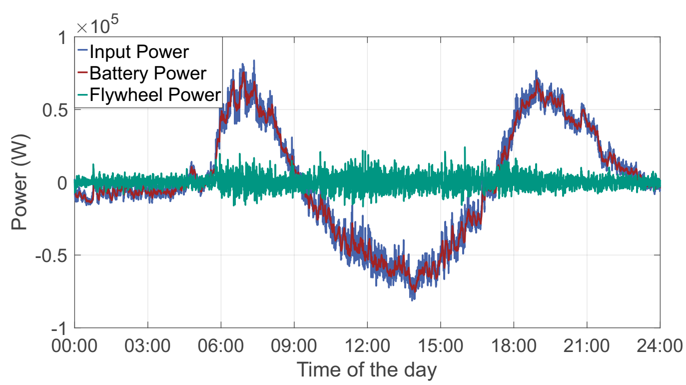

Fig. 7. Power allocation for the battery and flywheel storage systems with the optimal cut-off frequency of $88.4mHz$

and life loss of a single battery with an optimal HESS are shown in table II. While with only the battery storage system compensating for the input power, the number of cycles by RFC for the battery's energy profile is 219, using an optimal HESS leads to 11 rainflow cycles, and the life loss of the battery decreases by the cost slightly increasing with the additional energy storage. This is due to the fact that using a HESS reduces the stress on the battery, which results in a longer life of it, while the cost of the system is optimized by the proper choice of the controller.

TABLE II
COMPARISON OF THE OPTIMAL HESS WITH A SINGLE BATTERY

	Total Cost	RFC Cycle	Life Loss
Single Battery	25.74e+07	219	1.28e+09
Optimal HESS	25.72e+07	11	1.27e+09

V. CONCLUSION

The power control strategy is essential in the planning and operating HESS, where an appropriate cut-off frequency plays an important role. While the cost of the HESS is an important factor in choosing the cut-off frequency and battery contribution, the importance of the battery degradation should not be underestimated. This paper provides a more in-depth analysis of how the cost and degradation of the battery change by choosing a different cut-off frequency for the power controller dispatching filter. A multi-objective optimization model is defined for solving the two cost functions using a genetic algorithm and Pareto front analysis, with whom the optimal cut-off frequency for sizing the HESS is obtained.

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