Sizing of Energy Storage Systems in Electric Vehicles based on Battery-Supercapacitor Technology

Denny Alfani
Department of Electrical Engineering
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
denny.alfani@gmail.com

Dimas Febry Adityanugraha
Department of Electrical Engineering
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
dimas.febry2728@gmail.com

Vita Lystianingrum
Department of Electrical Engineering
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
vita@ee.its.ac.id

Feby Agung Pamuji
Department of Electrical Engineering
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
feby@ee.its.ac.id

***Abstract*— The purpose of this research is to determine the ideal hybrid energy storage system (HESS) size with the goal to improve the effectiveness and efficiency of combined battery and supercapacitor energy storage in electric vehicles. The research uses Mixed Integer Linear Programming (MILP) to determine the most suitable configurations using simulation data from a modeled electric vehicle. The results show that MILP works at identifying the specific capacity needs of the storage system, which change based on the vehicle's power and energy capacity. The innovation provides a paradigm for the development of sustainable and highly efficient electric vehicles in the future, while also enhancing the functionality of current electric vehicles.**

***Keywords*— batteries, electric vehicles, hybrid energy storage systems, mixed integer linear programming (MILP), optimization, supercapacitor.**

I. INTRODUCTION

Motor vehicles powered by fossil fuels, which are commonly utilized today, emit greenhouse gases that worsen climate change. Hence, there is an escalating demand for the creation of vehicles that are not only efficient but also friendly to the environment. When it comes to alternatives, electric vehicles—which run on electricity, stand out as a particularly promising alternative in this regard. However, electric vehicles still face several challenges, such as the range and efficiency of energy use [1]. Selecting an appropriate capacity for energy storage systems is crucial to augmenting the performance and efficiency of electric vehicles [2][3]. The energy storage system of such vehicles typically encompasses both a battery and a supercapacitor; the former stores substantial electrical energy for prolonged use, while the latter stores smaller quantities but with rapid charging and discharging capabilities [4]. Integrating batteries and supercapacitors can significantly enhance the performance and efficiency of electric vehicles [5][6].

A Hybrid Energy Storage System (HESS) combines multiple storage technologies with differing electrical characteristics to efficiently meet energy and power demands [7]. Batteries, known for their high energy density, are adept at sustaining long-duration energy needs in various frequency settings [8]. Batteries, known for their high energy density, are adept at sustaining long-duration energy needs in various frequency settings [2][9]. Consequently, the precise calibration of battery-supercapacitor energy storage capacities is paramount for optimizing electric vehicle performance and efficiency [10]. A multi-objective optimization framework is developed to concurrently reduce the overall size of the Energy Storage System (ESS) and extend the battery's lifecycle by employing a designated penalty function. [11]. The precise calibration of a hybrid energy storage system, coupled with an executable real-time power management strategy, is crucial for attaining satisfactory vehicular range and battery longevity [12]. Research [13] studies have identified and utilized optimal efficiency points for determining the appropriate dimensions of a Hybrid Energy Storage System (HESS). These efficiency points are instrumental in ascertaining the ideal capacity of the HESS, which, in turn, is pivotal in minimizing the losses associated with charging and discharging processes.

This study aims to determine the best size for a hybrid energy storage system (HESS) in electric vehicles, focusing on a battery-supercapacitor setup. It will analyze factors like power and energy capacity. Simulation models will be used to optimize the system, improving vehicle performance and efficiency. The findings are expected to benefit environmental sustainability and the automotive industry by promoting more efficient electric vehicles.

II. MATERIALS AND METHODS

This section covers the data, optimization challenge, and system configuration. The study uses mixed-integer linear programming (MILP) in MATLAB. The first step is setting up the optimization problem. The results will be compared with a rule-based approach.

A. System Design

This study's system configuration includes a number of parts that are intended to efficiently store and handle electrical energy for use in electric vehicle applications are as follows:

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The study introduces a HESS for electric vehicles, designed to improve efficiency and extend the system's lifespan. The system uses a DC/DC converter to manage power flow between a supercapacitor and a battery, both connected to a DC bus. This bus supplies power to an inverter that converts DC to AC for the electric motor. The high-power density of the supercapacitor and the high energy density of the battery work together to optimize power management, enhancing performance and reducing battery wear, thereby extending equipment life.

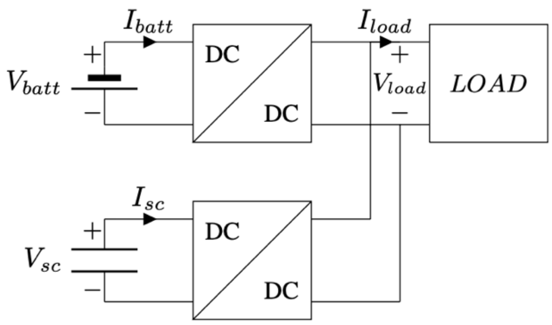

Fig. 1 Block Diagram of HESS[14].

System modeling includes a Single Line Diagram (SLD) of the hybrid storage system (Figure 1). The SLD visually represents the system but doesn't account for specific component constraints. Additionally, the model simulates an electric vehicle without a hybrid energy storage system to create a power load profile for HESS optimization. This comprehensive approach lays a solid foundation for improving the performance and efficiency of hybrid energy storage systems in electric vehicles.

B. Methods

Using Mixed Integer Linear Programming (MILP), the best possible setup for a hybrid battery-supercapacitor energy storage system is determined. This method optimizes performance and cost to improve electric vehicle power systems. To model and improve the efficiency of the system, data must be obtained and constraints such as energy capacity, power output, and expenses must be taken into consideration.

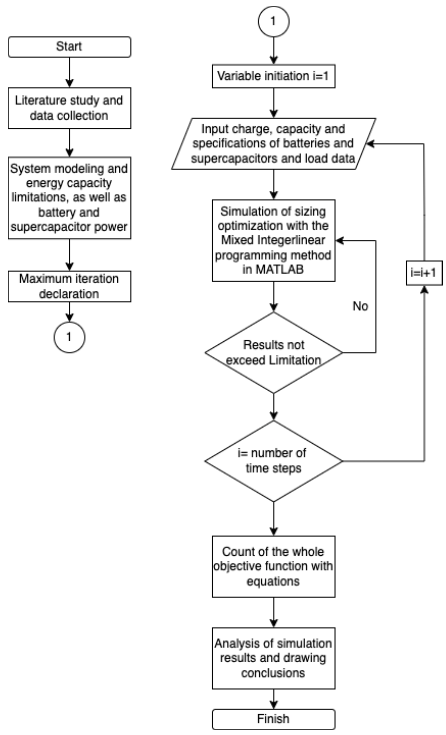

Fig. 2.Diagram flow this research.

The detailed flow diagram describes the process for optimizing the capacity of a hybrid battery-supercapacitor energy storage system using MILP in MATLAB. The procedure begins with an initial phase and continues with a thorough literature review and data obtaining to collect the relevant details regarding the features, costs, and performance metrics of batteries and supercapacitors. The next step is system modeling, which incorporates cost, power output, and energy capacity limits according with industry standards.

There is a maximum number of iterations defined in order to guarantee computational efficiency. At *i=1*, variables are initialized with the value from the first iteration. The model receives input parameters in the form of charge, capacity, specifications, and load data. The hybrid energy storage system's size is optimized using MATLAB's MILP approach, which iteratively adjusts control variables to find the ideal configuration.

Each iteration's results are checked against predefined constraints. The iteration count increments *(i=i+1)* until it matches the number of time steps. The objective function, including total project and operational costs, is calculated using normalized equations. Finally, the simulation results are analyzed to identify the optimal system configuration, balancing cost-effectiveness, reliability, and durability. The process concludes with a comprehensive analysis and finalization of the optimal energy storage system.

C. Objective Function

The objective function to minimize is as follows:

$$\min_{P_{Bat,Sc,}E_{Bat,Sc,}} F\left(P_{Bat}, E_{Bat,}P_{SC}, E_{SC}\right) = \sum_1^i P_{bat(i)}(TPCb + O\&MCb) + \sum_1^i P_{sc(i)}(TPCsc + O\&MCc) + TPCbe \cdot E_b + TPCsce \cdot E_{sc} \quad (1)$$

$$i = 1,2 \ldots., n$$

This function is expressed as $F(P_{Bat}, E_{Bat,} P_{SC}, E_{SC})$ and is calculated by summing the products of power outputs $P_{bat(i)}$ and $P_{sc(i)}$ for each timestep i (Wh), each multiplied by their respective total project costs plus operation and maintenance costs. Specifically, for BESS the costs are calculated as 0.00001 \$/kW per second, derived from the sum of $TPCb$ and $O\&MCb$ (0.00000967862 + 0.00000032), and for SCESS, the costs are 0.0000038 \$/kW per second, calculated from $TPCsc$ and $O\&MCc$ (0.00000376883 + 0.00000003). Additionally, the total project costs normalized annually are incorporated, with $TPCbe$ at 7.63063 \$/kWh per year and $TPCsce$ at 594.909 \$/kWh per year, multiplied by the energy capacities E_b and E_{sc}, respectively.

D. Variable Control

Power (P) and energy capacity (E) must be carefully controlled in order to size a hybrid battery-ultracapacitor system in a way that maximizes the performance of the energy storage system. The battery and supercapacitor systems' power and energy capacities are represented by the following control variables:

P_{bat}: battery power
E_{bat}: battery energy capacity
P_{Sc}: supercapacitor power
E_{Sc}: supercapacitor energy capacity

The lifespan of the system can be extended and operational demands can be satisfied more successfully by carefully modifying certain factors. This method guarantees a productive and balanced integration of battery and ultracapacitor components in hybrid systems. To determine these variables' ideal values that minimize the objective function, adjustments are made iteratively.

E. Constraints

- Equality Constraints
  The power balance equation of the grid is denoted in

$$P_{Bat(i)} + P_{SC(i)} = P_{load(i)} \quad (2)$$

$$i = 1,2 \ldots, n$$

$P_{Bat}(i)$ denotes the power delivered by the battery at any given time i (Wh), P_{Sc} shows power from supercapacitor at the time i (Wh), $P_{Load}(i)$ shows power from load demand at the time i (Wh).

- Inequality Constraints
  The operation is subject to the following inequality constraints:

$$E_{minj} \le E_{i,j} \le E_{maxj} \quad (3)$$

Total energy capacity E for each energy storage has a maximum storage capacity and minimum capacity, power at time i, type of energy storage technology j.

$$-P_j \le PE_{i,j} \le P_j \quad (4)$$

Equal to,

$$PE_{i,j} \le |P_j| \quad (5)$$

$$-PE_{i,j} \le |P_j| \quad (6)$$

The power threshold is denoted as P , and the power and energy PE at the time i, entering the hybrid energy storage system, must not surpass the rated power$P$ for each storage technology type j.

$$\underline{E} \le E_0 + \sum_{i}^{n} P_{i,j}\,\Delta t \le \overline{E} \quad (7)$$

The energy capacity boundary is established by the total accumulated energy E where E_0 is the initial energy stored, $\overline{E}$ and $\underline{E}$ are the subsequent upper and lower energy limits, respectively, if accumulated during charging and discharging cycles while staying within the energy capacity confines.

$$\underline{RP_j} \le PE_{i+1,j} - PE_{i,j} \le \overline{RP}_j \quad (8)$$

Equal to,

$$PE_{i+1,j} + PE_{i,j} \le |P_j| \quad (9)$$

$$PE_{i+1,j} - PE_{i,j} \le |P_j| \quad (10)$$

The ramp rate boundary, labeled as RP, is the permissible change in power during the charge or discharge phases at time i. Where $\underline{RP_j}$ is the ramp rate at time i and $\overline{RP}_j$ immediately after. The power and energy PE at the time of i entering the hybrid energy storage must adhere to the ramp rate limits for the specific energy storage technology j.

- Bound
  The lower and upper bounds of the variables to be optimized (x) are represented by the row vectors lb and ub. The lower bounds (lb) are set to the values of MatriksChargeBES and MatriksChargeSCES for each battery and supercapacitor, while for Unb and Unc, the lower bounds are set to 0. Conversely, the upper bounds (ub) are set to the values of MatriksDischargeBES and MatriksDischargeSCES for each battery and supercapacitor, while for Unb and Unc, the upper bounds are set to 1.

F. Mixed Integer Linear Programming (MILP)

The model attempts to find the ideal HESS sizing, using the MILP method is carried out using the MATLAB software. In MATLAB, MILP is simulated using the "*intlinprog*" syntax with the following specifications and formulations[15]:

$$\min_x f^T(x) including = \begin{cases} x(intercon) are\ integer \\ A\,.x \le b \\ Aeq\,.x = beq \\ lb \le x \le ub \end{cases} \quad (11)$$

Where *F, x, intcon, b, beq, lb,* and *ub* are vectors, while *A* and *Aeq* are matrices. Following the stipulated formulation, it is necessary to define the formulation of the objective function *(F(x))*, control variables (*x*), and constraints (*A, B, Aeq, Beq, lb, ub*) for the problem in this research.

G. Data for Battery Storage System

Lithium iron phosphate is the type of battery that is utilized. Table I presents parameter data that the battery uses as optimization factors[16].

TABLE I. Predictions for Cost and Parameter of BES [16]

Parameter	Li-ion Battery	
	(2018)	*(2025)*
Capital Cost – Energy Capacity ($/kWh)	*(223-323)* ***(271)***	*(156-203)* ***(189)***
Power Conversion System ($/kW)	*230-470* ***(288)***	*(184-329)* ***(211)***
Balance of Plant (BOP) ($/kW)	*(80-120)* ***(100)***	*(75-115)* ***(95)***
Construction and commissioning ($/kWh)	*(92-110)* ***(101)***	*(87-105)* ***(96)***
Total Project Cost ($/kW)	*(1,570-2,322)* ***(1,876)***	*(1,231-1,676)* ***(1,446)***
Total Project Cost ($/kWh)	***469***	***362***
O&M Fixed ($/kW-year)	*10*	
Life (Years)	*10*	

From the provided table, the parameters used for calculations include the Total Project Cost (TPC) of $1,876 per kW and $469 per kWh, an O&M Fixed cost of $10 per kW-year, and a lifespan of 10 years for the Li-ion battery. These values are used to normalize the Total Project Cost (TPC) per year and per second for the Battery Energy Storage System (BESS).

H. Data for Supercapacitor Storage System

Supercapacitors were used in the investigation for this study. Table II displays the supercapacitor's parameter data[16].

TABLE II. Predictions for Cost and Parameter of SCES [16]

Parameter	Supercapacitor	
	(2018)	*(2025)*
Capital Cost – Energy Capacity ($/kWh)	*(240-400)* ***400***	
Power Conversion System ($/kW)	*350**(211)***	
Balance of Plant (BOP) ($/kW)	*100**(95)***	
Construction and Commissioning ($/kWh)	***80** (20% from Capital cost)*	
Total Project Cost ($/kW)	*(930)* ***835***	
Total Project Cost ($/kWh)	(66,640) **74,480**	
O&M Fixed ($/kW-year)	*1*	
Life (Years)	*16*	

From the provided table, the parameters used for calculations include the Total Project Cost (TPC) of $930 per kW and $74,480 per kWh, an O&M Fixed cost of $1 per kW-year, and a lifespan of 16 years for the supercapacitor. These values are used to normalize the Total Project Cost (TPC) per year and per second for the Supercapacitor Energy Storage System (SCES).

I. Power Requirement Data

To determine the power and energy needs of the electric vehicle, we will use the ADVISOR program in MATLAB. This simulation requires vehicle parameters and the driving cycle. The general specifications of the Wuling Air EV are summarized in Table III.

The UDDS (Urban Dynamometer Driving Schedule) is the chosen driving cycle for simulation. It is commonly used for vehicle testing, covering a distance of 12 km in 1370 seconds.

TABLE IIII. Parameters of Wuling Air EV

Wuling Air EV Standard Range (200 KM)	
Nominal Range	200 KM
Battery Type	*Lithium Iron Phosphate* (LFP)
Battery Capacity	17,3 kWh
Rated Voltage	115 V
Drive Layout	Rear Wheel Drive
Drive Motor	30 kW (40HP) AC *Permanent Magnet Synchronus Motor* (PMSM)
Charging Reqirement	2.0 kW AC
Charging Time (20%-100%)	8.5 hr @ 2.0 kW
Weight	888 Kg

TABLE IV. Driving Cycles Data

Drive Cycle	UDDS
Time (sekon)	1370
Distance (Km)	11.99
Maximum Speed (Km/h)	91.25
Average Speed (Km/h)	31.51
Stop Time (sekon)	259
Number of Stop (sekon)	17

J. Capital Recovery Factor

The annualized total cost recovery for each energy storage technology is impacted by the respective lifespan of the storage system.

$$CRF = \frac{i(1+i)^T}{(1+i)^T - 1} \tag{122}$$

The Capital Recovery Factor (CRF) pertains to the financial formula used to calculate the yearly cost of an investment over the lifetime (T) of an energy storage technology, with 'i' representing a 10% interest rate[17].

K. Cost Calculation for HESS

The ideal sizing of a HESS is determined by the Total Project Cost (TPC) and Operation and Maintenance (O&M) costs. TPC is calculated in two ways: annually ($/kWh-year) and per second ($/kW-seconds). Similarly, O&M costs are expressed per second ($/kW-seconds). The formula to be utilized is as follows:

- Total Project cost (TCP)

The TCP will follow this formula:

$$TCP = \frac{1}{t}(CRF \times Total\ project\ cost) \tag{13}$$

- Total Project cost normalized per year ($\frac{\$}{\text{kWh}}$)

The Total Project Cost energy will be normalized annually by dividing it by the respective lifetime of each energy storage system, where the battery has a lifetime of 10 years and the supercapacitor has a lifetime of 16 years from Table I and Table II.

$$TPC_{Be} = \frac{1}{10}(CRF \times TPC) \tag{14}$$

$$TPC_{SCE} = \frac{1}{16}(CRF \times TPC) \tag{15}$$

- Total Project cost normalized per second ($\frac{\$}{\text{Wh}}$)

The TCP will be normalized per second for each energy storage system, it can be divided by 31,536,000 seconds to determine the cost per second

$$TPC_B = \frac{1}{31536000}(CRF \times Total\ project\ cost) \tag{16}$$

$$TPC_{sc} = \frac{1}{31536000}(CRF \times Total\ project\ cost) \quad (17)$$

- O&M cost normalized per second ($O\&MC$)
  The O&MC will be normalized per second

$$O\&MCb = \frac{10}{31536000} \quad (18)$$

$$= 0.00000032\ \frac{\$}{\text{kW}} \text{per detik}$$

$$O\&MCsc = \frac{1}{31536000} = 0.00000003\ \frac{\$}{\text{kW}} \text{per detik} \quad (19)$$

III. THE SIMULATION AND ANALYSIS

The simulation results and analysis from the MATLAB program Mixed Integer Linear Programming (MILP) will be covered in this chapter. The program's goal is to solve the optimal sizing problem for hybrid battery and supercapacitor energy storage systems in electric vehicles. In addition, two case studies with distinct approaches will be compared to the MILP method, with a focus on its cost implications. Consequently, two simulation results will be covered in this chapter.

1. The result of optimal EV scheduling with a Hybrid Energy Storage System (HESS) comprising batteries and supercapacitors, utilizing a rule-based method.

2. The result of optimal EV scheduling with a HESS comprising batteries and supercapacitors, utilizing the Mixed Integer Linear Programming (MILP) method.

To ensure a responsible comparison across all three simulation outcomes, both cases were simulated using the same electric vehicle parameters, except for the differences in the Battery Energy Storage (BES) and Supercapacitor Energy Storage System (SCES) capacities.

A. *Drive Cycle UDDS Simulation Result*

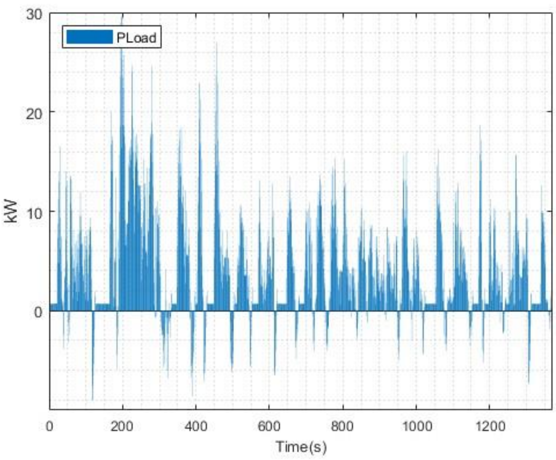

Fig. 3. Load Profile

In the Fig. 3, Data from an Urban Dynamometer Driving Schedule (UDDS) obtained using the ADVISOR simulation framework is investigated. The data spans 1370 seconds and corresponds to approximately 12 kilometers of driving time. The electric car demonstrated a varied urban driving profile within the simulation's limits, reaching a maximum speed of 91.25 km/h and maintaining an average speed of 31.51 km/h. Interestingly, the vehicle idled for 259 seconds in total. This is a sign of stationary phases where power is continuously used at low levels to sustain essential subsystems like electronics and temperature control systems. The vehicle also came to a complete stop 17 times throughout the test, which is a trait typical of urban transit systems.

The mentioned findings carry significant value in the exploration of power consumption patterns and the optimization of energy storage control in electric vehicles. Specifically, it relates to the enhancement of system effectiveness and maintaining of power under repose conditions.

B. *Case Study I: EV with HESS Utilizing Rule-Based Method*

A simulation was used in the first case study to estimate the size of an electric car with a hybrid energy storage system (HESS) that consists of a supercapacitor and a battery. In this case, MATLAB was used to optimize the HESS through a rule-based approach. This method follows a predetermined set of guidelines that specify the limitations of the simulation. Essentially, when the power demand decreases below a predetermined level, the algorithm instructs the application to use power from the Battery Energy Storage (BES). On the other hand, the BES is used to the maximum capacity possible when the power demand beyond the predetermined limit, and the Supercapacitor Energy Storage System (SCES) supplies any extra power needed. Fig. 4 illustrates the outcomes of the electric vehicle simulation using the HESS in this particular case study

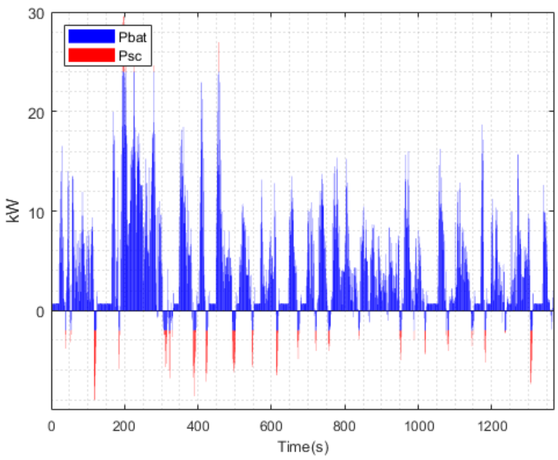

Fig. 4. Capacity Energy Battery vs Supercapacitor

The simulation results for Scenario I, shown in the graph, demonstrate the strategic sizing of the BESS and the SCESS, showing that the power demand specifications were continuously met for 1370 seconds. When the load power exceeded this threshold, the BESS's operational limit of up to 18kW would activate continuously. In addition to extending the systems' lifespan and performance, this method guarantees a balanced energy supply. To further optimize energy distribution and storage efficiency within the integrated system, a charging strategy is also used during periods of power feedback. Excess energy flows to the SCESS, and the BESS receives a consistent 2 kW for storage.

Moreover, tests with varying energy capacities ensure power and energy requirements are continuously satisfied, even during peak operating periods. For instance, at crucial times like the graph's spikes, the battery and supercapacitor's combined capacities to meet maximum charge and discharge needs are checked, demonstrating the system's effectiveness in managing real-world situations. By ensuring that the energy systems function within their capacity limits, this strict testing framework preserves the stability and dependability of the systems.

C. *Case Study II: EV with HESS Utilizing MILP Method*

The graph is derived from optimization results with a single load test covering a distance of 11.99 km in 1370 seconds. To extend its usage, we multiply this by 8, assuming eight load tests per day, resulting in 95.92 km (8 times the test distance) and 10960 seconds (8 times the test duration) in a day. Assuming this usage throughout the year, the projected annual distance is 35010.8 km (365 days multiplied by the daily distance).

In this simulation, a Battery Energy Storage System (BESS) with a capacity of 16.3 kWh and a Supercapacitor Energy Storage System (SCES) of 1 kWh are employed, alongside the Urban Dynamometer Driving Schedule (UDDS) to emulate driving cycles. To perform optimal scheduling using the Mixed-Integer Linear Programming (MILP) approach, six variables are utilized, which include $P_{b(t)}$, $P_{sc(t)}$, Unb, and Unc. However, the variables Unb and Unc serve as constraints within the program and therefore do not appear in the graphical output of the HESS scheduling results. **Error! Reference source not found.**5 illustrates the outcome of the electric vehicle simulation using HESS configured with MILP for Case II.

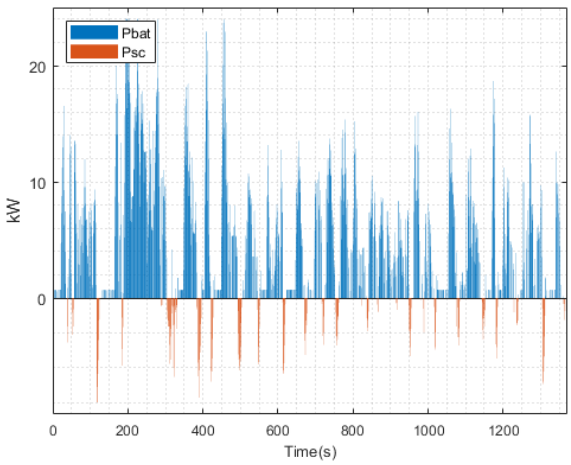

Fig. 5. Graphic Sizing case II

In **Error! Reference source not found.** analyze the financial effects of operating strategies in a HESS in this study. A cross-sectional decrease in the BESS and an increase in the SCESS occur when energy capacities over 18 data points are analyzed. In particular, the stored energy in the BESS consistently decreases from an initial 59,400 kWs to 1,800 kWs, but the SCESS shows a reverse trend, increasing from 1,800 kWs to 59,400 kWs. The HESS's strategic energy transfer protocol is demonstrated by this different behavior.

The graph is based on optimization results from a single load test that takes 1370 seconds to reach 11.99 km. We assume eight of these load tests each day to extrapolate its consumption, which comes out to a daily distance of 95.92 km and a total time of 10,960 seconds. When 365 days are considered to project this daily usage over a year, the estimated annual distance covered is 35,010.8 km. This long-term usage scenario demonstrates the system's ability to control consistent, large-scale energy transfers, demonstrating its durability and effectiveness in responding to fluctuating energy requirements over time.

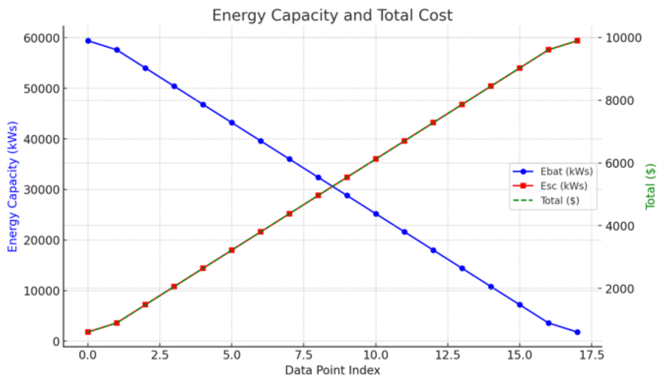

Fig. 6. Annual Result Optimal Sizing to HESS

Fig. 6 At the same time, an examination of all expenses related to the operation of the system appears in Fig. 8 to capture the financial aspects of this operational strategy. Over all of the 18 data points, the cost data shows a progressive an increase from \$606.38 to \$9898.56. This increase corresponds with the energy capacity shift from the BESS to the SCESS, demonstrating that the energy management system utilizes the SCESS as a buffer to manage high demand while optimizing the BESS discharge cycle in order to prioritize cost-efficiency.

The model's minimal cost savings highlight how effectively SCES is integrated into the HESS. The SCES's fast discharge capabilities allow for higher energy prices during high demand periods, which results in the progressive increase in overall expenses, even if the BESS offers a baseline energy supply. The data provided substantiates the theory that the addition of SCESS considerably lowers overall costs, resulting in an approximate 3.14% decrease in operating expenditures.

IV. Conclusion

The results mentioned previously indicate the potential of a rule-based energy management approach to effectively utilize the combined advantages of BESS and SCESS, which leads to enhanced energy efficiency and financial gains for electric vehicle systems. Thus, the suggested approach offers insights into the efficient use of HESS, especially when it comes to electric vehicle energy systems, where it can have a big impact on cost-effectiveness and performance metrics.

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