

Lead-Acid Battery and Supercapacitor Based Hybrid Energy Storage Systems in Microgrid for Energy Control System

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Abstract

Lead-acid batteries are a common energy storage option in modern microgrid applications. This study suggests installing an Energy Management System (EMS) that is managed by a hybrid energy storage system (HESS) consisting of lead-acid batteries and supercapacitors (SCs). Lower operating costs and longer battery life are the goals. Lead acid battery state of charge (SOC) depletion and daily cycle stress are reduced by SCs, which control and supply the high-frequency, power-dense section of the load cycle. But it's crucial to size the HESS correctly, taking into account load demand, available power sources, and budgetary restrictions. This article explains an algorithm that outlines the HESS's energy management control. One of the main advantages of using HESS versus passive systems is that it reduces the overall size of the system. By estimating future load dynamics using load current, the proposed energy management system primes the system for impending changes.

Keywords: Energy Management System, Hybrid Energy Storage System, Microgrid, Supercapacitor, Lead-Acid Batter.

1. Introduction

The technology used for renewable energy are becoming better every day. The advantages of integrating two or more energy sources are becoming more and more popular. For example, pairing a diesel generator with solar power or a solar power plant with batteries may lead to increased efficiency. The output of hybrid energy systems is more consistent and balanced. Crucially, hybrid energy solutions may also be adjusted to the environment, adjusting to variations like shifting weather patterns and periods when wind and solar energy are most abundant. They may be used with already in place power production systems to provide businesses and communities the ability to fully utilize their resources and guarantee a steady supply. Hybrid energy is especially important for the growth of distant nations, many of whom are seeing a rapid increase in their electrical needs.

2. Literature Reviews

The assessment of current integration specifications and control strategies for grid-connected renewable energy systems was examined by Ali Q. Al-Shetwi et al. [1]. Here different requirement and issues, which are introduced into the grid when we integrate different renewable sources, are reviewed. Sushil Kumar Bhoi et. al [2] used the game theory technique by which they determine optimal hourly clearing electricity price in an electrical system. After analyzing this they conclude that optimal hourly clearing time is benefit for both consumer and suppliers. MIMO forecasting engine and hybrid forecasting framework integrated to anticipate demand and pricing together. Using the data association mining (DAM) method developed by Amir Motamedi et al., this forecasting system makes price and demand predictions [3]. Kanzumba

Kusakana [4] proposed two control strategies for optimal power flow of hybrid system to minimize the operating cost. In this all-non-linearity curve of Diesel generator, PV system and load are taken. The mathematical model for estimating the state of charge (SOC) of a rechargeable battery was conceived by Wen-Yeau Chang [5]. The battery's impedance, which changes with age, determines the State of Health (SOH) of the battery. The SOH of the battery is ascertained by Monika Kwiecien et al. [6] using electrochemical impedance spectroscopy (EIS) measurement. The optimum predictive power scheduling method is used by Yann Riffonneau et al. [7] to regulate power flow in grid-connected PV systems as efficiently as possible. This optimization is performed by Dynamic Programming (DP) method. Conventional optimization techniques are complex due to presence of non-linearity in HESS component. Rodolfo Dufp-Lopez et. al [8] use a Genetic algorithm (GA) for design of HESS in an efficient way. S. Kumaravel et. al [9] describe a power management controller for HESS for batter control and power management. Additionally, a simulation model is designed to assess the system's performance under various circumstances. Battery is one of the most essential components in HESS. Kusum Lata Tharani et. al [10,11] gives an idea of selection of battery for HESS. HOMER software is used for modelling of

HESS and this model is tested with different batteries.

3. Objective and Motivation

The goal of this study is to provide a technique that will reduce the hybrid energy system's overall cost by enhancing battery health. The main objectives of the thesis are outline below:

1. To minimize the power consumption of the battery
2. To minimize fluctuation of battery current

4. Hybrid Energy Storage System

Energy storage devices provide a variety of benefits, including the ability to better balance output and demand, increase power quality, smooth out the intermittent nature of renewable resources, and enable ancillary services like frequency and voltage management in microgrid (MG) operation. The coupling of two or more energy storage technologies has given rise to hybrid energy storage systems (HESSs), which use the best aspects of many technologies to reach the required performance. Since ESS technologies vary in terms of longevity, cost, energy and power density, and dynamic responsiveness, they are unable to perform the intended function when used alone. As a result, many HESS setups that take into account the kind of storage, interface, control scheme, and service offered have been put out in the literature, as shown in Figure 1.

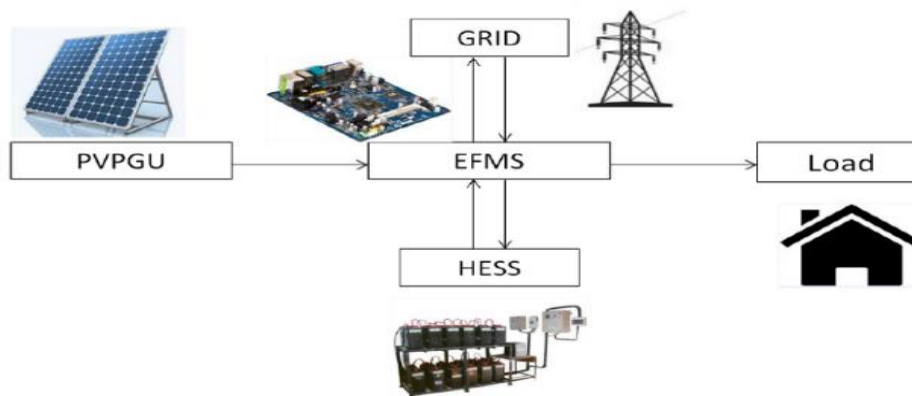


Figure 1 The Presented Micro Grid Block Diagram

4.1. Battery and Supercapacitor Theory

Prior to examining how well batteries and SCs function in microgrid applications, it is critical to comprehend the fundamental ideas behind the behavior of these hybrid energy storage components. This chapter contains the background knowledge that is required, which is detailed in Table 1.

Table 1 Battery Comparison Measurement's Dimensions

Battery Comparison	Measurement's Dimensions
Lifespan	Due to the number of charge and discharge cycles and/or due to the lifetime that remains from its functionality up to 80%
Safety	Overheating caused by the reactions, overcharging or fast discharging causes fire. The remedies for this issue could be the usage of robust battery box, cooling system and/or monitoring the charging and discharging rate.
Specific Energy	Rate of energy storage based on the Kg of the weight
Specific Power	Rate of power storage based on the Kg of mass
Performance	Based on managing thermal conditions. The ability to work during minimum temperatures in cold winters and maximum temperatures in hot summers.
Cost	Component production, cell production, module production, packs assembly, installation including accessories, lifetime and recycling

The major factor that limits the batteries' charging and discharging capability is their internal resistance. Of the batteries' drawbacks, it is possible to count

their low power density, low cycle life, and long recharging time. Combining the supercapacitor and battery as a hybrid unit is one approach to get over these restrictions. This will increase the supercapacitor's life cycle, increase its efficiency in regenerative braking, and give it more power for acceleration.

4.2. The Mathematical Modelling of Lead Acid Batteries

The behavior of a lead-acid battery is influenced by a number of elements, such as internal resistances, current limitations, SOC, and battery temperature. The design of a single lead-acid battery reduces to an ideal voltage source, $V_{Bi,1}$ in series with an internal resistance, R_B , if the battery temperature is kept at 25°C.

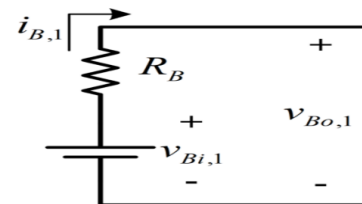


Figure 2 Single Lead-Acid Battery Schematic

In the circuit shown in Figure 2, applying Kirchhoff's Voltage Law (KVL) across the closed loop yields

$$V_{Bo,1}(t) = V_{Bi,1}(t) - i_{B,1}(t)R_B \quad \text{----- (1)}$$

where, when producing the current $i_{B,1}(t)$, $V_{Bo,1}(t)$ represents the voltage across the leads of a single battery. Additionally, using Watt's Law yields the following formulas for a single lead-acid battery's input power $P_{Bi,1}(t)$, output power $P_{Bo,1}(t)$, and resistive loss $P_{BR,1}(t)$:

$$P_{Bi,1}(t) = V_{Bi,1}(t) i_{B,1}(t) \quad \text{----- (2)}$$

$$P_{BR,1}(t) = i_{B,1}(t)^2 R_{B,1} \quad \text{----- (3)}$$

And,

$$P_{Bo,1}(t) = V_{Bi,1}(t) i_{B,1}(t) = P_{Bi,1}(t) - P_{BR,1}(t) \quad \text{----- (4)}$$

5. Problem Formulation

5.1. Theory Problem One (Prediction Optimization)

For a supercapacitor, the relation between its current and voltage is defined as $i_{sc} = C_{sc} V'_{sc}$, where V'_{sc} is the

derivative of the supercapacitor's voltage, V_{sc} . Now, this relation is discretized to obtain in discrete time domain as follows,

$$i_{sc} = C_{sc} \cdot \frac{V_{sc}(t) - V_{sc}(t-1)}{\Delta} \quad \text{----- (5)}$$

Where Δ is the sampling period and is the sample number in discrete time domain. Then, it was interested to derive an optimization problem, aiming to achieve two objective terms:

- a) to minimize the power consumption of battery
- b) to minimize fluctuation of the battery's current

To achieve the first objective term, the constraint was put on the power consumption of battery V_{BiB} , and since the battery is assumed to have a constant voltage, the square current of battery was minimized as, $(i_B)^2$. To achieve the second objective term, the square of battery's current difference in two consecutive samples was minimized as $(i_B(t) - i_B(t-1))^2$. The optimization problem Was derived to find a reference supercapacitor's voltage, $V_{sc}(t)$, where $t \in [1, \dots, T]$, and T is the number of samples to be solved in the optimization problem. To relate the $V_{sc}(t)$ to the battery's current, it was needed to use other equations. First, the Kirchhoff's current law between the battery, supercapacitor, and load was considered in the DC bus as, $i_B(t) + i_{sc}(t) = i_L(t)$. Second, the current-voltage relation of the supercapacitor,

$V_{sc} = \int i_{sc} dt$, was discretized and then the

$V_{sc}(t) = -\sum_{\tau=1}^t (\frac{\Delta}{C_{sc}} i_{sc}(\tau))$ was obtained. Instead of deriving $V_{sc}(t)$ from equation (3.2-1), this integral equation is used to consider all supercapacitor's current samples, resulting in a smoother solution for V_{sc} .

Problem statement one

$$\text{Min } \alpha \sum_{t=1}^T (i_B(t))^2 + \beta \sum_{t=2}^T (i_B(t) - i_B(t-1))^2 \quad \text{----- (6)}$$

Subject to:

$$i_B(t) + i_{sc}(t) - i_L(t) = 0 \quad \text{----- (7)}$$

Simulation Results and Discussion

6. Solution of the Problem

As from the problem, it could be understood that it is

a minimization nonlinear function that includes an objective, equality constraints and inequalities constraints.

6.1. Preparing the Main Objective Function

To solve it, at first some variables were found in the constraints and substituted with their equivalents in the objective function. Then the function was managed so that a main objective function was built up from the i_L and V_{sc} to be minimized.

$$1. \text{ Min } \alpha \sum_{t=1}^T (i_B(t))^2 + \beta \sum_{t=2}^T (i_B(t) - i_B(t-1))^2 \quad \text{---- (8)}$$

$$2. i_B(t) + i_{sc}(t) - i_L(t) = 0 \Rightarrow i_B(t) = i_L(t) - i_{sc}(t) \quad \text{---- (9)}$$

From (1) & (2) $\Rightarrow \text{min } \alpha \sum_{t=1}^T (i_B(t))^2 + \beta \sum_{t=2}^T (i_L(t) - i_L(t-1) - (i_{sc}(t) - i_{sc}(t-1)))^2$

$$V_{sc}(t) = \sum_{\tau=1}^t \frac{\Delta}{C_{sc}} i_{sc}(\tau) \quad \text{----- (10)}$$

The above format could be solved by MATLAB programming. However, as soon as the load current starts to fluctuate, the algorithm forces the supercapacitor voltage to raise to be able to provide current for the current surge demand which happened on the load side and V_{sc} reaction plot is shown in Figure 3.

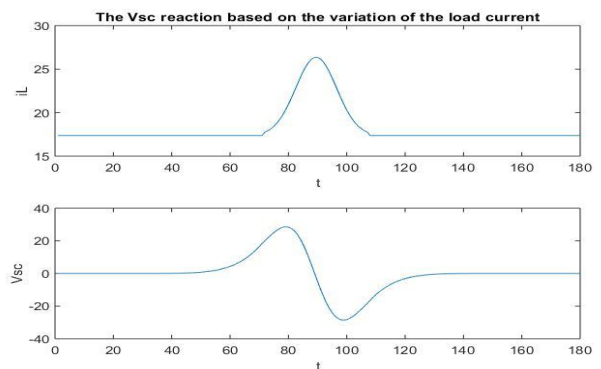


Figure 3 The V_{sc} responds to the Sudden Change in the i_L

7. Further Improvement Based on Predicted Data

The described solution of problem 1 suffers from discontinuity between consecutive cycles, resulting in spikes in the supercapacitor voltage and current. In order to provide a smooth reference voltage of the

supercapacitor, we add samples from the previous cycle to the calculation of the reference samples of supercapacitor of the next cycle.

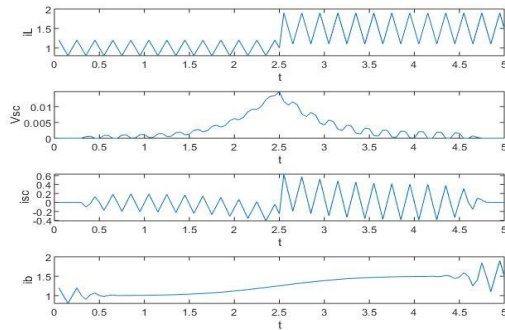


Figure 4 DC part and the Fluctuation of Signal divided between the Supercapacitor Current and the Battery Current

As can be seen from the Figure 4, the written algorithm was able to divide the sample i_L signal into two portions between the supercapacitor current and the battery current. However, this happened in a way that the DC part was driven from the battery and the fluctuated part was driven from the supercapacitor current. Even in the condition of a sudden change in the total rate of the load current's (i_L) profile, the battery current share was still very smooth and the main changes and fluctuated parts were handled by the supercapacitor current. This could be a test or checking that the written algorithm works well and the applied solution is correct.

8. Future Load Profile

The problem at this point was how the load profile could be predicted for at least two periods ahead of the real time period. After the load current (i_L) was measured and identified in the discreet manner with a transducer or a sensor from the load side, the $n-1$ and n were available. However, to predict the load current profile the $n+1$ and $n+2$ was needed as well. Therefore, a mathematic prediction method was required to build the future load consumption curve. The $i_L \{n-N, \dots, n\}$ is obtained by linear prediction of the $i_L^{\wedge} \{n-N, \dots, n, n^{\wedge}+1, n^{\wedge}+2\}$. There were a

couple of ways to do this important job, such as using ARMA (Auto Regressive Moving Average), a Kalman Filter constraint or using the LPC (Linear Prediction Coefficients) in the MATLAB. The ARMA method predicts completely with the stochastic method. A Kalman Filter uses probability and mathematics. To determine the filter coefficients, LPC employs the autoregressive (AR) modeling technique of autocorrelation. According to the MATLAB Help, the Autocorrelation LPC block minimizes the prediction error in the least squares sense to find the coefficients of an N-step forward linear predictor for the time-series in each Length-M input channel, as shown in Figure 5.

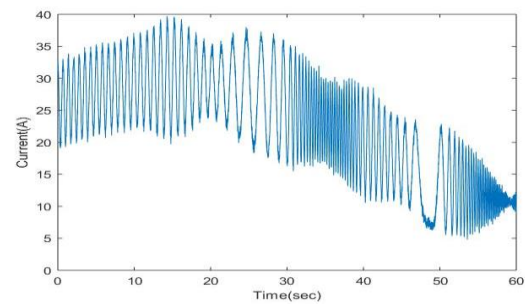


Figure 5 Part of the Daily Residential Current Consumption

A MATLAB program was written to use the LPC command and predict the first predicted point. The program generated the error based on the different order of the LPC algorithm, which could be seen in Figure 6.

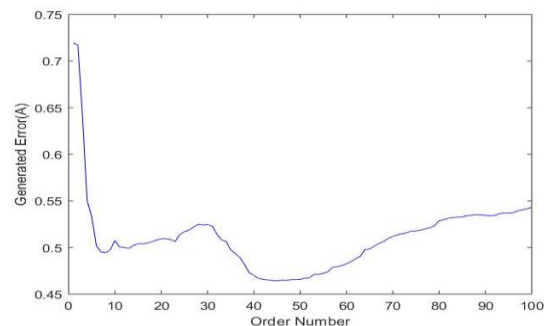


Figure 6 Illustrates the Error Amount of the Predicted Current Point for the Order Number of the LPC Algorithm

The LPC with order number 45 is a best choice and provides less error. Although this order number is based on each load profile, in order to have a better understanding of the error generated by usage of the LPC algorithm two programs were written to generate a random load profile on each time. The first one compares the load and its prediction and plots them on same graph with the difference error on each time, as in Figure 7 & 8.

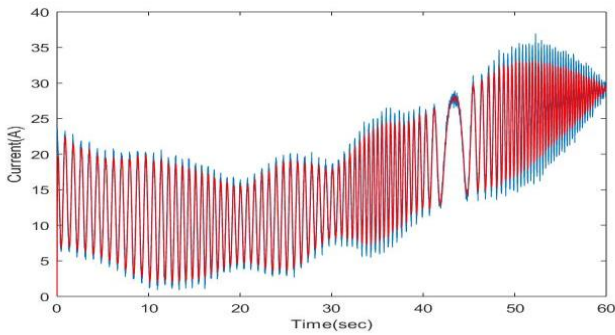


Figure 7 Load Profile (blue) and the Predicted Profile (red)

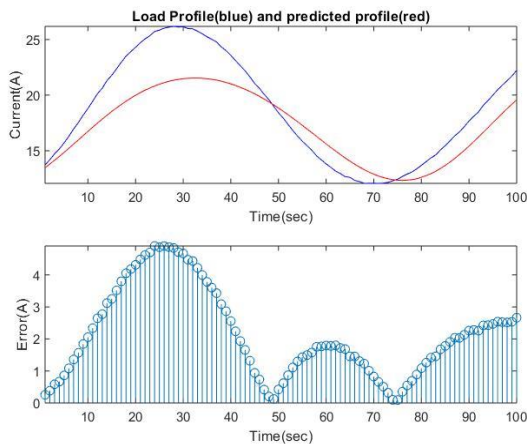


Figure 8 Load and Predicted Profile and their Generated Error

The next program generated the predicted profile with LPC and then compared the two profiles based on different orders. In the next step, the program calculated the error on each order and plotted the graph of the error via order number, as in Figure 9 & 10.

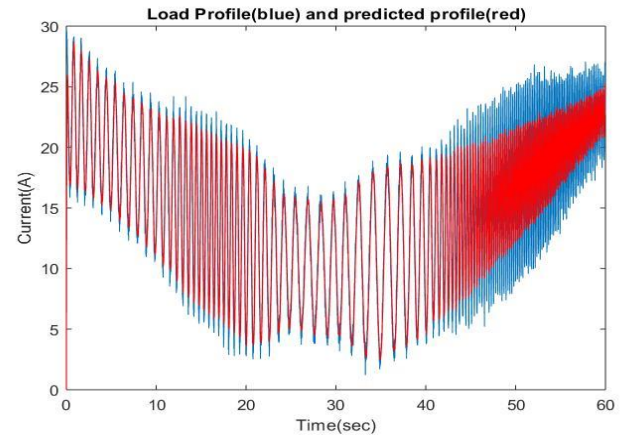


Figure 9 Load Profile (blue) and the Predicted Profile (red) on one of the Trials

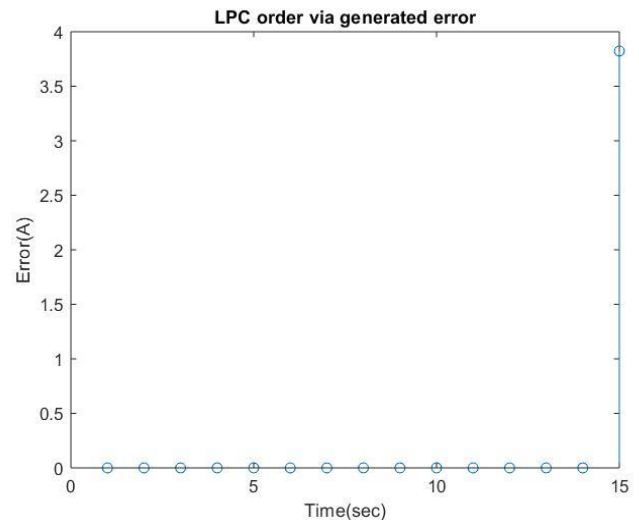


Figure 10 The LPC Order Number via the Amount of Error in one of the Trials

Further improvements on the program by usage of the LPC prediction program and the best LPC order with the fewest generated errors produced the following Figure 11. By observation of the plots, it was realized that the algorithm was working properly by using prediction. This means that the main fluctuated part of the load current was transferred to the supercapacitor, which has no harm for the battery lifespan, remained on the battery current. The

modified optimization (contribution on the supercapacitor voltage differences).

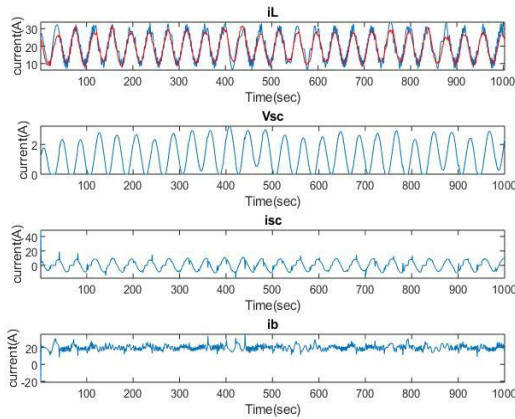


Figure 11 Load Current (i_L), Supercapacitor Voltage (V_{sc}), Supercapacitor Current (i_{sc}) and Battery Current after usage of the LPC Prediction

After investigation and detailed analysis of the offered optimization technique and main objective function, it was realized that the contribution of the supercapacitor voltage term (the term that minimized the difference of the supercapacitor actual voltage and the voltage reference which was generated in the first algorithm) was not on the level that could have any significant influence on the optimization calculations. As observed, the correction on the main objective function works under the favors of the modified optimization method. The graphs demonstrate that the load current demand was distributed in an optimized way between the battery and supercapacitor such that the whole load current dynamic and huge fluctuation (20 A) are demanded from the supercapacitor.

Conclusion and Future Scope

The primary goal of the project is to reduce power consumption and battery current fluctuation by incorporating supercapacitors into an effective Hybrid Energy Storage System (HESS). This connection lowers the system's overall cost and enhances the health of the storage, making the system more accessible to users. Through the use of the LPC

technique for prediction and the integration of many prior supercapacitor voltage samples inside the current cycle, discontinuities are efficiently eliminated and a continuous, smooth extrapolation supercapacitor reference voltage is obtained. Because of its predictive capacity, the system can anticipate future changes or spikes in demand. The optimization algorithm's practical effectiveness is shown by its successful segmentation of load current samples into two components: supercapacitor current and battery current, when implemented in MATLAB. In the future, the HESS optimization algorithm might make it easier to schedule grid-tied PV systems optimally, which would lower consumer prices and improve system performance. Potential future improvements may include including the cost and discharge cycle of every battery cell, which would increase battery longevity. Moreover, for real-time energy management in microgrids, the algorithm might be improved and combined with optimization-based power flow control techniques. Another direction for future study is investigating alternate topologies in supercapacitor bank design, such as optimizing switching to improve capacity and lower current capacity. In order to ensure optimum operation and system lifespan, it would also be advantageous to include battery management systems to monitor temperature and performance of both supercapacitor banks and batteries in both monitoring and generating modes.

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