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An adaptive learning control strategy for standalone PV system with battery-supercapacitor hybrid energy storage system

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HIGHLIGHTS

- The operation of Battery-Supercapacitor HESS is not restricted by pre-defined rules.
- The control strategy is optimized every minute based on predicted power demand.
- The SOM-PSO method offers faster convergence and shorter optimization time.
- The control strategy can compensate prediction error of predicted power demand.
- The control strategy performs consistently in different scenarios.

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ABSTRACT

Contrary to Rule-based Controller and Fuzzy Logic Controller, which are usually restricted by pre-defined rules, the proposed control strategy implements power distribution algorithm to offer higher flexibility to the Battery-Supercapacitor Hybrid Energy Storage System by introducing a charging threshold and a discharging threshold. It allows the Hybrid Energy Storage System to be charge/discharged without constraints. The proposed optimization method, which comprises Self-Organizing Map and Particle Swarm Optimization, optimizes the parameters of power distribution algorithm every minute based on predicted one-hour power demand and supercapacitor state-of-charge to mitigate peak demand and short charge-discharge cycles of battery. The proposed optimization method initializes the initial population of particles within the range of optimal solution instead of randomizing the particles like the conventional method. This method offers faster convergence and reduces the optimization time up to 68.97% as compared to conventional method. The simulation results show the proposed control strategy can compensate the prediction error of prediction model and outperform the Filtration-based Controller and Particle Swarm Optimization-optimized Fuzzy Logic Controller in different scenarios. Moreover, it significantly increases the supercapacitor utilization by 7.33 times and reduces the mean absolute rate of change of battery power and battery peak demand up to 91.94% and 61.36%, respectively.

1. Introduction

Battery-Supercapacitor Hybrid Energy Storage System (HESS) is an effective approach to minimize the size and stress level of the battery and to reduce the total capital cost of the system in a standalone photovoltaic (PV) system [1–4]. Control strategy is an algorithm which decides and controls the operation of the Battery-Supercapacitor HESS based on the states of the system. An optimal control strategy can significantly improve the performance and the economic viability of the overall system. A recent review article highlighted that Filtration Based Controller (FBC) [5–10], Rule-Based Controller (RBC) [11–17], and Fuzzy Logic Controller (FLC) [18–21] are the most common control strategies for HESS. In Ref. [9], the authors proposed low pass filter (LPF) based FBC for DC-link voltage stabilization in a PV-based DC grid. The authors in Ref. [10] implemented a LPF based FBC with an adaptive rate limiter to mitigate the high charge/discharge rate of the battery. The control strategy of both [9] and [10] neglected the state-of-charge (SOC) of the energy storage systems. In fact, the supercapacitor in FBC is commonly underutilized and ineffective in minimizing the peak power demand of the battery as it can only process the frequency of the power demand [22].

In the common approach, most control strategies tend to charge the HESS only when the power generation of renewable energy source is higher than load demand [11,12,23–28]. The authors in Ref. [29]

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Nomenclature

$\lvert\Delta P_{batt}\rvert$	Absolute value of the rate of change of battery power (W)
$\lvert\Delta P_{batt}\rvert_{\mathrm{mean}}$	Mean absolute power rate (W s^{-1})
$\lvert\Delta P_{batt}\rvert_{\mathrm{total}}$	Total absolute power rate (W s^{-1})
$\lvert Ah\rvert_{SC}$	The absolute value of the accumulated ampere-hours of supercapacitor (Ah)
ANN	Artificial neural network
dip	Power deficit between P_{pv} and P_{load} (W)
dP_{HF}	High frequency components of *dP* (W)
dP_{LF}	Low frequency components of *dP* (W)
$dP_{LF\_prediction}$	Predicted one-hour ahead power demand of HESS (W)
$\mathrm{dP_{LF\_predictionmax}}$	Minimum point of $\mathrm{dP_{LF\_Prediction}}$ (W)
$\mathrm{dP_{LF\_predictionmin}}$	Maximum point of $\mathrm{dP_{LF\_Prediction}}$ (W)
EA	Evolutionary algorithm
ELM	Extreme learning machine
f1(x)	Fitness function 1
f2(x)	Fitness function 2
FBC	Filtration based controller
FLC	Fuzzy logic controller
GA	Genetic algorithm
gbest	Global best
HESS	Hybrid energy storage system
It_{max}	Maximum number of iterations to obtain the optimal solution
It_{total}	Total number of iterations
L(t)	Learning rate at *t*
LPF	Low pass filter
M	Set of Neurons in the input space
MAF	Moving average filter
m_c	Winning neuron
MF	Membership function
m_i	Neuron number *i*
n	Number of dimensions
P_{batt}	Battery power (W)
P_{batt_max}	Maximum point of battery power (W)
P_{batt_min}	Minimum point of battery power (W)
P_{batt_peak}	Battery peak power (W)
Pbest	Personal best
P_{HF}	High frequency component (W)
P_{load}	Load power demand (W)
P_{PV}	Power Generation of PV (W)
P_{SC}	Supercapacitor power (W)
P_{SC}'	Supercapacitor power after Power Conversion (W)
P_{SC_PDA}	Reference supercapacitor power produced by Power Distribution Algorithm (W)
P_{SC_ref}	Reference supercapacitor power (W)
P_{SC_ref}	Reference power to be shared by supercapacitor (W)
P_{SC_ref}'	P_{SC_ref} before Over-charged/discharged Protection (W)
PSO	Particle Swarm Optimization
PV	Photovoltaic
Q	Total number of Neuron in the input space
RBC	Rule Based Controller
RMSE	Root Mean Squared Error
S	Set of home and neighbour neurons
S_0	Home neuron
S_j	Neighbour neuron *j*
SOC	State of charge (%)
SOC_{SC}	State of charge of supercapacitor (%)
SOM	Self-Organizing Map
SVR	Support Vector Regression
T_C	Charging threshold (W)
T_{C_1}	Charging threshold 1 (W)
T_{C_2}	Charging threshold 2 (W)
T_{C_3}	Charging threshold 3 (W)
T_{C_range}	Range of optimal charging threshold (W)
T_{Ck}	Set of optimal T_C (W)
T_d	Discharging threshold (W)
T_{d_1}	Discharging threshold 1 (W)
T_{d_2}	Discharging threshold 2 (W)
T_{d_range}	Range of optimal discharging threshold (W)
T_{dk}	Set of Optimal T_d
T_{it}	Average optimization time per iteration (s)
$T_{optimization}$	Total optimization time (s)
T_S	Moving sampling time window (s)
V_i	Input vector
$V_i(t)$	Input vector at *t*
WCA	Water Cycle Algorithm
β	Multiplier
ΔSOC_{SC}	Variation of SOC_{SC} (%)
λ	Time constant (total epoch)
ξ	Input vector
$\sigma(t)$	Area of neighbourhood
σ_0	Size of the neighbourhood at time t_0

proposed a RBC that prioritized the charging of battery over supercapacitor when the wind power output is higher than load demand. In Ref. [13], the charging/discharging operation of supercapacitor is restricted by pre-defined thresholds. In a recent literature [30], the supercapacitor is implemented as the primary storage to supply for power demand while the battery recharges the supercapacitor when the SOC of supercapacitor (SOC_{SC}) is below a pre-defined thresholds [30]. These pre-defined thresholds and rules restrain the potential of HESS as the operating conditions of the system are constantly varying. The control strategy with rigid parameters can fail to fulfil the desired objectives in certain unpredicted events.

With the capability of predicting electrical load [31–35] and solar irradiance [36–39] using machine learning algorithms, the prediction output can be integrated with the control strategies to achieve optimal energy management [40,41]. However, accurate prediction of PV output and load profile are challenging due to the randomness and noisy disturbance. In Ref. [34], the authors evaluated some popular machine learning methods for one-hour ahead building energy consumption prediction [34]. The results indicated that the Root Mean Square Error (RMSE) for the prediction error of the machine learning methods are ranging from 59.1812 W to 89.9583 W. The prediction task is even more difficult in standalone PV system as the PV output is strongly dependent on the weather condition. In Ref. [42], the authors evaluated the accuracy of hourly PV output power prediction using artificial intelligence methods, namely Support Vector Regression (SVR), Artificial Neural Network (ANN), and Extreme Learning Machine (ELM) [42]. The results highlighted that the RMSE for the prediction accuracy of the presented methods are ranging from 55.32 W to 145.38 W.

To effectively utilize the information of predicted power demand, several studies employ evolutionary algorithm (EA), such as Genetic Algorithm (GA) [19] and Particle Swarm Optimization (PSO) [25], to optimize the control strategy with the aim to solve multi-objectives optimization problems. The authors in Ref. [18] optimized the membership functions (MF) of FLC using WCA to minimize the Loss of Power Supply Possibility and Operation & Maintenance cost in a PV/Wind power system with Battery-Hydrogen Storage System HESS [18]. The computational efficiency of the optimization algorithm in solving optimization problem with 37 dimensions is not presented in Ref. [18]. EA can be ineffective when applied to large and complex problems such as problem with high dimensionality [43]. In fact, EA with faster convergence, lower computational, and better reliability are highly desired