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Maximum Self-Consumption Planning Framework Considering Energy Management System for Optimal Photovoltaic-Battery System in Distribution Network

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Abstract: Power production from photovoltaic (PV) has advanced as Renewable Energy Resources (RES) power technology and is now a worthwhile alternative to conventional power generating. To effectively stabilize the process of connecting to the grid and increase power controllability owing to changing PV power production, energy storage systems (ESS), with their flexible charging and discharging capabilities, are most often used to cooperate with RES power generation. However, ESS's rapid rate of charging and discharging might cause it to age more quickly than it should and reduce its lifespan. Therefore, this study proposed an effective planning framework of optimal penetration of PV-ESS system associated with effective energy management systems (EMS). The proposed framework, the optimal PV size, PV location and maximum State of Charge (SOCmax) are determined. The fixed minimum State of Charge (SOCmin) based on load conditions is applied to minimize the degradation while maximizing PV self-consumption. The result shows that when applying different SOCmin during at off-peak and peak time load demand, the degradation cost is reduced to 19.40%.

Keywords: Energy, Energy Management System, Renewable Energy, Optimization, Battery degradation, State of Charge

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1. INTRODUCTION

Nowadays, pollution has increased in Malaysia due to the continually rising energy consumption as the generation is reliant on fossil fuels [1]. Increased usage of Renewable Energy (RE) to replace Non-Renewable Energy (Non-RE) reduces negative environmental and ecological consequences caused by emission control, greenhouse gas emissions, and fossil fuel extraction techniques. As a result, significant and far-reaching actions in RE generation must be done to assure long-term power development and ease energy transition [2]. The implementation of Distributed Generation (DG) systems based on RE sources is encouraged as a means of producing electricity. This approach has various advantages, especially in maximizing power reliability, reducing total power loss, and enhancing power flow performance in the system [3].

However, there are many challenges and technical issues associated with the penetration of RE-based DG into the power system network from a variety of perspectives. The RE power output varies significantly as weather changes from time to time. Photovoltaic (PV) systems, as an example, normally produce low energy in the morning and evening, yet the electricity consumption for a typical household is high at these hours. Consequently, the mismatch of load variation and the PV power production profile leads to excess PV power and higher purchase of power from the utility grid than expected.

Hence, several different techniques to guarantee that there will always be adequate to fully utilize DG power to supply in the system are proposed. Hybrid systems, such as those that combine wind and PV, have a better chance of being able to supply the load in a more consistent manner because they combine more than one type of RE technology, each of which has distinct or overlapping periods of low generation and high generation. The production of PV is contingent on daylight hours and irradiation levels, but the production of wind power is independent of irradiation levels but is entirely reliant on the activity of the wind. The constancy of the supply is distributed more equally because of this, although in certain circumstances, this will not be adequate. Unfortunately, in Malaysia, because of its location in an area with low average wind speeds, Malaysia confronts more difficult obstacles while attempting to expand its wind energy industry [4].

Therefore, within the framework of RE system, the incorporation of an Energy Storage System (ESS) in PV is essential to the upkeep of a stable energy balance and maximize PV self-consumption. The ESS can be used to store energy during minimum load and the stored energy will be then utilized at peak load time so that the quality of supply energy is improved [5].

However, one of the challenges in PV-ESS system penetration into the distribution network is to identify the suitable system size and their location. If an improper size and location of the PV and ESS are implemented, the network experiences negative impacts. Furthermore, ESS degradation is another concern in installing PV-ESS system as ESS is dominating cost in PV-ESS systems. Charging and discharging rate, depth of discharge (DOD), state of charge (SOC) and temperature are part of the parameters that cause ESS deterioration. The number of charge and discharge cycles that an ESS goes through before seeing a significant loss in capacity is called cycle life. Hence, the ESS capabilities deteriorate as the ESS is exposed to more cycles. Even when an ESS is not in use, it may deteriorate over time due to factors such as self-discharge and chemical interactions. This is referred to as calendar life degeneration. Thus, proper usage, and maintenance, such as monitoring the charge level to avoid overcharging and undercharging, balancing the cells, and ensuring the ESS is used on a regular basis are very important to ensure the ESS degrades as little as possible to reduce capacity loss and enlarge its lifetime.

As a solution, a proper and effective planning framework for optimal PV size and location and ESS size incorporating energy management systems (EMS) is designed in this study. The EMS considering the features of ESS as well as degradation factor parameters is important to monitor and control the energy flow within the system effectively while reducing the ESS degradation. Employing data analytics and machine learning approaches in EMS can predict the maintenance of the ESS so that unexpected failures can be avoided and prolong the life of the ESS. Another challenge of PV-ESS system installation is deciding suitable size and location. improper size of PV-ESS may lead to an oversized system, cost loss, and deteriorate the system stability and reliability.

1.2 Related Work

The suitable PV and ESS size and the proper EMS design is important to achieve the best system performance and low degradation effect. As ESS is used in the system, degradation cost is very important not to be overtaken as the cost is very important in the planning. Authors in [6] proposed a power management algorithm to enable the user to view and regulate the energy flow in the system which mainly minimizes the system cost. However, the optimal RE and ESS size is predefined. Based on this study, the fixed state of charge (SOC) limit of ESS is considered as a constraint, but the degradation issue is not highlighted. Study in [7] proposed a mixed-integer linear programming (MILP) to calculate the optimal sizing of a hybrid wind-photovoltaic power plant in an industrial area. This approach is suitable for any generic industrial site, including those that do not operate all year long and the integrated technical-economic procedure is useful for correctly defining the investments according to the different Company's objectives. However, the size of ESS is predefined, and the EMS is not addressed in this study. Authors in [8] introduced an efficient artificial bee swarm optimization (ABSO) algorithm for optimum sizing of a stand-alone PV/WT/FC hybrid system. The proposed methodology is applied to a real case study, and it is seen that at loss of power supply probability maximum (LPSPmax) set to 0%, 0.3% and 1%, the PV/WT/FC is the most cost-effective energy system and at LPSPmax = 2%, the WT/FC is the most cost-effective hybrid system. The limit SOC of ESS in the system is chosen and considered but the degradation problem as well as EMS are not addressed. EMS that focuses on low-cost hardware and embedded optimization has been built in [9]. By monitoring the PV production and the electricity load data, the EMS automatically optimizes the required battery charge/discharge power to provide the lowest energy bill. However, this system does not consider any control to reduce the degradation in the result.

The optimization and multiple-criteria decision analysis (MCDA) of a stand-alone photovoltaic and battery energy system (PV-BES) has been used in [10]. This research provides the best type of battery to be used and its DOD through nine optimization algorithms were used to find the optimum configuration of the PV-BES. The Mayfly algorithm provided the best optimal values in all six configurations and demonstrated robustness and fast convergence efficiency by finding the global optimal solutions. The results show that the PV-BES based on the Ni single bond Fe battery has the lowest. This study analyzes the lifetime of the PV and ESS throughout comparison of the nine optimization algorithm results but does not consider a method to control the degradation. In the study of [11], rule-based energy management strategies (EMS) based on the modifications of the traditional load following (LF) and circuit charging (CC) have been proposed and developed to effectively coordinate the operation of an integrated multi-carrier hybrid energy system. The proposed model can reduce the dumping of power and emissions from the optimal system, by reducing the hourly commitments of the back-up in fulfilling the load. In addition, it enhances the cooling and heating generation potentials of the multi-carrier energy system, by improving the quality of the combustion flue sent to these units. However, the size of RE and ESS were not optimized, and the degradation cost was neglected.

Researcher in [12] proposed EMS uses a combination of Fuzzy Logic (FL) and a rule based-algorithm to optimally control the PV-battery system while considering the day-ahead energy forecast including forecast error and the battery State of Health (SOH). In this research, the battery is optimized to be more utilized during peak hour while in the off-peak hour, the discharging battery is lower as to consider the degradation battery. However, the optimization size of RE and ESS were concerned and there is no method to control the degradation applied as it only depends on the peak and off-peak hour. While the impact of aging when using various SOC levels for an electrified vehicle is investigated in [13]. An extensive test series is conducted on Li-ion cells, based on graphite and NMC/LMO electrode materials. Lifetime cycling tests are conducted during a period of three years in various 10% SOC intervals, during which the degradation as a function of number of cycles is established. From the result, by keeping the battery at 15% SOC during parking and limiting the time at high SOC, the contribution from the calendar aging could be substantially reduced. However, no energy management was considered for further analysis as well as the size of RE and ESS.

In research by [14], the authors evaluated the deterioration processes of Li-ion batteries (Li-ion) under various operating situations. The work gave insights into the impacts of temperature, cycle rate, and state of charge (SOC) on battery deterioration using detailed experimental analysis and mathematical modeling, offering light on ways for minimizing degradation in Li-ion batteries.
Comparison summary of related work above mentioned study between recent studies are given in Table 1. Table 1 provides the difference idea between other methods and shows the gaps between the studies. Mainly, many studies that optimized RE and ESS did not pay much attention to ESS degradation. While, when the studies concerned the degradation issue, the RE and ESS optimization was overtaken in the study. In addition, different SOC limits values are applied in different studies. Using the fixed SOC limit throughout the usage may affect ESS degradation.

Table 1. Comparison of recent study and proposed system

Ref.	EMS	Degradation	ESS	System Cost	Optimization RE and ESS size
[6]	/	x	/	/	x
[7]	x	x	/	/	MILP model
[8]	x	x	/	/	ABSO
[9]	/	x	/	/	Python package, CVXOPT with linear programming solver
[10]	/	/	/	/	Mayfly optimization algorithm
[11]	/	x	/	/	(NSGA-II) algorithm
[12]	/	x	/	/	x
[13]	x	/	/	/	x
Proposed system	/	/	/	/	DEPSO

To prevent negative impacts on the system, it is imperative to appropriately size both the Photovoltaic (PV) and Energy Storage System (ESS) components, ensuring their effectiveness and efficiency. Therefore, an optimization method is essential to determine the optimal size and location for PV installations and the size of ESS units within a system. Additionally, an effective Energy Management System (EMS) is required to schedule ESS operations and manage degradation issues.

This research proposed planning framework addresses these challenges by integrating EMS into the optimization process for PV size and location, as well as ESS size. The key features of the framework include:
1) Optimize the size and location of PV and size of ESS.
2) Optimize SOCmax to control degradation.
3) Implemented fixed SOCmin based on load conditions to minimize the degradation while maximizing PV self-consumption.

In this paper, an approach by incorporating a rule-based EMS into the optimization process is introduced. This EMS, coupled with a hybrid Particle Swarm Optimization and Differential Evolution (PSO-DE) algorithm, effectively manages ESS conditions based on peak or off-peak load demands, thereby mitigating ESS deterioration. This research's contribution lies in the introduction of this rule-based EMS, which enhances the overall efficiency and robustness of the optimization framework.

The following study is divided into 4 parts. The approach is described in Section 3; here, the problem formulation and limitations are discussed. The simulation findings are shown in Section 4 while the study's conclusion is presented in Section 5.

2. METHODOLOGY

2.1 Introduction

The objective of the optimization of the PV-ESS system in the distribution network is to minimize degradation cost, non-REDG cost and excessive power cost using the hybrid PSO-DE algorithm. In this study, the IEEE 33-bus radial system is selected to represent the distribution network and it is simulated using MATLAB software.

The system that consists of PV as REDG, ESS and diesel generator as non-REDG are installed in the distribution system as shown in Figure 1.

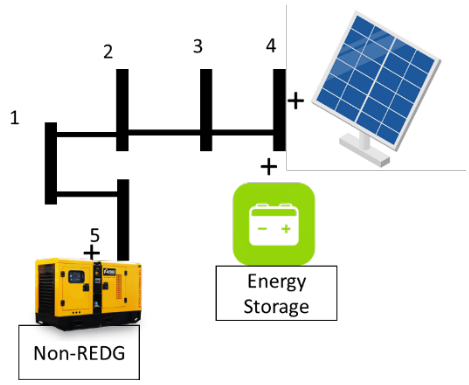

Figure 1. PV/ESS/DIESEL System in the Distribution System

2.2 PV Modelling

The power generated by Solar Panel is calculated using eq. (1) [15].

$$P_{pv} = A \times B \times U, \quad (1)$$

where A is the area of the solar panel, B is the efficiency of the PV panel and U is solar irradiance data.

2.3 Load Modeling

The load variation is modeled using IEEE Reliability Test System model during spring season [16]. The hourly peak load in percent of daily peak is taken at spring condition as it is like in Malaysia.

2.4 Energy Management Strategy

The load demand varies with time. To fully utilize the ESS at peak and off-peak hours while considering reducing the degradation, a schedule for ESS at certain times is important. Thus, the EMS is illustrated in Figure 2 to show the flow of energy. During peak time hours of load demand, the SOCmin is set to 20% while at off-peak time hours, the SOCmin is set at 30%. This is to fully utilize the energy from the battery and indirectly to reduce the DOD of the battery to reduce the degradation.

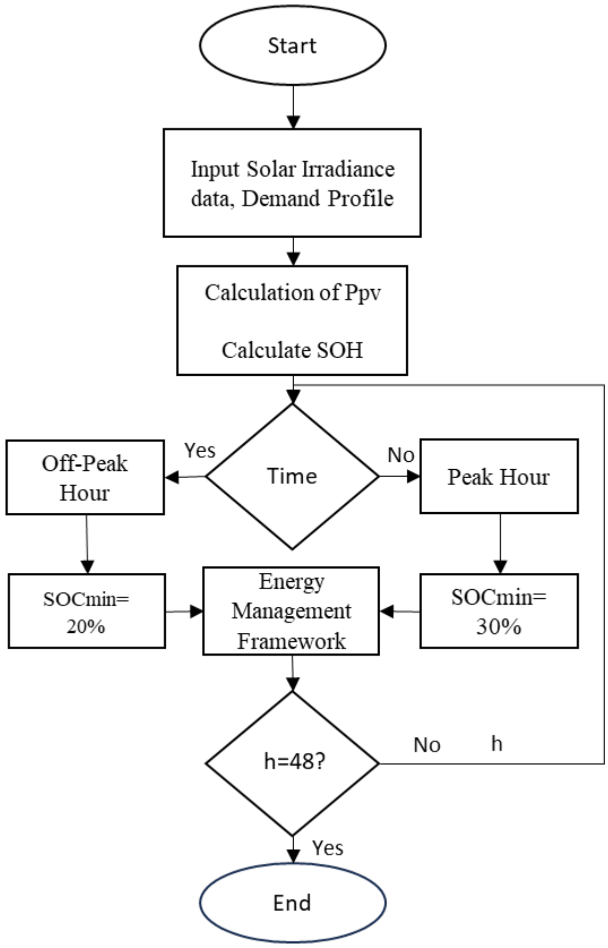

Figure 2. Energy management strategy considering peak and off-peak conditions.

The EMS is designed for grid connected distribution systems with PV, ESS and NON-REDG for distribution systems. Figure 2 describes the flow of energy at each hour for EMS.

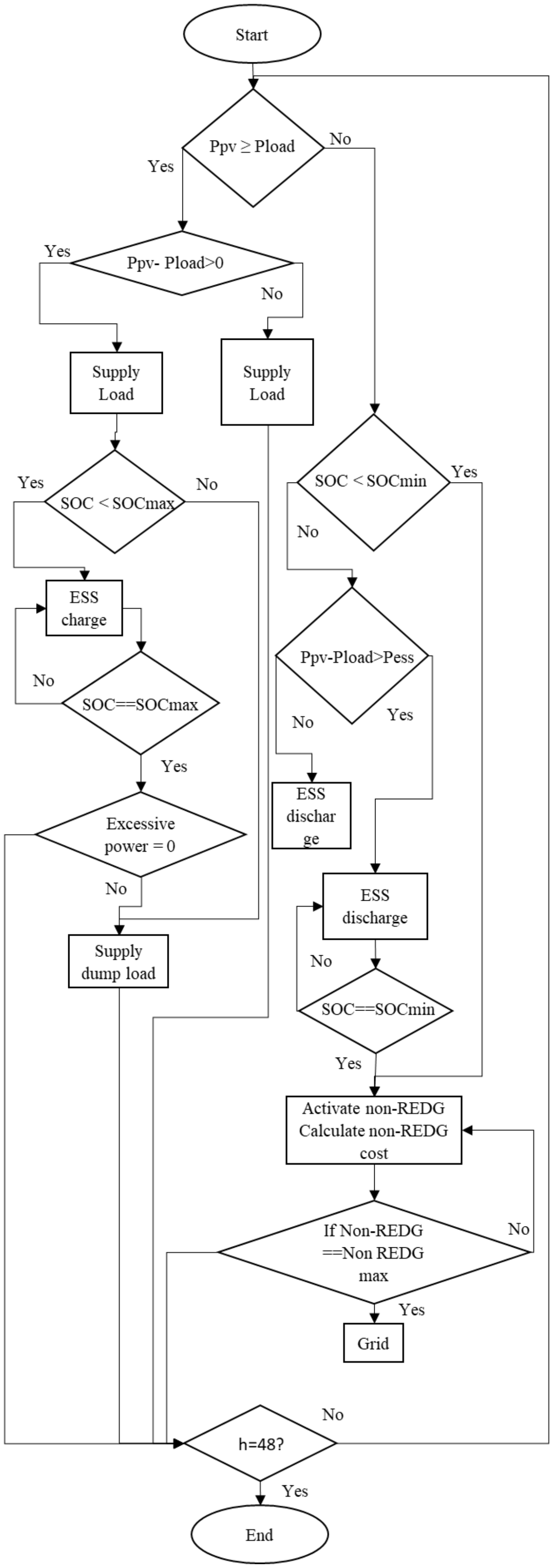

Figure 3. Energy Management Framework

The generated power of the PV can be used for load supply and battery charging. The installed ESS can only be charged by solar PV. Hence, there is a power connection between the installed PV and the ESS. The solar PV can charge the ESS. The system is also included with non-REDG and used when the load demand is higher than generated power by PV and energy in ESS.

2.5 Problem Formulation

The multi objective of the optimization problem is to find the optimal size and location for PV-ESS, and SOCmax to minimize the degradation cost, non-REDG cost and excessive power cost using hybrid PSO- DE algorithm.

a) Degradation cost

$$Degcost=(SOHinitial - SOHi)ESScapitalcost \quad (3)$$
$$Degcost = \Delta SOHxESScapitalcost \quad (4)$$

b) Non-REDG cost

The non-REDG cost is used based on the diesel generator producing power. The Fuel Consumption Approach is used to determine the volume of liter diesel used in a generator.

$$P_{non-REDG\ cost}\text{=Q*2.15RM/L} \quad (5)$$

Where,

Q = N*q/R, where
Q – (in l/h) maximum theoretical fuel consumption in grams per 1 hour of engine operation at maximum power.
q – (in g/kWh) specific fuel consumption for power N.
N – (in kW) engine power.
R – (kg/m3) fuel density. Diesel fuel density: 820 – 860 kg m3

c) Excessive power cost

$$P_{excessive\ cost}= P_{excessive}\ \text{x 141.1RM/MWh} \quad (6)$$

2.5.1 Degradation Approach

Assuming ESS enclosure can maintain temperature almost constantly, a linearized model for ESS capacity fade ($Ccal(t)$) in each hour due to calendric aging is used [17].

$$C_{cal(t)}\text{=6.6148 x 10 ^-6 x soc(t) + 4.6404 x 10^-6} \quad (7)$$

where $Ccal(t)$ is the calendric aging and SOC is the variable representing BESS SOC at the given time step.

Capacity loss due to cyclic aging $Ccyc(t)$,which is dependent on charge throughput, up to any given time step can be given as

$$C_{cyc(t)}, + \frac{P_b\ (\Delta t)}{L_{cyc}+ E_b} \quad (8)$$

where $Ccyc(t)$ is the cyclic aging and Eb is the original battery capacity in kWh and Pb is taken as the battery charge or discharge power at any time step. As explained in Ref. [11], a superposition rule is used to estimate the overall aging ($Ctotal(t)$) of the battery at any time step.

$$C_{total(t)} = C_{cal(t)} + C_{cyc(t)} \quad (9)$$

2.5.2 Constraints

The optimization process must meet several constraints such as:

a) Voltage constraint

Following the PV output adjustment, the voltage value for all buses in the distribution network must operate within the allowed limit, which is ±5% of the rated value [18].

$$0.95 \quad p.u \leq Vm \leq 1.05\ p.u \quad (10)$$

b) Generator operation constraint:

$$P_{min} \leq P_{DGi} \leq P_{max}; \qquad 0 \leq P_{DGi} \leq 2MW \quad (11)$$

All PV units must operate between minimum PV output, $Pmin$ and maximum PV output, $Pmax$. Therefore, PV sizing results must not exceed this limit during initialization or updating in optimization.

c) Power balance constraint

$$\sum_{i=1}^{k}(P_{PV} + P_{ESS} + P_{non-REDG}) = P_{\ Load} + P_{Loss} \quad (4)$$

where P_{PV} is the real power generated by PV, P_{Grid} is real power injected from the grid to the system, $P_{\ Load}$ is demand real power and P_{Loss} is the real power loss in the system.

The total power generated in the network which is from DG units and the grid must be equal to the summation of total load and the total power loss.

d) Reverse Power Flow

$$P_{DG} < P_{\ Load} \quad (12)$$

e) The constraints on SOC are as follows.

$$soc_{\ min} < soc < soc_{max} \quad (13)$$

2.6 Hybrid PSO-DE Algorithm

The DEPSO hybrid algorithm combines the Differential Evolution (DE) and Particle Swarm Optimization (PSO) algorithms, leveraging the strengths of both techniques for enhanced optimization performance. DEPSO has been widely employed in various optimization problems due to its ability to effectively explore the search space and exploit promising regions efficiently.

One notable feature of DEPSO is its hybrid nature, which allows it to adaptively adjust its exploration and exploitation capabilities during the optimization process. This adaptability is particularly beneficial in complex optimization tasks where the search landscape may exhibit non-linear and multi-modal characteristics. Several studies have demonstrated the effectiveness of DEPSO in solving challenging optimization problems. For instance, [19] applied DEPSO to optimize the design of a renewable energy system, achieving superior performance compared to other optimization techniques.

In this study, degradation cost, non-REDG cost and excessive power cost are aimed to be minimized. Hybrid Differential Evolution (DE) with Particle Swarm Optimization (PSO) is used to run this multi objective function implemented the proposed EMS. Figure 3 shows the flow of the optimization of the algorithm to optimize the problem.

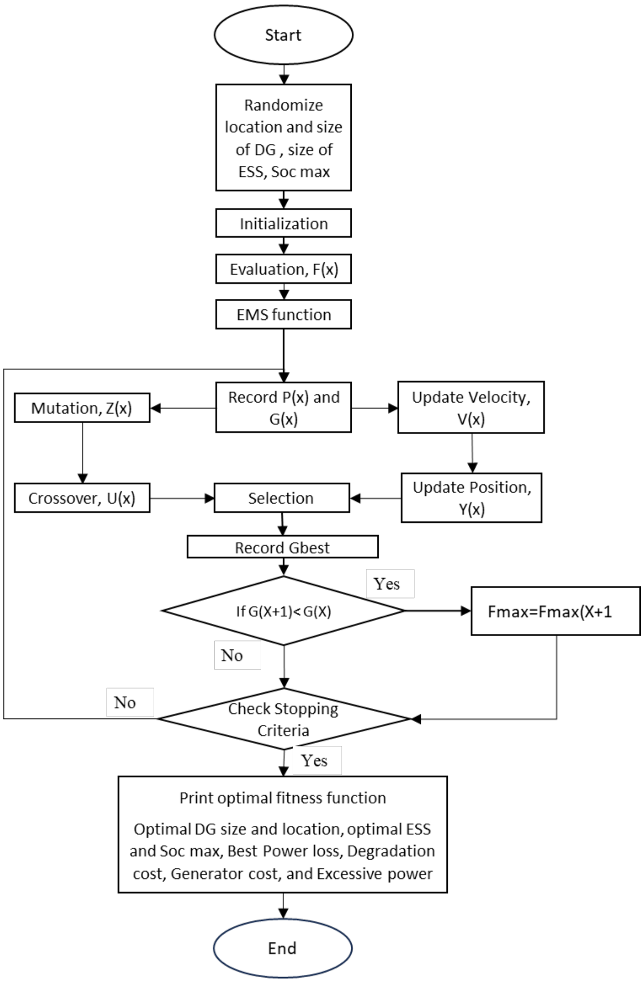

Figure 4. Hybrid DE-PSO algorithm flowchart

The algorithm will randomize the size of PV, ESS and SOCmax. The input data will go through the initialization and will be evaluated to produce the personal best and the global best. The population data will go through the PSO and DE part to produce the fitness function value to compare which is the best for the record. The optimal result will be printed to show the best value.

2.6.1 Simulation Parameter

In the DEPSO hybrid algorithm, the following parameter values were used:

- Weightage for Multiple Objectives:
  - Degradation Cost (w1): 0.2
  - Non-REDG Cost (w2): 0.5
  - Excessive Power Cost (w3): 0.3

- PSO Parameters:
  - Cognitive Parameter (c1): 1
  - Social Parameter (c2): 1
  - Inertia Weight Damping (wdamp): 0.99
  - Velocity Range Parameters (r1, r2): 1

- DE Parameters:
  - Maximum Iterations (MaxIt): 50
  - Population Size (nPop): 20
  - Scaling Factor Range (beta_min, beta_max): [0.2, 0.8]
  - Crossover Probability (pCR): 0.55

2.7 Implementation of EMS in optimization process

The EMS framework as shown in Figure 3 is positioned in an optimization process. During optimization, each particle in the hybrid DE-PSO algorithm carries randomized PV size, DG location, and the SOCmax. These randomized variables are used to calculate the PV power output and subsequently utilized for controlling energy flow for 48 hours using the proposed EMS framework to determine the fitness value. In other words, during each iteration, each particle undergoes the complete process of the Energy Management System (EMS) to calculate its fitness value. This process is repeated for several iterations to find values that are close to the optimal solution.

3. RESULT AND DISCUSSION

In this study, four case studies are carried out by varying the EMS criteria, PV size and location to observe the effectiveness of proposed ESS management and DG optimization to reduce degradation. The explanation for all cases is follows.

Case A: The PV size, PV location, SOCmin and SOCmax are specified. This case study is treated as a base case.

Case B: Different SOCmin is applied depending on the load demand condition as stated in Figure 2. Meanwhile, the PV size, PV location and SOCmax are specified in this case study. The purpose of analysis in case B is to observe the effect of degradation clearly and to observe the effect of different SOCmin at different times.

Case C: The PV size, PV location and the SOCmax are optimized. While SOCmin remains constant regardless of the load demand condition. The purpose of analysis in case C is to observe the degradation of ESS when the SOCmin is vary and to observe the pros of optimized SOCmax in the analysis.

Case D: The PV size, PV location and the SOCmax are optimized and the different SOCmin is applied depending on the load demand condition. The purpose of analysis in case D is to observe the impact of the proposed planning framework on the degradation.

3.1 SOC Level of ESS

Figure 5 presents the load profile and PV profile generated by all cases. The load profile is all the same due to the implementation of IEEE reliability test system which follows the spring condition by hour during weekdays. Meanwhile, the power generated by the PV is the same for all cases as the size of PV optimized in all cases is the same. Then Figure 6 shows the SOC level of ESS in every case for 48 hours. It shows that case B and D have the higher SOCmin level due to the ESS type of time implementation. This indicates the power discharged from the ESS is lower to reduce the degradation as the Depth of Discharge (DOD) is low. While for the case A and C, the DOD is higher than B and D which leads to the degradation is high.

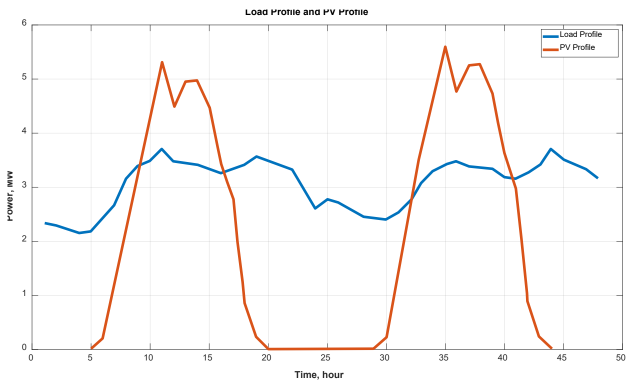

Figure 5. Load and PV profile

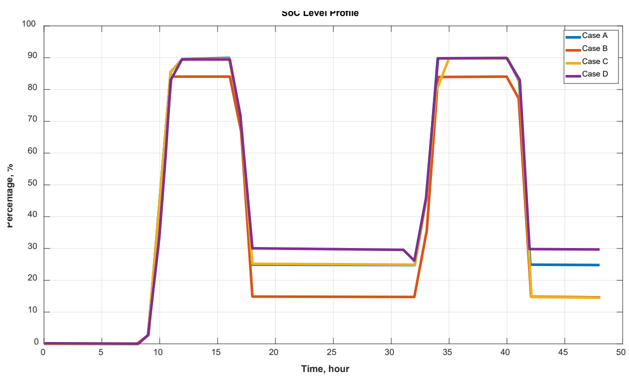

Figure 6. SOC level of ESS Profile

3.2 The Excessive Power in System

The excessive power produced from the system is shown by Figure 7 and indicates that case B has the lowest excessive power while case D is at the second lowest. Summarily, the system which has the implementation of ESS management of the type of time produced low excessive power in the system. For case D, the optimization of PV location and size affects the excessive power produced as can be seen in case C has a higher excessive power than case D. The size of PV is optimized so that the production of extra power is decreased.

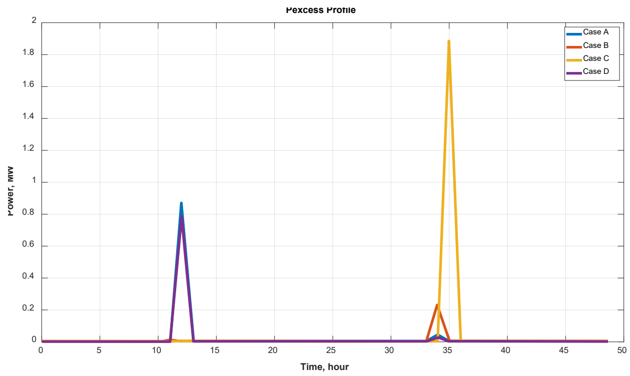

Figure 7. Excessive Power Profile

3.3 The Energy Usage of Non-REDG

The power used by generators to supply the system when the energy from PV and ESS is not adequate is pictured in Figure 8. Clearly, when the optimization of PV takes place, the power from the generator is reduced. Case C and D show lower generator power used than case A and B. In case A and B, although it has an objective function to minimize the generator power, when the size of PV is not optimized properly, the power produced by the generator will have negative effect.

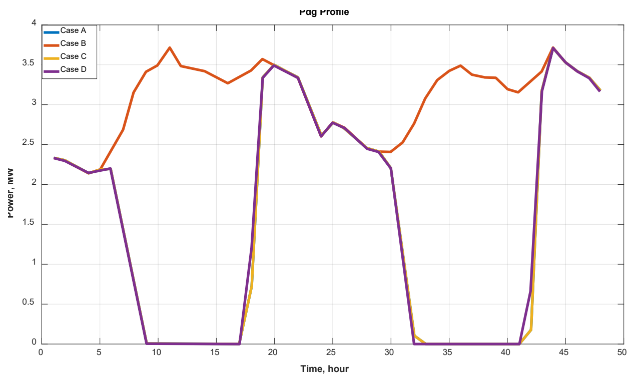

Figure 8. Power of Generator

3.4 The State of Health of ESS

The State of Health (SOH) of ESS is taken to analyze the final SOH of ESS at the end of simulation. The SOH provides insights into the overall performance and reliability of a system to observe the flow of degradation in ESS. SOH for 48 hours simulation is displayed in Figure 9. Case B produces the best SOH due to the limitation of SOCmin implementation at certain hours. As the SOCmin is changing, the DOD is controlled to reduce and decrease the degradation or the capacity fading in ESS was low and maintain high SOH at hour 48. Case A gives the second-best SOH but in this case the PV optimization is not included. The SOH for case C is the worst, this is because the DOD is not controlled like case B and D. The SOH of case C is lower than A because the optimization of PV is considered but the optimal DG size and location without a method to reduce degradation will give much worse SOH in ESS. Finally, even though case D is not the best in terms of degradation reduction, with a proper PV optimization, the SOH can be reduced.

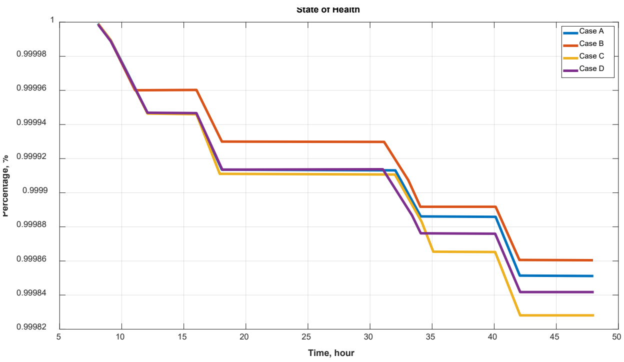

Figure 9. SOH Level of ESS

Table 2. Optimal Result for All Cases

Case / Parameter	A	B	C	D
SOCmin	0.15	-	0.15	-
SOCmax	0.9	0.84	0.9	0.9
PV Size (MW)	2	2	2	2
Location	-	-	2	29
ESS SIZE (MW)	3.18	3.16	3.2	3.2
SOH (%)	99.98	99.99	99.98	99.98
Degradation Cost (RM)	469.45	378.39	471.95	435.75
Degradation Percentage Reduction (%)	-	19.40	-0.49	7.67
Generator Cost (RM)	50057	50891	50024	50602
Excessive Power (RM)	383.07	34.19	377.67	114.96
Total cost (RM)	50909.52	51303.58	50873.62	51152.71

Table 2 shows overall optimal results for all cases and the total cost in terms of degradation, generator, and excessive power cost. The best PV proposed in the algorithm is 2 MW and the ESS size is range between 3.16 to 3.2 MW. Case B has the best SOH at 99.99 % at hour 48 while the others are at 99.98% because the optimization of PV is neglected so that the optimization mainly focuses on reducing the degradation as well as the cost of degradation for that case is at the lowest which is RM 378.39. From Table 1, the degradation cost objective is decreased when the implementation of ESS management in the system. The reduction of degradation is 19.40% and 7.67% respectively for case B and D when energy management is used.

In terms of generator cost, case C is the cheapest price as the generator production is lower by the optimization size of PV in that system. However, when considered with the energy management method, the production power of the generator is increased as the limitation of ESS to discharge leads the generator to supply the extra power for the system. The excessive power produced is reduced when there is energy management. Excessive power costs for case B and D are RM 34.19 and RM 114.96 respectively are lower than case A and C.

Case C is the best as the total cost is the lowest, RM 50873.62 while RM 52303.58 is the highest in case B. Although the total cost for cases which have the degradation reduction method is not reduced, the degradation cost is clearly seen as reduced.

4. CONCLUSION

In this study, a method to reduce degradation is proposed with a combination of optimization of PV size and location. The degradation cost can be reduced with proper optimization of PV combined with energy management in the system. Mainly, the objective to reduce the reduction of degradation is achieved, which is 19.40% and 7.67% respectively for case B and D. It can be concluded that the reduction of generator power and degradation is contradictory. However, with a proper optimization of PV included ESS parameters, the total cost can be reduced. For instance, total cost case D is 0.3% reduced from case B that does not consider PV optimization.

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REFERENCES

[1] F. S. Mohd Chachuli, N. Ahmad Ludin, M. A. Md Jedi, and N. H. Hamid, "Transition of renewable energy policies in Malaysia: Benchmarking with data envelopment analysis," *Renewable and Sustainable Energy Reviews,* vol. 150, p. 111456, 2021/10/01/ 2021, doi: https://doi.org/10.1016/j.rser.2021.111456.

[2] M. Davis, A. Moronkeji, M. Ahiduzzaman, and A. Kumar, "Assessment of renewable energy transition pathways for a fossil fuel-dependent electricity-producing jurisdiction," *Energy for Sustainable*

Development, vol. 59, pp. 243-261, 2020/12/01/ 2020, doi: https://doi.org/10.1016/j.esd.2020.10.011.

[3] R. O. Bawazir and N. S. Cetin, "Comprehensive overview of optimizing PV-DG allocation in power system and solar energy resource potential assessments," *Energy Reports,* vol. 6, pp. 173-208, 2020/11/01/ 2020, doi: https://doi.org/10.1016/j.egyr.2019.12.010.

[4] H. Lip-Wah, "Wind energy in Malaysia: Past, present and future," *Renewable and Sustainable Energy Reviews,* vol. 53, pp. 279-295, 2016, doi: https://doi.org/10.1016/j.rser.2015.08.054.

[5] G. Coppez, S. Chowdhury, and S. P. Chowdhury, "Review of battery storage optimisation in Distributed Generation," in *2010 Joint International Conference on Power Electronics, Drives and Energy Systems & 2010 Power India*, 20-23 Dec. 2010 2010, pp. 1-6, doi: 10.1109/PEDES.2010.5712406.

[6] C. K. Andal and R. Jayapal, "Design and implementation of IoT based intelligent energy management controller for PV/wind/battery system with cost minimization," *Renewable Energy Focus,* vol. 43, pp. 255-262, 2022/12/01/ 2022, doi: https://doi.org/10.1016/j.ref.2022.10.004.

[7] R. Lamedica, E. Santini, A. Ruvio, L. Palagi, and I. Rossetta, "A MILP methodology to optimize sizing of PV - Wind renewable energy systems," *Energy,* vol. 165, pp. 385-398, 2018/12/15/ 2018, doi: https://doi.org/10.1016/j.energy.2018.09.087.

[8] A. Maleki and A. Askarzadeh, "Artificial bee swarm optimization for optimum sizing of a stand-alone PV/WT/FC hybrid system considering LPSP concept," *Solar Energy,* vol. 107, pp. 227-235, 2014/09/01/ 2014, doi: https://doi.org/10.1016/j.solener.2014.05.016.

[9] K. E. Ouedraogo, P. O. Ekim, and E. Demirok, "Feasibility of low-cost energy management system using embedded optimization for PV and battery storage assisted residential buildings," *Energy,* vol. 271, p. 126922, 2023/05/15/ 2023, doi: https://doi.org/10.1016/j.energy.2023.126922.

[10] T. Salameh *et al.*, "Best battery storage technologies of solar photovoltaic systems for desalination plant using the results of multi optimization algorithms and sustainable development goals," *Journal of Energy Storage,* vol. 55, p. 105312, 2022/11/01/ 2022, doi: https://doi.org/10.1016/j.est.2022.105312.

[11] G. T. Udeh, S. Michailos, D. Ingham, K. J. Hughes, L. Ma, and M. Pourkashanian, "A modified rule-based energy management scheme for optimal operation of a hybrid PV-wind-Stirling engine integrated multi-carrier energy system," *Applied Energy,* vol. 312, p. 118763, 2022/04/15/ 2022, doi: https://doi.org/10.1016/j.apenergy.2022.118763.

[12] A. Sorour, M. Fazeli, M. Monfared, A. A. Fahmy, J. R. Searle, and R. P. Lewis, "Forecast-Based Energy Management for Domestic PV-Battery Systems: A U.K. Case Study," *IEEE Access,* vol. 9, pp. 58953-58965, 2021, doi: 10.1109/ACCESS.2021.3072961.

[13] E. Wikner and T. Thiringer, "Extending Battery Lifetime by Avoiding High SOC," *Applied Sciences*, vol. 8, no. 10, doi: 10.3390/app8101825.

[14] P.-Y. Lee, A. Nagar, K. Yoo, and J. Kim, "Impedance-based health indicators determination for degradation diagnosis and fault identification of lithium-ion batteries under extreme operating conditions," *Journal of Electroanalytical Chemistry,* vol. 942, p. 117572, 2023/08/01/ 2023, doi: https://doi.org/10.1016/j.jelechem.2023.117572.

[15] C. Yammani, S. Maheswarapu, and M. Kumari, "Optimal Placement of Multi DGs in Distribution System with Considering the DG Bus Available Limits," *Energy and Power,* vol. 2, pp. 18-23, 08/31 2012, doi: 10.5923/j.ep.20120201.03.

[16] P. M. Subcommittee, "IEEE Reliability Test System," *IEEE Transactions on Power Apparatus and Systems,* vol. PAS-98, no. 6, pp. 2047-2054, 1979, doi: 10.1109/TPAS.1979.319398.

[17] U. G. K. Mulleriyawage and W. X. Shen, "Optimally sizing of battery energy storage capacity by operational optimization of residential PV-Battery systems: An Australian household case study," *Renewable Energy,* vol. 160, pp. 852-864, 2020/11/01/ 2020, doi: https://doi.org/10.1016/j.renene.2020.07.022.

[18] P. D. Huy, V. K. Ramachandaramurthy, J. Y. Yong, K. M. Tan, and J. B. Ekanayake, "Optimal placement, sizing and power factor of distributed generation: A comprehensive study spanning from the planning stage to the operation stage," *Energy,* vol. 195, p. 117011, 2020/03/15/ 2020, doi: https://doi.org/10.1016/j.energy.2020.117011.

[19] M. Akhtar, A. K. Manna, and A. K. Bhunia, "Optimization of a non-instantaneous deteriorating inventory problem with time and price dependent demand over finite time horizon via hybrid DESGO algorithm," *Expert Systems with Applications,* vol. 211, p. 118676, 2023/01/01/ 2023, doi: https://doi.org/10.1016/j.eswa.2022.118676.