International Journal of Aquatic Research and Environmental Studies 6(1) 341-361 2026

Optimising depth-of-discharge (DOD) to extend battery life in solar-powered aquaculture and water resource systems

Hayder Al-Madhhachi[1]; Ahmed M. Ajeena[2];
Mensour Almadhhachi[3*]

Received: 10 January 2026; Revised: 29 January 2026; Accepted: 18 March 2026; Published: 20 April 2026

Abstract

The growing use of solar photovoltaic (PV) systems in aquaculture farms and water-resource management facilities has provided the groundwork for developing systems that require reliable and long-life energy storage solutions, especially in remote and/or off-grid locations that require powering aeration devices, water circulation pumps, monitoring devices, and control systems on a continuous basis. Battery aging, driven by inappropriate Depth of Discharges (DOD) as a main system costs and sustainable operating challenge, is still the weakest link in the system reliability, sustained operational cost, and long-term adequacy. This is particularly true for systems in (PV-coupled) energy for aquaculture applications. This study discusses the possible design of an intelligent DOD management system that ranked the possible designs according to the remaining energy in the battery during the charging cycle at the optimised solar PV–battery hybrid energy system, streaming tier applications. A system of mathematically informed approaches developed provides a quantitative measure of solar energy, the use of inverter systems, battery systems, and their storage systems to regulate a range of unloaded solar PV modules. A Genetic Algorithm (GA)-based multi-objective optimisation framework is used to find the optimal depth of discharge (DOD) while minimising both the Loss of Load Probability (LLP) and the Cost of Energy (COE), and simultaneously maximising the battery life and the system efficiency. The optimisation takes battery ageing behaviour, discharging, and charging efficiencies and operational constraints into account. Simulations reveal that the optimal DOD that balance's reliability, battery cost, and longevity is 32%. At this operating point the system loss of load is completely eliminated, the battery longevity is 5 years, and there is an 85 - 90\% decrease in daily dependence on the electrical grid. The study confirms that the optimised battery depth of discharge (DOD) enhances the performance and economically feasible use of solar PV

1- Department of Mechanical Engineering, Faculty of Engineering, University of Kufa, Najaf, Iraq; Institution of Mechanical Engineers, Engineering Council, London, United Kingdom.
Email: hayder.almadhhachi@uokufa.edu.iq, ORCID: https://orcid.org/0000-0001-9440-9015
2- Department of Mechanical Engineering, Faculty of Engineering, University of Kufa, Najaf, Iraq.
Email: ahmedm.dhayea@uokufa.edu.iq, ORCID: https://orcid.org/0000-0002-8443-365X
3*- Department of Mechanical Engineering, Faculty of Engineering, University of Kufa, Najaf, Iraq.
Email: al-madhhachi.mensour.saheb.malek@phd.uni-mate.hu; mensours.almadhhachi@uokufa.edu.iq,
ORCID: https://orcid.org/0000-0002-3944-2872
*Corresponding author

DOI: 10.70102/IJARES/V6I1/6-1-23

systems in aquaculture and water-resource management systems. The solution is efficient and versatile in sustainable energy use in aquatic systems and technologies.

Keywords: Solar PV–battery systems, Aquaculture power demand, Depth of discharge (DOD), Battery optimisation, Genetic algorithm (GA), Energy savings

Introduction

The water resource and aquaculture industries have seen increasing adoption of solar photovoltaic (PV) equipment. These industries require a consistent, dependable power supply for their equipment, including aeration systems, water-quality processors, circulation pumps, and automated feeders. For most aquaculture farms and water treatment facilities, PV–battery systems are the most appropriate and convenient power supply option given their remote or off-grid locations. However, storing energy for later use significantly impacts the overall reliability and uninterrupted operation of the system, given the unobstructed, fluctuating nature of solar energy and the constant power demand of the aquatic systems (Mahadevan and Ramakrishnan, 2025; Shrestha, Thapa and Gautam, 2019).

Rising fossil fuel prices, Greenhouse gas emissions, and the growing demand for clean energy have all contributed to the recent global expansion of PV Modules (Ahmed *et al.,* 2021). PV Modules work by converting sunlight into electricity with the assistance of semiconductor materials (Wang *et al.,* 2019). Batteries serve as an energy buffer within PV systems; PV systems would be unable to operate for long periods, and hence storage systems are needed to smooth output arbitrarily to the moment of energy isolation (Yap, Chin and Klemeš, 2022). The most commonly used deep-cycled devices, such as Li-ion and Lead-acid, are cycled and discharged quite frequently (Tomar and Vyas, 2022; Kavaliauskas *et al.,* 2023). The deep-cycle devices employed affect the system's efficacy, cost, and reliance over the years.

The significance of the battery selection process and battery management in PV systems has been discussed in other studies. Though Li-ion batteries are more expensive than lead-acid batteries, they are healthier and cheaper in the long run because of their higher efficiency and longer life cycle (Muxitdinov, 2023; Keshan, Thornburg and Ustun, 2016). Also, battery storage systems have been shown to improve grid flexibility and reduce the need for additional infrastructure in areas with higher PV (Li and Wang, 2019). On top of that, more sophisticated battery management systems (BMS) with thermal regulation, charge estimation, and cell balancing have been reported to prolong battery life by 20% (Asadipooya and Nezhad, 2019; Gabbar, Othman and Abdussami, 2021). This data demonstrates the necessity of robust battery management in PV–battery systems.

According to Hlal *et al.,* 2019, in PV systems, battery life is influenced by temperature, operating cycle frequency, depth of discharge (DOD), and maintenance. Lithium-ion batteries have spanned over a decade and a half, while lead-acid batteries have shorter life cycles of three to five years and are far more sensitive to deep discharges (Yudhistira, Khatiwada and Sanchez, 2022). The effect of the given operating conditions is significant, with studies indicating that lifespans could be amplified by 50% the temperature is kept within the optimal range (Shanmugasundaram, Srinivasan and Lavanya, 2023; Spitthoff, Shearing and Burheim, 2021). Internal stress is lower in low DOD, and so are deterioration rates. In contrast, high DOD leads to accelerated deterioration, with wear more pronounced in the aquatic environment, where humidity and temperature vary (Woody *et al.,* 2020).

According to Xie *et al.,* 2019, the DOD is a primary factor in usable energy and battery life for PV-based systems. A higher Deep Discharge state (DOD) leads to electrode and electrolyte degradation, reducing battery life. Studies suggest that DODs of 80% and 50% can almost double the cycle life for Li-ion batteries (Al-Saadi *et al.,* 2022). In practice for PV systems, DODs of 20–50% are the standard to conserve battery health (Hou *et al.,* 2020). Most Advanced Battery Management Systems (BMS) aim to balance operating conditions to adjust DOD for efficiency and longevity optimally.

Battery-powered aeration devices and automated water circulation systems used in solar-powered aquaculture units and solar-powered water management facilities require a reliable, constant power supply to sustain biochemical and mechanical processes. Adjustments needed due to power fluctuations in aeration and water circulation systems can lead to rapid and critical instauration of a healthy pond ecosystem. Hence, there is a need to optimize DOD to minimize battery availability while keeping the system functioning without interruption.

To address the need for quadraplex optimization, we propose a hybrid photovoltaic system designed to power aquaculture systems in both grid-connected and off-grid configurations. The aim is to provide reliable power to the aquaculture systems and minimize energy usage from the power grid. Using a genetic algorithm to operate within the optimum DOD has the potential to reduce battery cycling, improve the economic feasibility, and enhance the operational sustainability of energy in aquaculture systems.

Key Contributions

- For aquaculture and water resource applications, a dedicated solar PV-battery system model is developed to capture continuous load demand and environmental conditions in an ecosystem.
- Proposed is a Genetic Algorithm-based, multi-objective optimization framework for determining the optimal Depth of Discharge (DOD) with reverse Loss of Load Probability (LLP) and Cost of Energy (COE) minimization.
- To enhance system reliability and economic performance, battery aging, efficiency degradation, and operational restraints are tempered the optimization sequence.
- The simulation results achieved are optimal, with 32% DOD and no loss in load, extended battery life, and a reduction of 90% in energy dependence from the grid.

The rest of this paper is structured as follows. The solar PV–battery hybrid system if for aquaculture and water-resource management applications is modeled and analyzed in Section 2. This includes PV modules, inverter sizing, and battery storage functions. The optimization framework is explained in detail, and energy saving is analyzed in Section 3. The simulation results are explained in Section 4 and show how the optimal Depth of Discharge (DOD) leads to system reliability and reduction in grid dependence. This paper also presents some conclusions, describes the most significant results in Section 5, and details possible work for the next researchers.

Literature Survey

In solar photovoltaic (PV) systems battery energy storage is of the most pivotal importance. It even determines the economic viability of solar battery hybrid systems. Depth of discharge is a factor that determines battery life. It also predetermines how electrochemical DOD stress will affect age behaviour of batteries in the system as well as system replacement costs. There is a good amount of literature on batteries, the impact of the PV on systems and the optimisation of the management of batteries in systems. Based on previous studies on lithium-ion batteries, there are key operating conditions namely temperature and DOD that strongly affect degradation mechanisms and the cycle life of lithium-ion batteries. It has been shown that high and low temperature combined with deep discharges, will limit the usability of batteries in renewable energy applications (Hou *et al.,* 2020). Performance degradation is significantly impacted by insufficient thermal management due to repeated charge and discharge cycles. This highlights the importance of setting boundaries on operational PV and battery systems (Spitthoff, Shearing and Burheim, 2021).

In order to solve these problems, new Battery Management Systems (BMSs) that control charge, discharge, and temperature have been proposed. Current research on BMSs shows that controlling battery state and creating intelligent systems to manage energy can increase battery life and safety (Hu *et al.,* 2021). DOD regulation is one of the main features of these systems, and for good reason since it is the most effective way to decrease cycling of the battery. The effect of DOD on the life span of the battery has been the main focus of many studies. It has been proven that for applications that periodically cycle, such as renewable energy systems and electric vehicles, the life of the battery is significantly increased by limiting the DOD (Park *et al.,* 2023). The same has been observed for off-grid solar PV systems, since there is less DOD, it is more reliable, and there is reduced cost for long term upkeep (Hlal *et al.,* 2019).

The methods of batteries and how they compare to one another. Previous studies compare and contrast lead-acid batteries with lithium batteries for their stationary and off-grid uses. From these studies, lead-acid batteries do cost less of an investment at the beginning, but they do have an issue with discharging and have a significantly lower service lifetime. In microgrid isolation, the chosen technology and the depth of discharge (DOD) limitations were the determining factors for the overall reliability of the system and the decrease of the system replacement needed (Santos-Pereira *et al.,* 2021). At the system level, the optimal energy management and the overall performance of the PV-battery installation system has greatly amplified. Controlled management of continuous charging and discharging disbalances load demand and generation. This, overall, improves the system efficiency and cuts down the cost of operations in grid-connected and hybrid energy systems (Li and Wang, 2019). In addition to this, the techniques for multi-objective optimisation have used genetic algorithms to successfully determine the optimal hybrid renewable energy system while balancing cost, reliability, and the lifetime of the system components (Mayer, Szilágyi and Gróf, 2020).

Most recently, the understanding of the battery degradation control strategies has deepened, particularly the one where DOD, temperature, and cycling frequency control are addressed simultaneously to maximize service life. Such studies are of practical value to those aiming to design systems with batteries of long utility in support of renewable energy (Woody *et al.,* 2020).

All in all, the literature is consistent in showing DOD optimization as one of the design and operational parameters of highest relevance in PV–battery systems. Yet, very few studies have applied DOD optimization in scenarios with continuous (non-interruptible) loads (e.g., aquaculture, water-resource management systems). This is precisely the reason for the current study that aims to optimize DOD to prolong battery life, and improve the overall reliability and cost-effectiveness of the system, using a genetic algorithm approach.

PV System Modelling for Aquaculture and Water-Resource Applications

Aquatic environments and water resource distributions also add extra operational parameters for solar photovoltaic systems (higher moisture content and water surface variable reflective reflectivity) that affect evaporative cooling and photovoltaic control variables within battery cycling, and reliability of the entire system's operation on aquaculture farms, floating sensor networks, reservoirs, and water treatment facilities. Therefore, the modelling of solar photovoltaic modules, PV inverters, and battery storage systems must be based solely on water-centric environments to accurately represent system behaviour and ensure the continuous operation of water-dependent loads.

Resource selection for the integration of renewables is also essential, as the interconnection of system modules for optimal performance and to avoid performance issues requires element-to-element interactivity or system-formed current in various transformations within the network. This generates multiple system configurations. Those configurations can be divided into three main types. They are DC, AC, and hybrid solar. In this case, the systems are defined based on the UPA system application outlines (Sharma 2014): best DC, best AC, or best hybrid.

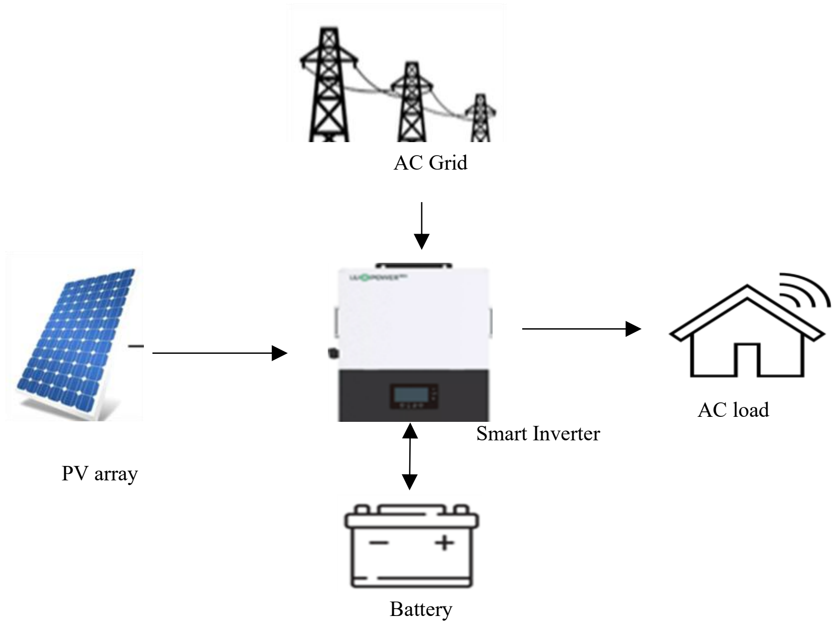

Figure 1: Schematic diagram of the solar PV–battery hybrid system integrated with the grid.

Predicting the output of solar energy systems, given solar radiation and system factors, is and will always be a difficult modelling task in energy systems. A hybrid system with a battery bank is recommended. It is well known that solar energy systems are expensive and have a short lifespan (Dei and Batjargal, 2022). For this reason, it is essential to consider and optimise the battery's behaviour during the sizing of the PV array and the battery. From this, a reduction in the cost of energy (COE) can be achieved, enabling investment in the value capture of renewable energy plants (Fadlallah and Serradj, 2020). If a model is developed based on the costs of reducing battery life and increasing depth of discharge, it will make such renewable energy systems financially sustainable. The design of a solar energy system comprising a battery, an inverter, PV (photovoltaic) modules, and an AC grid connection arm is illustrated in figure 1.

PV Modules

The two most significant determinants of a solar PV system's performance are solar radiation and ambient temperature. Under aquaculture conditions, where PV modules are commonly mounted adjacent to ponds, tanks, or water bodies, humidity, cloud cover, and reflective surfaces can amplify fluctuations in irradiance. During clear-sky periods, solar radiation can reach 1100 W/m², or peak sun intensity, leading to higher output currents and better system performance. However, ambient temperatures in humid aquaculture zones are usually higher, which negatively affects the open-circuit voltage of PV modules. As the temperature rises, the voltage drops, thereby reducing PV efficiency (Zensu and Dalimi, 2022). Solar PV system output power (PPV) can be defined by equation (1) and equation (2).

$$:P_{PV}(t) = PV_{STC^*}\left(\frac{G}{G_{ref}}\right) + \left(\gamma^* \left(T_c - T_{ref}\right)\right) * \eta_{wire} * \eta_{inv} \quad (1)$$

$$T_c = T_a + (NOCT - 20) * \left(\frac{G}{800}\right) \quad (2)$$

Where G is the solar radiation (W/m2), Gref represents standard test conditions at STC (1000 W/m2), γ is the PV temperature coefficient, TC is the temperature of the PV cell, Tref=25°C, ηwire is the wire efficiency, which equals 1, and ηInv is the inverter efficiency, which equals 0.95. The nominal operating cell temperature (NOCT) is determined under controlled test conditions at an ambient temperature of 20°C and a solar radiation level of 800 W/m². (Hassanian, Yeganeh and Riedel, 2024; Abbes, Martinez and Champenois, 2014). Assume that the solar PV array's energy output, which depends on hourly weather conditions, equals the PV array's power output (PPV). In that situation, equation (3) and equation (4) can be used to characterise the solar system's net energy.:

$$\Delta E_{net} = E_{pv}(t) - E_L(t) \qquad (3)$$

$$E_{PV}(t) = N_{PV} * P_{PV}(t) \qquad (4)$$

Where EL (t) is the load demand for the corresponding period, (t) is the time length, which is equivalent to one hour, ΔEnet is the net energy, NPV is the number of PV modules, and EPV is the energy generated by the solar PV modules.

The Inverter

An apparatus that converts DC power to AC power is called an inverter. As a result, the maximum AC load requirement should be satisfied by the inverter power (PINVERTER). In this instance, equation (5) is used to determine the inverter's size.

$$P_{INVERTER} = P_L * 1.25 \qquad (5)$$

Where PL denotes total load demand, and 1.25 represents the projected oversize factor.

Battery Storage Requirements in Aquaculture and Water-Resource Systems

The incorporation of battery energy storage hybrid energy systems is essential to mitigate variations in energy output caused by weather conditions affecting solar generation systems. Within the energy sector, one of the most emphasized areas of study is energy storage technology, aimed at minimizing the overall costs of different energy systems. Solar energy systems have gained international acclaim for their capacity to provide energy to off-grid rural areas at a lower price than extending the utility grid. Solar power systems can provide electricity to rural areas at a lower cost than extending the power grid. Batteries used for energy storage in hybrid systems include lead-acid, gel-type, and lithium-ion. A comparison of battery types is shown in table 1.

The batteries powering aerators, water quality monitors, recirculation pumps, automated feeders, and other devices in water and aquaculture systems must provide reliable, uninterrupted operation despite power supply dropouts. Otherwise, oxygen levels will drop, water quality will shift, or a critical monitor will lose power. These devices often operate in remote and off-grid locations, so the batteries must endure long discharge durations and frequent cycles, and the weather must be variable. To keep systems sustainable and cost-effective, the Depth of Discharge (DOD) must be optimized to prolong battery life and ensure reliability. These systems would be far less reliable without the durable, DOD-optimized batteries.

For the reasons indicated in the preceding chart, lead-acid batteries are inexpensive and widely used in small- and large-scale battery energy storage systems (Santos-Pereira *et al.,* 2021; Bullich-Massagué *et al.,* 2020).

Table 1: Comparison of advantages and limitations of lead–acid, lithium-ion, and gel batteries.

Battery	Pros	Cons
Lead–acid	▪ Low initial cost. ▪ Easy to work with. ▪ The self-discharge is slow. ▪ Safer than other types, especially in cold locations.	▪ Less power than others. ▪ Less lifespan.
(Li-ion)	▪ High energy density. ▪ Lower cost for maintenance. ▪ Longer lifespan. ▪ Fast charging rate. ▪ High efficiency.	▪ High cost. ▪ Requires a protection circuit to limit voltage and current. ▪
Gel-batteries	▪ Low maintenance cost. ▪ Safer, the risk of explosion or leakage is minimised because the electrolyte is contained within a gel. ▪ Wide range of operating temperatures. ▪ Long life cycle.	▪ High cost. ▪ Limited efficiency. ▪ More sensitive to high current.

The capacity of this battery is a function of the energy it produces, in what units of energy, and of the fully discharged state and the cut-off voltage. This is what equation (6) demonstrates and how this is related to the capacity of watt-hours:

$$C_B = A_h * V_B \tag{6}$$

Where Ah is the battery size, which can produce current for up to an hour, and VB is the battery voltage. The DOD (Depth of Discharge) is restricted across the solar system to prevent overcharge and overdischarge and to extend battery life. In this study, we will investigate (or deal with) the DOD% %. There are several methods for designing (or approximating) a battery, depending on the level of detail and the features to be modelled. The model for a solar PV system that includes a battery should account for the battery state of charge (BSC).

Considering all three cases, namely the battery charging, discharging, and standby, the battery's BSC in Watt-hours is calculated, as shown in figure 2.

- In charging cases where the energy produced by the PV source exceeds the energy in the load, i.e., EPV (t) > EL (t), the Battery State of Charge (BSC) is calculated. The additional energy is used to charge the battery bank. Consequently, the BSC must be checked to determine whether PPV exceeds the load power. If the battery is fully charged, all additional energy must be diverted (or discharged). On the other hand, if the battery is not fully charged, the additional energy can be used to charge the battery bank. The relationship is expressed in more detail by equation (7) as follows:

$$BSC(t+1) = BSC(t) + \Delta E_{net}(t+1) * \eta_{Bat-c} \tag{7}$$

The BES discharge is sufficient to meet the linked load demand in the discharging scenario when EPV(t) < EL (t). Thus, equation (8) can be used to predict the BES's discharge quantity at hour (t):

$$BSC(t) = \frac{BSC(t+1)+\Delta E_{net}(t)}{\eta_{Bat-dis}*\eta_{cc}*\eta_{wire}*\eta_{inv}} \quad (8)$$

In the standby situation, when EPV(t) = EL(t) or ΔEnet(t + 1) = 0, the battery capacity remains constant. In this circumstance, the BSC of the battery can be computed using equation (9).

$$BSC(t) = BSC(t+1) \quad (9)$$

The battery's charging and discharging efficiencies, denoted by ηBat_c and ηBat_disc, are equal to 0.8. The charge controller efficiency (ηCC) is 0.95 (Yan *et al.,* 2010). The BSC constraints/ are shown in the following equations (10), (11) and (12):

$$BSC_{max} \geq BSC(t) \geq BSC_{min} \quad (10)$$

$$BSC_{min} = \left(1 - DOD(\%)\right) * C_n \quad (11)$$

$$C_n(Wh) = N_B * C_B \quad (12)$$

The battery's highest charge is denoted by BSCmax, and its minimum by BSCmin. The maximum depth of discharge, or DOD (%), is known. NB is the number of batteries, while Cn is the capacity of the battery bank.

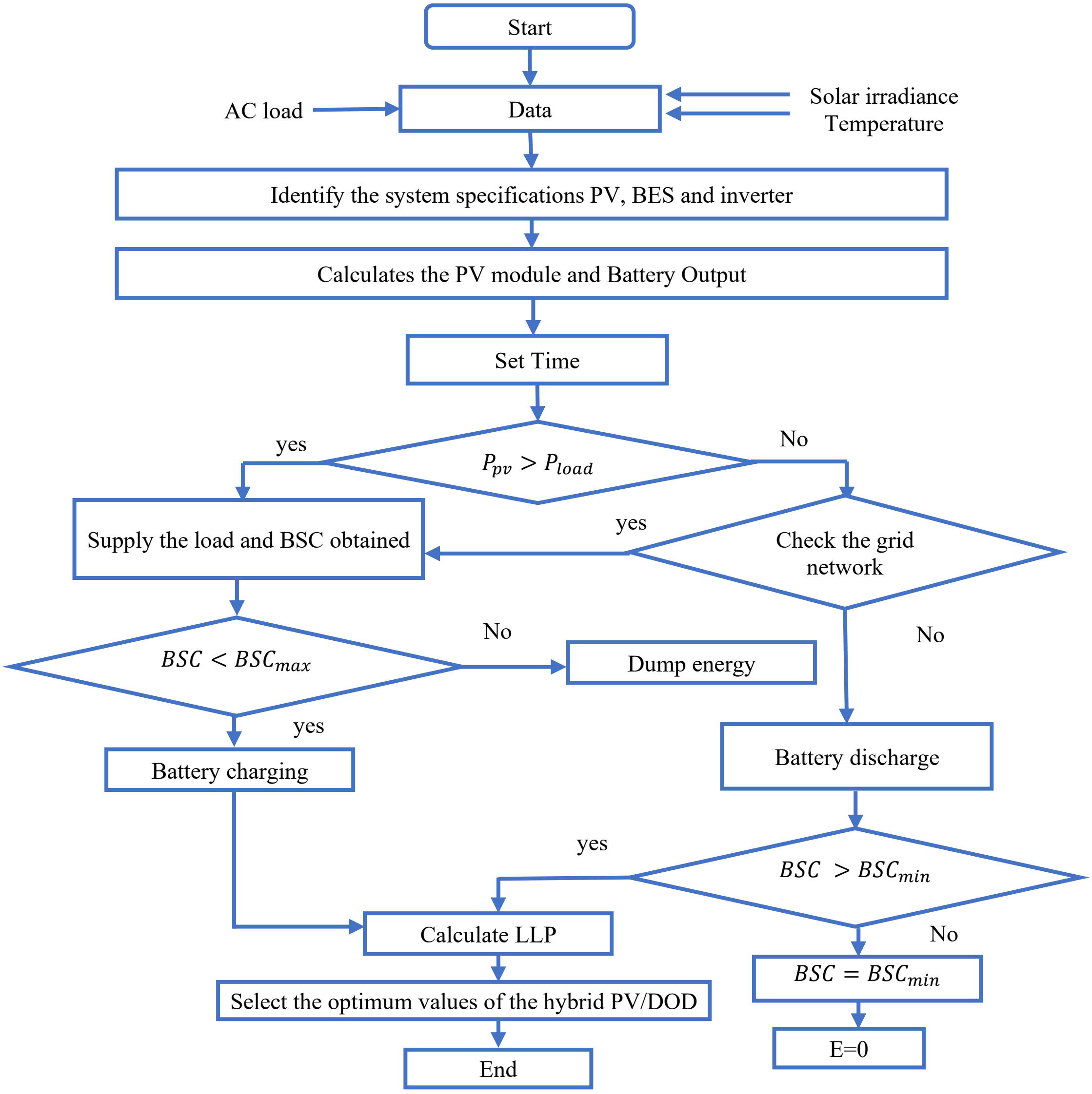

Figure 2: Flowchart of the depth of discharge (DOD) optimisation process in the solar PV system.

Table 2 provides solar system parameters and battery specifications. Additional details can be found in references (Dawood, Barwari and Akroot, 2023; Hassan *et al.,* 2021).

Table 2: Technical specifications and parameters of the solar PV system components.

PV module	
Short circuit current (A)	14.6
Open circuit voltage (V)	49.6
Maximum operating voltage (V)	40.9
Maximum operating current (A)	13.45
Operating temperature (°C)	-40 to 85
Module efficiency	22%
Lifetime (year)	25
Rated power (W)	550
Inverter	
Rated power (W)	10000
Efficiency	98%
Lifetime (year)	10
Battery	
Battery model	MU 10000
Rated capacity (Ah)	200
Battery voltage (V)	51.2
Efficiency (%)	80
Lifetime (year)	5

Results and Discussions

To enhance the effectiveness of solar PV-battery arrangements in aquaculture and water resource management, one must consider the intricate interdependencies among the technology's functionality, the reliability of on-site renewable energy, and the ecosystem's long-term logistical viability. In aquatic systems, it's critical to have power systems free of potential interruptions that could adversely affect aeration, water recirculation, filtration, and inline water quality monitoring. Given that the systems run nonstop and the solar batteries need to be replaced, and their useful life cycled, this presents some challenges. Across the solar system's bodies, the water surface's solar irradiance will be constantly variable due to humidity, clouds, and reflective surfaces. This will cause excessive battery cycling, leading to system failure. It's also critical to determine the constraints on energy flows to model the batteries economically. This modeling enables these powered systems with PV-discretized renewable sources to operate with some autonomy and stability in power-constrained environments, such as aquaculture and water resource management systems (Sagar *et al.,* 2022).

When configuring a PV system to suit the dimensional constraints best, both technical and economic factors must be considered. Accordingly, multi-objective optimization based on the theoretical best global dependability values should be employed to determine the optimal sizing. In this paper, based on optimal operation of the PV system and the grid network, the system COE and the LLP trade-off optimization have been performed, considering PV and battery sizing and the targeted DOD.

Software Information

Implementation Environment

The modelling, optimisation, and simulation of the system were done in a computing and simulation environment with the ability to do numerical analysis on nonlinear equations and evolutionary algorithms.

Tool Used for Optimisation

The built-in toolbox on the Genetic Algorithm for the Optimisation of a given problem was used to derive the optimum Depth of Discharge (DOD) with respect to the Loss of Load Probability (LLP), Cost of Energy (COE), and battery life.

Simulation and Results

The software was used to run simulations regarding PV generation, charge and discharge behaviour of batteries, and the grid for various scenarios in terms of irradiance, temperature, and load. Performance indicators were presented in the form of convergence and parametric plots.

Optimising Depth of Discharge (DOD) for Aquatic Solar PV–Battery Reliability

In aquaculture and water-resource settings, the operational Depth of Discharge (DOD) affects the reliability of energy supply for critical loads, such as aerators and water-quality sensors. Balancing battery capacity with the chosen DOD level is essential, as higher DOD levels can accelerate battery degradation, disrupting crucial aquatic operations and resulting in economic losses (Duraisamy and Deepa, 2021). While lower DOD dissolution levels result in longer battery lifespan, there is the possibility of no energy availability during low solar irradiance. This trade-off is exacerbated in aquatic environments, leading to stress on battery chemistry. This is why a DOD level is needed, where the trade-off between battery lifespan and system reliability is minimal, while still meeting the energy demands of aquaculture and water-resource management. For that, Optimail Genetic Algorithms (GA) methodologies must be employed (Upadhyay and Sharma, 2014).

Using Genetic Algorithms (GAs) to process pertinent information to assess the most efficient Depth of Discharge (DOD) as it relates to the Battery Storage of a Solar PV System will ultimately improve effectiveness of the Systems Overall Performance, Longevity, and Cost effectiveness, as there is ability gained in determining the equilibrium as to how to maximize energy usage and conserve battery health over a period of time.

In the current literature, the genetic algorithm is a promising approach for improving the performance of a solar PV system. (Mayer, Szilágyi, and Gróf 2020). When there are competing objectives, it is possible to generate a set of alternative solutions.

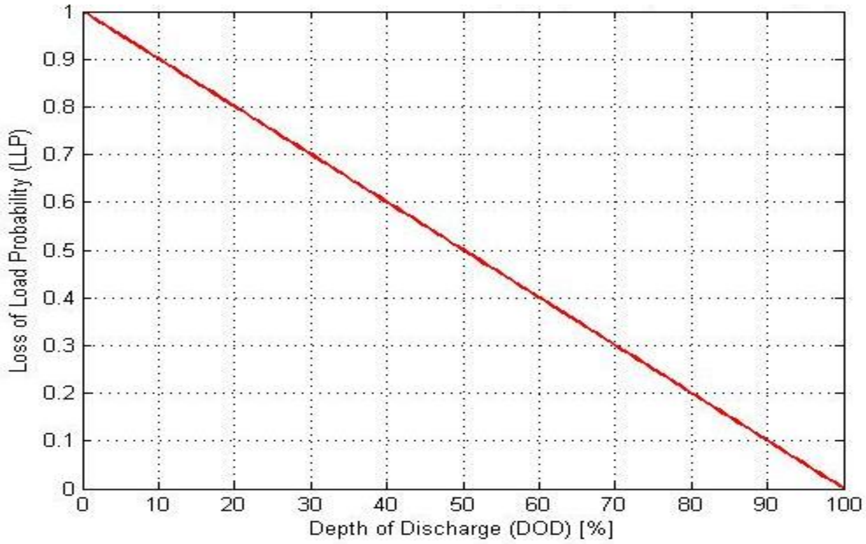

Figure 3: Relationship between loss of load probability (LLP) and depth of discharge (DOD) in the hybrid PV system.

The most efficient formulation in this research is the one that considers LLP. The LLP is to assess the system's performance. The availability of the hybrid solar PV system is used to determine the performance. If LLP=0 or availability is 100%, it indicates that the load demand can be met continuously and optionally all year round. However, as illustrated in figure 3, a hybrid solar PV System does not meet the load demand year-round if it has 0% availability or LLP = 1.

The high costs of constructing double-depended hybrid solar photovoltaics make a heuristic unavailable. (Khatib and Elmenreich, 2014) defined the LLP value of a hybrid PV/BES system. A hybrid System is designed with an LLP value of less than 0.01. 12 The LLP can be expressed in the following form in the given equation, and it is given as a portion of the annual energy deficit to the total annual load demand as shown in equation (13).

$$LLP = \frac{\sum_t^T E_{Deficits}(t)}{\sum_t^T E_l(t)} \qquad (13)$$

Where EDeficits is the energy deficit of a solar PV system in a year.

Given the two preceding objectives, designing a hybrid photovoltaic system is a very complex optimization problem. The present proposal for the Multi-Objective Optimization will be based on the Genetic Algorithm (GA). The steps involved in the Genetic Algorithm model and energy savings analysis to derive the optimum DOD and the energy cost savings are as follows:

Battery Life Estimation

Battery life estimation is a design consideration for energy storage systems, especially in solar PV applications. To do this, one must estimate how long the battery will last by predicting factors such as depth of discharge (DOD), operating temperature, maintenance practices, and charge and discharge cycles. Obtaining an accurate estimate is crucial to optimise battery usage and reduce costs while ensuring a reliable energy supply. The estimated battery life is determined using equation 14, while figure 4 illustrates the correlation between battery life and DOD and it is denoted by equation (14)

$$L_{battery}(DOD) = L_{max} \times (1 - \frac{DOD}{DOD_{max}})^{\alpha} \quad (14)$$

where: Lbattery (DOD): Estimated battery life at a given DOD, Lmax: Maximum battery life at the minimum DOD, DODmax: Maximum allowable DOD, and α: Empirical constant depending on battery type.

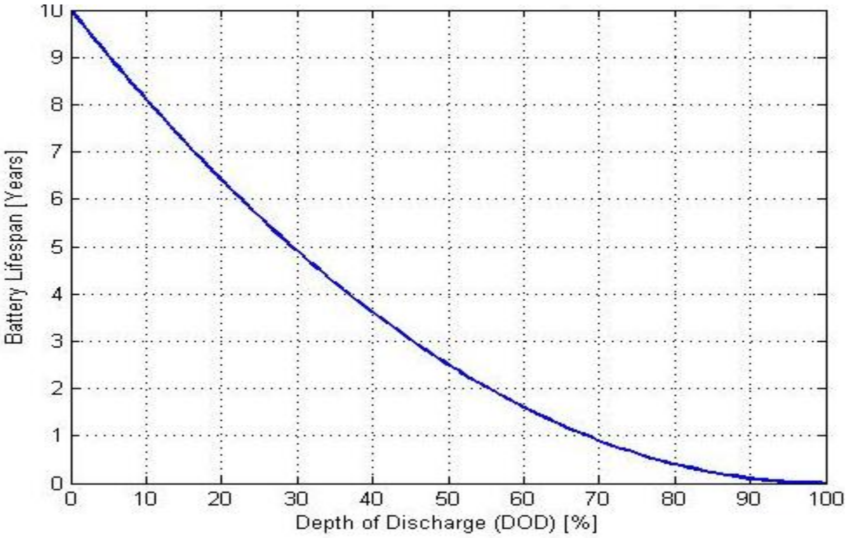

Figure 4: Effect of depth of discharge (DOD) on battery lifespan.

Energy Efficiency

$$\eta_{battery}(DOD) = \eta_{nominal} \times (1 - \frac{DOD}{DOD_{max}})^{\beta} \quad (15)$$

In Equation (15) ηbattery (DOD): Battery efficiency at a given DOD. *η*nominal: Nominal efficiency at the minimum DOD and β: Empirical constant depending on battery type.

Cost Function

$$C_{battery}(DOD) = \frac{C_{initial}}{L_{battery}(DOD)} + C_{operational}(DOD) \quad (16)$$

In equation (16), Cbattery (DOD): Total cost associated with a given DOD, Cinitial: Initial cost of the battery, and Coperational (DOD): Operational cost at a given DOD.

Overall Objective Function

$$\boldsymbol{Fitness(DOD) = \omega_1 \times L_{battery}(DOD) + \omega_2 \times \eta_{battery}(DOD) - \omega_3} \quad \textbf{(17)}$$

In equation (17), ω1, ω2, ω3: Weighting factors to balance the influence of battery life, efficiency, and cost.

Energy Savings and Operational Efficiency in Aquaculture Facilities

Aquaculture farms, hatcheries, and water-treatment facilities often operate around the clock, requiring continuous energy for aeration, pumping, filtration, and monitoring systems. These operational costs are considerable, especially in areas with high and variable electricity costs. The integration of a PV–battery system reduces grid dependence and stabilises supply during critical periods, such as overnight for aeration (Nagabhooshanam *et al.,* 2025). Estimating energy savings is a key factor for cost savings and improving the operational resilience and sustainability of aquatic systems.

Energy Consumed by Aquaculture Load

Aquaculture systems operate with both continuous and intermittent electrical loads. Continuous loads include aerators, water-circulation pumps, biofiltration units, and oxygenation equipment. Intermittent loads consist of feeders, monitoring sensors, and automated control units. The sum of the energy consumed by these loads over a specified time can be calculated with the use of equation (18)

$$E_{Load} = P_{load} \times t \quad (18)$$

Where: ELoad: Energy consumed by aquaculture system loads (kWh), Pload: Total power rating of pumps, aerators, feeders, etc. (kW), and t: Duration time of energy consumption (hours). In aquaculture systems, the aerators run for about 10-20 hours a day to keep dissolved oxygen levels in the water sufficient. This makes them one of the costliest components to run. Under typical aquaculture operating conditions, figure 5 shows the relationship between PV generation, load demand, and grid contribution over 1 day.

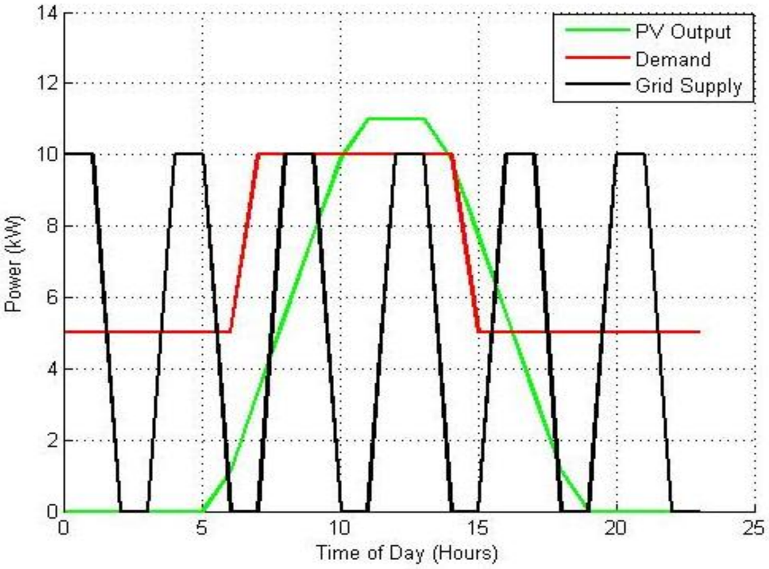

Figure 5: Daily power flow of the solar PV system showing PV generation, load demand, and grid contribution.

Energy Drawn from the Grid

In situations with low solar irradiance (early morning, evening, and cloudy conditions) or during peak operational hours, a portion of the energy demand must be supplied by the grid. The energy imported from the grid is calculated using Equation (19):

$$E_{Grid\_Used} = E_{Load} - E_{PV} \qquad (19)$$

Where: EGrid_Used: Energy drawn from the grid.

In aquaculture environments, minimizing grid energy use is especially advantageous, as electromechanical aeration and pumping operate for long hours, making electricity a high ongoing operational cost.

Energy Saving

Energy savings represent the decrease in grid electricity consumption enabled by the PV-battery system. For aquaculture operations, which usually entail constant aeration and circulating water, these savings reduce costs and enhance ecosystem sustainability. Energy savings are defined by equation (20).

$$E_{Saving} = E_{Load} - E_{Grid\_Used} \qquad (20)$$

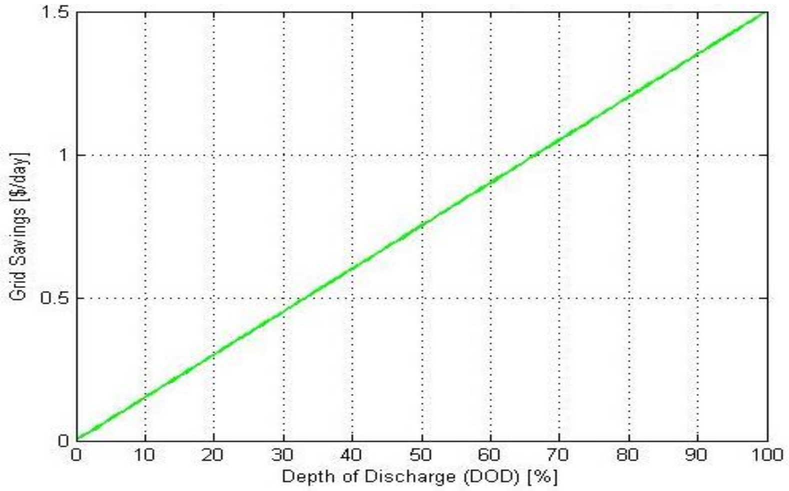

Figure 6: Variation of grid energy savings with respect to depth of discharge (DOD).

Where: ESavings: A higher value of ESavings. Even when the system continued to rely on the grid, the percentage indicates greater confidence in solar energy. Results shown in figure 6 suggest that the selected Depth of Discharge (DOD) value of 32% is best suited to preserving the battery for long-term use and to yield the most significant capacity reduction in the grid, with dependence on 85 to 90% during the day in most aquaculture systems.

Battery Degradation with DOD

The extent to which a battery deteriorates depends on various factors such as discharge cycles, temperature, humidity, and Depth of Discharge (DOD). In aquaculture, there are continuous electrical loads and the use of humid environments, which can further deteriorate the battery. Equation (21) specifies the battery's growing deterioration rate in relation to humidity:

$$D_{battery}(DOD) = D_{max} \times \left(\frac{DOD}{DOD_{max}}\right)^{\gamma} \quad (21)$$

Where: Dbattery (DOD): Battery degradation rate at a given DOD, Dmax: Maximum degradation rate, and γ: Empirical constant. DOD spikes to higher values increase the battery's available capacity. However, this also increases chemical stress, resulting in a shorter battery lifespan and higher costs for aquaculture farms. For this reason, finding a good DOD is essential, as it strikes a good balance between usable energy and system longevity.

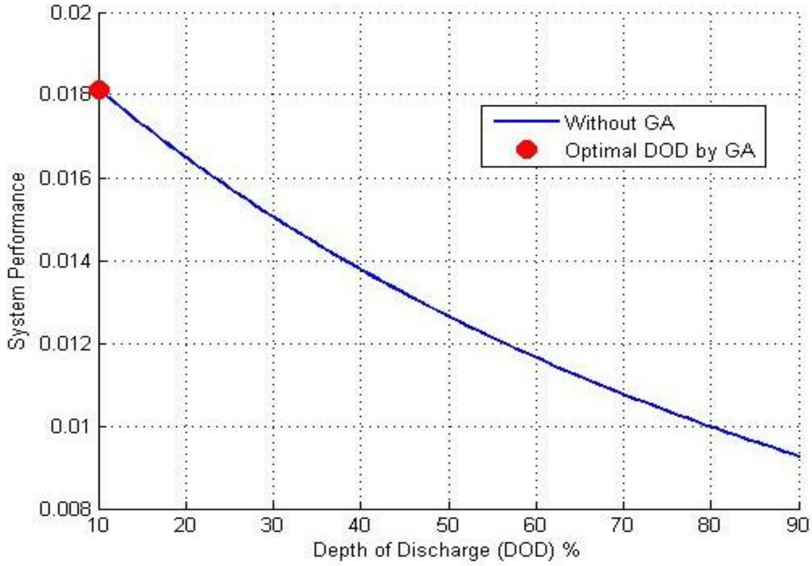

Figure 7: Optimised multi-objective PV–battery system configuration showing the pareto front of LLP and COE.

Discussions

A Genetic Algorithm (GA) was employed to optimise the Depth of Discharge (DOD) in the PV–battery system, enabling determination of the operational point at which the battery can energise the aquaculture and water-resource operations system without losing useful life (i.e., maximum DOD cycle). The DOD cycle GA showed convergence behaviour, steadily improving the DOD candidate solutions with each generation. Early DOD GA generations showed high diversity in the population DOD sets, which indicated that the DOD GA was making spectrum search efforts. With many DOD GA iterations, it was observed that the population began to narrow into a succinct band of high-fit DOD population solutions, indicating that the population had converged on the DOD optimum. This behaviour of the DOD GA population confirms the diligence of the population and the DOD GA overall.

The control of Depth of Discharge (DOD) for the batteries is paramount if a system will integrate open-water aquaculture with the constant need for aeration and water recirculation. There will be periods of low solar production, which means the batteries will be required to deliver a stable DO and operate beyond the typical DO, aaccelerating cycle life and affecting computer design life of the systemize fish farms and hatcheries spend a great deal of time operational, DOD efficiencies mean there will be less cycle stress on the battery, and therefore extended life and reduced cost for system design and replacement utilising energy storage.

The results of the multi-objective optimisation exercise spanning the entire operational day are shown in figure 7. The data are partitioned into a Pareto front, demonstrating the trade-off between Loss of Load Probability (LLP) and Cost of Energy (COE). All the data points on the Pareto front represent achievable states of the system, with PV module counts, DOD percentages, and a unique cost associated with each state. A DOD 0 choice was made from the options where LLP 0 was available. In an aquaculture system, the absence of aeration can rapidly degrade water quality and lead to stock losses. Thus, uninterrupted pumping must also be avoided.

Using the GA for analysis, the optimal DOD was determined to be 32%, which represents the best trade-off among system dependability, energy costs, and battery longevity. With this DOD, the system achieved a COE of 0.2494 USD/kWh and successfully maintained LLP = 0, indicating no interruption to powering all essential loads throughout the year. While a lower DOD, for instance, 10% DOD, could extend battery longevity to 8 years, the battery's capacity would be insufficient to meet the energy demand of the aquaculture systems, resulting in greater reliance on the grid and lower cost-efficiency. Hence, the optimized DOD of 32% presents a more reasonable and more equilibrated operating condition.

The analysis underscores the need for accurate battery modelling in the design of solar-powered aquaculture facilities. The lead-acid batteries, used for their cost/availability, were showing accelerated degradation at high DOD. Selecting a moderate, optimized DOD ensures the system reliably delivers energy when the energy load is highest, while the DOD replacement schedule remains sustainable. The GA algorithms with the given parameter set have proven helpful for designing cost-efficient, high-performing energy systems for the aquaculture sector.

An 85-90% reduction in reliance on the grid with the combined PV-battery system is reliable, as the system supports aquaculture activities. This reduction in grid reliance is significant, as it performs all operations while providing the sustainability needed in aquaculture systems. This is why the points discussed in this paper are of great value to aquafarms, fish hatcheries, pond management, and rural water resource facilities as well.

Conclusions

This research focused on planning the operational optimisation of solar PV–battery hybrid energy systems for aquaculture and water-resource management. The systems must ensure constant energy supply for aeration, pumping, and water quality control. The research combined energy-flow modelling and optimisation based on a Genetic Algorithm and focused on the trade-off between system cost and reliability, battery degradation, and energy costs. The research results identified the 32% DOD as optimal and cost-effective at 0.2494 USD/kWh, given that the system achieves 0% Loss of Load Probability (LLP). At this DOD level, the battery cycling was constrained and battery longevity was ensured, as was the reduction on the system reliance on grid power for both daytime and nighttime operations. The results indicate that the most significant variable in DOD battery management systems is the DOD level for aquaculture and water-resource management which affects the overall system's value.

Future Work

Future studies might consider applying the proposed optimisation framework to other climatic and geographical areas to evaluate the framework's flexibility to varying levels of solar radiation and temperature. The use of advanced battery management systems with frameworks that monitor performance in real-time and actively control system parameters to increase flexibility and operational adaptiveness is an extremely positive avenue to pursue. Other studies could also focus on the unused potential of new battery materials and different combinations of energy storage technologies in order to lessen system inefficiencies and associated growth of negative impact on the environment. In addition, the addition of other parameters, such as return on investment (ROI), lifecycle cost, and carbon cost/savings, to the economic analysis would provide a better basis for extensive deployment. Experimental testing of the proposed method in actual fish farms would, for example, increase the credibility of the proposed method.

References

Abbes, D., Martinez, A. and Champenois, G., 2014. Life cycle cost, embodied energy and loss of power supply probability for the optimal design of hybrid power systems. *Mathematics and Computers in Simulation*, *98*, pp.46-62. https://doi.org/10.1016/j.matcom.2013.05.004

Ahmed, W., Sheikh, J.A., Ahmad, S., Farjana, S.H. and Mahmud, M.P., 2021. Impact of PV system orientation angle accuracy on greenhouse gases mitigation. *Case Studies in Thermal Engineering*, *23*, p.100815. https://doi.org/10.1016/j.csite.2020.100815

Al-Saadi, M., Olmos, J., Saez-de-Ibarra, A., Van Mierlo, J. and Berecibar, M., 2022. Fast charging impact on the lithium-ion batteries' lifetime and cost-effective battery sizing in heavy-duty electric vehicles applications. *Energies*, *15*(4), p.1278. https://doi.org/10.3390/en15041278

Asadipooya, K. and Nezhad, R.K., 2019. Optimal utilization of DEZ dam reservoir considering drinking water demand by dynamic programming technique. *International Academic Journal of Science and Engineering*, *6*(1), pp.132-144. https://doi.org/10.9756/IAJSE/V6I1/1910013

Bullich-Massagué, E., Cifuentes-García, F.J., Glenny-Crende, I., Cheah-Mañé, M., Aragüés-Peñalba, M., Díaz-González, F. and Gomis-Bellmunt, O., 2020. A review of energy storage technologies for large scale photovoltaic power plants. *Applied Energy*, *274*, p.115213. https://doi.org/10.1016/j.apenergy.2020.115213

Dawood, T.A., Barwari, R.R.I. and Akroot, A., 2023. Solar Energy and Factors Affecting the Efficiency and Performance of Panels in Erbil/Kurdistan. *International Journal of Heat & Technology*, *41*(2). https://doi.org/10.18280/ijht.410203

Dei, T., and Batjargal, N., 2022. Technical and Economical Evaluation of Micro-Solar PV/Diesel Hybrid Generation System for Small Demand. *International Journal of Renewable Energy Development*, *11*(4), p. 1101-1112. https://doi.org/10.14710/ijred.2022.46747

Duraisamy, T. and Deepa, K., 2021. Evaluation and comparative study of cell balancing methods for lithium-ion batteries used in electric vehicles. *International journal of renewable energy development*, *10*(3), p.471. https://doi.org/10.14710/ijred.2021.34484

Fadlallah, S.O. and Serradj, D.E.B., 2020. Determination of the optimal solar photovoltaic (PV) system for Sudan. *Solar Energy*, *208*, pp.800-813. https://doi.org/10.1016/j.solener.2020.08.041

Gabbar, H.A., Othman, A.M. and Abdussami, M.R., 2021. Review of battery management systems (BMS) development and industrial standards. *Technologies*, *9*(2), p.28. https://doi.org/10.3390/technologies9020028

Hassan, Q., Abbas, M.K., Abdulateef, A.M., Abdulateef, J. and Mohamad, A., 2021. RETRACTED: Assessment the potential solar energy with the models for optimum tilt angles of maximum solar irradiance for Iraq. https://doi.org/10.1016/j.cscee.2021.100140

Hassanian, R., Yeganeh, N. and Riedel, M., 2024. Wind velocity and forced heat transfer model for photovoltaic module. *Fluids*, *9*(1), p.17. https://doi.org/10.3390/fluids9010017

Hlal, M.I., Ramachandaramurthy, V.K., Sarhan, A., Pouryekta, A. and Subramaniam, U., 2019. Optimum battery depth of discharge for off-grid solar PV/battery system. *Journal of Energy Storage*, *26*, p.100999. https://doi.org/10.1016/j.est.2019.100999

Hou, J., Yang, M., Wang, D. and Zhang, J., 2020. Fundamentals and challenges of lithium ion batteries at temperatures between− 40 and 60° C. *Advanced Energy Materials*, *10*(18), p.1904152.

https://doi.org/10.1002/aenm.201904152

Hu, X., Deng, Z., Lin, X., Xie, Y. and Teodorescu, R., 2021. Research directions for next-generation battery management solutions in automotive applications. *Renewable and Sustainable Energy Reviews*, *152*, p.111695. https://doi.org/10.1016/j.rser.2021.111695

Kavaliauskas, Ž., Šajev, I., Blažiūnas, G. and Gecevičius, G., 2023. Electronic life cycle monitoring system for various types of lead acid batteries. *Applied Sciences*, *13*(8), p.4746. https://doi.org/10.3390/app13084746

Keshan, H., Thornburg, J. and Ustun, T.S., 2016, November. Comparison of lead-acid and lithium-ion batteries for stationary storage in off-grid energy systems. In *4th IET clean energy and technology conference (CEAT 2016)*. Stevenage UK: IET. https://doi.org/10.1049/cp.2016.1287

Khatib, T. and Elmenreich, W., 2014. Optimum availability of standalone photovoltaic power systems for remote housing electrification. *International Journal of Photoenergy*, *2014*(1), p.475080. https://doi.org/10.1155/2014/475080

Li, X. and Wang, S., 2019. Energy management and operational control methods for grid battery energy storage systems. *CSEE Journal of Power and Energy Systems*, *7*(5), pp.1026-1040. https://doi.org/10.17775/CSEEJPES.2019.00160

Mahadevan, P., and Ramakrishnan, V., 2025. Design and performance evaluation of floating solar farms on aquaculture ponds. *International Journal of Aquatic Research and Environmental Studies, 5*(1), pp.612–621. https://doi.org/10.70102/IJARES/V5I1/5-1-56

Mayer, M.J., Szilágyi, A. and Gróf, G., 2020. Environmental and economic multi-objective optimization of a household level hybrid renewable energy system by genetic algorithm. *Applied Energy*, *269*, p.115058. https://doi.org/10.1016/j.apenergy.2020.115058

Muxitdinov, S., 2023, June. Results of econometric modeling of management in multifunctional farms. In *American Institute of Physics Conference Series* (Vol. 2789, No. 1, p. 040060). https://doi.org/10.1063/5.0145615

Nagabhooshanam, N., Singh, R.P., Kaur, M., Nirsanametla, Y., Kalyani, K. and Rajaram, A., 2025. Sustainable energy integration for seawater desalination. *Toxicological & Environmental Chemistry*, *107*(8), pp.1582-1605. https://doi.org/10.1080/02772248.2025.2553247

Park, S.J., Song, Y.W., Kang, B.S., Kim, W.J., Choi, Y.J., Kim, C. and Hong, Y.S., 2023. Depth of discharge characteristics and control strategy to optimize electric vehicle battery life. *Journal of Energy Storage*, *59*, p.106477. https://doi.org/10.1016/j.est.2022.106477

Sagar, BS., Hampannavar, S., Deepa, B., and Bairwa, B., 2022. Applications of battery management system (BMS) in sustainable transportation: A comprehensive approach from battery modeling to battery integration to the power grid.

World Electric Vehicle Journal, *13*(5), p.80. https://doi.org/10.3390/wevj13050080

Santos-Pereira, K., Pereira, J.D., Veras, L.S., Cosme, D.L., Oliveira, D.Q. and Saavedra, O.R., 2021. The requirements and constraints of storage technology in isolated microgrids: A comparative analysis of lithium-ion vs. lead-acid batteries. *Energy Systems*, pp.1-24. https://doi.org/10.1007/s12667-021-00439-7

Shanmugasundaram, V., Srinivasan, G. and Lavanya, M., 2023. Salp swarm algorithm applied to optimal capacitor allocation problem in distribution network for annual cost savings. *International Journal of Applied Science and Engineering*, *20*(3), p.2020276. https://doi.org/10.6703/IJASE.202309_20(3).001

Shrestha, A.K., Thapa, A. and Gautam, H., 2019. Solar radiation, air temperature, relative humidity, and dew point study: Damak, Jhapa, Nepal. *International Journal of Photoenergy*, *2019*(1), p.8369231. https://doi.org/10.1155/2019/8369231

Spitthoff, L., Shearing, P.R. and Burheim, O.S., 2021. Temperature, ageing and thermal management of lithium-ion batteries. *Energies*, *14*(5), p.1248. https://doi.org/10.3390/en14051248

Tomar, A., and Vyas, N., 2022. Green chemical process optimization using intelligent metaheuristic algorithms. *International Academic Journal of Innovative Research, 9*(3), pp.1–6. https://doi.org/10.71086/IAJIR/V9I3/IAJIR0918

Upadhyay, S. and Sharma, M.P., 2014. A review on configurations, control and sizing methodologies of hybrid energy systems. *Renewable and Sustainable Energy Reviews*, *38*, pp.47-63. https://doi.org/10.1016/j.rser.2014.05.057

Wang, G., Yao, Y., Chen, Z. and Hu, P., 2019. Thermodynamic and optical analyses of a hybrid solar CPV/T system with high solar concentrating uniformity based on spectral beam splitting technology. *Energy*, *166*, pp.256-266. https://doi.org/10.1016/j.energy.2018.10.089

Woody, M., Arbabzadeh, M., Lewis, G.M., Keoleian, G.A. and Stefanopoulou, A., 2020. Strategies to limit degradation and maximize Li-ion battery service lifetime-Critical review and guidance for stakeholders. *Journal of Energy Storage*, *28*, p.101231. https://doi.org/10.1016/j.est.2020.101231

Xie, S., Hu, X., Qi, S., Tang, X., Lang, K., Xin, Z. and Brighton, J., 2019. Model predictive energy management for plug-in hybrid electric vehicles considering optimal battery depth of discharge. *Energy*, *173*, pp.667-678. https://doi.org/10.1016/j.energy.2019.02.074

Yan, J., Cheng, Z., Xu, G., Qian, H. and Xu, Y., 2010, September. Fuzzy control for battery equalization based on state of charge. In *2010 IEEE 72nd Vehicular Technology Conference-Fall* (pp. 1-7). IEEE.

https://doi.org/10.1109/VETECF.2010.5594380

Yap, K.Y., Chin, H.H. and Klemeš, J.J., 2022. Solar Energy-Powered Battery Electric Vehicle charging stations: Current development and future prospect review. *Renewable and Sustainable Energy Reviews*, *169*, p.112862. https://doi.org/10.1016/j.rser.2022.112862

Yudhistira, R., Khatiwada, D. and Sanchez, F., 2022. A comparative life cycle assessment of lithium-ion and lead-acid batteries for grid energy storage. *Journal of Cleaner Production*, *358*, p.131999. https://doi.org/10.1016/j.jclepro.2022.131999

Zensu, S. and Dalimi, R., 2022. Implementation of 100% Electric Vehicle in Bali with the Supply of Potential Independent Solar Energy. *International Journal of Mechanical Engineering Technologies and Applications*, *3*(1), pp.72-78. https://doi.org/10.21776/MECHTA.2022.003.01.10