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Techno-Economic Optimal Sizing Design for a Tidal Stream Turbine–Battery System

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Abstract: This article deals with the techno-economic optimal sizing of a tidal stream turbine (TST)–battery system. In this study, the TST system consists of a turbine rotor and a permanent magnet synchronous generator (PMSG) associated with a three-phase converter coupled to a DC bus. A battery is used within the system as an energy storage system to absorb excess produced power or cover power deficits. To determine the optimal sizing of the system, an iterative approach was used owing to its ease of implementation, high accuracy, and fast convergence speed, even under environmental constraints such as swell and wave effects. This technique is based on robust energy management, and the recursive algorithm includes the deficiency of power supply probability (DPSP) and the relative excess power generation (REPG) as technical criteria for the system reliability study, and the energy cost (EC) and the total net present cost (TNPC) as economic criteria for the system cost study. As data inputs, the proposed approach used the existing data from the current speed profile, the load, and economic parameters. The desired output is the system component optimal sizing (TST power, and battery capacity). In this paper, the system sizing was studied during a one-year time period to ensure a more reliable and economical system. The results are compared to well-known methods such as genetic algorithms, particle swarm optimization, and software-based (HOMER) approaches. The optimization results confirm the efficiency of the proposed approach in sizing the system, which was simulated using real-world tidal velocity data from a specific deployment site.

Keywords: tidal stream turbine; battery; optimal sizing; algorithm; energy management; cost-minimization; reliability

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1. Introduction

Currently, renewable energies such as tidal energy are defined as clean, natural, and abundant resources. These renewable energies present great importance to guarantee sustainable development in the near future [1]. Moreover, they are considered significant technologies for rural areas, which are faced with the problem of limited electricity access [2,3].

Moreover, distributed energy storage devices have been added to tidal stream turbine systems [4] to absorb excess power or cover an energy deficit [5], including electrolyzers, super capacitors, hydrogen banks, and batteries. Indeed, in [6], the hydrogen bank was used for a PV–TST system to meet the load during fluctuations. In [7], an islanded DC system was studied, including tidal energy, solar energy, and wind energy, along with battery storage. In [8], as energy storage components, a combination of an electrolyzer, hydrogen storage, and a fuel cell stack was used for a TST system. This can increase the system cost because of the high price of the distributed energy storage devices. Authors in [9] studied a tidal turbine generator: they used a vanadium redox battery energy storage system thanks to its ability to store large amounts of energy at competitive cost. In our case, the battery was chosen because of its fast response in supplying the load demand.

Additionally, it is more suitable for systems with long-term variations (minutes or even hours) [5].

Nevertheless, the TST system, installed under the sea (with the existence of the swell effect and waves), may be exposed to higher voltages and/or current transits, which may make the output power fluctuate very much [4], causing disturbances in the load supply. Therefore, to overcome this problem, sizing and cost studies are required.

However, before these studies, it is important to present the different evaluation criteria, which have a great impact on the system. These criteria consist in reliability, and economic, social and environmental indicators [10]. In fact, reliability criteria are required because of the high effect of the weather conditions on the system power generation, which leads to unreliable systems. They are considered for the evaluation of the system's ability to supply the load demand. The most used reliability indicators are the deficiency of power supply probability (DPSP) [11], the loss of power supply probability (LPSP) [12], the loss of load probability (LOLP) [13], the loss of load expected (LOLE) [14], and the expected energy not supplied (EENS) [15].

Economic criteria are used in order to meet the load demand at minimum cost. Indeed, these indicators include the energy cost (EC) [16], the total net present cost (TNPC) [17], the annualized cost of system (ACS) [18], the life cycle cost (LCC) [14], and the total annual cost (TAC) [19].

In order to reduce the pollution of the environment and ensure its sustainable progress, some criteria are required, such as carbon emission (CE) [20], carbon footprint of energy (CFOE) [21], embodied energy (EE) [22], and life cycle assessment (LCA) [23].

Social criteria have been used to estimate system social performance. Indeed, a few indicators have been considered for system capacity optimization such as the human development index (HDI) [24], social cost of carbon (SCC) [25], job creation (JC) [26], social acceptance (SA) [27], and portfolio risk (PR) [28].

Furthermore, different techniques have been proposed for optimal sizing such as traditional techniques, artificial intelligence techniques, simulation tool-based methods, and hybrid techniques [29,30].

Traditional methods, based on statistical calculations, need meteorological information (wind speed, current speed, solar radiation, temperature) and a big database to take into account the energy source uncertainties [31]. For traditional techniques, we can distinguish analytical, numerical, graphic construction, probabilistic, and iterative techniques. For example, authors in [28] adopted a numerical method, based on calculations, for a photovoltaic panel (PVP)–battery system in Oman to optimize the inclination angle and the capacity of the PVP. In [32], an analytical method was used to solve the sizing problem. Analytical and numerical techniques are time-efficient and computationally easy [33], although estimation of mathematical equations is difficult [30]. A graphic construction technique was adopted in [34]. While it is easy to use and is not complex, it requires a large amount of data, some of which can be ignored [35]. Thus, the system under study can be either over- or under-sized. In [36], a probabilistic method, using changes in meteorological information [37], was adopted to reduce carbon dioxide emissions from a wind–hydrogen system. While this approach features simple implementation, it cannot provide dynamic performance for the system under study [35–38]. Iterative methods use recursive algorithms to find the optimal configuration (minimum cost without deficit). An iterative algorithm was used in [39] to reduce the cost of a wind–PVP–fuel cell–battery system. In [40], a techno-economic algorithm was proposed for a sizing problem of a hybrid system installed within batteries and biogas generators. Although this technique needs a large amount of meteorological data, it features easy computation and reduced time consumption [31].

Artificial intelligence methods, such as the genetic algorithm (GA), particle swarm optimization (PSO) algorithm, simulated annealing (SA), cuckoo search (CS), artificial bee colony (ABC), flower pollination algorithm (FPA), grasshopper optimization algorithm

(GOA), tabu search (TS), and harmony search (HS) can be good solutions for nonlinear and complex sizing problems [14].

The genetic algorithm is a heuristic search method inspired by natural selection, evolution, and genetics, such as mutation and crossover. It uses random searches to resolve sizing problems, and its key benefit is its capability of finding the global optimal solution, which can be difficult to determine using other methods. In [41], GA was used for lead–acid battery sizing, and in [42], it was applied to optimize a wind farm layout.

The particle swarm optimization algorithm, based on stochastic optimization [43], is among the most widely used artificial intelligence approaches for sizing. It features high accuracy and fast convergence [14–44]. The PSO algorithm uses particles that are characterized by a space vector to represent the problem variables. Each PSO particle solution has two properties: velocity and position. It flies through the search space to improve its position; then, it memorizes the best experience found. Indeed, the PSO technique was used in [19–45] to reduce energy cost (EC). This algorithm was also adopted in [12] for wind farm sizing in Iran. In [3], the authors used genetic algorithms and particle swarm optimization to study a wind–tidal–PV system for electricity supply on the French island of Ouessant.

The simulated annealing algorithm is a general optimization technique that searches for global optima by considering multiple local optima. Instead of using the energy of a material, it uses the objective function of an optimization problem. An example of using SA can be found in [46].

The cuckoo search algorithm is a meta-heuristic optimization method based on the interesting breeding behavior of cuckoos [47]. It operates by maintaining a population of eggs or nests and having each cuckoo lay an egg in a randomly selected nest. CS is known for its reduced computation time [48] and has been applied to a PV–wind–battery system [49]. Its superiority compared to other optimization methods like PSO and GA has been demonstrated in [50].

The artificial bee colony algorithm is a meta-heuristic method for solving sizing problems, inspired by the intelligent foraging behavior of honeybees. It uses three components: employed foraging bees, unemployed foraging bees, and good sources. The first two components work to find the third. The ABC algorithm also has two modes of collective intelligence, namely forager recruitment and poor source abandonment. In [51], the authors proposed using ABC to determine the most reliable and cost-effective configuration for a wind–PVP–biomass–battery system.

The flower pollination algorithm is a recent meta-heuristic method that takes inspiration from the process of pollination in flowering plants [52]. This algorithm has been utilized by authors in various studies [53,54] as a way to optimize and reduce the annual cost in a hybrid system.

The grasshopper optimization algorithm is also a recently developed optimization method designed to size systems. It is inspired by the social interaction and food-seeking behavior of grasshopper swarms, which are known to cause harm to agricultural production [55]. The algorithm has been applied to a hybrid system located in Nigeria [56].

Tabu search, which was used in [57], is an iterative method that starts from an initial solution and aims to find a better one. To prevent becoming trapped in local optima, a tabu list and an aspiration criterion are necessary components of the TS method [58].

The harmony search method, which was adopted in [59], is based on an algorithm that uses the pitch-adjusting rate, harmony memory consideration rate, and generation bandwidth as parameters. These parameters are used to regulate the convergence rate of the algorithm towards the optimal solution.

Artificial intelligence methods can lead to a reliable and cost-effective system; however, they lack fast convergence speeds to reach optimal performance.

HOMER (Hybrid Optimization Model for Electric Renewables) is the most widely used software-based technique for solving sizing problems and has been developed for both on-grid and off-grid systems. It was employed in [60] to size a hybrid system for rural areas in Saudi Arabia, Algeria, and Ethiopia. The HOGA (Hybrid Optimization by GA) software was used in [61] to enhance sensitivity in an autonomous system. These software-based methods are known for their user-friendliness [62], but they do not account for probability analysis or net measurements [63].

Hybrid techniques combining different approaches have been used to enhance the sizing outcome. In [64], the authors combined simulated annealing and tabu search algorithms for an off-grid system to decrease computational time. In [65], a non-dominated sorting genetic algorithm (NSGA) and multi-objective particle swarm optimization (MOPSO) were adopted to simultaneously minimize carbon dioxide emissions and system cost.

Most of the previously discussed approaches have been shown to be effective in addressing sizing problems, especially the iterative methods. This is because they are easy to implement, highly accurate, and have fast convergence speeds, even in challenging environments with constraints (such as the presence of swell and waves in our case). For these reasons, we selected to use and further advance an iterative approach in our optimal-sizing-design study.

In this context, an off-grid tidal system with a battery is studied in this paper. In fact, a battery is used for energy storage due to its ability to offer both energy density and power. An iterative technique, which incorporates the DPSP and REPG as technical criteria for reliability analysis and the EC and TNPC as economic criteria for cost analysis, is used to address the optimal sizing issue. The simulation results are compared to those from well-known methods such as genetic algorithms, particle swarm optimization, and software-based (HOMER) approaches to highlight the efficiency of the proposed method in improving reliability (with 0% DPSP) and reducing costs.

This paper is structured as follows: the proposed system model and control are described in Sections 2.1 and 2.2, respectively. The energy management strategy is outlined in Section 2.3.3. The development of the sizing approach is described in Sections 2.3.2 and 2.3.3. Simulation results are analyzed in Section 3, and the paper concludes in Section 4.

2. System Study and Method Description

In order to describe the adopted iterative method, it is necessary to first establish a model and a control system for the studied system.

2.1. Tidal Stream Turbine–Battery Modeling

The proposed system is shown in Figure 1 and includes tidal turbine as an energy resource and a battery for storage. Power converters (AC/DC and DC/AC) are used to support the power management strategy [66,67].

2.1.1. Tidal Current Velocity Modeling

Tidal currents result from the interactions of Earth, the sun, and the moon. The force of the moon is much greater (68%) than that of the sun (32%). Indeed, tidal currents are affected by the different phases of the moon. When the moon is full, tidal currents are strong, and they are called "spring currents." When the moon is in the first or third quarter phases, tidal currents are weak; they are called "neap currents" [68].

The SHOM (French Navy Hydrographic and Oceanographic Service, Brest, France) records and presents tidal current data for every coastal site. It gives the current velocities for spring and neap tides. These data are given at hourly intervals starting at 6 hours before high waters and ending at 6 hours after. Tidal current velocity can be presented by a simple and practical model given by Equation (1) [5].

$$\mathrm{v_t} = \mathrm{v_{nt}} + \frac{(\mathrm{C} - 45)(\mathrm{v_{st}} - \mathrm{v_{nt}})}{95 - 45} \tag{1}$$

where C is the tide coefficient. It characterizes each tidal cycle (45 and 95 are, respectively, the neap and the spring tide medium coefficient). v_{st} and v_{nt} are, respectively, the spring and the neap tide current velocities (m/s).

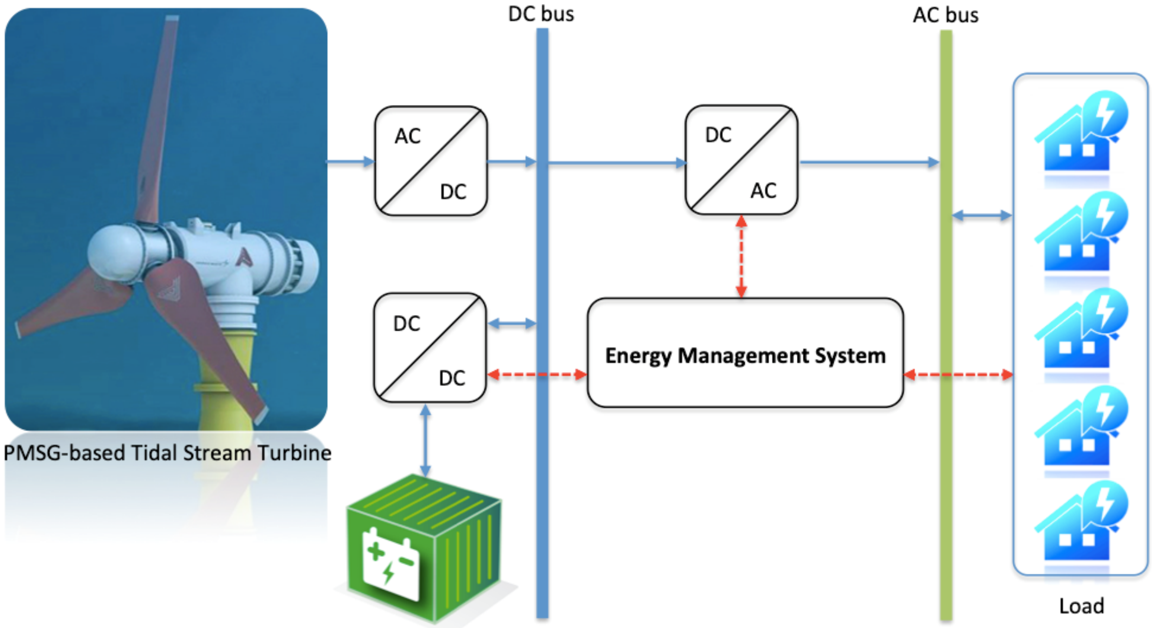

Figure 1. TST–battery system configuration.

2.1.2. Tidal Power Modeling

The tidal power extracted from marine currents is expressed by Equation (2) [69].

$$P_t = \begin{cases} 0 \text{ if } v_{cut-out} < v_t < v_{cut-in} \\ \frac{1}{2}\rho\pi r^2 C_p v_t^3 \text{ if } v_{cut-in} < v_t < v_r \\ P_{r-tt} \text{ if } v_r < v_t < v_{cut-out} \end{cases} \quad (2)$$

where v_r is the rated velocity (m/s); $v_{cut\text{-}in}$ is the cut-in velocity (m/s); $v_{cut\text{-}out}$ is the cut-out velocity (m/s); v_t is the tidal velocity (m/s); $P_{r\text{-}tt}$ is the rated output power (W); ρ is the fluid density (1027 kg/m^3); r is the turbine radius (m); and C_p is the turbine power coefficient, which allows calculating the produced power from tidal energy using a tidal stream turbine (typical values are between 0.3 and 0.5). In order to enhance reliability, a non-pitchable TST was selected [70,71]. This means that the C_p can only depend on the tip speed ratio (λ). Figure 2 shows the C_p curve adopted for simulations. The maximum value C_{pmax} = 0.4, which corresponds to the optimal tip speed ratio λ_{opt} = 6.8.

2.1.3. Generator Modeling

A direct-drive PMSG-based tidal stream turbine configuration was adopted thanks to its high efficiency, high dynamic performances, and increased reliability (no gearbox) [72].

The PMSG dynamic modeling is given by Equation (3) [73].

$$\begin{cases} \frac{di_d}{dt} = -\frac{R_s}{L_s} i_d + p\Omega i_q + \frac{V_d}{L_s} \\ \frac{di_q}{dt} = -\frac{R_s}{L_s} i_q - p\Omega i_q - \frac{p\psi_m}{L_s}\Omega + \frac{V_q}{L_s} \\ \frac{d\Omega}{dt} = \frac{p}{J} T_m - \frac{p}{J} T_{em} - \frac{p}{J} f\Omega \\ T_{em} = \frac{3}{2} p\psi_m i_q \end{cases} \quad (3)$$

where R_s, L_s, and ψ_m are the stator resistance (Ω), self-inductance (H), and permanent magnet flux (Wb), respectively. Ω is the rotor turbine speed (rad/s); p is the number of pole pairs; J is the total inertia (kgm^2); f is the viscosity coefficient (Nm/s); and T_m and T_{em} are the mechanical and the electromagnetic torque (Nm), respectively.

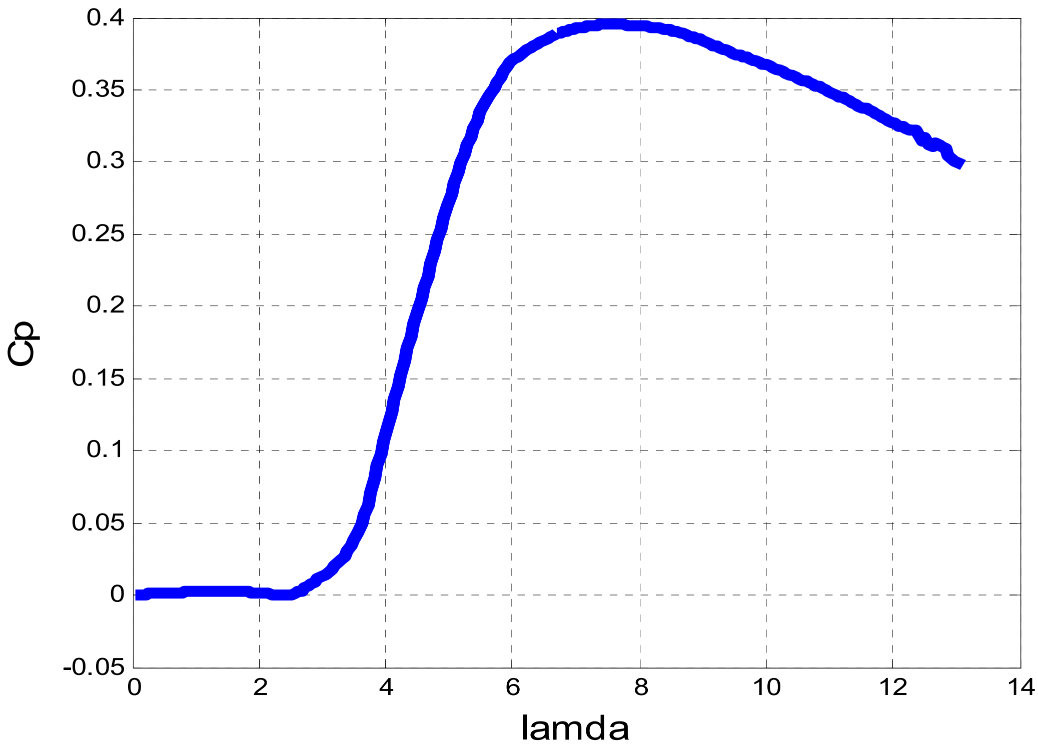

Figure 2. Power coefficient C_p curve.

2.1.4. Battery Modeling

The use of a battery is necessary to meet the energy demand when the tidal stream energy output is deficient. The battery capacity and its stored energy are described by Equation (4) and Equation (5), respectively [74].

$$C_{Bat} = \frac{L_D D_{aut}}{DOD_{max} V_{Bat} \eta_{Bat}} \tag{4}$$

$$E_b(t) = \begin{cases} E_b(t-1)(1-\sigma) + \left[E_t(t) - \frac{E_L(t)}{\eta_{inv}}\right]\eta_{Bat} \\ \text{during battery charging} \\ E_b(t-1)(1-\sigma) - \left[\frac{E_L(t)}{\eta_{inv}} - E_t(t)\right] \\ \text{during battery discharging} \end{cases} \tag{5}$$

where L_D is the daily electricity usage; D_{aut} is the autonomy day; DOD_{max} is the maximum depth of discharge; and V_{Bat} and η_{Bat} are the battery voltage (V) and efficiency, respectively. E_t is the produced tidal energy (W); E_L is the load power demand (W); σ is the hourly self-discharge rate of the battery; and η_{inv} is the inverter efficiency.

The battery state of charge is given by Equation (6)

$$SOC_{min}(t) \le SOC(t) \le SOC_{max}(t) \tag{6}$$

where

$$\begin{cases} SOC_{max} = C_{Bat} V_{Bat} \\ SOC_{min} = C_{Bat} V_{Bat} (1 - DOD_{max}) \end{cases} \tag{7}$$

2.1.5. Inverter Modeling

The inverter is modeled by its efficiency, which is expressed by Equation (8) [74].

$$\begin{cases} \eta_{inv} = \frac{P_1}{P_1+P_0+mP_1^2} \\ P_0 = 1 - 99\left(\frac{10}{\eta_{10}} - \frac{1}{\eta_{100}} - 9\right)^2 \\ P_1 = \frac{P_{out}}{P_{n-inv}} \\ m = \frac{1}{\eta_{100}} - P_0 \end{cases} \tag{8}$$

where P_{out} is the output inverter power (W); $P_{n\text{-}inv}$ is the inverter rated power (W); and η_{10} and η_{100} are the efficiency at 10% and at 100% of the inverter rated power, respectively.

2.2. Tidal Stream TurbineBattery Control

The tidal stream turbine control system, depicted in Figure 3, is primarily ensured by PI controllers and consists of two current controllers and a speed controller.

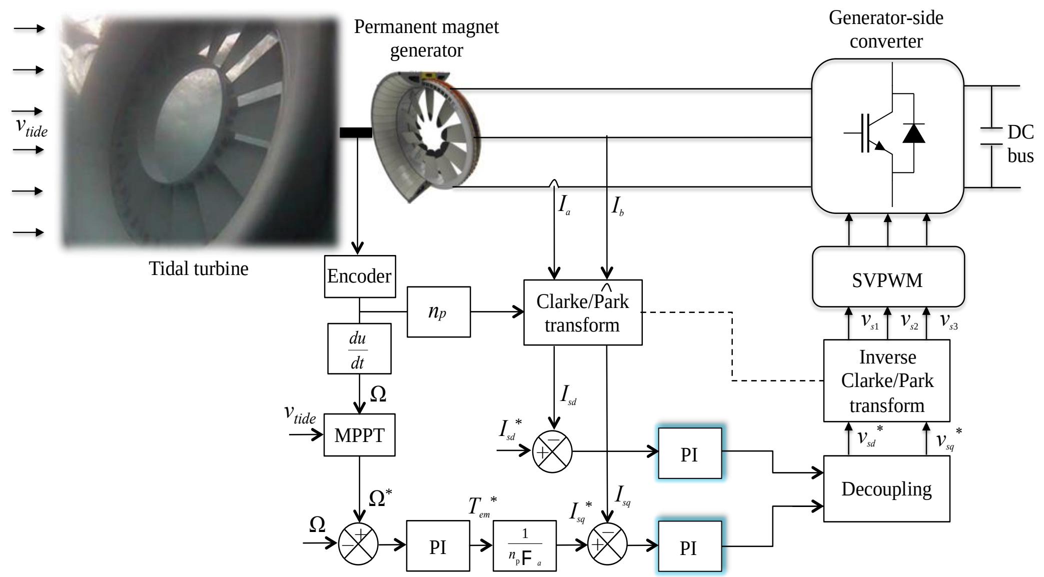

Figure 3. TST control.

The control system is expressed by Equation (9)

$$\begin{cases} i_{sd} = \frac{1}{R_s+L_s s}(v_{sd} + \omega\psi_{sq}) \\ i_{sq} = \frac{1}{R_s+L_s s}(v_{sq} - \omega\psi_{sd}) \end{cases} \tag{9}$$

where

$$\begin{cases} \psi_{sd} = L_s i_{sd} + \Phi_a \\ \psi_{sq} = L_s i_{sq} \end{cases} \tag{10}$$

The control system for the tidal stream turbine in this study uses an MPPT-based variable speed technique. The optimal tip speed ratio is fixed to maximize tidal power extraction, and the turbine speed, expressed by Equation (11) [75,76], is regulated to operate around the maximum power. If the tidal velocity exceeds 3.2 m/s, the extracted power will be limited to its maximum capacity [75].

$$\Omega_{ref} = \frac{v_t \lambda_{opt}}{r} \tag{11}$$

2.3. Method Description

The technique that was adopted involves a recursive algorithm that integrates both technical and economic criteria, with a focus on implementing robust energy management.

2.3.1. Energy Management Strategy

An energy management strategy is vital in meeting energy demand [4]. It takes into account energy consumption at any time of the year. Tidal velocity and system component parameters (TST, battery, load, and inverter) are the input data. Two cases can be considered:

- Charging process: When the tidal energy exceeds the load demand ($E_t(t) > E_L(t)$), the TST will therefore supply the load, while the energy surplus will charge the battery until $E_{BT}(t) > E_{BTMax}(t)$.
- Discharging process: When the TST energy is insufficient to cover the load demand ($E_t(t) \leq E_L(t)$), whilst the battery is properly charged ($E_{BT}(t) < E_{BTMin}(t)$), the energy deficit is covered by the battery.

2.3.2. Optimal Sizing Approach

The objective function of the optimal sizing technique is to minimize system cost while improving system reliability. The used indexes of reliability are the deficiency of power supply probability (DPSP) and the relative excess power generated (REPG). For cost reduction, the energy cost (EC) and the total net present cost (TNPC) are used as economic indexes.

Reliability Indexes

To ensure the TST–battery system reliability, the deficiency of power supply probability and the relative excess power generated are required.

- Deficiency of Power Supply Probability

The DPSP, chosen as a reliability index, is a statistical parameter that indicates the power supply deficiency probability due to technical failure or low power given by the TST system [67]. It allows us to determine the configuration that presents a DPSP = 0% [74]. The DPSP is calculated using Equation (12).

$$\begin{cases} \mathrm{DPSP}(\%) = \dfrac{\sum_{t=1}^{T} \mathrm{D(t)}}{\sum_{t=1}^{T} \mathrm{E_L(t)}} \times 100 \\ \mathrm{D(t)} = \mathrm{E_L(t)} - [\mathrm{E_t(t)} + \mathrm{E_{BT}(t-1)} - \mathrm{E_{BTMin}}] \times \eta_{\mathrm{inv}} \end{cases} \quad (12)$$

where T is the period during which the data were used (8760 h); $E_{BT}(t-1)$ is the battery energy capacity at $(t-1)$; E_{BTMin} is the battery minimum energy capacity; and $D(t)$ is the deficiency energy supply at hour t.

- Relative Excess Power Generated

The REPG is the ratio of the energy surplus to the sum of the load energy demands. It is expressed by Equation (13) [77].

$$\begin{cases} \mathrm{REPG} = \dfrac{\sum_{t=1}^{T} \mathrm{R(t)}}{\sum_{t=1}^{T} \mathrm{E_L(t)}} \\ \mathrm{R(t)} = \left(\mathrm{E_t(t)} - \left[\dfrac{\mathrm{E_L(t)}}{\eta_{\mathrm{inv}}} + \dfrac{(\mathrm{E_{BTMax}} - \mathrm{E_{BT}(t-1)})}{\eta_{\mathrm{Bat}}}\right]\right) \end{cases} \quad (13)$$

where E_{BTMax} is the battery maximum energy capacity, and $R(t)$ is the energy surplus at for every hour t.

Economic Indexes

To minimize cost, the total net present cost and energy cost of the TST–battery system are considered.

- Total Net Present Cost The TNPC includes C_T (capital cost), $C_{O\&M}$ (operation and maintenance cost), and C_{Rep} (replacement cost) [78]:
  1. Capital cost: It represents the used component procurement cost sum (TST, battery, and inverter) [79];
  2. Operation and maintenance cost: It represents all the system component operation and maintenance costs during the year. It depends on the system lifetime and the interest rate [79];
  3. Replacement cost: It depends on some component replacement.

  The total net present cost can be finally calculated using Equation (14).

$$\begin{cases} \mathrm{TNPC}(\$) = \mathrm{C_T} + \mathrm{C_{O\&M}} + \mathrm{C_{Rep}} \\ \mathrm{C_T} = \mathrm{C_T^{TST}} + \mathrm{C_T^{Bat}} + \mathrm{C_T^{invr}} \\ \mathrm{C_{O\&M}} = \left(\mathrm{C_{O\&M}^{TST}} + \mathrm{C_{O\&M}^{Bat}}\right) \times \gamma \\ \mathrm{C_{Rep}} = \left(\mathrm{C_{Rep}^{Bat}} \times \mu_1\right) + \left(\mathrm{C_{Rep}^{inv}} \times \mu_2\right) \\ \gamma = \frac{(1+k)^{\tau}-1}{k(1+k)^{\tau}} \\ \mu_1 = \sum_{p=1}^{\left(\frac{\tau}{\tau_{Bat}}-1\right)} \left(1 + \frac{1}{(1+k)^{p\tau_{Bat}}}\right) \\ \mu_2 = \sum_{p=1}^{\left(\frac{\tau}{\tau_{inv}}-1\right)} \left(1 + \frac{1}{(1+k)^{p\tau_{inv}}}\right) \end{cases} \tag{14}$$

where C_T^{TST} is the TST investment cost; C_T^{Bat} is the battery investment cost; C_T^{inv} is the inverter investment cost; $C_{O\&M}^{MCT}$ is the TST maintenance cost; $C_{O\&M}^{Bat}$ is the battery maintenance cost; C_{Rep}^{Bat} is the battery replacement cost; C_{Rep}^{inv} is the inverter replacement cost; τ is the system lifetime; k is the interest rate (8%); τ_{Bat} is the battery lifetime; and τ_{inv} is the inverter lifetime.

- Energy Cost

  The energy cost (per-unit produced energy cost) is calculated using Equation (15) [62].

$$\begin{cases} \mathrm{EC}(\$/\mathrm{KWh}) = \frac{\mathrm{TNPC}}{\sum_{t=1}^{8760} \mathrm{E_{WT}}(t)} \times \psi(k,\tau) \\ \psi(k,\tau) = \frac{k(1+k)^{\tau}}{(1+k)^{\tau}-1} \end{cases} \tag{15}$$

where Ψ is the capital recovery factor.

2.3.3. Proposed Sizing Approach

The proposed algorithm for the optimal sizing of the TST–battery system is shown in Figure 4. As input data, the tidal speed and the system component parameters (load, TST, battery, and inverter) are given throughout a year (365 × 24 h = 8760 h). This algorithm has two objectives. The first one is to improve the system reliability using the DPSP and the REPG concepts. The second objective is to reduce the produced energy cost through the TNPC and EC criteria. Consequently, the sizing approach consists in determining the optimal configuration (TST power and battery capacity) that ensures a well-designed system with minimal costs. The following steps describe the proposed algorithm flow:

1. Input the following over a year: the load power, the tidal velocity, and the battery minimal and maximal states of charge;
2. If the energy obtained from the tidal source exceeds the current load, the surplus of energy is stored in the battery. Then, the new state of charge is determined using Equation (5);

3. If the load demand exceeds the energy produced by tidal source, the battery will be used to meet the load demand. Then, the new state of charge is obtained using Equation (5);
4. Size the system's different components that ensure system reliability (DPSP = 0) over a year with minimal EC and TNPC, and EC;
5. Stop when cost is minimal, with zero DPSP;
6. Save the obtained (TST power, battery capacity) configuration.

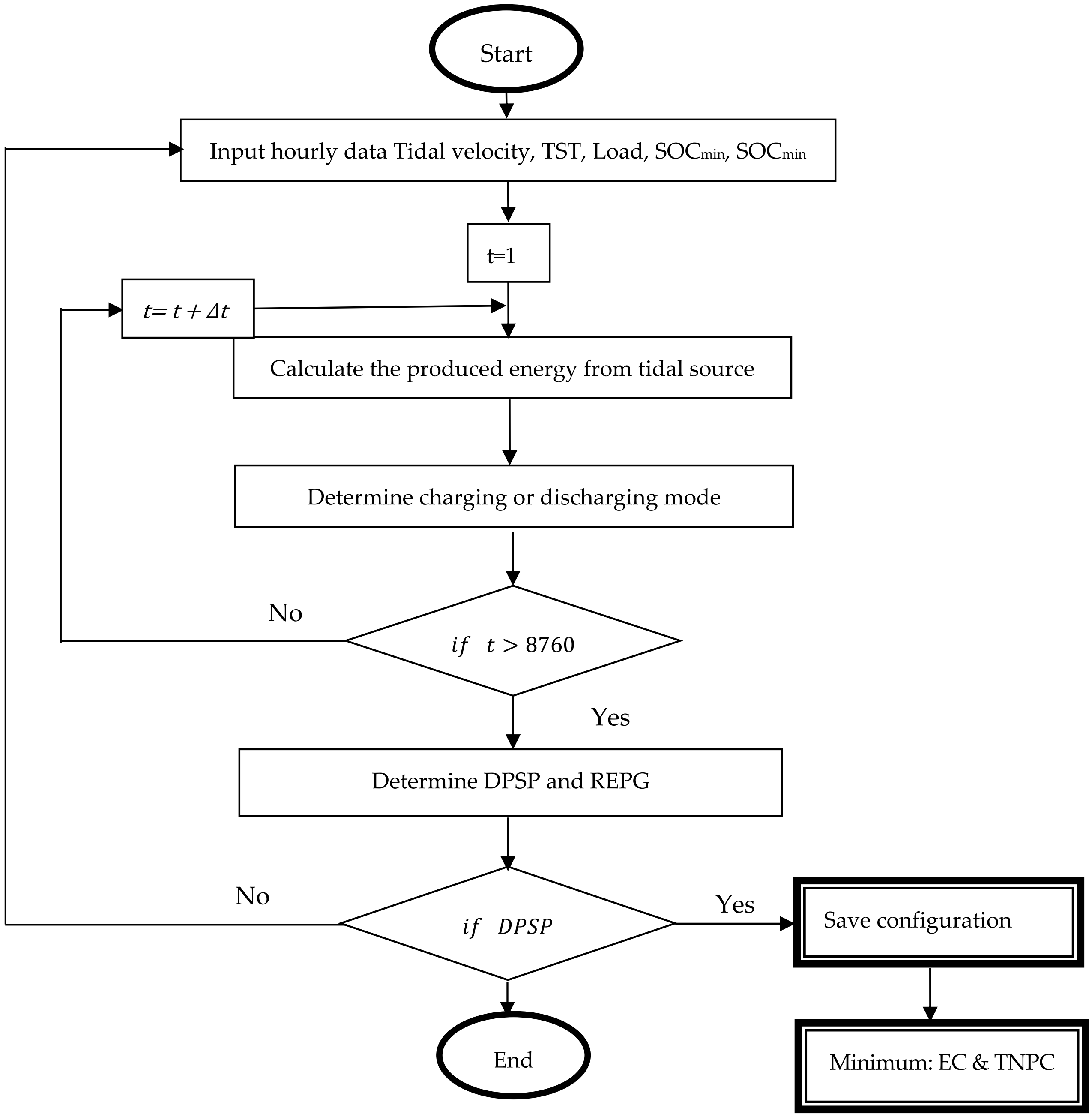

Figure 4. Optimal sizing algorithm flow chart.

3. Results and Discussion

The parameters of the studied TST–battery system are given in Table 1. The first-order model (Equation (1)) was used for each hour of the year (1 January 2007 to 31 December 2007) to calculate the tidal current velocity (Figure 5) in the Raz de Sein in the Bretagne (France).

Figures 6 and 7 show, respectively, the annual power generated by the TST and the annual load demand.

Table 1. System parameters.

	Parameter	Value
TST	Rated power	50 kW
	Tidal velocity	3 m/s
	Cut-in tidal velocity	1 m/s
	Cut-out tidal velocity	3.8 m/s
	Radius	8 m
	Rated speed	25 rpm
	Stator resistance	0.0081 Ω
	d-axis inductance	1.2 mH
	q-axis inductance	1.2 mH
	Permanent magnet flux	2.458 Wb
	System total inertia	1.3131×10^{6} kg·m^2
	Viscosity coefficient	8.5×10^{-3} Nm/s
	Capital cost	5000 USD/kW
	Operation and maintenance costs	150 USD/kW
	Lifetime	20 years
Battery	Capacity	800 Ah
	Voltage	240 V
	Efficiency	0.85
	DOD	0.7
	Lifetime	5 years

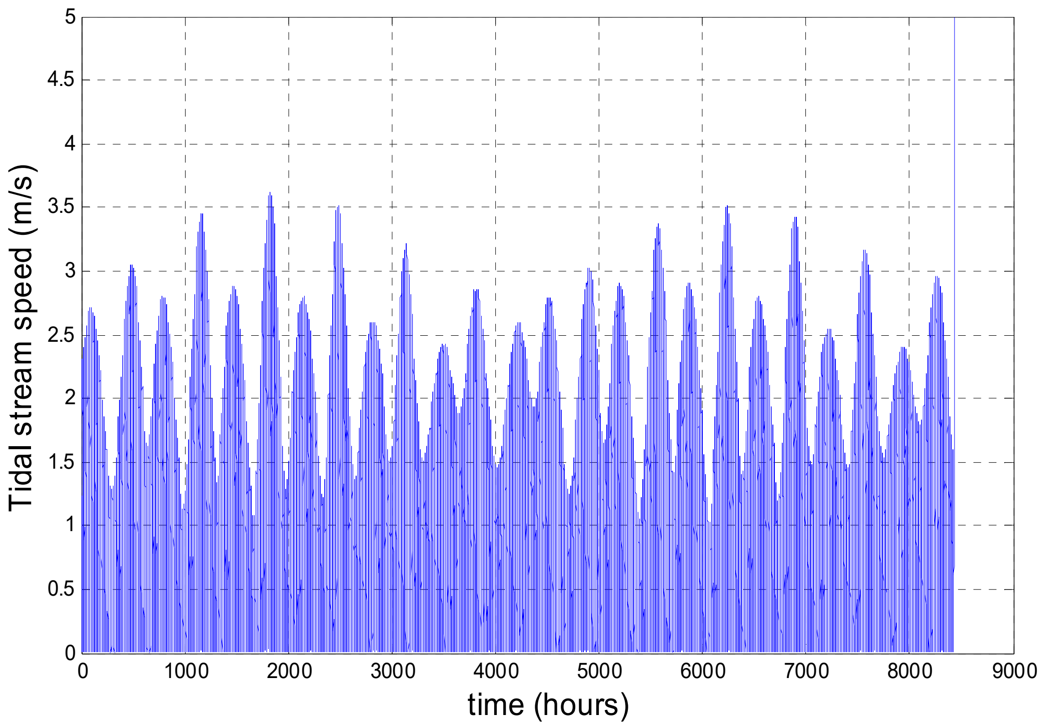

Figure 5. Tidal velocity for one year.

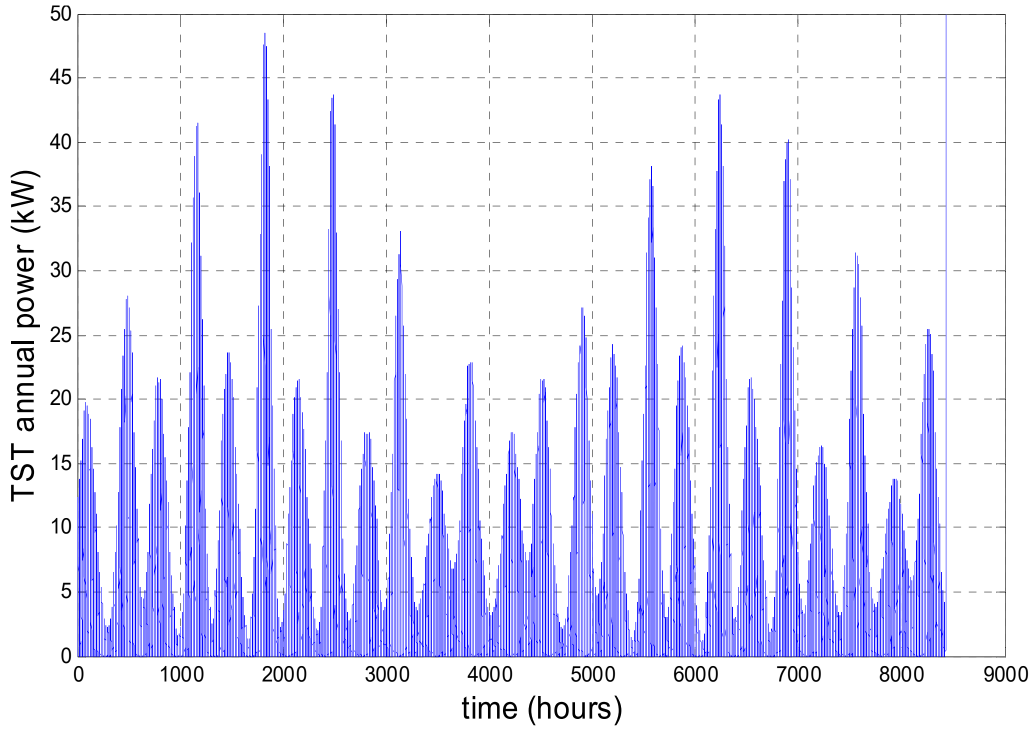

Figure 6. TST annual power.

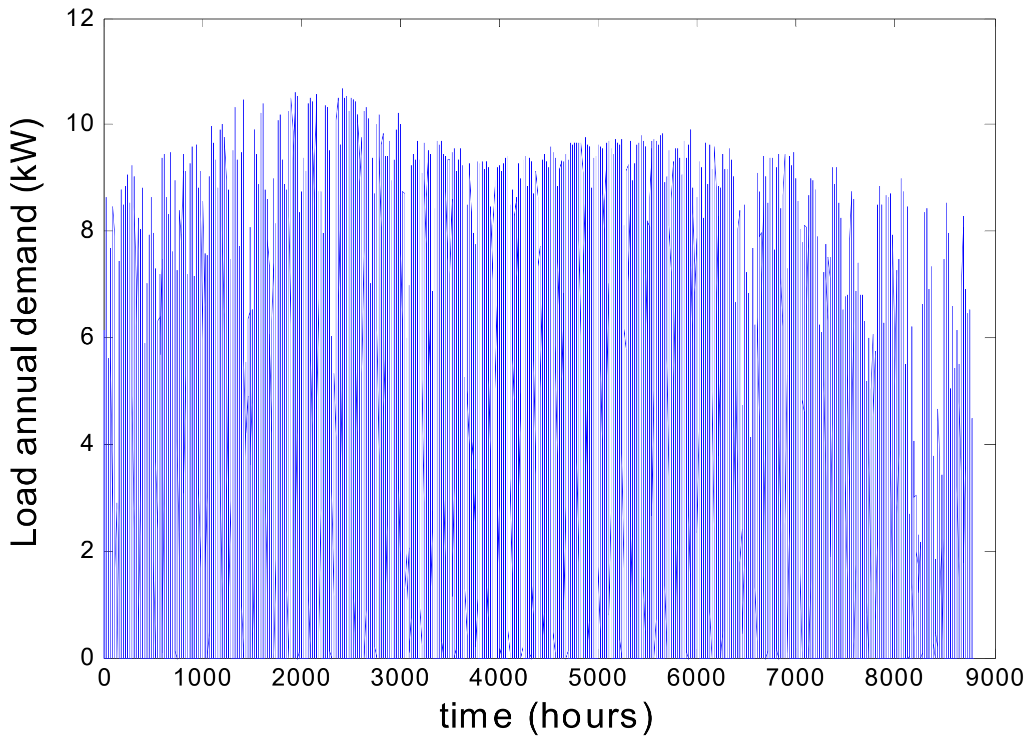

Figure 7. Load annual demand.

The simulation results achieved by the proposed sizing algorithm are summarized in Figure 8 and Table 2. They both show the optimal sizing results for different combinations of TST and battery. Indeed, to determine the configuration that ensures a DPSP = 0%, a battery capacity and a TST power less than 800 Ah and 43.8 kW, respectively, are rejected. Therefore, a battery with a capacity of 800 Ah or more with a TST of 43.8 kW or more is recommended. Hence, to minimize the cost of the system, the authors have chosen the smallest battery capacity (800 Ah). To this end, a 47.8 kW–800 Ah configuration was selected. With this configuration, the TNPC is USD 28,647, and the EC is USD 1.164/kWh.

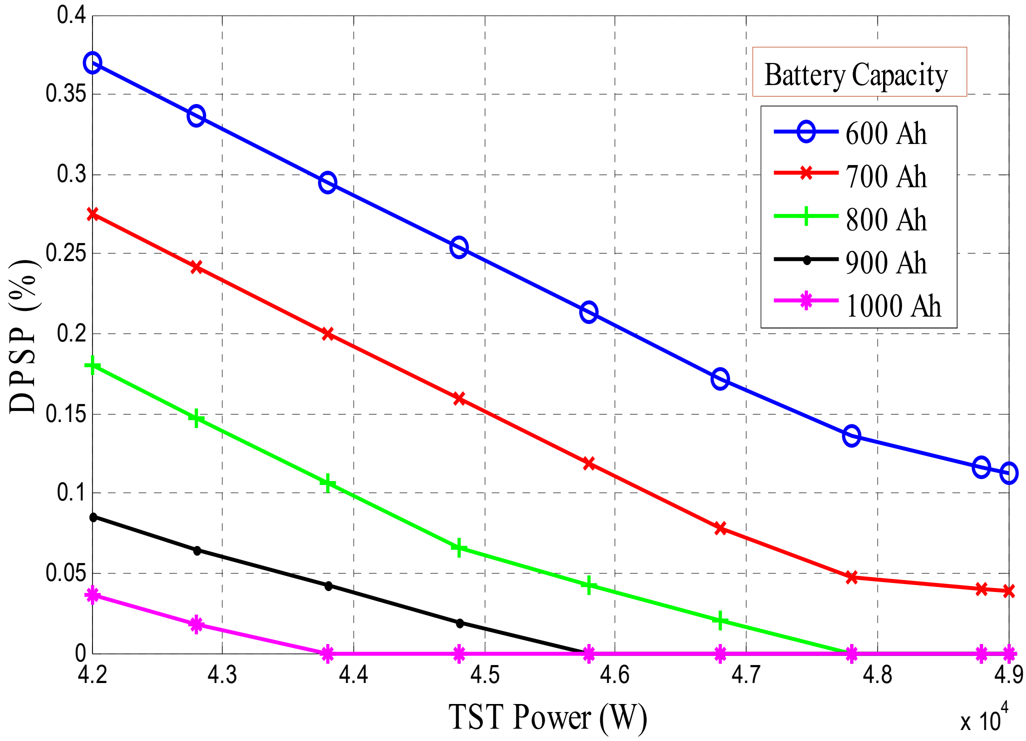

Figure 8. Annual DPSP for different TST power and battery capacity configurations.

Table 2. DPSP for different combinations.

TST Power (kW)	Battery Capacity (Ah)	DPSP (%)	Decision
Whatever	600	$\neq$0	Rejected
Whatever	700	$\neq$0	Rejected
<43.8	Whatever	$\neq$0	Rejected
<47.8	800	$\neq$0	Rejected
≥47.8	**800**	**0**	**Accepted**
<45.8	900	$\neq$0	Rejected
≥45.8	900	0	Accepted
≥43.8	1000	0	Accepted

Figure 9 and Table 3 propose a comparison of the proposed approach to other techniques (genetic algorithm, particle swarm optimization, and HOMER software) at 0% DPSP. The achieved results clearly confirm the effectiveness of the proposed techno-economic optimization approach in obtaining a reliable and cost-effective TST–battery system. In this context, the particle swarm optimization technique achieves the second-best ranking, with a TNPC of USD 30,200 and an EC of 1.296 USD/kWh. In contrast, the genetic algorithm technique is ranked the lowest, with a TNPC of USD 59,042 and a CE of 1.761 USD/kWh.

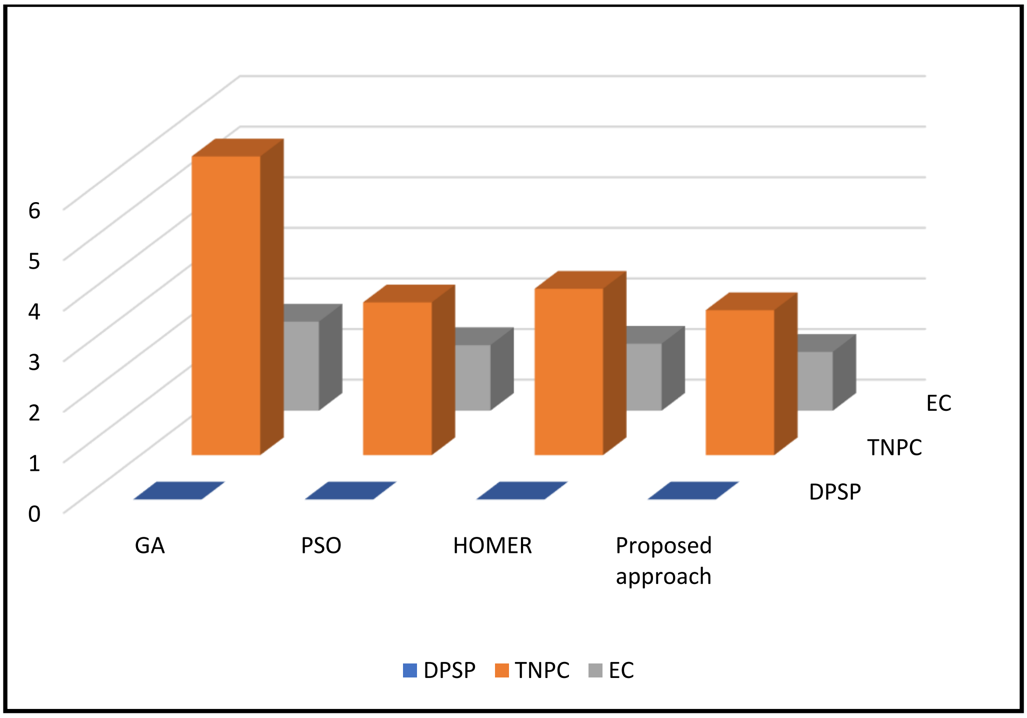

Figure 9. Comparison of DPSP, TNPC, and CE among compared approaches.

Table 3. Comparative evaluation of the proposed optimal sizing approach.

Approach	TST Power (kW)	Battery Capacity (Ah)	DPSP (%)	TNPC (USD)	EC (USD/kWh)
Genetic algorithm	98.52	2235	0	59042	1.761
Particle swarm optimization	53.4	1040	0	30200	1.296
HOMER	62.3	1100	0	32888	1.325
Proposed approach	**47.8**	**47.8**	**0**	**28647**	**1.164**

4. Conclusions

This paper presented an in-depth examination of an iterative optimal sizing method for a tidal stream turbine–battery system. The proposed approach used yearly tidal stream velocity and load demand as key input information for the optimization process. The results obtained from the application of this method clearly demonstrate its effectiveness in improving reliability (DPSP = 0%) and minimizing the overall cost of the system. The chosen configuration, at 47.8kW–800Ah, was found to have the most favorable techno-economic performance, with TNPC and EC values of USD 28,647 and 1.164 USD/kWh, respectively. The proposed approach has also been compared to well-established approaches, namely genetic algorithm, particle swarm optimization, and HOMER software. The achieved results clearly show that the iterative optimal sizing methodology allows obtaining a reliable and cost-effective TST–battery system.

The significance of this study lies in the ability to confirm the validity of the theoretical results through experimental study, providing a strong foundation for the practical implementation of this approach in the future.

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