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Review article

Review on sizing and management of stand-alone PV/WIND systems with storage

Jean Guétinsom Kafando [a], Daniel Yamegueu [a,*], Etienne Tchoffo Houdji [b]

[a] Laboratoire Energies Renouvelable et Efficacité Energétique, Institut International d'Ingénierie de l'Eau et de l'Environnement (2iE), Rue de la Science, Ouagadougou, Burkina Faso
[b] Department of Renewable Energy, National Advanced School of Engineering of Maroua, University of Maroua, Cameroon

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ABSTRACT

Extending the public electricity grid to rural or peri-urban areas is sometimes very costly and unprofitable due to their remoteness, low population density and sometimes difficult accessibility. In view of this, and in the concern of a sustainable development, the autonomous PV and/or wind power systems is increasingly used. However, these fluctuating source systems remain unreliable due especially to their intermittent nature, what justifies the integration of battery storage systems to them. They are also still expensive, particularly in the African context, limiting their access to the greatest number of the population. In addition to these problems of cost and reliability, the issue of optimal sizing of such systems is essential. In this paper, energy storage technologies, performance criteria, basic energy production and storage models, configuration types, sizing and management techniques discussed in the literature for the study of stand-alone solar and/or wind power systems in isolated sites are reviewed. The findings of the present study reveals that electrochemical battery is the main technology used for energy storage in stand-alone PV-wind systems due in particular to their maturity compared to the other storage technologies. However, it also shows that while batteries are the most widely used energy storage technology for solar and wind power systems, they are still expensive. The paper also revealed that traditional methods of optimal sizing and management of autonomous solar and wind power generation systems are being used less and less, in favor of artificial intelligence methods, due mainly to their limited flexibility and inability to solve complex problems.

1. Introduction

In most developing countries, especially in Africa, rural and peri-urban areas are the most disadvantaged in term of access to electricity supply [1]. Indeed, for these areas, grid extension is very costly and unprofitable due to their remoteness or low population density. In these areas, energy systems based on diesel generators are often used. These solutions are not economical for the population with low-income levels, especially those from rural areas. On the other hand, these solutions are not environmentally friendly because of CO_2 emissions into the atmosphere by these generators [2,3]. Fossil fuels currently account for nearly 80 % of world's primary energy consumption, while global demand is expected to grow by 2.3 % per year between 2015 and 2040 [3]. In this context, stand-alone photovoltaic (PV) and/or wind energy systems with electrochemical storage and/or hydrogen fuel cells are seen as

* Corresponding author.
E-mail addresses: daniel.yamegueu@2ie-edu.org, dan.yamegueu@gmail.com (D. Yamegueu).

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Abbreviations

AC	Alternative current
ACO	Ant Colony Optimization
ACS	Annualized Cost of System
CRF	Capital Recovery Factor
C_{Bat}	battery Capacity(Ah or Wh)
BAO	Bat Algorithm Optimization
DPSP	Deficiency of Power Supply Probability
DCHR	Discrete Chaotic Harmony Research
HS	Harmony Search
SA	Simulated Annealing
OM	Operating and maintenance
EMS	energy management system
PV	Photovoltaic
WT	Wind Turbine
P_{PV}	Photovoltaic Field power (Watts)
P_{WT}	Wind field Power (Watts)
S_{PV}	Total area of PV field (m^2)
S_{WT}	Total area of wind turbine (m^2)
DC	Direct current
DEMO	Differential Evolution Multi-Objectif
GA	Genetic algorithm
PSO	Particle Swarm Optimization
MPSO	Modified PSO
PSO-CF	PSO with Constriction Factor
PSO-RF	PSO based on Repulsion Factor
PSO-W:	PSO with adaptive inertia weight
PEMFC	Proton Exchange Membrane Fuel Cell
AFC	Alkalin Fuel Cell
DMFC	Direct Methanol Fuel Cell
MCFC	Molten Carbonate Fuel Cell
SOFC	Solid Oxide Fuel Cell
PAFC	Phosphoric Acid Fuel Cell
EL:	Electrolyzer
FC	Fuel cell
FA	firefly optimization algorithm
FPA	Flower pollination algorithm
LOLP	Loss Of Load Probability
LPSP	Loss of Power Supply Probability
LCOE	Levelized Cost of Energy
LOEE	Lost Of Energy Expectation
LCC	Life Cycle Cost
TCC	Total Capital Cost
NPC	Net Present Cost
TAC	Total Annualized Cost
TIC	Total Investment Cost
TS	Tabou Search
HSS	Hydrogen Storage System
NAD	Number of Autonomy Days
MFO	Moth Flame Optimization
MPPT	Maximum Power Point Tracker
MAS	Multi Agent System
REP	Replacement
SOC	State Of Charge
DOD	Deep Of Discharge
ANN	Artificial Neural Network

sustainable and environmentally-friendly means of power generation suitable for electrification (households, schools, health centers, commerce …), water pumping, telecommunications and street lighting in isolated sites [1,4]. However, there are still a number of obstacles to their widespread use. These include fluctuating production sources, high investment costs linked to expensive technologies and unsuitable design methods [4,5].

In [6] it has been demonstrated that the cost storage using supercapacitor is approximately €16,000/kWh. Despite their high performance, supercapacitors remain prohibitively expensive for the general public. A study by Diaf et al. [7] examines the optimization of a PV-wind system with battery storage across various sites in Islands. This research reveals that the suitability of the location and the system's configuration not only impact storage capacity but also influence the evolution of the storage's state of charge and the Levelized Cost of Energy (LCOE). Several other optimization studies have been carried out in order to obtain reliable and economically accessible autonomous systems. These are mainly techno-economic sizing studies [4,8–11] or techno-economic feasibility analysis [2,12–16]. In Ref. [17], a statistical analysis was carried out using data extracted from the 550 most relevant and recent articles published between 1995 and 2020 on stand-alone or grid-connected PV-wind hybrid systems. This analysis reveals that stand-alone PV-wind hybrid systems are the most studied for residential applications. In addition, it is shown that Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and HOMER and MATLAB software are the most widely used methods and tools for techno-economic studies of these systems. Allywn et al. [18] conducted a techno-economic analysis of a PV-Battery system for public lighting in Oman. They explored the impact of the autonomy on the system cost by comparing a system with battery storage with a system without any storage. They used genetic algorithm for optimization. Loss of Power Supply Probability (LPSP) and Levelized Cycle Cost (LCC) were used as technical and economic criteria, respectively. The study assumed a battery autonomy of three days and a battery lifespan of seven years.

One can notice that very often, aberrant and unjustified considerations of the number of days of storage autonomy, the absence of analysis of storage ageing according to user consumption profiles, and the use of inefficient energy management strategies are considered in the various studies shown above.

The aim of this article is to review energy storage technologies, and the sizing and management techniques used for the design and/or management of stand-alone fluctuating source systems (solar, wind) in isolated sites. The keys contributions of this work can be listed as follows.

- Identify the best storage technology for stand-alone PV/wind power systems based on the maturity and cost of different storage technologies.
- Identify and classify sizing methods and tools for stand-alone photovoltaic and/or wind energy systems with storage.
- Analysis of different energy management techniques for stand-alone photovoltaic and/or wind power systems with storage.
- Highlight gaps in the literature about the optimal choice of storage autonomy and battery lifetime.

The paper is structured into nine main sections. Section 2 presents the storage technologies used in PV and/or wind systems. Section 3 presents the configuration types of stand-alone PV and/or wind hybrid systems with storage encountered in the literature. Sections 4 and 5 present respectively, the sizing techniques for stand-alone solar and/or wind-powered systems with storage, and the performance criteria used. Section 6 presents basic mathematical models of solar and wind power generation and storage. Section 7 reviews the state of the art in energy management techniques and studies of autonomous hybrid systems. A discussion of the various aspects of autonomous systems with fluctuating sources covered in the previous sections is given in Section 8. The paper ends with a conclusion in Section 9.

2. Energy storage types in fluctuating source systems

Autonomous systems for producing electricity from fluctuating sources such as the sun and wind are clean, sustainable means of producing electricity from hundred Watts to some kilo Watts, suitable for electrifying buildings (households, schools, health centers, shops, etc.), pumping water, telecommunications and public lighting in isolated locations (islands, rural or peri-urban areas). These systems do not offer security of supply due to the intermittent nature of the sources [4]. Energy storage systems such as electrochemical

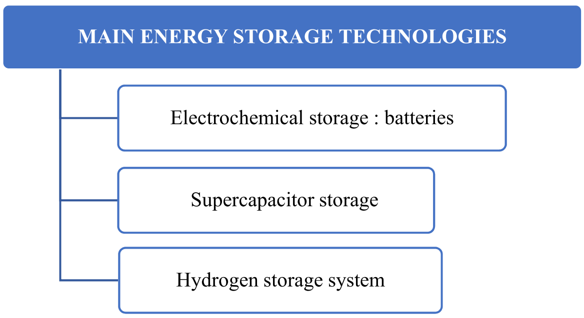

Fig. 1. Energy storage systems for isolated sites.

storage or batteries, supercapacitors and hydrogen storage systems (Electrolyser-Fuel Cell-Hydrogen Tank) can be used alone or in hybridization to tackle this issue [19] (Fig. 1).

2.1. Individual storage systems

2.1.1. Electrochemical storage: batteries

Batteries or electrochemical accumulators are systems used to store electrical energy in the form of chemical energy for later use. They are used both in nomadic applications (portable electronics and automobiles) and in stationary applications such as mass storage of electricity from renewable energies [20]. Depending on their "chemistry", there are three main battery technologies on the market [6]: lead-acid, nickel-cadmium and lithium-ion. Other types of batteries exist, but are still in the development and demonstration stages [20]. These include flow batteries, sodium-ion batteries and metal-air batteries (zinc-air, Li-air). Table 1 gives a comparison of the characteristics of the most widely electrochemical batteries used in stand-alone power systems today.

Of these three technologies, lithium-ion technologies offer the best performance but cost 2 to 3 times more than nickel-cadmium technologies and 5 to 10 times more than lead-acid technologies. Battery life time varies according to operating regime or conditions, but in terms of years is generally between 5 and 10 years [6].

2.1.2. Supercapacitor storage

Supercapacitors are systems capable of storing electrical energy in the form of electrostatic energy for later use. Mainly considered as power sources, supercapacitors have a high capacity (from a few Farad to several thousand Farad) and a low voltage withstand (from 1V in aqueous media to 3.5V in organic media) [20]. They are frequently used in the transport sector, where their technology generally satisfies starting requirements. They are also used as back-up power supplies for computer memories and brake energy recovery (elevators, streetcars, subways, etc.) [6]. In conjunction with batteries, they also extend battery life time by supplying the power peaks that place the greatest strain on the battery. Today, the main challenge is to increase the energy density of supercapacitors [20]. Supercapacitors have a lifetime of around 8–10 years, an efficiency of around 95 %, a self-discharge of around 5 % per day and a capacity of up to 5000 F [6]. At their average level of maturity, supercapacitors have the highest investment costs. To store one kWh of electrical energy, they cost around 15,000€ [6].

2.1.3. Hydrogen storage system

Hydrogen is a fuel generally obtained by electrolysis of water and can be used in a fuel cell (FC) to produce electricity or heat [3,14]. It is the fuel for the fuel cell, just as diesel is for the diesel generator. This makes the fuel cell an alternative to diesel generators. It can therefore be used in stand-alone power systems as a backup source to compensate intermittencies. In PV and/or wind power systems, the fuel cell can also be used in combination with an electrolyzer to convert surplus solar and/or wind power into dihydrogen [3,14]. In this case, as shown in Fig. 3, the electrolyzer consumes the surplus electricity produced by the PV and/or wind power system, and converts the water molecules stored in a tank into dihydrogen. The hydrogen thus produced is stored under high pressure in another tank to power the fuel cell, which in turn generates electricity to meet demand in case of insufficient or absence of solar or wind power. The combination of these two tanks, the electrolyzer (EL)and the fuel cell (FC) is called a Hydrogen Storage System (HSS). The cost of such a storage system is currently unaffordable, not only because of the high cost of the materials used in their manufacture (platinum), but also because of the cost and complexity of the accessories (converters, compressors, etc.) that go with them [14,21]. Although hydrogen offers many advantages, it still faces a major challenge in terms of safety, durability and high-efficiency storage [12,22,23]. In addition, the high intrinsic power consumption of HSS limits their electrical performance compared with battery storage systems [14,22]. Today, the fuel cell is seen as an alternative to diesel generators, which are considered polluting and noisy, but there are still a number of obstacles limiting its widespread use on both a small and large scale [2]. There are currently six types of fuel cell, but most are still at the R&D stage [21]. Only PEMFC (Proton Exchange Membrane Fuel Cell) technology is suitable for residential use, because of its low operating temperature and wide power range (Table 2). Its disadvantage is that its lifetime is short and its cost is still high, due to the platinum used as a catalyst and which constitutes the key element of this Cell [12,21–23]. Indeed, platinum is a noble metal widely used as a catalyst due to its chemical stability. Research into new materials as catalysts is underway to break the barrier of high cost and short-term durability imposed by platinum on PEMFCs [10]. Uncertainty remains on the real costs of the other fuel cells currently under development, as shown in Table 2.

Table 1
Characteristics of the three most common battery technologies on the market [6].

Accumulators	Energy density (Wh/kg)	Power density (W/kg)	Discharge time	Shelf life	Self-discharge (%/month)	Efficiency (%)	Life time (number of cycles)	Cost (€/KWh)
Lead acid	25–45	280–150	15min-100h	>1 month	40	60–98	300–1500	50–200
Nickel-cadmium	20–60	100–800	15min-100h	<1 month	25	60–80	300–1500	200–600
Lithium-ion	80–150	500–2000	45min-100h	Several month	20	90–100	>1500	700–1000

Table 2
Some characteristics of different fuel cells [6,12,21].

Fuel cell's name	Proton Exchange Membrane Fuel Cell (PEMFC)	Alkalin Fuel Cell (AFC)	Phosphoric Acid Fuel Cell (PAFC)	Molten Carbonate Fuel Cell (MCFC)	Solid Oxide Fuel Cell (SOFC)	Direct Methanol Fuel Cell (DMFC)
Efficiency(%)	~35 - 50	60–70	~37 - 42	50–60	40–65	
Operating temperature (°C)	40–100	60–220	180–220	600–660	700–1000	60–100
Power	<1 kW–100 kW	1 kW–100 kW	50 kW - 10 MW	500 kW - 10 MW	1 kW - 10 MW	–
Cost(€/KWh) (H_2+Fuel cell)	500–1500	–	–	–	–	–
Application	Vehicle, autonomous system	Aeronautics	Power plant	Power plant	Power plant	Power plant

2.2. Hybrid energy storage systems

In stand-alone systems or microgrids using fluctuating renewable energy sources such as solar or wind, the storage systems are sometimes hybridized in order to increase the technical reliability and economic viability of these systems [2,13], [24–26]. Several economic feasibility studies have been carried out on this issue [2,13,24,25]. In the literature, hybrid battery-supercapacitor or battery-hydrogen storage systems are generally found (see Table 7). In these hybrid storage systems, each storage plays a specific role in contributing to the overall reliability or viability of the stand-alone system or microgrid. For example, in a microgrid using a hybrid battery-supercapacitor storage system, the batteries can be used to smooth production or regulate the microgrid frequency, while the supercapacitors can be used to absorb consumption peaks, helping to improve not only the system reliability but also battery lifetime. It should be noted that, unlike supercapacitors, batteries do not cope well with the absorption of power peaks. While energy storage systems and hybrid energy storage systems are important in stand-alone systems or in isolated-site microgrids, these systems are still expensive, especially supercapacitors, as Fig. 11 clearly shows.

3. Configuration of stand-alone HYBRID PV/WIND systems with storage

In order to improve the reliability and viability of autonomous systems with fluctuating sources, hybridization of sources and storage is being used [2,13,24,25]. However, the reliability and cost of these systems depend not only on the quality of the resources and types of storage, but also on the types of configuration used. For example, an optimization study of a PV-wind system with battery storage carried out for several sites in Island by Diaf et al. [7] has shown that the quality of the potential as well as the configuration of the system had an influence not only on the storage capacity but also on the evolution of the state of charge of the storage and the Levelized Cost of Energy (LCOE). They also show that hybridization of sources was the best option compared to PV-only or wind-only generation [7]. There are six widely studied stand-alone PV and/or Wind power generation systems with storage (S1 to S6) as illustrated in Fig. 2. Among them, the most tested or studied are the PV-Wind-Battery stand-alone hybrid systems (S5) [17]. This is confirmed by Tables 3, 4 and 6.

For hybrid autonomous systems such as S8, the main elements (sources, storage system and load) are related by one or two buses (DC and/or AC) through power converters. There are three types of configurations (DC bus configuration, AC bus configuration and DC-AC buses configuration) listed in Refs. [27–29].

- **DC bus configuration**

In this configuration, as illustrated in Fig. 3, apart from DC loads which are fed directly from the DC bus, all sources, storage systems and AC loads are connected to a common DC bus via appropriate power converters to match their voltage to that of the bus. This is the configuration most widely used in the literature, due to its easiness of management. However, it involves more converters and can

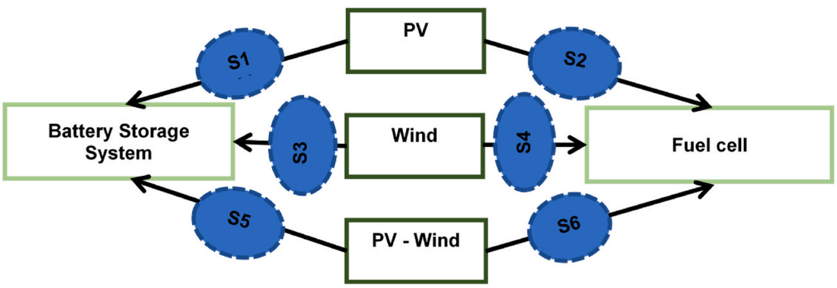

Fig. 2. Possible configurations of stand-alone PV and/or wind power systems with storage [25].

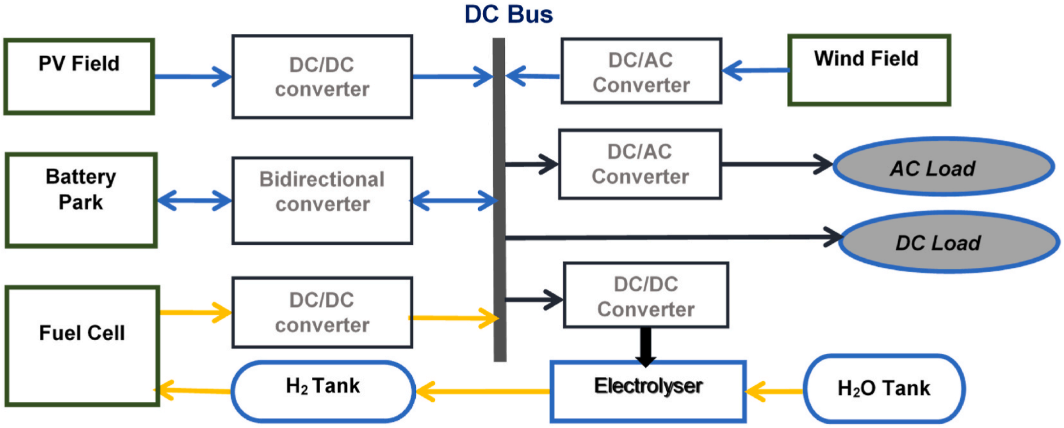

Fig. 3. DC bus configuration of the PV-wind system with hydrogen and battery storage.

Table 3
Classic formulas for sizing a PV or wind power system.

PV field size or power in Watt peak (Wp) is [38] [41,42]	$P_{PV_1} = \frac{C_J}{k^*I_J}$ (1) or $P_{PV_2} = \frac{C_J}{\eta_{PV}^*\eta_{INV}^*PHS^*S_{PV}}\mu,$ (2) With C_J: daily consumption (Wh); I_J: Daily solar irradiation (kWh/m^2/day); k: coefficient taking into account the efficiencies of all converters; η_{PV}: module efficiency; η_{IN}: coefficient taking into account the efficiencies of all converters; μ : safety coefficient taking into account cell temperature and joule losses; *PHS* (Peak Sun Hours): number of hours in the day with 1000W/m^2 ; S_{PV}: Total area of PV field (m^2).
Size or capacity of wind field ($\boldsymbol{P_{WT}}$ in W) [7,8,39,40]. [43]	$P_{WT} = \frac{1}{2}C_P.\eta_M.\eta_g.\rho.S_{WT}.V^3_{moy},$ (3) With C_P : BERTZ limit(0.59); η_M : Multiplier efficiency; η_g : Generator efficiency; ρ : air density (1.293 kg/m^3) S_{WT} : Total area of wind turbines (m^2); V_{moy}: Average annual wind speed(m/s).
Park battery capacity (Ah) [38,41,43]	$C_{Bat} = \frac{C_J^*N_J}{U_B^*DOD^*\eta_B}$ (4) With N_J: Number of days of autonomy (days); U_B : park battery terminal voltage (V); *DOD*: maximum depth of discharge (%); η_B: battery efficiency.
Size of PV-wind-battery hybrid system [7,8,39,40].	, $S_{PV} = F\frac{C_J}{\eta_{PV}I_J}$ (5) $S_{WT} = (1-F)\frac{C_J}{E_w}$ (6) With: C_J: daily energy consumption (Wh); S_{PV} : Total surface area of PV field (m^2); S_{WT} : Total surface area of wind turbines (m^2); F: fraction of demand covered by PV generation; (1-F): contribution from wind turbines; η_{PV} :PV generator efficiency (%); E_w : energy produced per unit of wind surface area (KWh/m^2)

therefore be costly. Authors such as Belmonte et al. [14], Belouda et al. [30], for example, have used this configuration for economic analysis and optimization studies.

- **AC bus configuration**

In this configuration, the PV field, the fuel cell and the battery park are connected to a common AC bus via appropriate power converters, enabling their voltages to be matched to that of the bus (see Fig. 4). The AC load and wind field are directly connected to the AC bus. However, two AC/DC converters are required in the configuration to power both the DC load and the electrolyzer. The management of such a system is more complicated than that of a DC bus system, due to the high fluctuation of the AC bus voltage.

Table 4
Summary of studies based on traditional optimization methods.

References	Method	Systems	Optimization parameters	Optimization functions	Constraints or performance criteria	System or storage lifetime	Outcomes
Kellogg et al. [51]	Iterative	PV-wind-battery system	Number of PV modules, number of wind turbines, Storage capacity	TAC (Total Annualized Cost)	Energy balance between demand and production	System:20 years Battery:4 years	The optimum system size has been found for powering an isolated residential house in Montana.
Belmili et al. [50]	Iterative	PV-wind-battery system	Number of PV modules, number of wind turbines, Number of days of autonomy	LCOE (Levelized Cost Of Energy)	LPSP (Loss of Power Supply Probability)	System:20 years Battery:4years	A technical and economic sizing tool for PV-wind-battery hybrid systems has been designed.
Yang et al. [72]	Iterative	PV-wind-battery system	Number of PV modules, number of wind turbines, Number of days of autonomy	LCOE	LPSP	System:25 years Battery:4 years	An optimal technical-economic sizing method has been developed for stand-alone PV-wind-battery hybrid systems.
Alimi et al. [4]	Iterative	PV and/or wind system with battery	Number of PV modules, number of wind turbines	TCC (Total Capital Cost)	Optimum battery capacity	System: 20 years Battery: 1500 cycles	An iterative method for optimal technical and economic sizing has been developed for stand-alone PV and/or wind-battery systems.
Prasad et al. [10]	Iterative	PV-wind-battery system	Number of PV modules, number of wind turbines, Number of days of autonomy	LCC (Life Cycle Cost), LCOE,LUC (Life Cycle Unit Cost)	DPSP (Deficiency of Power Supply Probability)	System:25 years Battery:4 years	A simulation software was developed to perform the analysis in order to optimize the size of the integrated system for a given location.
Kaabèche et al. [9]	Iterative	PV-wind-battery system	Number of PV modules, number of wind turbines, Number of days of autonomy	LCOE	DPSP (Deficiency of Power Supply Probability)	System:25 years Battery:4 years	The optimal system size was determined for supplying an isolated residential household in Algeria by applying the iterative method.
Olcan [49], Bakelli et al. [73]	Iterative	PV system - motor pump - water tank	Number of modules, Tank capacity	LCOE	DPSP	Système:25 years Réservoir:25 years	An iterative method for the technico-economic dimensioning of a stand-alone PV system for water pumping has been proposed.
Khatod et al. [52]	Analytical	Stand-alone PV and/or wind power system	PV field size, wind field size	Available energy	LOEE (Lost Of Energy Expectation)		Optimal PV and/or wind field sizes were found. The proposed analytical method was found to be better in terms of execution time than the Monte-Carlo method.
Kaldellis et al. [54]	Analytical	PV-battery system	PV field size, storage capacity	Life cycle Energie	EPBP (Energy Pay Back Period)		Optimal PV array and storage sizes have been found for an EPBP of 15 years or less.
Khatib et al. [55]	Analytical	PV-battery system	PV field size, storage capacity	Balance between demand and production	LOLP (Loss Of Load Probability)		The approach provided the optimal PV field size and storage capacity using LOLP and daily insolation data.
Viveros et al. [56]	Analytical	PV-battery system	PV field size, storage capacity	autonomy	Balance between demand and production		The approach provided values for autonomy factors enabling the optimum combination of peak power and storage capacity to be found for best load satisfaction.
Jakhrani et al. [53]	Analytical	PV-battery system	PV field surface area, storage capacity	System cost	LOLP		A new sizing method (Markvart's method) has been proposed, which is

(continued on next page)

Table 4 (*continued*)

References	Method	Systems	Optimization parameters	Optimization functions	Constraints or performance criteria	System or storage lifetime	Outcomes
							estimated to be better than other methods.
Yang et al. [57]	Probabilistic	PV-wind-battery system	PV field size, wind field size, storage capacity	LPSP	Balancing demand and production SOC (State Of Charge)		It was found that an LPSP of 0 % could be achieved with a battery bank with a storage capacity of 5 days.
Bagul et al. [58]	Probabilistic	PV-battery system	PV field size, Storage capacity	LOLP			The optimum system configuration has been found.
Abbes et al. [60]	Multi-objective	PV-wind-battery system	PV field surface area, Wind field surface area, Storage capacity	LCC, LPSP et EE (Embodied Energy)	LPSP	System: 25 years Battery: 5 years	120 Pareto optimum points were found for an LPSP of 5 %.
Bilal et al. [61]	Multi-objective	PV-wind-battery system	number of modules, turbines, batteries, controllers and inverters	ACS LPSP	LPSP		For fixed LPSP and for several load profiles the optimal system configuration has been found
Semassou et al. [59]	Multi-objective	PV-battery system	number of modules, number of batteries, module type, battery type and cable cross-section	Nine criteria considered (LOLP, LCOE …)			A number of possible solutions were identified after a systematic scan of design variables
Ridha et al. [43]	Multi-objective	PV-wind-battery system	number of modules, number of turbines, number of batteries	LPSP, LCC, Dumped Power		System: 20 years Battery: 2 years	Optimum system configuration found for residential applications in Malaysia and South Africa.
Borowy et al. [74]	Graphics	PV-battery system	number of modules, number of batteries	System cost	LPSP		A correlation between the number of PV modules and the number of batteries has been found.
Kaabeche et al. [9]	Graphics	PV-wind-battery system	number of modules, number of batteries	System cost	LPSP		For a given load profile, turbine size and LPSP, the optimum torque is found.
Mokheimer et al. [63]	Graphics	PV-wind-battery system	number of modules, number of batteries	LCOE	LPSP		A correlation was found between the number of PV modules and the number of batteries, allowing the optimum number of PV modules and batteries to be found for a given LPSP.
Kaushika et al. [68]	Linear integer programming	PV-battery system	Number of modules, number of batteries	LPSP	LPSP		Taking into account panel orientation, solar tracking and simple cost analysis, the best system configuration was found
Nogueira et al. [69]	Linear integer programming	PV-wind-battery system	number of modules, number of turbines, number of batteries	LCOE	LPSP	System:20 years Battery: 4 years	For a given load profile and LPSP, the optimum system configuration is obtained.
Fetanat et al. [70]	Linear integer programming	PV-wind-battery system	Number of modules, number of turbines, number of batteries	System cost	LPSP	System:20 years Battery: 4 years	For a given load profile and LPSP, the optimum system configuration is obtained.
Ridha et al. [46]	Intuitive, iterative, multi-objective and VIKOR	PV-battery system	Number of modules, number of batteries	LOLP, LCC et LCOE		System:20 years Batterie: Lead acid (2 years); AGM (3 years) and Li-ion (10 years)	The best configuration was found with the system integrating lead acid batteries.

Table 5
Summary of studies based on artificial intelligence methods.

References	Methods	Systems	Optimized parameters	Optimization functions	Constraints	Results
Yang et al. [72]	GA	PV-wind-battery system	number of turbines, number of PV modules, number of batteries, module tilt angle, mast height	ACS (Annualized Cost of system)	LPSP	Applied to a case study (relay station), the optimal solution found is 3 or 5 days of storage for an LPSP of 1 % or 2 %.
Amer et al. [81]	PSO	Multi-source system- Storage	Number of sources, power demand and storage capacity	LCOE	Balance between demand and production	Source sizes and storage capacity are optimized by minimizing the LCOE.
Zhou et al. [82]	GA and PSO	PV-wind-battery system	number of modules, number of wind turbines, number of batteries, converters and angle of inclination of modules	LCC	Balance between demand and production	The optimal configuration was found by minimizing the LCC using both methods
Ghorbani et al. [24]	GA-PSO (hybrid) and MOPSO (Modified PSO)	PV-battery system; wind-battery system and PV-wind-battery system	number of modules, number of wind turbines, number of batteries	LCOE	LPSP	The optimum configuration for each system was obtained by minimizing the LCOE and for LPSPmax of 2 %, 5 % and 10 %. Both methods produced better results than HOMER
Arabali et al. [79]	GA	PV-wind-battery system	PV field surface area, Wind turbine surface area Storage capacity	System cost		Optimization procedure optimizes system cost and increases efficiency
Suhane et al. [78]	Ant Colony Optimization (ACO)	PV-wind-battery system	Number of modules, turbines, batteries, converters	LCOE	LPSP	The optimal solution obtained by ACO was found to be slightly better than that obtained by conventional techniques.
Bilal et al. [61]	GA	PV-wind-battery system	numbers of PV modules, wind turbines, batteries, inverters and regulators	Total Cost of System	LPSP	The system has been technically and economically sized
Xu et al. [83]	GA	PV-wind-battery system	PV field size, Size of wind field Storage capacity	Initial investment cost	LPSP	The optimal system configuration was found by minimizing the cost for an LPSP of 1 %
Fathima et al. [84]	BAO (Bat Algorithm Optimization)	PV-wind-battery system	Storage capacity	Initial investment cost		Optimum storage capacity and revenue losses were determined
I.Tégani et al. [85]	GA	PV-wind-battery system	Number of modules, turbines, batteries, MPPT controllers, power converters	Initial investment cost	Balance between production and demand	The minimized cost using GA was compared to that using conventional optimization methods. The GA was found to be better
Askarzadeh [86]	Discrete Chaotic Harmony Research (DCHR), HS et HSSA	PV-wind-battery system	Number of modules, turbines, batteries	Annual system cost		DCHR performed better than the others
Belouda et al. [30]	NSGAII	PV-wind-battery system	Number of modules, turbines and batteries	Total cost of system (TCS) LPSP		A set of Pareto solutions have been found
Allwyn et al. [18]	GA	PV-battery system	The number of modules and batteries	LCC	LPSP	It was found that the LCC of the system taking NAD into account is higher than that of the system not taking NAD into account (Number of days of autonomy)
Bi et al. [80]	DA (Dichotomy Algorithm)	PV system-Electrolyser-Fuel cell-Battery	Size of PV field			The size of the PV array was optimized. The sizes of the other components have been conventionally evaluated
Hatata et al. [87]	clonal selection algorithm (CLONALG)	PV-wind-battery system	The number of modules, turbines and batteries	System cost	LPSP	A comparative study of one case showed that the method compared favorably with the genetic algorithm, in that it led to the best solution.

(*continued on next page*)

Table 5 (*continued*)

References	Methods	Systems	Optimized parameters	Optimization functions	Constraints	Results
Maleki et al. [77]	TS, SA, HS, PSO, MPSO, PSO, (PSO-RF), (PSO-CF), (PSO-W)	PV-wind-battery system	The number of modules, turbines and batteries	TAC	Balance between production and demand	Of all these methods, PSO with constriction factor (PSO-CF) proved to be the most effective.
Farès et al. [76]	GA, CS, HS, SA, FA, FPA, MFO, BSO-OS, S-SSA,	PV-wind-battery system	The number of modules, turbines and batteries	TNPC (Total Net Present Cost)	DPSP	Of these ten algorithms, simulated annealing and the flower pollination algorithm were the best in terms of offering the best-quality solution
Ramoji et al. [31]	GA et Teaching Learning Based Optimization (TLBO).	PV-wind-battery system	PV field surface area, Wind turbine surface area Storage capacity	TAC		The optimum configuration is obtained by minimizing the total cost of the system.
Khatib et al. [5]	ANN (Artificial Neural Network) and analytic method	PV-battery system	The number of modules, turbines and batteries	LOLP		The method showed high accuracy in terms of system size prediction. Applied to a given load profile, an LLOP of 0.5 % is obtained.
Khatib et al. [42]	DEMO (Differential Evolution Multi-Objectif) algorithm	PV-battery system	The number of modules and batteries	LOLP LCC		This method was found to be better than the numerical method in terms of execution time and accuracy.

- **Two-bus configuration (AC and DC)**

The DC-AC hybrid configuration has a DC bus and an AC bus as one can see in Fig. 5. The PV field, fuel cell, battery park and electrolyzer are connected to the DC bus via appropriate power converters, while the wind field and AC load are directly connected to the AC bus. The number of converters used is reduced by one compared with the DC bus configuration, which means slightly lower cost and higher efficiency [27,29]. The disadvantage of this configuration is that the control and energy management are much more complex due to the addition of the AC bus. What's more, if the inverter connecting the two buses fails, overall system operation will be severely disrupted. Under these conditions, the battery will no longer receive energy from the wind field, and the AC load will only be supplied by the wind field. In Refs. [2,31] such a configuration was used for an optimization study.

4. Sizing methods and tools for fluctuating-source stand-alone systems

Sizing an electrical system involves finding the characteristics of the various system components that will enable it to meet the load demand. Optimal system sizing therefore means finding the optimum characteristics (optimum capacities of PV/wind generators, batteries, etc.) by minimizing or maximizing a cost function, while ensuring system reliability. Various methods and tools for sizing autonomous systems with fluctuating sources such as solar or wind have been reviewed by a number of authors in the literature [27,29,32–37]. In this article, they are grouped into four main categories: traditional classical methods, traditional optimization methods, artificial intelligence methods and software (see Fig. 6).

4.1. Classic traditional methods

Classic traditional methods are based on simplified equations, as shown in Table 3, for dimensioning PV and/or wind systems, avoiding hourly or daily profiles of sunshine and/or wind speed [38]. These methods are not optimization methods. In fact, they are simply based on two options for possible average values of sunshine or wind speed [7,8,39,40]. These are the option for the annual average value and the option for the monthly average value of the worst month [37].

With classical sizing options, storage is sized on the basis of daily consumption and the number of days of autonomy [7,8,39,40]. Two to three days of autonomy are generally considered in sizing [44]. In Refs. [45,46], intervals of 2–9 days and 3–5 days of autonomy are mentioned respectively. These methods are very simple and easy to use. However, they generally lead either to oversizing, in which case the user is confronted with an additional economic cost, or to undersizing, in which case the user is confronted with a system reliability problem. Undersizing can even lead to premature battery ageing due to overuse. Authors such as Khadimi et al. [39] and Diaf et al. [7] have used the annual mean value and the monthly value of the worst month to size a stand-alone PV-wind-battery hybrid system. They also used a factor representing the fraction of the load produced by the PV array. Kaushika et al. [47] have proposed a classical sizing tool for PV systems with or without storage for the Indian region. The method uses monthly and daily average values of insolation or consumption to evaluate the size of the system. An autonomy of 3 days was considered. In Ref. [48], Herteleer et al. have proposed an intuitive program for sizing stand-alone PV systems for offices in Africa. They then proposed a simple tool (a spreadsheet) to help non-experts in the field. Belmonte et al. [14] have classically designed a PV-EL-FC system and a PV-battery (Li-ion) system for stand-alone applications in Turin, Italy, and then carried out an economic analysis of the two systems to compare

Table 6
Inputs, outputs, advantages and limitations of the above software and sizing methods [8,24,27,34,36–38,71,92–94].

Tools and Methods	Inputs	Outputs	Limits	Advantages
HOMER (Free 30-day trial available at www.homerenergy.com)	Load demand, resource data, component costs, constraints, control system, emissions data.	Net present cost, cost of energy, cost of capital, unmet load, surplus energy, fuel consumption, fraction of renewable energy.	- Does not take into account: battery DOD, intra-hour variability, bus voltage variation - Impossible to import time series data - Based on monthly solar or wind values - Does not support simultaneous multi-objective optimization	- Plots results in graphs - Easy to understand - Uses first-degree linear equations
HYBRID2 (Free and downloadable from www.ceere.org/rerl/rerl hydripower. Html)	Load demand, resource data, system component details, financial data	Technical analysis, optimal sizing and financial evaluation.	- Need for long-term data for better economic analysis of hybrid systems - Limited access to parameters and lack of flexibility. - Takes a long time to simulate - Although the project is successfully written, some simulation errors are displayed	- Many electric charging options
HOGA (Paid Pro version and free EDU version downloadable from www.unizar.es/rdufo/grhyso.htm)	Constraints, resource data, component data, economic data	Multi-objective optimization, life-cycle emissions, energy supply analysis	- Limited to an average daily load of 10 kWh. - No sensitivity analysis - No probability analysis - No net metering	- Allows single- or multi-objective optimization - Low simulation time step.
HYBRIDS (Paying)	Average daily load data	Energy costs, percentage of greenhouse gas emissions	- Simulate only one configuration at a time. - Can not optimize	
TRNSYS (Paying)	Weather data, models from own library	Dynamic simulation of the behavior of thermal and electrical energy systems	Impossible to simulate nuclear, wave, tidal and hydro power.	- Flexibility in simulation - High precision with graphics
RETScreen (Free and downloadable from www.retscreen.net)	Climate database, Project database, Product database, hydrological database	Technical, financial and environmental analysis, sensitivity and risk analysis, energy efficiency, cogeneration	- Does not take into account the effect of temperature on panels. - No option to import time series data files. - Limited options for search, extraction and visualization functions, - No optimization option	- Best weather database - Excel-based tool
PVSYST (Paying, www.pvsyst.com/en/download)	Monthly average weather data, load demand, system component specifications, module inclination	PV field size, storage capacity and inverter power ratings	- Does not allow economic analysis - Limited to PV systems only.	- Switch from monthly to hourly data - Ability to import or export data
Classic	Average monthly or annual sun and/or wind speed values, daily consumption	PV and/or wind field size, storage size	- Does not take into account sunshine and wind speed profiles, - Oversizing or undersizing of systems due to outliers (worst month, autonomies)	- Very easy to understand and use
Iterative	Hourly or daily profiles of sunshine, wind speed and power consumption	Optimum technical, economic and environmental sizing	- Does not optimize PV module tilt angle and turbine mast height - Only optimizes turbine and PV sizes - Uses time series data	- Easy coding
Analytical	Hourly or daily profiles of sunshine, wind speed and power consumption	Optimum technical, economic and environmental sizing	- Less suitable for sizing, - Allows evaluation of system performance - Very limited number of optimization parameters	- Simulates the performance of several PV-wind system configurations

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Table 6 (*continued*)

Tools and Methods	Inputs	Outputs	Limits	Advantages
Probabilistic	Hourly or daily profiles of sunshine, wind speed and power consumption	Optimum technical, economic and environmental sizing	- Cannot represent dynamic hybrid system performance - Very limited number of optimization parameters	- No need for data time series
Graphic	Hourly or daily profiles of sunshine, wind speed and power consumption	Optimum technical, economic sizing	- Can only take two optimization parameters. - Very limited number of optimization parameters	- Easy to understand and use
Multi-objective	Hourly or daily profiles of sunshine, wind speed and power consumption	Optimum technical, economic and environmental sizing	- Complex - Long runtime - Very limited number of optimization parameters	- Takes into account several objective functions
Linear integer programming	Hourly or daily profiles of sunshine, wind speed and power consumption	Optimum technical, economic and environmental sizing	Limited to linear optimization models or problems	- The most flexible of traditional methods - Software available using the method
Artificial Intelligence	Hourly or daily profiles of sunshine, wind speed and power consumption	Optimum technical, economic and environmental sizing	Complex (difficult to code)	- The most flexible dimensioning method, - Offers high-quality solutions in reasonable times - Takes many optimization parameters - Allows multi-objective optimization

the types of storage used. An autonomy of 2 days was considered for the batteries. Their analysis showed that the PV-EL-FC system is much more expensive. This reflects the high cost of the hydrogen storage system. In their analysis, the lifetimes of the modules, batteries, electrolyzer and fuel cell were taken to be 25 years, 10–15 years, 15 years and 15 years respectively.

4.2. *Traditional optimization methods*

This category includes iterative, probabilistic, multi-objective, graphical and mixed integer linear programming methods. These are methods for finding the minima or maxima of a constrained or unconstrained objective function. They generally take as input hourly, daily or monthly meteorological data on sunshine, wind speed and ambient temperature. The iterative approach consists of using a recursive or incremental process to find the best system configuration to meet demand, by minimizing a cost function such as the Levelized Cost of Electricity (LCOE), using time series data [27,49,50]. The process stops when the best configuration has been found according to the technical constraints imposed, such as the Loss of Power Supply Probability (LPSP). Techno-economic dimensioning studies of PV and/or wind systems with battery storage using this technique consider the number of PV field modules, the number of wind generators, and the number of batteries or the number of days of autonomy as optimization parameters [9,49–51]. Some studies based on this method are proposed in Refs. [9,49–51] and summarized in Table 4. The analytical method evaluates the optimal system configuration based on mathematical computational models, often allowing the dynamic performance of the system to be assessed, [52,53]. Some studies based on the analytical approach are proposed in Refs. [54–56] and summarized in Table 4. The probabilistic approach takes into account the random nature of variations in sunshine and wind speed for system design [37]. In contrast to the iterative and analytical methods, the probabilistic approach does not use time series data, nor does it evaluate the dynamic performance of the system [34,57,58]. Some studies based on the probabilistic approach are proposed in Refs. [57,58] and summarized in Table 4. There are two common approaches to multi-objective design [27]. The first general approach is to merge all individual objective functions into a single one [59]. The second approach is to determine a set of Pareto optimal solutions [60]. The resulting solution is said to be Pareto optimal if it is dominant among the various solutions in the solution space. A Pareto optimal solution cannot be improved with respect to one objective without deteriorating at least one other objective. The main objective of a multi-objective optimization algorithm is to know the solutions in the Pareto optimal set [27]. Some studies based on the probabilistic method are also presented in Refs. [27,59–61] and summarized in Table 4. As far as the graphical method is concerned, only two decision variables are taken into account in the optimization (number of PV modules and number of batteries or number of PV modules and number of wind turbines). Significant factors such as the angle of inclination of the solar panels and the installation height of the wind turbine are completely ignored. Some sizing studies using the graphical method are presented in Refs. [62–64] and summarized in Table 4. Integer linear programming is a widely used technique for sizing and optimizing renewable systems. It is characterized by the linearity of the optimization problem and includes both positive integer and binary variables. Binary variables can represent operating states (on or off) or tripping states of the system or its components. It is mainly used in mini-grid design for storage sizing and energy management [65–68].

Some dimensioning studies using the graphical method are presented in Refs. [69,70] and summarized in Table 4. In general,

Table 7
Summary of software-based studies of autonomous systems with fluctuating sources.

References	Type of study	Tools	Studied system	Performance indicators	Application	Location	Lifetime	Results
Das et al. [15]	Technico-economic feasibility	HOMER	PV-Fuel Cell (FC)-Battery System PV-FC system	NPC (Net Present Cost) LCEO	Residential	East Malaysia	System: 25 years Battery: 3 years FC: 40000 h	The FC-based system has higher costs, so despite its advantages, it is not suggested as the best system for the situation
Khan et al. [2]	Energy, Economic and Environmental sensitivity analysis (3E)	HOMER	PV-EL-FC-Battery system	NPC LCEO Tonnes de CO_2 émise	Rural community	Pakistan	System: 25 years Battery:15 years EL: 15 years, FC: 15000h	It emerges that the proposed system is financially, technically and ecologically a feasible solution for rural electrification compared with the diesel generator
Pelaez et al. [3]	Technico-economic optimization	HOMER	PV-EL-FC system	NPC LCEO	Residential (Cogeneration)		System: 25 years EL: 15 years FC: 40000 h	Their analysis shows that the system is not economically viable, but technically feasible.
Sharafi et al. [25]	Simulation and Technico-economic optimization	HOMER	Six systems: PV/battery, wind/battery, PV/wind/battery, PV/PC, wind/FC and PV/wind/FC	NPC LCEO COH (Cost Of the Hydrogen production)		Kingdom of Saudi Arabia	System: 25 years EL: 15 years, FC: 40000 h	The analysis revealed that only the PV/wind turbine/battery system was profitable for the Yanbu region out of four regions considered
Fazelpour et al. [16]	Economic feasibility	HOMER	PV-wind-battery; wind-battery wind-electrolyser-fuel cell; wind-electrolyser-fuel cell-battery; PV-wind-electrolyser-fuel cell-battery	NPC LCEO	Household	Teheran, Iran	System: 25 years Battery: 4–15 years EL: 15 years, FC: 15000 h	The analysis revealed that the PV-wind-electrolyser-fuel cell-battery system was economically feasible.
Silva et al. [13]	Economic feasibility	HOMER	PV-battery system, wind-battery system, PV-electrolyser-fuel cell system	NPC LCEO	Remote community	Brazil's Amazon region	System: 25 years Battery: 4 years EL: 15 years, FC: 30000 h	Only PV-battery system found economically feasible.
Andrew Mills et al. [91]	Design and simulation	HYBRID2	PV-wind-battery system PV-wind-battery-fuel cell system	Energy performance	Stand-alone application	Chicago.		They showed that there was no need to include the fuel cell, as only the PV-wind-battery system met the requirement.
N. Ahmed et al. [90]	Optimization	HOGA	PV-battery system; wind-power + battery system and stand-alone PV-wind-battery system.	NPC	Stand-alone application	Several sites in Egypt		For each site and for the same load, the system with the lowest NPC (Net Present Cost) or considered optimal
Anoune et al. [95]	Sizing	TRNSYS	PV-wind power system		Thermal applications in isolated sites			An optimal system configuration was found using a deterministic approach

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Table 7 (*continued*)

References	Type of study	Tools	Studied system	Performance indicators	Application	Location	Lifetime	Results
Cano et al. [96]	Economic feasibility	HOMER HOGA Matlab	PV-wind-battery-El-FC system	NPC	Stand-alone application			The configuration is obtained using Simulink-Design-Optimization in Matlab

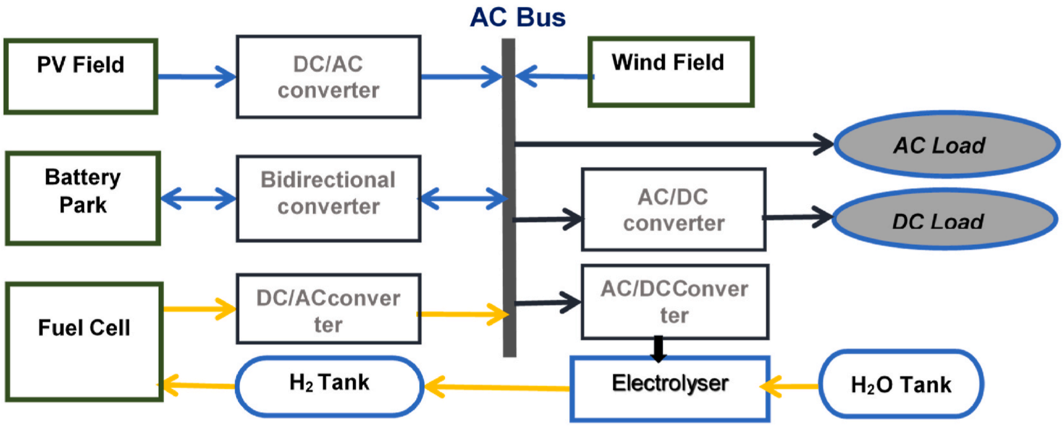

Fig. 4. AC bus configuration of the PV-wind system with hydrogen and battery storage.

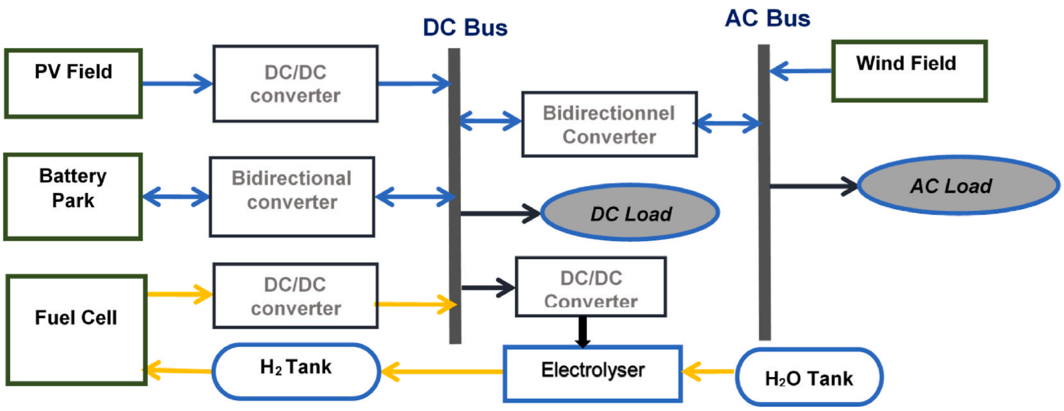

Fig. 5. Two-bus configuration (AC and DC) of a PV-wind-battery-hydrogen system.

traditional optimization methods lead to approximate solutions. They are easy to understand and use. However, their level of use is declining in favor of artificial intelligence methods, due to their long execution times and their inability to find exact solutions to problems [36].Among these traditional optimization methods, linear programming is considered the most flexible in Ref. [36], while the iterative method in Ref. [37] is estimated to have a level of accuracy, execution time and complexity comparable to artificial intelligence methods. The iterative method is indicated in Ref. [71] as being the most widely used for PV-wind-battery system sizing among traditional optimization methods. Table 4 below summarizes studies of autonomous systems with fluctuating sources based on traditional optimization methods.

4.3. *Artificial intelligence methods*

Artificial intelligence approaches are trajectory- or population-based meta-heuristic algorithms inspired by natural behaviors or biological systems [35,75,76]. They are flexible and even efficient in large-scale optimization problems, offering high-quality solutions in reasonable times [33]. Path-based algorithms are iterative methods with a single solution, based on neighborhood search. They start with an initial solution and improve it step by step by selecting a new solution in its neighborhood. Simulated Annealing (SA) and

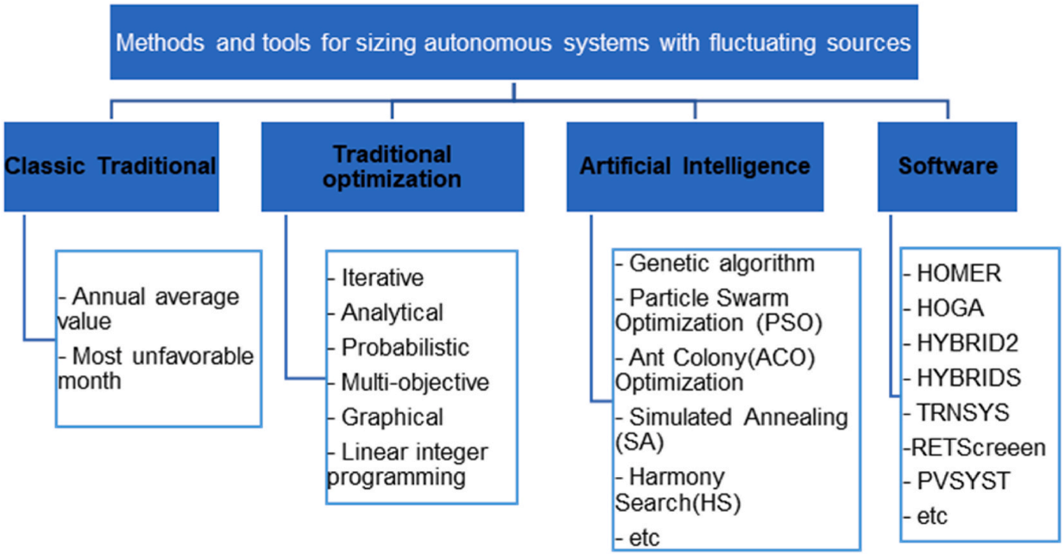

Fig. 6. Methods and tools for sizing autonomous systems with fluctuating sources.

Tabou Search (TS) are the most widely used algorithms for optimizing power systems with storage. The limitation of these methods is that their efficiency depends very much on how the internal parameters (Tabu list, temperature) are constructed and used [75–77].

Algorithms based on a population of solutions, unlike single-solution algorithms, start with at least two initial solutions and modify them at each iteration by means of operators such as crossover and mutation. There are several population-based algorithms in the literature. However, the most widely used in PV and/or wind power optimization are generally the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) or a hybrid of these techniques (GA-PSO). These algorithms are even integrated into Matlab software, enabling complex non-linear problems to be solved. These methods are highly flexible, efficient especially for large optimization problems, and can deliver good-quality solutions (not necessarily optimal). Their drawback is the existence of parameters to be set in order to obtain satisfactory convergence [24,75,76]. For example, the mutation and crossover rates used in genetic algorithms.

Artificial intelligence approaches can be hybridized between trajectory-based approaches (e.g. HSSA) and population-based approaches (e.g. GA-PSO). Authors such as Suhane et al. [78] have proposed an approach based on Ant Colony Optimization (ACO) to obtain optimal sizing of the PV-wind hybrid system with battery storage. The numbers of modules, turbines, batteries and converters were optimized by minimizing the system's LCOE for a fixed LPSP of 5 %. They preferred this method over traditional methods in view of the non-linearity of the problem introduced by the dependence on atmospheric factors of the energy sources exploited. Arabali et al. [79] have minimized the cost and increased the efficiency of an autonomous PV-wind system with battery storage using a Genetic Algorithm (GA) and a two-point estimation method. They also calculated the maximum storage system capacity and Excess Energy (EE) for different percentages of charge transfer.

In [77], Maleki et al. have found the optimal configuration of an autonomous PV-wind-battery system using several artificial intelligence approaches namely Tabu Search (TS), Simulated Annealing (SA), Harmonic Search (HS), PSO and its variants which are: Modified PSO (MPSO), PSO based on Repulsion Factor (PSO-RF), PSO with Constriction Factor (PSO-CF), and PSO with adaptive inertia weight (PSO-W). Of all these applied methods, PSO with Constriction Factor (PSO-CF) performed best. Allwyn et al. [18] have used the Genetic Algorithm (GA) based optimization tool in MATLAB, to optimize the PV field and battery size in a public lighting PV/battery system with and without number of days of autonomy for three different lamp types, HPS, LED and discrete LED by LLSP minimization. Taking into account the Number of Autonomy Days (NAD) and after an economic sensitivity analysis on the LCC, they found that the LCC of the system taking into account the NAD is higher than the one without taking into account the NAD due to the higher number of batteries required and the consequent higher cost. Bi et al. [80] have proposed a method for optimized sizing and management of a PV-Electrolyser-Fuel Cell-Battery system aimed at improving the technical reliability of the system. In this method, only the PV field size was optimized by the dichotomy algorithm, the other parameters (electrolyzer size, cell size, battery size) being deduced by simple mathematical formulas.

Moreover, the method did not consider costs. Many other authors have carried out studies based on artificial intelligence methods, also known as next-generation methods. Fares et al. [76] have evaluated ten meta-heuristic algorithms by applying them to an autonomous PV-wind-battery system to find the optimal configuration. The ten algorithms involved are the genetic algorithm, cuckoo search (CS), simulated annealing (SA), harmony search (HS), yaya algorithm, firefly optimization algorithm (FA), flower pollination algorithm (FPA), Moth Flame Optimization (MFO). Among these ten algorithms, simulated annealing and the flower pollination algorithm were the best in terms of offering the best-quality solution. Table 5 summarizes studies of autonomous systems with fluctuating sources (solar-wind) based on artificial intelligence methods.

4.4. Softwares

Many tools or software for designing autonomous systems exist today. Most of these tools have been reviewed by authors such as Belmili et al. [50], Chauhan et al. [27], Sinha et al. [88]. Among these tools, we find: HOMER (Hybrid Optimization Model Electric Renewable) from the National Renewable Energy Laboratory in the USA. Developed in 1993 for rural electrification [88], it can be used to simulate and optimize stand-alone or grid-connected electricity generation systems from renewable and conventional sources on a net present cost or life-cycle basis [89]. It offers simulation with a time step of 1 h and over an entire year [24]. HOGA (Hybrid Optimization Genetic Algorithm) from the University of Zaragoza in Spain solves single and multi-objective optimization problems. It enables hourly simulation for the dimensioning of hybrid energy systems [88,90]. HYBRID 2 from the University of Massachusetts in the USA is a probabilistic/time-series computational model that uses statistical methods to account for intertemporal variations and can perform detailed long-term performance analysis, economic analysis and performance prediction of various hybrid systems. It was developed in 1996 and can perform real-time simulations for time steps typically between 10 min and 1 h [88,91].

TRNSYS from the University of Wisconsin in the USA is a software package capable of modeling and dimensioning applications as well as conventional buildings. It was developed in 1975 [88] and enables dynamic simulation with time steps ranging from 0.01 s to 1 h [27,88]. RETScreen from the Canadian Ministry of Human Resources is a Microsoft Excel spreadsheet based on the analysis of energy projects for the dimensioning of different renewable energy system configurations [27,88],. PVSYST from the University of Geneva in Switzerland is a free tool for sizing, simulating and analyzing stand-alone or grid-connected PV systems [6]. It can be used to determine PV size and battery capacity, taking into account a user's load profile and the acceptable duration during which the load cannot be satisfied. It takes monthly weather data and converts it statistically into hourly data. Many of the details (inputs, outputs, limitations and benefits) concerning these tools are recorded in Table 6.

Of all these software packages, according to the study by Mazzeo et al. [17], HOMER is the most widely used for the simulation and optimal design of stand-alone or grid-connected systems with storage. One of the disadvantages of this software is that it does not allow the lifetime of storage systems (battery, fuel cell) to be calculated according to real conditions of use. Battery lifetime is intuitively taken between 3 and 15 years by users [15,16]. A summary of technico-economic studies based on the above-mentioned software is presented in Table 7.

5. Technical and economic sizing criteria

In the literature, there are several technical and economic criteria used to assess the performance of power generation systems [7,27,32,97]. The mention of technical criteria focuses attention on the crucial aspect of system reliability. In power generation, reliability is paramount to ensure continuous and uninterrupted supply, which is essential for meeting the demands of various consumers. Technical criteria likely encompass factors such as efficiency, capacity, availability, and resilience to disturbances or failures. These metrics provide insights into the system's ability to function optimally under different operating conditions and external challenges. On the other hand, the inclusion of economic criteria highlights the importance of considering financial aspects in evaluating power generation systems. Profitability and affordability are critical factors, especially in today's energy landscape, where cost-effectiveness is a significant concern. Economic criteria may involve assessing capital costs, operational expenses, revenue generation potential, and overall return on investment. These metrics help stakeholders determine the financial viability of a power generation system and its long-term sustainability in the market.

5.1. Technical performance criteria

Many technical criteria exist [24,25,30,97]. However, the most widely used or most important are Loss of Power Supply Probability (LPSP) or the energy load-shedding rate, and LOLP (Loss of Load Probability) or the time load-shedding rate [59].

- **LPSP (Loss of Power Supply Probability [%])**

This is the fraction of the energy loss out of the energy demanded by the load for a given analysis period T [59]. It is therefore the ratio of the sum of all LPS(t) energy loss values for the same period to the energy demanded. It is given by equation (7):

$$LPSP = \frac{\sum_{t=1}^{N}((P_{load}(t) - P_{tot}(t))^{*}\Delta t)}{\sum_{t=1}^{N} P_{load}{}^{*}\Delta t} \tag{7}$$

With:

$P_{tot}(t)$: total power supplied by the system, including the contribution of storage

Δt: time step of simulation and P_{load} :power consumed by the load.

N: simulation period or time (number of minutes or hours or days in a year)

The LPSP is the technical performance indicator most widely used in the literature for the design of power systems integrating fluctuating sources [9–11,24,71,73,97],. It guarantees a threshold of coverage of the user's needs. An LPSP of 0 % means that the user will always be satisfied, whereas an LPSP of 100 % means that the user will never be satisfied.

- **LOLP (Loss Of Load Probability [%])**

It is defined by equation (8) as the ratio of the cumulative time the power demand of the load was not met to the total system operating time [72], [98]. It corresponds to the percentage in time and not in energy of load shedding or service failure over a given period T.

$$LOLP = \frac{\sum_{t=0}^{T} Time(P_{tot}(t) < P_{load}(t))}{T} \tag{8}$$

A LOLP of 0 % means that the consumer is satisfied at all times during the corresponding period. There is a difference between LOLP and LPSP in terms of their definition. What's more, for the same values, the two will not necessarily give the same results in terms of sizing. These criteria should therefore be handled with great care.

5.2. Economic performance criteria

In the literature, several economic criteria are used for economic analysis or for the optimal design of energy production systems [71]. However, the most relevant and widely used are.

- **Total cost of investment (TIC)**

In the case of stand-alone systems with energy storage and using intermittent renewable energy sources, the Total Investment Cost (TIC) is given by equation (9)) [9,59]. It represents the initial cost of all system components plus labor and installation costs.

$$TIC = C_S{*}S + \sum_E C_E{*}P_{inst} + \sum_c C_c{*}P_c + C \tag{9}$$

With:
S: storage capacity in Wh;
P_{inst}: installed peak power of a source in W or KW;
C_S: unit cost of storage per Wh or per storage module;
C_E: unit cost of installed peak power per W or per module,
C_c: unit cost per W or per converter of a given type of power converter (inverters, transformers, choppers).
C: cost of labor and installation.
P_c: Power of converter in W or kW

- **Net Present Value (NPV)**

The Net Present Value (NPV) given by equation (10) reflects the real present value of a cost or income discounted by the value of capital in year n. It considers the initial investment cost, the net present value of replacement costs and the net present value of Operation and Maintenance costs [9,59,73]:

$$NPV = TIC + NPV_{REP} + NPV_{OM} \tag{10}$$

Operating and maintenance (OM) costs are current annual costs and can be discounted by an overall discount factor F_a. Several formulations of this factor exist in the literature [9,59,73]. However, in all cases, it depends on the lifetime of the project and the real interest rate, as expressed by equation (11):

$$F_a(r,n) = \frac{(1+r)^n - 1}{r(1+r)^n} \tag{11}$$

With r the real interest rate and n the lifetime of the system or project.

The replacement (REP) cost discount factor is differently formulated because replacement costs are periodic (not annual) costs [59,71]. This factor depends on the component's lifetime and the real annual interest rate [43,72], as shown in equation (12):

$$F_a(r,m) = \sum_{k=1}^{N_r} \frac{1}{(1+r)^{k{*}m}} \tag{12}$$

where m corresponds to the component lifetime N_r the number of component replacements and k the order of component replacement.

- **Total Annualized cost of System (TAC)**

The TAC defined by equation (13) is calculated by taking into account the Net Present Value of total costs (initial investment, maintenance and replacement costs) over the period, annualized via the Capital Recovery Factor expressed by equation (14) [7,9,98]:

$$TAC = NPV{*}CRF \tag{13}$$

$$CRF(r,n)=\frac{r(1+r)^n}{(1+r)^n-1} \tag{14}$$

With r the real interest rate and n the system lifetime (years).

In [98], the discount or real interest rate is defined by equation (15):

$$r=\frac{e-\mathrm{i}}{1+\mathrm{i}} \tag{15}$$

With e the nominal interest rate and i the inflation.

- **Levelized Cost of Energy (LCOE)**

The LCOE is the ratio of the total annualized cost of the system to the electrical energy produced over the lifetime of the system. It is defined by equation (16):

$$LCOE=\frac{TAC}{E_{TOT}} \tag{16}$$

where E_{TOT} is the annual energy produced.

The LCOE represents the cost to be spent to produce one kWh of energy. It fosters informed decision-making in energy planning and policy formulation by elucidating the financial implications of adopting different energy generation technologies. Whether comparing traditional fossil fuel-based power plants with renewable energy sources like solar or wind, the LCOE provides a standardized framework for assessing the cost-effectiveness and feasibility of diverse energy pathways. However, special care must be taken when making comparisons, as it is highly dependent on calculation assumptions [99,100].

6. Basic models of production and storage

When sizing or managing stand-alone systems using renewable sources such as sun and wind, mathematical modeling of the system's components is unavoidable. PV and wind fields are generally modeled by their power output.

6.1. Models of solar production

The power delivered by a PV array depends mainly on the type of PV module used, the solar irradiance and the ambient temperature [4,28], [101,102]. The most complete model is given by equation (17):

$$P_{PV}(t)=N_{PV}{}^{*}P_{PV_{STC}}{}^{*}f_{PV}{}^{*}\frac{G(t)}{G_{STC}}{}^{*}\left[1-\delta\left(T_{\mathrm{mod}_{PV}}(t)-T_{PV_{STC}}\right)\right] \tag{17}$$

Where $T_{\mathrm{mod}_{PV}}(t)=T_{air}(t)+G(t)\left[\left(T_{c,NOCT}-T_{a,NOCT}\right)/G_{STC}\right]$ (18)

With:

N_{PV}: total number of modules in the PV field

$P_{PV}(t)$: Instantaneous power produced by the photovoltaic field in watts;

$P_{PV_{STC}}$: Peak power of modular PV array under Standard Test Conditions (STC);

$G(t)$: Average hourly solar radiation falling on the photovoltaic system matrix at at a given time t (W/m^2);

f_{PV}: PV system downgrading factor (85 %) generally due to dust;

G_{STC}: Solar radiation under STC condition (W/m^2);

δ: Module temperature coefficient (%W/°C);

$T_{\mathrm{mod}_{pv}}(t)$: Instantaneous temperature of PV module (°C);

$T_{air}(t)$: instantaneous temperature of ambient air;

$T_{\mathrm{mod}\ ule_{STC}}$: PV module temperature under STC conditions (°C)

$T_{c,NOCT}$: Nominal module operating temperature supplied by the manufacturer (°C);

$T_{air,NOCT}$: ambient temperature at nominal module operating temperature (20 °C).

The theoretical annual solar potential available at a site is given in Wh or kWh by equation (19) [27]:

$$E_{TOT}=\sum_{i=1}^{8760}P_{PV-moy}(i) \tag{19}$$

With $P_{PV-moy}(i)$, average hourly power at the PV generator output and at the ith hour of the year.

6.2. Models of wind power production

The power output of a wind turbine depends on the type of turbine used and the wind speed. For a wind farm, the output power can be formulated as a function of the nominal characteristics of the wind generator by the system of equation (20) [10,11]:

$$P_{WT}(t) = N_{WT}^* \begin{cases} 0 \quad \text{si} \quad \mathrm{v(t)} < \mathrm{v_{in}} \; ou \; \mathrm{v(t)} \geq v_{co} \\ P_{WT,rated}^* \left(\dfrac{\left(v^k(t) - v_{in}^k\right)}{\left(v_r^k - v_{in}^k\right)} \right) \quad \text{si} \quad v_{in} < v(t) < v_r \\ P_{WT,rated} \quad \text{si} \quad v_r \leq v(t) < v_{co} \end{cases} \tag{20}$$

With:

N_{WT}: total number of wind turbines

$P_{WT}(t)$: power supplied by the wind field at each instant;

$P_{WT,rated}$: Rated power of wind turbine;

v(t): wind speed at height h_{hub} ;

$\mathrm{v_{in}}$: switching or starting speed;

v_r: rated speed;

v_{co}: cut-off speed;

k: shape factor usually applied to describe the wind speed data

The Wind speed v(t) at given height h_{hub} is formulated by equation (21) when knowing reference speed $\mathrm{v_{ref}}$ at reference height h_{ref}.

$$\mathrm{v(t)} = \mathrm{v}_{ref}{}^* \left(\frac{h_{hub}}{h_{ref}} \right)^{\lambda} \tag{21}$$

Where:

λ: is the exponent of the power law, set at 0.2;

$\mathrm{v_{ref}}$: reference speed at reference height h_{ref}.

Knowing the output power of the wind farm allows us to evaluate the theoretical wind potential available at a given site. The theoretical wind potential available at a given site is expressed by equation (22) [4]:

$$E_{TOT} = 365^*24^* \sum_{v=0}^{V_{cut-out}} P_{WT}{}^* f(v, k, c) \tag{22}$$

With P_{WT} the average power at the wind field outlet and $f(v,k,c)$ the Weibull probability density function of wind speed, given by equation (16):

$$f(v, k, c) = \frac{k}{c} \left(\frac{v}{c} \right)^{k-1} {}^*\exp\left[-\left(\frac{v}{c} \right)^k \right] \tag{23}$$

k is a shape parameter (k = 2 or 3) and C a scale parameter (c > 0). The two are linked by equation (17):

$$c = \frac{\overline{v}}{\Gamma(1 + 1/k)} \tag{24}$$

Where $\overline{v}$ represents the yearly average speed of wind and Γ Gamma function.

6.3. Model of battery storage

The storage system model is a key parameter in the sizing of a multi-source electrical power generation system with storage. In the literature, the first, simplest and most widely used approach is based on estimating the battery's state of charge [60,98,103]. Knowledge of the battery's state of charge is essential for sizing and even managing fluctuating-source systems with energy storage in batteries. The second approach consists in taking account of battery ageing over its lifetime [97,104,105]. The cycling aging model is based on extracting the number of cycles by applying the Rain Flow algorithm to the evolution of the storage state-of-charge. The Rain Flow algorithm is a cycle counting algorithm for estimating the equivalent cycle number for battery life assessment. Ke et al. [105] have estimated battery lifetime using the Rain flow algorithm. The storage model applicable to any type of battery and taking account of battery aging is given by the system of equation (25) below [106]:

$$\begin{cases} soc(t) = soc(t-1) + \left(P_G(t) - \dfrac{P_{load}(t)}{\eta_{dcac}{}^*\eta_{INV}}\right)^* \dfrac{\eta_{Bat}}{V_{bus}}{}^*\Delta t \\ SOC_{\min} \leq SOC(t) \leq SOC_{\max} \text{ où } SOC_{\min} = (1-DOD).SOC_{\max} \\ T_V = \sum_{\ddot{N}c=1}^{651} \left(T_{V/C}(DOD)\right) \text{ où } T_{V/C(DOD)} = \dfrac{1}{N_C(DOD)} \end{cases} \tag{25}$$

With:

soc: battery's state of charge;
$SOC_{\min}$: battery's minimum state of charge
$SOC_{\max}$: battery maximum state of charge
Δt: time step of simulation (30 min);
$P_G(t)$: Power supplied by all sources;
$P_{load}(t)$: Power required by the load at time t;
η_{Bat}: Battery charge-discharge efficiency, equal to 1 during charging and equal to 0.8 during discharging;
V_{bus}: bus voltage;
$T_{V/C(DOD)}$: aging rate per cycle;
T_V: annual aging rate (%);
$DOD_{\max}$: battery's maximum Depth Of Discharge
$N_C(DOD)$: number of charging/discharging cycles versus DOD
DOD: amplitude of battery charging/discharging cycle found by Rain flow algorithm
Nc_T: Total number of battery charging/discharging cycles counted on one year operation of system using Rain flow algorithm
η_{INV}: efficiency of the inverter.

7. Energy management techniques for stand-alone HYBRID systems in isolated locations

In order to facilitate the management of energy flows between sources, storage elements and loads, an energy management system (EMS) is generally integrated into a stand-alone hybrid system, as shown in Fig. 7 [107]. Energy management consists in taking actions or issuing commands while complying with a certain number of constraints in order to satisfy one or more objectives. For example, to ensure a permanent power supply to the load, fluctuations in bus voltage can be avoided by controlling the storage or controllable sources (fuel cell or diesel generator), either by imposing current, voltage or power [107].

The EMS represents the intelligence of the system based on its own algorithms: for example, it can decide when a battery should be charged or discharged, or when the storage system should be connected or disconnected to the source or load, depending on production, observed consumption and the state of charge of the battery. To develop an energy management algorithm or technique, the first step is defining the objectives to be met, the constraints to be respected and the actions to be taken. Examples of objectives, constraints and actions are given in Table 8.

Several strategies for managing autonomous systems have been proposed in the literature. They can be grouped into two main categories (Fig. 8): classical management techniques (current control, voltage control, power balance and centralized management)

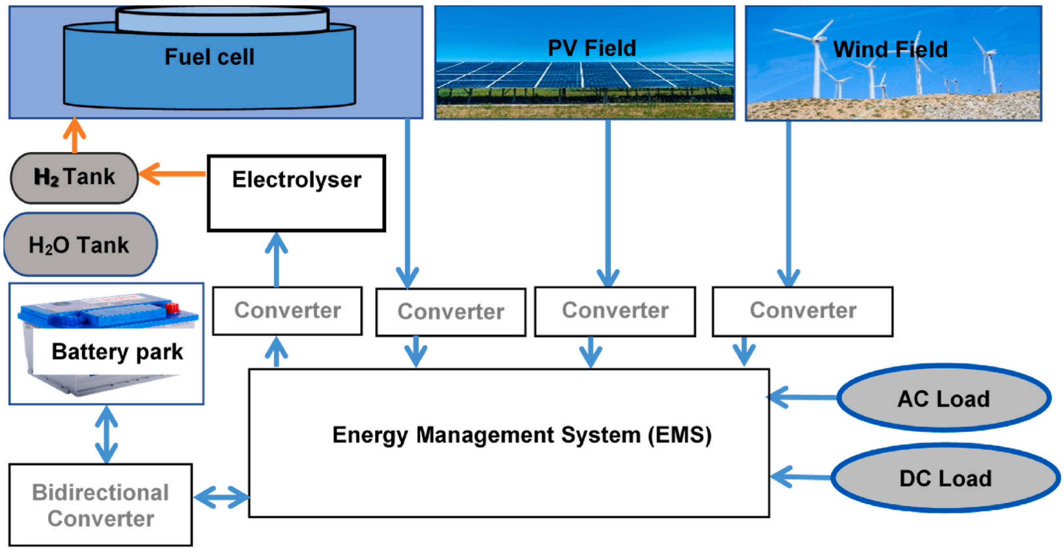

Fig. 7. Schematic diagram of a hybrid wind-photovoltaic-fuel cell system with storage, integrating an Energy Management System (EMS).

Table 8
Examples of objectives, constraints and actions for an autonomous hybrid system management strategy [107–109].

Objectives	Constraints	Actions
Satisfy demand or ensure permanent load supply **Make the most of production sources**	Avoid battery overcharging and deep discharging. Avoiding excess or deficit production	Connect or disconnect or reconnect load or source. Operate or shut down a diesel generator or fuel cell
Protecting the storage system	Avoid exceeding voltage, current, power and temperature limits for storage	Reducing production
Maintain a constant bus voltage	Avoid bus voltage fluctuations	Adding a load shedder

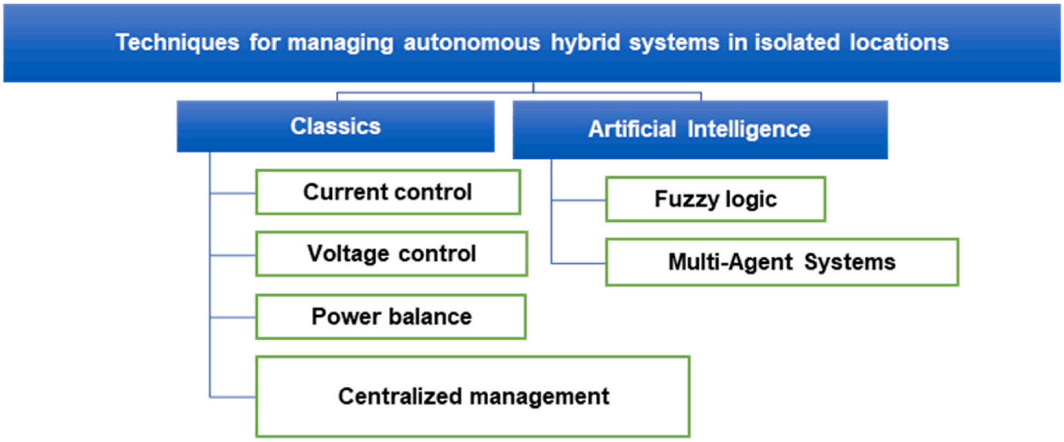

Fig. 8. Management and supervision techniques for small autonomous systems.

and artificial intelligence methods (fuzzy logic and multi-agent systems).

7.1. Classic techniques of energy management

These techniques are based on classical algorithms, i.e. sequences of instructions based on simple established rules using the following syntax: "If … Then …; Otherwise Then … end". For example, a rule might be: "If the battery's state of charge is between 30 and 90 %, then discharge, otherwise stop discharging". As shown in Fig. 8, these techniques include current-controlled management, voltage-controlled management, power balance and centralized management.

7.1.1. Energy management technique with voltage control

This technique consists of imposing four battery voltage thresholds as illustrated in Ref. [107]. Two threshold voltages or a range of bus voltages around the nominal battery voltage to limit fluctuations in bus voltage to allow continuous supply to the load. Moreover, two further battery threshold voltages to protect the battery against overcharge and deep discharge. Energy management depends primarily on the battery voltage control strategy. For example, if the battery voltage remains within the hysteresis band, the renewable generators are in normal operating mode and the flow of energy to the bus is not restricted. If the battery voltage exceeds the maximum threshold (VBat Nominal + hysteresis), then the supervisor stops charging the battery while reducing the power on the DC bus by degrading the power of the generators (MPPT = 0) and supplying power to the load. Otherwise, if the battery voltage falls below the limit (V Bat Nominal-Hysteresis), the system stops supplying power to the load. At this point, the MPPT is activated (MPPT = 1) to better exploit the renewable generators until the bus voltage returns to a stable range. The battery is disconnected from the source or load when the voltage at its terminals reaches VBat Max or VBat Min.

7.1.2. Energy management technique with current control

This management principle consists in making the best possible use of available resources by avoiding excess or deficit production to supply the load, and monitoring the battery's state of charge by imposing a zero Battery current in the event of overload or deep discharge. Dackher et al. [107] have proposed this management strategy for the supervision of an autonomous PV-wind hybrid system with battery storage. Their strategy is designed to avoid overcharging (SOC > SOCmax) and deep discharging (SOC < SOCmin) of the battery by current control, while ensuring the distribution of the power to be supplied. It is based on two operating modes, namely normal mode when the battery's state of charge is between the two state of charge thresholds imposed on the battery (SOCmin < SOC < SOCmax), and degraded mode when the estimated state of charge exceeds the thresholds as shown in Ref. [107].

Other authors such as Fathima et al. [84] have developed an energy management strategy for a PV-wind-battery system based on current control. Bi et al. [80] have also proposed a deterministic rule-based energy manager within a multi-source (PV-battery-fuel cell) hybrid system. Their energy management strategy is an algorithm that determines at each instant the sharing of power between different system components, while imposing zero power on either the battery or the fuel cell as required. The battery and fuel cell are mobilized according to the battery's state of charge.

7.1.3. Power balance management technique

This is the simplest energy management strategy of the classic techniques. There is no imposition of current or voltage. It is purely power-based. With this approach, in the event of a surplus production, the technique uses the excess to charge the storage system (battery or fuel cell), and in the event of a deficit, the storage system is mobilized to help meet demand. Kotb et al. have developed this strategy [101], by proposing an energy strategy in which all energy conversion systems (wind and PV) operate in power maximization mode. Valenciaga et al. [110] have modeled and simulated a power balance-based management strategy for a PV-wind-battery system. The management objective was to satisfy the power demand by making the best possible use of the sources, with wind power as the main source, and to regulate the battery's state of charge to protect it and increase its service life.

In [111], Ipsakis et al. have proposed and tested three energy management strategies for a PV-wind-hydrogen-battery system already in operation at Neo olvio de Xanthi in Greece. The objective of the management was to satisfy the power demand of the load by efficiently exploiting the hydrogen storage system and controlling the battery. Kang et al. [112] have modeled and simulated a management strategy for a stand-alone PV-FC-battery system in an isolated site based on a power balance. The management objective was to increase the lifetime of storage systems by reducing the number of operating mode changes (charging and discharging) with the help of measurement and timing elements. However, they were not concerned with the variation in their state of charge, which is an accelerating factor in ageing.

7.1.4. Centralized energy management technique

In this approach, the elements of the electrical system (source, storage, load) are all connected to a DC bus via suitable converters. Based on two types of controllers (central and local), it aims to maintain a constant bus voltage to ensure permanent power supply to the load [109]. Each converter is associated with a local controller, such as an Integral Proportional (IP) controller, to control the current supplied to or received by each element of the electrical system. The central controller receives information on the state of the elements (state of charge of the storage, availability of sources) and then sends current or voltage references to the local controllers, as illustrated in Fig. A single element is chosen from all the elements of the electrical system to regulate the bus voltage. The chosen element is usually the storage for small stand-alone systems, and the grid for small grid-connected systems.

However, if the chosen element or the central controller fails, the whole system stops working. This is the major drawback of this solution. Such a management system is governed by a long series of exhaustive rules. It is therefore difficult to design, since it involves controlling almost all the elements of the electrical system (i.e. having information on the states of all the elements). Moreover, it's not open-ended, i.e. it doesn't allow the electrical system to be extended (i.e. new elements to be added). Conventional centralized management is suitable for multi-source, multi-storage and multi-load systems. Fig. 9 shows the principle of centralized management for hybrid energy systems.

Torreglosa et al. [113] have modeled and simulated a centralized energy management system of an autonomous PV-wind-hydrogen-battery system using Matlab-Simulink. The management objective was to satisfy load demand while maintaining not only constant bus voltage but also hydrogen level and battery state-of-charge between targeted margins.

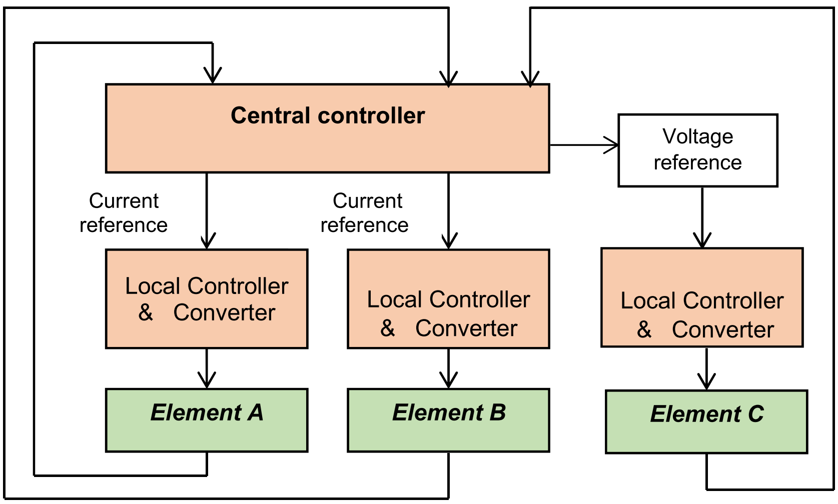

Fig. 9. Centralized Energy Management System [111].

7.2. Artificial intelligence techniques of energy management

7.2.1. Fuzzy logic management technique

Based on the fuzzy rules, i.e. rules based on linguistic variables (low, very low, medium, high, very high …) established from digital inputs (DP, SOC, DSOC), a specific output or action to be taken (charge/discharge current control, source operation control …) is decided with the aim of ensuring permanent supply to the load [114–116]. The fuzzy supervisor is generally composed of three main stages, namely fuzzification, base rules and defuzzification, as shown in Fig. 10.

It first converts numerical inputs (ΔP and SOC) via input membership functions into linguistic variables (fuzzification). Next, the linguistic variables are used to build up bases rule on which output decisions (linguistic variable) is based. Finally, the output linguistic variable is converted into an output numerical variable to decide on the command or action to be taken (defuzzification). Y. Chen et al. [117] have designed and implemented an energy management system for a PV-wind-fuel cell system with battery storage using fuzzy logic in a Matlab/Simulink environment coupled with LabView software. The objective is to ensure the energy balance between production and consumption, while maintaining the battery's state of charge in order to improve the battery's life cycle. The input variables of the fuzzy controller were ΔP and ΔSOC. The controller output was the battery charge/discharge current.

7.2.2. Multi-agent system management technique

The Multi-Agent System (MAS) is an artificial intelligence technique initially used in several fields, such as industrial applications for process control, telecommunications or the Internet for information processing and management, and robotics [118]. Today, it is of interest in the energy field, where it is used for energy management of multi-source-multi-storage systems, such as micro-grids or autonomous hybrid systems made up of several elements (sources, storage, loads). Each element of the system is associated with an Agent, enabling it to be controlled either in voltage or in current via a PI controller. The Agent here can be defined as an active physical or virtual entity in the system, endowed with intelligence capable of perceiving, communicating, acting, rendering or requesting a service [109,119]. Unlike centralized energy management system, which has a central controller responsible for collecting all the states of all the elements in the electrical system and then controlling all the inverter controllers, the MAS-based energy management strategy has several agents, each of which can control an element with which it is associated and regulate the DC bus voltage while communicating with the others [109,120].

In the case of load, the agent is rather an observer. Indeed, load control depends on the user's needs, and does not require any control from the power management system. A communication bus is integrated into the MAS, enabling dialogue between the Agents. In the case of failure of one element, or if it disconnects from the communication bus, other elements can continue to normally operate. However, if the communication bus fails, there is no longer any coordination between various agents in the system. This is the shortcoming of MAS. The big advantage of MAS over centralized systems is that it makes it possible to build scalable or even distributed electrical systems [109,120]. Table 9 presents the interests and limitations of the small-scale autonomous system management techniques described above.

7.3. Energy management system design and modelling

Among the energy management techniques previously mentioned, three of them are also applicable to autonomous microgrids integrating fluctuating energy sources such as solar and wind. These are centralized management, fuzzy logic management, and multi-agent systems [122]. Whether concerning autonomous and micro-grids and regardless of the level of application or the energy management technique to be implemented, modeling of the components of the electrical system or parameters to be controlled as well as control systems is essential. Once the models of the electrical system components (sources, storage, and loads), control systems, and management strategies are developed, they are integrated into a simulation environment to enable better analysis of the system's behavior based on the management objectives pursued. Modeling of control systems is generally based on two categories of mathematical models [122,123], namely.

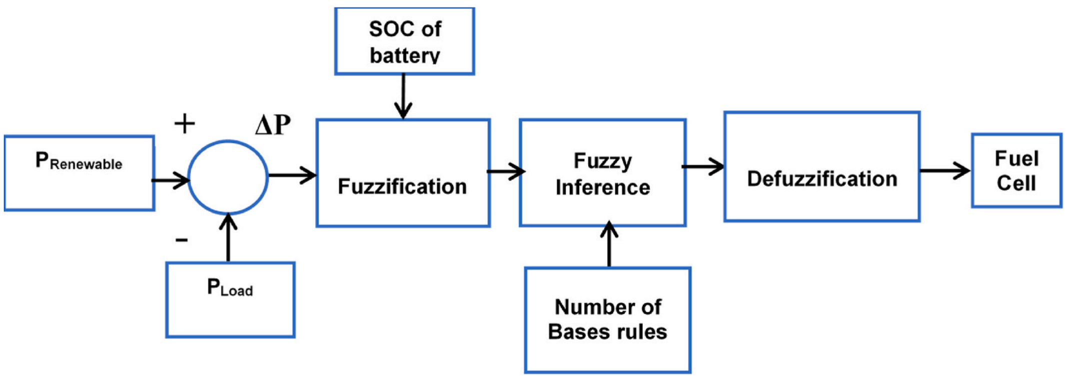

Fig. 10. Fuzzy logic controller structure for energy management system [114].

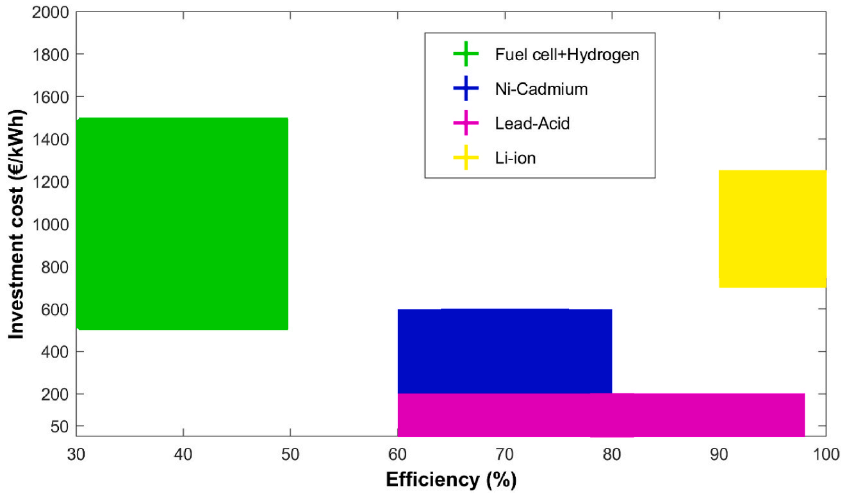

Fig. 11. Efficiency and investment cost range of energy storage technologies suitable for storing solar or wind energy in isolated sites.

Table 9
Principles, advantages and limits of autonomous systems management techniques.

References	Management techniques	Principles/Objectives	Advantages	Limits
[107]	Voltage control (bus voltage regulation)	Impose a bus voltage range around the nominal battery voltage (two threshold voltages) for continuous supply to the load. Impose two other battery threshold voltages to protect against overloads and deep discharges.	- MPPT system operation; - Battery voltage monitoring; - Easy to implement.	- No monitoring of SOC and battery current; - Bus voltage only imposed by the battery; - Frequent disconnections of generation and storage sources due to high fluctuation of battery voltage; - Does not allow system expansion (impossible to add a generation or storage source).
[107]	Current control (battery current regulation)	Make the best possible use of resources, avoiding excess or shortfalls in production to ensure proper supply of the load. Impose zero battery current in the event of overload or deep discharge by monitoring the battery's state of charge.	- Battery SOC monitoring; - Avoids frequent source disconnections; - Prevents battery disconnections; - Easy to implement.	- Does not allow electrical system expansion; - No monitoring of battery voltage and current; - No bus voltage regulation.
[110] [111]	Power balance (no voltage or current control)	Mobilize sources in order of priority to balance the energy balance, storing surplus energy in batteries and protecting them against overloads and deep discharges.	- Very easy to install; - Battery SOC monitoring.	- Only power-based management; - Does not allow electrical system expansion; - No battery voltage monitoring, - No battery current monitoring.
[113], [109]	Centralized management	A central controller monitors the status (SOC, availability) of electrical system components and makes decisions by controlling the current or voltage of local controllers associated with each system component in order to maintain a constant bus voltage to ensure permanent power supply to the load.	- Battery SOC monitoring; - Suitable for multi-source, multi-storage systems.	- Only one local controller or element is used for bus voltage regulation; - Standstill of the overall electrical system in the event of failure of the central controller or the one responsible for bus voltage regulation; - Difficult design; - Does not allow electrical system expansion.
[109], [120]	Multi-Agent System (MAS)	Each element of the electrical system (source, storage, load) is associated with an agent capable of autonomously regulating the bus voltage while controlling all the elements of the electrical system in terms of current or voltage.	- Battery SOC monitoring; - Adaptable for scalable power systems; - Fault tolerance versus centralized system.	- No coordination in case of communication bus failure; - Very complex design and implementation.
[114, 115], [117], [121]	Fuzzy Logic	Based on the fuzzy rules, a specific output or action to be taken is decided with the aim of ensuring permanent power supply to the load.	- Surveillance du SOC de la batterie - Adapter pour les systèmes multi-sources, multi-stockages.	- Does not allow for electrical system expansion; - Complex design and implementation.

- Dynamic models (time-based) which include state models, linear, and basic quadratic models. When these basic models consider uncertainties or time series data, they are called stochastic or deterministic models. If these models are used to predict the future behavior of the system, they are referred to as predictive models. PI (Proportional Integral) controllers, PID (Proportional Integral Derivative) controllers are examples of control approaches based on linear or nonlinear models. A presentation of stochastic linear predictive model can be found in Ref. [124] and the discrete linear predictive model is presented in Ref. [125]. The two models are widely used both in industry and for optimized energy management of electrical systems, for example to minimize operating costs of a microgrid.
- Frequency models that are solely based on frequency. This is the case with transfer equations or functions [122].

Beyond these two categories of control system models and certains artificial intelligence algorithms presented above (genetic algorithm, fuzzy logic, Deep Learning, neural network, etc.), the Internet of Things (IoT) can be used for the control of certain systems in real-time, such as electrical systems [122,125]. In general, the choice of model type or control system type depends on the complexity of the system, the specific objectives of modeling as well as the availability of input data.

8. Discussion

In this review article, several aspects of stand-alone solar- and/or wind power systems adapted for the electrical energy needs of isolated sites have been addressed. These include the storage systems used, configuration types, sizing and management methods, mathematical models of energy production and storage as well as techno-economic performance criteria.

- **Storage options for remote site applications**

Due to the intermittent nature of solar and wind power sources, energy storage is unavoidable for permanent load supply. Three possible storage options for isolated site applications have been identified in the literature: batteries, supercapacitors and hydrogen storage systems. Fig. 11, based on elements from Tables 1 and 2, shows these three storage options with their performance ranges and investment costs per kWh of stored energy. This figure clearly shows that supercapacitors, though high-performance, are an extremely expensive option, and therefore out of the reach of the general public. To store just 1 kWh with supercapacitors, you would need to spend around 16,000€, which is an enormous sum.

Fig. 12 shows the cost and efficiency ranges of the hydrogen storage system and the most widespread battery technologies currently on the market. It is clearly shown that, between the hydrogen storage system and the batteries, the most efficient and least expensive are the batteries. In fact, the high intrinsic power consumption of hydrogen storage systems makes them less efficient. In addition to low performance, maintenance of hydrogen storage systems is more complicated due to the complexity of the related accessories. Fig. 12 also shows that the best compromise in terms of investment cost and performance is offered by lead-acid battery technologies. They are not only the least expensive, but their performance is also close to that of lithium battery technologies, which are also the most efficient. However, the main drawback of lead-acid battery technologies is their short lifetime compared with lithium battery technologies. They do not also tolerate high depths of discharge, contrary to lithium technologies. Although lead-acid batteries enable a project's overall initial investment cost to be lower, they do not guarantee the lowest cost of kWh of energy produce; their short lifetime leads to replace the storage system many times over the project's lifetime. Thus, lithium batteries would also be a more appropriate choice, given that storage lifetime is a key parameter in a project cost analysis.

- **Hybrid stand-alone PV/Wind system configurations**

In terms of types of sources and storage used, six main PV/Wind standalone configurations have been identified as shown in Fig. 2. With regard to the type of bus connection, there are three types of configuration for such systems: DC bus configuration (Fig. 3), AC bus configuration (Fig. 4) and DC-AC coupled bus configuration (Fig. 5). A comparison of these three configurations is shown in Table 10 below. It shows that the DC bus configuration is the most widely used, because it's easier to size and manage. However, it involves slightly more converters, which undoubtedly contributes to the overall cost of the system. The AC bus configuration and the DC-AC coupled bus configuration can reduce the number of converters in the system, and therefore the cost, but they are complex to manage.

- **Sizing methods and tools**

There are several methods and tools for sizing stand-alone PV and/or wind power systems available in the literature. In this article, they are grouped into four categories (Fig. 6): traditional classical methods, traditional optimization methods, artificial intelligence methods and software. Table 11 provides a clear comparison of these four categories of techniques in terms of accuracy, complexity, flexibility and execution time.

As shown in Table 11, traditional classical methods are not optimization methods. While they are very easy to use, they do not provide optimal solutions. They are based on monthly or annual average values and on intuitive choices of storage autonomy (2–5 days), which very often lead to over-sizing. In addition, they do not use technico-economic performance indicators to measure or determine the system's level of reliability, or even its economic viability. From these difficulties, researchers have developed other methods for optimal sizing of considered power systems, such as iterative, analytical, probabilistic, multi-objective, graphical and integer linear programming methods, grouped here under the heading of traditional optimization methods with an acceptable level of

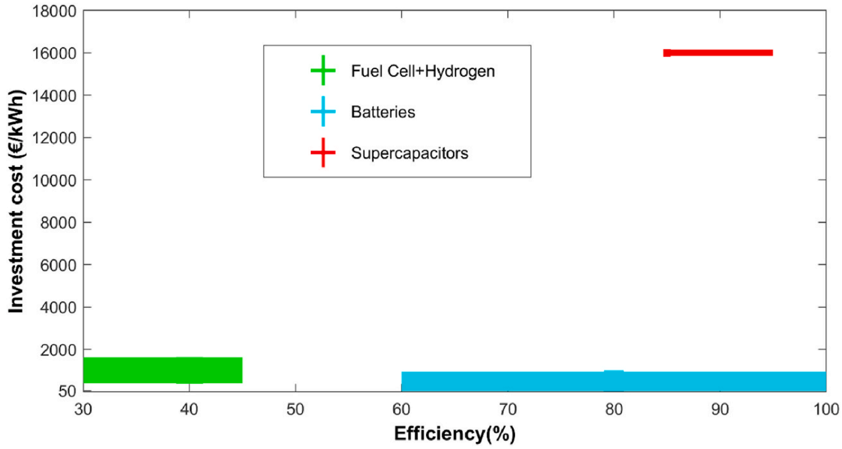

Fig. 12. Performance and investment cost range of the hydrogen storage system and the most common electrochemical storage technologies on the market.

Table 10
Comparison of fluctuating-source system configurations with storage.

Configuration type	Interest	Limits	Level of use
DC bus configuration	Easy to manage	High number of power converters involved	High
AC bus configuration	Number of power converters slightly reduced involvement	Complex management	Low
Two-bus configuration (DC and AC)	Reduced number of converters involved	Very complex management	Low

Table 11
Comparison of techniques and tools for sizing PV-wind systems.

Categories of techniques/tools	Optimization techniques or tools	Accuracy	Complexity	Flexibility	Run time	Number of optimization parameters	Most popular techniques in this category
Classic Techniques	No	Low	Low	Limited	Short	Very limited	–
Traditional optimization techniques	Yes	Average	Average	Limited	Long	Limited	- Iterative technique - Linear integer programming
Artificial intelligence techniques	Yes	High	High	High	long	High	- Genetic Algorithm (GA) - Particle Swarm Optimization (PSO)
Software	Yes for some	Average	Low for some	Limited	Short for some	Limited for some	HOMER

accuracy. However, these methods are criticized for their limited flexibility and long execution times. Among these traditional optimization methods, the iterative method is recognized to be the most widely used in the present study for the technico-economic sizing of stand-alone PV-wind-battery systems. Furthermore, it can only optimize a maximum of three parameters (number of PV modules, number of wind generators, number of days of storage autonomy). In addition, it doesn't take into account the actual conditions of use of the batteries when choosing the battery lifetime, which is an important parameter in cost analysis. In response to the drawbacks of traditional optimization methods, new methods have been developed, known as artificial intelligence or new-generation methods (AG, PSO, HR, SA, TS, etc.). These methods are flexible and can be used for complex problems with several optimization parameters. However, they still suffer from a convergence problem and even require appropriate choices of coding parameters to hope for good quality solutions. Thus, attempts have been made to hybridize or modify these methods (AG-PSO, HSSA, MOPSO, …) in order to find high-quality solutions to optimization problems. Genetic algorithms and particle swarm optimization are the most widely used artificial intelligence techniques. In addition to the above-mentioned methods, a number of software packages (HOMER, HOGA, PVSYST, etc.) are available for designing autonomous systems. HOMER remains the most popular of them. However, none of the sizing software packages discussed in this article, including HOMER, can predict or take into account the actual lifetime of storage elements (fuel cell batteries). They only consider the nominal lifetimes proposed by manufacturers under regular cycling regimes. In stand-alone systems using fluctuating sources, the things are quite different, as these storage devices are not always subjected to regular cycling. It can happen that a discharge occurs without the charge being complete. This reality of the storage system's behavior must be taken into account when predicting or assessing its lifetime, which is one of the key parameters in the technico-economic sizing of stand-alone systems. As a reminder, in the HOMER software, the lifetime of batteries is intuitively set between 3 years and 15 years, and that of fuel cells between 15,000h and 40,000h for sizing or economic feasibility studies, whereas for the same system a lifetime of 3 years chosen for batteries or 15,000h for fuel cells will not lead to the same result as a lifetime of 15 years chosen for batteries or 40,000h for fuel cells. Clearly, this parameter will have a strong influence on the result, especially from an economic point of view. It is therefore important to consider this reality of storage behavior in design softwares.

- **Energy management in stand-alone systems**

Energy management in stand-alone PV and/or wind power systems with storage is essential in improving system reliability and viability. Thus, several management strategies have been proposed in the literature. In this article, these strategies have been grouped into two classes: classical techniques and artificial intelligence techniques (Fig. 8). Classical techniques are based on simple rules, while artificial intelligence techniques are based on complex or fuzzy rules. Classical management techniques include voltage control, current control, power balance and centralized control. These techniques are easy to develop and implement. However, they are only suitable for fixed or closed stand-alone systems, as shown in Table 11. For a closed autonomous power system, contrary to a scalable power system, it is not possible to add or subtract an element to the system without rebuilding a new management algorithm. Artificial intelligence techniques include fuzzy logic and multi-agent systems (MAS). They are much more flexible, but complex and very difficult to implement. Of all these management techniques or strategies, MAS is the most suitable for a power system that is intended to be scalable. This technique deserves to be explored further in order to have at less complex and easily implementable strategies for managing open autonomous systems.

- **Technical and economic performance criteria**

LPSP and LOLP are the most widely parameters used technical performance indicators for measuring the reliability of PV and/or wind power systems with storage. However, no study on the influence of these two indicators on the technico-economic sizing of fluctuating-source systems with storage has been identified in the literature. Such a study could help determine which of the two parameters is the best. To measure the affordability of these systems, NPV and LCOE are the most widely used. Their choice depends on the objective set.

- **Basic models of production and storage**

Several PV and wind field production models exist in the literature. However, they are generally based on meteorological data (solar irradiation and ambient temperature for the PV field and wind speed for the wind field) and the characteristics of the PV and wind modules. In the majority of sizing studies, storage is modeled by its state of charge, which evolves according to the difference between production and demand. However, very few studies consider the storage aging model in the sizing.

9. Conclusion

Autonomous systems based on solar and/or wind power are highly recommended for isolated sites. This research study aimed to examine the different energy storage technologies, the types of configurations, the different technico-economic criteria, and the sizing and management techniques used for the design and/or management of such systems.Here are the main aspects of the review research.

- Among the storage options discussed, namely batteries, supercapacitors and hydrogen storage systems, batteries are recognized to be the most widespread and widely used due to their higher maturity, lower maintenance and lower cost. From the three battery technologies (lead-acid, nickel-acid and lithium-acid) most widely used on the market, lead-acid technology offers the best compromise in terms of performance, service life and cost. Lithium batteries would also be a more appropriate choice, because of their storage lifetime better than that of lead acid batteries. Supercapacitors are extremely expensive, while hydrogen storage systems are less efficient and difficult to maintain.
- Four categories of techniques and tools for sizing PV and/or wind power systems with storage have been identified: traditional classical techniques, traditional optimization techniques, artificial intelligence techniques and software. The iterative method and integer linear programming are the most widely used among traditional optimization methods, while the genetic algorithm (GA) and particle swarm optimization (PSO) are the most widely used among artificial intelligence methods. However, these methods still suffer from convergence problems and often need to be hybridized to offer high-quality solutions.
- HOMER is the most popular used software. However, neither HOMER nor other tools or techniques take into account the storage operating conditions when estimating the lifetime of the storage system.
- Several energy management strategies have been identified and discussed. The most flexible and best suited to scalable power systems is multi-agent systems (MAS). However, the big challenge with MAS is the communication between agents.
- LPSP, LOLP, NPC and LCOE have been identified as the most widely used technico-economic performance indicators for autonomous power systems, although it should be noted that they are highly dependent on study hypothesis. An analysis of the influence of LPSP, LOLP and storage ageing on the technico-economic sizing of fluctuating-source systems with electrochemical storage will be carried out in future work.

The review revealed that further works are needed concerning especially the optimal choice of the storage autonomy duration and the assessment of the real battery lifetime, as the battery state of charge changes irregularly due to the variability of energy sources.

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Data availability

Data will be made available on request.

CRediT authorship contribution statement

Jean Guétinsom Kafando: Writing – original draft, Software, Methodology, Formal analysis. **Daniel Yamegueu:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Etienne Tchoffo Houdji:** Writing – review & editing, Methodology, Formal analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Jean Guetinsom Kafando reports financial support was provided by Regional Scholarship and Innovation Fund (RSIF). The other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] I. Energy Agency, World energy outlook special report Africa energy outlook 2022 [Online]. Available: www.iea.org/t&c/, 2022.
[2] T. Khan, M. Waseem, H.A. Muqeet, M.M. Hussain, M. Yu, A. Annuk, 3E analyses of battery-assisted photovoltaic-fuel cell energy system: step towards green community, Energy Rep. 8 (Dec. 2022) 184–191, https://doi.org/10.1016/j.egyr.2022.10.393.
[3] S. Peláez-Peláez, A. Colmenar-Santos, C. Pérez-Molina, A.E. Rosales, E. Rosales-Asensio, Techno-economic analysis of a heat and power combination system based on hybrid photovoltaic-fuel cell systems using hydrogen as an energy vector, Energy 224 (Jun) (2021), https://doi.org/10.1016/j.energy.2021.120110.
[4] S. El Alimi, T. Maatallah, S. Ben Nasrallah, Break-even analysis and optimization of a stand-alone hybrid system with battery storage for residential load consumption - a case study, in: Renewable and Sustainable Energy Reviews, vol. 37, Elsevier Ltd, 2014, pp. 408–423, https://doi.org/10.1016/j.rser.2014.04.059.
[5] T. Khatib, W. Elmenreich, An improved method for sizing standalone photovoltaic systems using generalized regression neural network, Int. J. Photoenergy 2014 (2014), https://doi.org/10.1155/2014/748142.
[6] E. Korsaga, et al., Comparaison et détermination des dispositifs de stockage appropriés pour un système photovoltaïque autonome en zone sahélienne, vol. 4, 2018, pp. 2428–8500, https://doi.org/10.18145/jitipee.v4i1.161.
[7] S. Diaf, G. Notton, M. Belhamel, M. Haddadi, A. Louche, Design and techno-economical optimization for hybrid PV/wind system under various meteorological conditions, Appl. Energy 85 (10) (2008) 968–987, https://doi.org/10.1016/j.apenergy.2008.02.012.
[8] T. Khatib, I.A. Ibrahim, A. Mohamed, A review on sizing methodologies of photovoltaic array and storage battery in a standalone photovoltaic system, in: Energy Conversion and Management, vol. 120, Elsevier Ltd, Jul. 15, 2016, pp. 430–448, https://doi.org/10.1016/j.enconman.2016.05.011.
[9] A. Kaabeche, M. Belhamel, R. Ibtiouen, Sizing optimization of grid-independent hybrid photovoltaic/wind power generation system, Energy 36 (2) (2011) 1214–1222, https://doi.org/10.1016/j.energy.2010.11.024.
[10] A.R. Prasad, E. Natarajan, Optimization of integrated photovoltaic-wind power generation systems with battery storage, Energy 31 (12) (2006) 1943–1954, https://doi.org/10.1016/j.energy.2005.10.032.
[11] A.A. Mas'ud, "An Optimal Sizing Algorithm for a Hybrid Renewable Energy System,", 2017.
[12] L. Fan, Z. Tu, S.H. Chan, Recent development of hydrogen and fuel cell technologies: a review, in: Energy Reports, vol. 7, Elsevier Ltd, 2021, pp. 8421–8446, https://doi.org/10.1016/j.egyr.2021.08.003. Nov. 01.
[13] S.B. Silva, M.M. Severino, M.A.G. De Oliveira, A stand-alone hybrid photovoltaic, fuel cell and battery system: a case study of Tocantins, Brazil, Renew. Energy 57 (Sep. 2013) 384–389, https://doi.org/10.1016/j.renene.2013.02.004.
[14] N. Belmonte, et al., A comparison of energy storage from renewable sources through batteries and fuel cells: a case study in Turin, Italy, Int. J. Hydrogen Energy 41 (46) (Dec. 2016) 21427–21438, https://doi.org/10.1016/j.ijhydene.2016.07.260.
[15] H.S. Das, C.W. Tan, A.H.M. Yatim, K.Y. Lau, Feasibility analysis of hybrid photovoltaic/battery/fuel cell energy system for an indigenous residence in East Malaysia, in: Renewable and Sustainable Energy Reviews, vol. 76, Elsevier Ltd, 2017, pp. 1332–1347, https://doi.org/10.1016/j.rser.2017.01.174.
[16] F. Fazelpour, N. Soltani, M.A. Rosen, Economic analysis of standalone hybrid energy systems for application in Tehran, Iran, Int. J. Hydrogen Energy 41 (19) (May 2016) 7732–7743, https://doi.org/10.1016/j.ijhydene.2016.01.113.
[17] D. Mazzeo, N. Matera, P. De Luca, C. Baglivo, P.M. Congedo, G. Oliveti, A literature review and statistical analysis of photovoltaic-wind hybrid renewable system research by considering the most relevant 550 articles: an upgradable matrix literature database, Journal of Clean Prod 295 (May 2021) 126070, https://doi.org/10.1016/j.jclepro.2021.126070.
[18] R.G. Allwyn, A. Al-Hinai, R. Al-Abri, A. Malik, Optimization and techno-economic analysis of PV/Battery system for street lighting using genetic algorithm – a case study in Oman, Clean Eng Technol 8 (Jun. 2022) 100475, https://doi.org/10.1016/j.clet.2022.100475.
[19] S. Gherairi, Design and implementation of an intelligent energy management system for smart home utilizing a multi-agent system, Ain Shams Eng. J. 14 (3) (Apr. 2023), https://doi.org/10.1016/j.asej.2022.101897.
[20] P. Simon, Le stockage électrochimique de l'énergie : principes, applications et futurs défis, Annales des Mines - Responsabilité et environnement N° 78 (2) (2015) 67, https://doi.org/10.3917/re1.078.0067.

[21] APPLICATION DES SYSTEMES HYDROGENE POUR LES BESOINS DU DEVELOPPEMENT A HORIZON 2020-2025." [Online]. Available: www.enea-consulting.com.
[22] I.A. Hassan, H.S. Ramadan, M.A. Saleh, D. Hissel, Hydrogen storage technologies for stationary and mobile applications: review, analysis and perspectives, in: Renewable and Sustainable Energy Reviews, vol. 149, Elsevier Ltd, 2021, https://doi.org/10.1016/j.rser.2021.111311. Oct. 01.
[23] A. John, S. Basu, Akshay, A. Kumar, Design and evaluation of stand-alone solar-hydrogen energy storage system for academic institute: a case study, in: Materials Today: Proceedings, Elsevier Ltd, 2021, pp. 5918–5922, https://doi.org/10.1016/j.matpr.2021.04.461.
[24] N. Ghorbani, A. Kasaeian, A. Toopshekan, L. Bahrami, A. Maghami, Optimizing a hybrid wind-PV-battery system using GA-PSO and MOPSO for reducing cost and increasing reliability, Energy 154 (Jul. 2018) 581–591, https://doi.org/10.1016/j.energy.2017.12.057.
[25] A. Al-Sharafi, A.Z. Sahin, T. Ayar, B.S. Yilbas, Techno-economic analysis and optimization of solar and wind energy systems for power generation and hydrogen production in Saudi Arabia, in: Renewable and Sustainable Energy Reviews, vol. 69, Elsevier Ltd, 2017, pp. 33–49, https://doi.org/10.1016/j.rser.2016.11.157. Mar. 01.
[26] T.B. Nkwanyana, M.W. Siti, Z. Wang, I. Toudjeu, N.T. Mbungu, W. Mulumba, An assessment of hybrid-energy storage systems in the renewable environments, J. Energy Storage 72 (Nov. 2023) 108307, https://doi.org/10.1016/j.est.2023.108307.
[27] A. Chauhan, R.P. Saini, A review on Integrated Renewable Energy System based power generation for stand-alone applications: configurations, storage options, sizing methodologies and control, in: Renewable and Sustainable Energy Reviews, vol. 38, Elsevier Ltd, 2014, pp. 99–120, https://doi.org/10.1016/j.rser.2014.05.079.
[28] B.K. Das, N. Hoque, S. Mandal, T.K. Pal, M.A. Raihan, A techno-economic feasibility of a stand-alone hybrid power generation for remote area application in Bangladesh, Energy 134 (2017) 775–788, https://doi.org/10.1016/j.energy.2017.06.024.
[29] K. Anoune, M. Bouya, A. Astito, A. Ben Abdellah, Sizing methods and optimization techniques for PV-wind based hybrid renewable energy system: a review, in: Renewable and Sustainable Energy Reviews, vol. 93, Elsevier Ltd, 2018, pp. 652–673, https://doi.org/10.1016/j.rser.2018.05.032. Oct. 01.
[30] M. Belouda, M. Hajjaji, H. Sliti, A. Mami, Bi-objective optimization of a standalone hybrid PV–Wind–battery system generation in a remote area in Tunisia, Sustainable Energy, Grids and Networks 16 (Dec. 2018) 315–326, https://doi.org/10.1016/j.segan.2018.09.005.
[31] S. Kumar Ramoji, Bj Kumar, Optimal economical sizing of a PV-wind hybrid energy system using genetic algorithm and teaching learning based optimization [Online]. Available: www.ijareeie.com, 2007.
[32] R. Luna-Rubio, M. Trejo-Perea, D. Vargas-Vázquez, G.J. Ríos-Moreno, Optimal sizing of renewable hybrids energy systems: a review of methodologies, Sol. Energy 86 (4) (Apr. 2012) 1077–1088, https://doi.org/10.1016/j.solener.2011.10.016.
[33] S. Upadhyay, M.P. Sharma, A review on configurations, control and sizing methodologies of hybrid energy systems, in: Renewable and Sustainable Energy Reviews, vol. 38, Elsevier Ltd, 2014, pp. 47–63, https://doi.org/10.1016/j.rser.2014.05.057.
[34] N.T. Kalantari, M. Ahangari Hassas, K. Pourhossein, Bibliographic review and comparison of optimal sizing methods for hybrid renewable energy systems, Journal of Energy Management and Technology (JEMT) 2 (2018) 66, https://doi.org/10.22109/jemt.2018.102306.1039.
[35] S. Amara, S. Toumi, C. Ben Salah, A.S. Saidi, Improvement of techno-economic optimal sizing of a hybrid off-grid micro-grid system, Energy 233 (Oct. 2021), https://doi.org/10.1016/j.energy.2021.121166.
[36] S. Sinha, S.S. Chandel, Review of recent trends in optimization techniques for solar photovoltaic-wind based hybrid energy systems, in: Renewable and Sustainable Energy Reviews, vol. 50, Elsevier Ltd, Jun. 04, 2015, pp. 755–769, https://doi.org/10.1016/j.rser.2015.05.040.
[37] A.S. Al Busaidi, H.A. Kazem, A.H. Al-Badi, M. Farooq Khan, "A review of optimum sizing of hybrid PV-Wind renewable energy systems in Oman,", in: Renewable and Sustainable Energy Reviews, vol. 53, Elsevier Ltd, Jan. 09, 2016, pp. 185–193, https://doi.org/10.1016/j.rser.2015.08.039.
[38] T. Khatib, A. Mohamed, K. Sopian, A review of photovoltaic systems size optimization techniques, in: Renewable and Sustainable Energy Reviews, vol. 22, Elsevier Ltd, 2013, pp. 454–465, https://doi.org/10.1016/j.rser.2013.02.023.
[39] A. El Khadimi, L. Bchir, and A. Zeroual, "Dimensionnement et Optimisation Technico-économique d'un Système d'Energie Hybride Photovoltaïque-Eolien avec Système de Stockage," 2004.
[40] C.O. Okoye, O. Taylan, D.K. Baker, "Solar energy potentials in strategically located cities in Nigeria: review, resource assessment and PV system design,", in: Renewable and Sustainable Energy Reviews, vol. 55, Elsevier Ltd, Mar. 01, 2016, pp. 550–566, https://doi.org/10.1016/j.rser.2015.10.154.
[41] H.A. Kazem, T. Khatib, K. Sopian, Sizing of a standalone photovoltaic/battery system at minimum cost for remote housing electrification in Sohar, Oman, Energy Build. 61 (2013) 108–115, https://doi.org/10.1016/j.enbuild.2013.02.011.
[42] T. Khatib, D.H. Muhsen, Optimal sizing of standalone photovoltaic system using improved performance model and optimization algorithm, Sustainability 12 (6) (Mar. 2020), https://doi.org/10.3390/su12062233.
[43] H. Mohammed Ridha, et al., Multi-objective optimization and multi-criteria decision making aided by numerical method: framework and a case study of Malaysia and South Africa, Energy Convers. Manag. 274 (Dec. 2022), https://doi.org/10.1016/j.enconman.2022.116468.
[44] M.M.H. Bhuiyan, M. Ali Asgar, Sizing of a stand-alone photovoltaic power system at Dhaka, Renew. Energy 28 (6) (May 2003) 929–938, https://doi.org/10.1016/S0960-1481(02)00154-4.
[45] M. Sidrach-De-Cardona, L. Mora Lo′pezlo′pez, "A Simple Model for Sizing Stand Alone Photovoltaic Systems,", 1998.
[46] H.M. Ridha, C. Gomes, H. Hizam, M. Ahmadipour, D.H. Muhsen, S. Ethaib, Optimum design of a standalone solar photovoltaic system based on novel integration of iterative-PESA-II and AHP-VIKOR Methods, Processes 8 (3) (Mar. 2020), https://doi.org/10.3390/PR8030367.
[47] N.D. Kaushika, A.K. Rai, Solar PV design aid expert system, Sol. Energy Mater. Sol. Cell. 90 (17) (Nov. 2006) 2829–2845, https://doi.org/10.1016/j.solmat.2006.04.010.
[48] B. Herteleer, J. Cappelle, and J. Driesen, "An Autonomous Photovoltaic System Sizing Program for Office Applications in Africa.".
[49] C. Olcan, Multi-objective analytical model for optimal sizing of stand-alone photovoltaic water pumping systems, Energy Convers. Manag. 100 (Aug. 2015) 358–369, https://doi.org/10.1016/j.enconman.2015.05.018.
[50] H. Belmili, M. Haddadi, S. Bacha, M.F. Almi, B. Bendib, "Sizing stand-alone photovoltaic-wind hybrid system: techno-economic analysis and optimization,", in: Renewable and Sustainable Energy Reviews, vol. 30, Elsevier Ltd, 2014, pp. 821–832, https://doi.org/10.1016/j.rser.2013.11.011.
[51] W.D. Kellogg, M.H. Nehrir, G. Venkataramanan, V. Gerez, "E tion unit sizing and cost analysis for stand-alone ind, photovoltaic, AND HYBRID WINDPV SYSTEMS," (1998).
[52] D.K. Khatod, V. Pant, J. Sharma, Analytical approach for well-being assessment of small autonomous power systems with solar and wind energy sources, IEEE Trans. Energy Convers. 25 (2) (Jun. 2010) 535–545, https://doi.org/10.1109/TEC.2009.2033881.
[53] A.Q. Jakhrani, A.K. Othman, A.R.H. Rigit, S.R. Samo, S.A. Kamboh, A novel analytical model for optimal sizing of standalone photovoltaic systems, Energy 46 (1) (2012) 675–682, https://doi.org/10.1016/j.energy.2012.05.020.
[54] J.K. Kaldellis, D. Zafirakis, E. Kondili, Optimum autonomous stand-alone photovoltaic system design on the basis of energy pay-back analysis, Energy 34 (9) (2009) 1187–1198, https://doi.org/10.1016/j.energy.2009.05.003.
[55] T. Khatib, A. Mohamed, K. Sopian, M. Mahmoud, A new approach for optimal sizing of standalone photovoltaic systems, Int. J. Photoenergy 2012 (2012), https://doi.org/10.1155/2012/391213.
[56] P. Viveros, F. Wulff, F. Kristjanpoller, C. Nikulin, T. Grubessich, Sizing of a standalone PV system with battery storage for a dairy: a case study from Chile, in: Complexity, vol. 2020, Hindawi Limited, 2020, https://doi.org/10.1155/2020/5792782.
[57] H.X. Yang, L. Lu, J. Burnett, Weather data and probability analysis of hybrid photovoltaic-wind power generation systems in Hong Kong, Renew. Energy 28 (11) (2003) 1813–1824, https://doi.org/10.1016/S0960-1481(03)00015-6.
[58] A.D. Bagul, Z.M. Salameh, B. Borowy, "SIZING OF A STAND-ALONE HYBRID WIND-PHOTOVOLTAIC SYSTEM USING A THREE-EVENT PROBABILITY DENSITY APPROXIMATION,", 1996.
[59] G.-C. Semassou, et al., "Science Arts & Métiers (SAM),", 2012.
[60] D. Abbes, A. Martinez, G. Champenois, Eco-design optimisation of an autonomous hybrid wind-photovoltaic system with battery storage, IET Renew. Power Gener. 6 (5) (Sep. 2012) 358–371, https://doi.org/10.1049/iet-rpg.2011.0204.

[61] B. Ould Bilal, V. Sambou, P.A. Ndiaye, C.M.F. Kébé, M. Ndongo, Optimal design of a hybrid solar-wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP), Renew. Energy 35 (10) (Oct. 2010) 2388–2390, https://doi.org/10.1016/j.renene.2010.03.004.

[62] T. Khatib, A. Mohamed, K. Sopian, M. Mahmoud, Optimal sizing of hybrid PV/wind systems for Malaysia using loss of load probability, Energy Sources, Part A Recovery, Util. Environ. Eff. 37 (7) (Apr. 2015) 687–695, https://doi.org/10.1080/15567036.2011.592920.

[63] E.M.A. Mokheimer, A. Al-Sharafi, M.A. Habib, I. Alzaharnah, A new study for hybrid PV/Wind off-grid power generation systems with the comparison of results from homer, Int. J. Green Energy 12 (5) (May 2015) 526–542, https://doi.org/10.1080/15435075.2013.833929.

[64] A. Kaabeche, M. Belhamel, R. Ibtiouen, S. Moussa, M.R. Benhaddadi, "Optimisation D'un Système Hybride (Éolien-photovoltaïque) Totalement autonome.,", 2006.

[65] M. Amini, A. Khorsandi, B. Vahidi, S.H. Hosseinian, A. Malakmahmoudi, Optimal sizing of battery energy storage in a microgrid considering capacity degradation and replacement year, Elec. Power Syst. Res. 195 (Jun) (2021), https://doi.org/10.1016/j.epsr.2021.107170.

[66] I. Alsaidan, A. Khodaei, W. Gao, A comprehensive battery energy storage optimal sizing model for microgrid applications, IEEE Trans. Power Syst. 33 (4) (Jul. 2018) 3968–3980, https://doi.org/10.1109/TPWRS.2017.2769639.

[67] A. Boveri, F. Silvestro, M. Molinas, E. Skjong, Optimal sizing of energy storage systems for shipboard applications, IEEE Trans. Energy Convers. 34 (2) (Jun. 2019) 801–811, https://doi.org/10.1109/TEC.2018.2882147.

[68] N.D. Kaushika, N.K. Gautam, K. Kaushik, Simulation model for sizing of stand-alone solar PV system with interconnected array, Sol. Energy Mater. Sol. Cell. 85 (4) (Feb. 2005) 499–519, https://doi.org/10.1016/j.solmat.2004.05.024.

[69] C.E.C. Nogueira, et al., Sizing and simulation of a photovoltaic-wind energy system using batteries, applied for a small rural property located in the south of Brazil, Renew. Sustain. Energy Rev. 29 (2014) 151–157, https://doi.org/10.1016/j.rser.2013.08.071.

[70] A. Fetanat, E. Khorasaninejad, Size optimization for hybrid photovoltaic-wind energy system using ant colony optimization for continuous domains based integer programming, Applied Soft Computing Journal 31 (2015) 196–209, https://doi.org/10.1016/j.asoc.2015.02.047.

[71] F.A. Khan, N. Pal, S.H. Saeed, "Review of solar photovoltaic and wind hybrid energy systems for sizing strategies optimization techniques and cost analysis methodologies,", in: Renewable and Sustainable Energy Reviews, vol. 92, Elsevier Ltd, Sep. 01, 2018, pp. 937–947, https://doi.org/10.1016/j.rser.2018.04.107.

[72] H. Yang, L. Lu, W. Zhou, A novel optimization sizing model for hybrid solar-wind power generation system, Sol. Energy 81 (1) (Jan. 2007) 76–84, https://doi.org/10.1016/j.solener.2006.06.010.

[73] Y. Bakelli, A. Hadj Arab, B. Azoui, Optimal sizing of photovoltaic pumping system with water tank storage using LPSP concept, Sol. Energy 85 (2) (Feb. 2011) 288–294, https://doi.org/10.1016/j.solener.2010.11.023.

[74] B.S. Borowy, Z.M. Salameh, "Methodology for Optimally Sizing the Combination of a Battery Bank and PV Array in a Wind/PV Hybrid System,", 1996.

[75] N. Singh, S.B. Singh, A novel hybrid GWO-SCA approach for optimization problems, Engineering Science and Technology, an International Journal 20 (6) (Dec. 2017) 1586–1601, https://doi.org/10.1016/j.jestch.2017.11.001.

[76] D. Fares, M. Fathi, S. Mekhilef, Performance evaluation of metaheuristic techniques for optimal sizing of a stand-alone hybrid PV/wind/battery system, Appiedl Energy 305 (Jan. 2022) 117823, https://doi.org/10.1016/j.apenergy.2021.117823.

[77] A. Maleki, M. Ameri, F. Keynia, Scrutiny of multifarious particle swarm optimization for finding the optimal size of a PV/wind/battery hybrid system, Renew. Energy 80 (Aug. 2015) 552–563, https://doi.org/10.1016/j.renene.2015.02.045.

[78] P. Sarojrangnekar, A. Mittal, "Payal Suhane et al Optimal Sizing of Hybrid Energy System using Ant Colony Optimization,", 2014.

[79] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M.S. Fadali, Y. Baghzouz, Genetic-algorithm-based optimization approach for energy management, IEEE Trans. Power Deliv. 28 (1) (2013) 162–170, https://doi.org/10.1109/TPWRD.2012.2219598.

[80] B.E.B. Bi, P. Gbaha, K.B. Koua, M.P.E. Koffi, Dimensionnement et Gestion de l'Energie au Sein d'un Système Hybride de Production d'Energie, European Scientific Journal ESJ 14 (36) (Dec. 2018), https://doi.org/10.19044/esj.2018.v14n36p260.

[81] M. Amer, A. Namaane, N.K. M'Sirdi, Optimization of hybrid renewable energy systems (HRES) using PSO for cost reduction, in: Energy Procedia, Elsevier Ltd, 2013, pp. 318–327, https://doi.org/10.1016/j.egypro.2013.11.032.

[82] I.E.E.E. Staff, I.E.E.E. Staff, International Conference on Measurement, Information and Control, 2012.

[83] D. Xu, L. Kang, L. Chang, and B. Cao, "OPTIMAL SIZING OF STANDALONE HYBRID WIND/PV POWER SYSTEMS USING GENETIC ALGORITHMS.".

[84] H. Fathima, K. Palanisamy, Optimized sizing, selection, and economic analysis of battery energy storage for grid-connected wind-PV hybrid system, Model. Simulat. Eng. 2015 (2015), https://doi.org/10.1155/2015/713530.

[85] I. Tégani, A. Aboubou, M.Y. Ayad, M. Becherif, R. Saadi, O. Kraa, Optimal sizing design and energy management of stand-alone photovoltaic/wind generator systems, in: Energy Procedia, Elsevier Ltd, 2014, pp. 163–170, https://doi.org/10.1016/j.egypro.2014.06.020.

[86] A. Askarzadeh, A discrete chaotic harmony search-based simulated annealing algorithm for optimum design of PV/wind hybrid system, Sol. Energy 97 (Nov. 2013) 93–101, https://doi.org/10.1016/j.solener.2013.08.014.

[87] A.Y. Hatata, G. Osman, M.M. Aladl, An optimization method for sizing a solar/wind/battery hybrid power system based on the artificial immune system, Sustain. Energy Technol. Assessments 27 (Jun. 2018) 83–93, https://doi.org/10.1016/j.seta.2018.03.002.

[88] S. Sinha, S.S. Chandel, Review of software tools for hybrid renewable energy systems, Renew. Sustain. Energy Rev. 32 (Apr. 2014) 192–205, https://doi.org/10.1016/j.rser.2014.01.035.

[89] L. Khalil, K. Liaquat Bhatti, M. Arslan Iqbal Awan, M. Riaz, K. Khalil, N. Alwaz, Optimization and designing of hybrid power system using HOMER pro, in: Materials Today: Proceedings, Elsevier Ltd, 2020, pp. S110–S115, https://doi.org/10.1016/j.matpr.2020.06.054.

[90] N.M. Ahmed, H.M. Farghally, F.H. Fahmy, Optimal sizing and economical analysis of PV-wind hybrid power system for water irrigation using genetic algorithm, Int. J. Electr. Comput. Eng. 7 (4) (2017) 1797–1814, https://doi.org/10.11591/ijece.v7i4.pp1797-1814.

[91] A. Mills, S. Al-Hallaj, Simulation of hydrogen-based hybrid systems using Hybrid2, Int. J. Hydrogen Energy 29 (10) (Aug. 2004) 991–999, https://doi.org/10.1016/j.ijhydene.2004.01.004.

[92] C. Ammari, D. Belatrache, B. Touhami, S. Makhloufi, Sizing, optimization, control and energy management of hybrid renewable energy system—a review, Energy and Built Environment 3 (4) (Oct. 2022) 399–411, https://doi.org/10.1016/j.enbenv.2021.04.002.

[93] S. Bahramara, M.P. Moghaddam, M.R. Haghifam, Optimal planning of hybrid renewable energy systems using HOMER: a review, in: Renewable and Sustainable Energy Reviews, vol. 62, Elsevier Ltd, 2016, pp. 609–620, https://doi.org/10.1016/j.rser.2016.05.039.

[94] A. Mahesh, K.S. Sandhu, Hybrid wind/photovoltaic energy system developments: critical review and findings, in: Renewable and Sustainable Energy Reviews, vol. 52, Elsevier Ltd, 2015, pp. 1135–1147, https://doi.org/10.1016/j.rser.2015.08.008. Aug. 22.

[95] K. Anoune, A. Laknizi, M. Bouya, A. Astito, A. Ben Abdellah, Sizing a PV-Wind based hybrid system using deterministic approach, Energy Convers. Manag. 169 (Aug. 2018) 137–148, https://doi.org/10.1016/j.enconman.2018.05.034.

[96] A. Cano, F. Jurado, H. Sánchez, L.M. Fernández, M. Castañeda, Optimal sizing of stand-alone hybrid systems based on PV/WT/FC by using several methodologies, J. Energy Inst. 87 (4) (Nov. 2014) 330–340, https://doi.org/10.1016/j.joei.2014.03.028.

[97] R. LE Goff Latimier, B. Multon, H. Ben Ahmed, and M. Acquitter, "Co-optimisation de l'engagement de production et de la capacité de stockage associée à une ferme photovoltaïque, prenant en compte le vieillissement.".

[98] H. Yang, W. Zhou, L. Lu, Z. Fang, Optimal sizing method for stand-alone hybrid solar-wind system with LPSP technology by using genetic algorithm, Sol. Energy 82 (4) (Apr. 2008) 354–367, https://doi.org/10.1016/j.solener.2007.08.005.

[99] A.H.D.J. E Visser, Methodologies for estimating levelised cost of electricity (LCOE). A Report Complied within the European Project 'Cooperation between EU MS under the Renewable Energy Directive and Interaction with Support, 2014.

[100] EVi, Methodologies for estimating levelised cost of electricity (LCOE) [Online]. Available: www.ecofys.com, 2014.

[101] K.M. Kotb, M.R. Elkadeem, M.F. Elmorshedy, A. Dán, Coordinated power management and optimized techno-enviro-economic design of an autonomous hybrid renewable microgrid: a case study in Egypt, Energy Convers. Manag. 221 (Oct) (2020), https://doi.org/10.1016/j.enconman.2020.113185.

[102] Y.S. Mohammed, B.B. Adetokun, O. Oghorada, O. Oshiga, Techno-economic optimization of standalone hybrid power systems in context of intelligent computational multi-objective algorithms, Energy Rep. 8 (Nov. 2022) 11661–11674, https://doi.org/10.1016/j.egyr.2022.09.010.
[103] N. Yimen, et al., Optimal sizing and techno-economic analysis of hybrid renewable energy systems—a case study of a photovoltaic/wind/battery/diesel system in fanisau, northern Nigeria, Processes 8 (11) (Oct. 2020) 1381, https://doi.org/10.3390/pr8111381.
[104] S. De and G. Electrique, "Etude du vieillissement d'un banc de stockage plomb-acide dans un système hybride multi-sources.".
[105] X. Ke, N. Lu, C. Jin, Control and size energy storage systems for managing energy imbalance of variable generation resources, IEEE Trans. Sustain. Energy 6 (1) (Jan. 2015) 70–78, https://doi.org/10.1109/TSTE.2014.2355829.
[106] G. Champenois, Toufik Madani Layadi, "Etude du vieillissement d'un banc de stockage plomb-acide dans un système hybride multi-sources,", 2014.
[107] D. Abbes, A. Martinez, G. Champenois, B. Robyns, Real time supervision for a hybrid renewable power system emulator, Simul Model Pract Theory 42 (Mar. 2014) 53–72, https://doi.org/10.1016/j.simpat.2013.12.003.
[108] Zhenhua Jiang, " Power Management of Hybrid Photovoltaic–Fuel Cell Power Systems".
[109] J. Lagorse, D. Paire, A. Miraoui, A multi-agent system for energy management of distributed power sources, Renew. Energy 35 (1) (Jan. 2010) 174–182, https://doi.org/10.1016/j.renene.2009.02.029.
[110] F. Valenciaga, P.F. Puleston, Supervisor control for a stand-alone hybrid generation system using wind and photovoltaic energy, IEEE Trans. Energy Convers. 20 (2) (Jun. 2005) 398–405, https://doi.org/10.1109/TEC.2005.845524.
[111] D. Ipsakis, S. Voutetakis, P. Seferlis, F. Stergiopoulos, C. Elmasides, Power management strategies for a stand-alone power system using renewable energy sources and hydrogen storage, Int. J. Hydrogen Energy 34 (16) (Aug. 2009) 7081–7095, https://doi.org/10.1016/j.ijhydene.2008.06.051.
[112] D.-J.W. Ki-Hyeok Kang, Power management strategy of stand-alone hybrid system to reduce the operation mode changes, IEEE T&D Asia (2009).
[113] J.P. Torreglosa, P. García, L.M. Fernández, F. Jurado, Hierarchical energy management system for stand-alone hybrid system based on generation costs and cascade control, Energy Convers. Manag. 77 (2014) 514–526, https://doi.org/10.1016/j.enconman.2013.10.031.
[114] S. Al-Sakkaf, M. Kassas, M. Khalid, M.A. Abido, An energy management system for residential autonomous DC microgrid using optimized fuzzy logic controller considering economic dispatch, Energies 12 (8) (Apr. 2019), https://doi.org/10.3390/en12081457.
[115] A. Rouniyar and M. Karki, "Energy Management System for Hybrid PV-Wind-Battery Based Standalone System.".
[116] L. Olatomiwa, S. Mekhilef, M.S. Ismail, M. Moghavvemi, Energy management strategies in hybrid renewable energy systems: a review, in: Renewable and Sustainable Energy Reviews, vol. 62, Elsevier Ltd, 2016, pp. 821–835, https://doi.org/10.1016/j.rser.2016.05.040.
[117] Y.-K. Chen, Y.-C. Wu, C.-C. Song, Y.-S. Chen, "Design and Implementation of Energy Management System with Fuzzy Control for DC Micro-grid Systems,", 2011.
[118] E. Alonso, M. D'Inverno, D. Kudenko, M. Luck, J. Noble, Learning in multi-agent systems, Knowl. Eng. Rev. 16 (3) (Jun. 2001) 277–284, https://doi.org/10.1017/S0269888901000170.
[119] K. Khadedah, V. Lakshminarayanan, N. Cai, J. Mitra, Development of communication interface between power system and the Multi-Agents for micro-grid control, in: 2015 North American Power Symposium, NAPS 2015, Institute of Electrical and Electronics Engineers Inc., Nov. 2015, https://doi.org/10.1109/NAPS.2015.7335083.
[120] D. Saba, F.Z. Laallam, A.E. Hadidi, B. Berbaoui, Contribution to the management of energy in the systems multi renewable sources with energy by the application of the multi agents systems 'mAS, in: Energy Procedia, Elsevier Ltd, 2015, pp. 616–623, https://doi.org/10.1016/j.egypro.2015.07.792.
[121] S. Lalouni and D. Rekioua, "Modélisation, Simulation et Gestion d'énergie d'un Système Hybride (Photovoltaïque/Eolien) avec Stockage d'énergie.".
[122] N. T. Mbungu, A. A. Ismail, M. A. Alshabi, R. C. Bansal, A. Elnady, and A. K. Hamid, "Control and Estimation Techniques Applied to Smart Microgrids: A review.".
[123] N.T. Mbungu, R.M. Naidoo, R.C. Bansal, M.W. Siti, Model predictive control: a survey of dynamic energy management, in: Proceedings of the 18th International Conference on Informatics in Control, Automation and Robotics, ICINCO 2021, SciTePress, 2021, pp. 123–129, https://doi.org/10.5220/0010522201230129.
[124] A. Mesbah, Stochastic model predictive control: an overview and perspectives for future research, IEEE Control Syst. Mag. 36 (6) (Dec. 01, 2016) 30–44, https://doi.org/10.1109/MCS.2016.2602087. Institute of Electrical and Electronics Engineers Inc.
[125] D.P. Koottappillil, R.M. Naidoo, N.T. Mbungu, R.C. Bansal, Distribution of renewable energy through the energy internet: a routing algorithm for energy routers, Energy Rep. 8 (Dec. 2022) 355–363, https://doi.org/10.1016/j.egyr.2022.10.201.