Hybrid Meta-Heuristic Algorithms for Optimal Sizing of Hybrid Renewable Energy System: A Review of the State-of-the-Art

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Abstract
The hybrid renewable energy system (HRES) has been presented as the most studied solution for improving the sustainability of energy production infrastructures in isolated areas. With the rapid growth of HRES markets, various issues and aspects must be taken into consideration when the major working about the hybridization of renewable energy sources, consequently optimization problem solving for this system is a requirement. Therefore, this paper presents a state-of-the-art review of hybrid meta-heuristic algorithms applied for the optimal size of HRES. The relevant literature source and their distribution are presented firstly. We then review the literature from two viewpoints, including existing applied hybrid meta-heuristic algorithms for single-objective and for multi-objective design. Finally, some promising paths ranging from improving algorithms to technical applications are outlined to encourage researchers to conduct research in related fields.

1 Introduction
Increasing energy demand, fluctuating of fossil fuel price after the COVID-19 pandemic, as well as the environmental problems associated with the combustion of fossil fuels [1–3], have increased the need for alternative energy resources [4]. Renewable resources, which do not deplete, including sun, wind, land, and water. As a result, there has been an increase in the search for the development of technologies to use these resources [5]. Renewable energies are exploited in different ways in different parts of the world [6]. The ranges of renewable resources used include biomass, geothermal energy, wind power, hydroelectricity, and solar energy. Each of these renewable technologies has its advantages and disadvantages [7]. Hydro power and geothermal energy are specific to the location of their primary energies, which limits their use [8, 9]. The development of biomass has implications for food production because to produce this energy more efficiently, it requires occupying fertile land and therefore reducing agricultural production and leading to significant deforestation [10]. Wind turbines require regular maintenance due to moving parts and are not considered aesthetically attractive [11]. Solar energy also has its disadvantages. However, photovoltaic (PV) panels require minimal maintenance, generate no noise and their cost will continue to decrease over the next few years [12]. These energy sources, also known as dispersed production, can operate either in the presence of the grid (connected to the grid) where the system’s primary priority is to satisfy local demand for electricity and sometimes to supply surplus energy to the grid, or as a standalone power generation system regardless of the utility of the grid in isolated sites [13].

The implementation of decentralized hybrid renewable energy systems is the most studied solution for improving the sustainability of energy production infrastructures at isolated locations [14]. These systems combine two or more renewable energies. The main objective is to exploit the available renewable resources in order to improve the overall efficiency and cost-effectiveness of the system in terms of cost and availability, knowing that the ecological balance, is assumed a priori favorable [15]. Moreover, with the rapid growth of renewable energy markets, the importance of integrating multiple sources of energy in a renewable energy based hybrid system has drawn greater interest [16]. However, various issues and aspects must be taken into account when the primary debate is around the hybridization of renewable energy sources [17]. Indeed, due to the random nature of renewable energy supplies, the electrical load profile, as well as the non-linear response of characteristics...
system components, is not easy to evaluate the performance of the hybrid energy system [18], therefore, designing hybrid energy systems is a complex task. Optimization that most effectively sizes the hybrid system components to meet the economic, technical, and design objectives is necessary.

In recent research works for optimization of hybrid renewable energy design, there is an increase in usage of meta-heuristic algorithms, due they provide more accurate optimization results than traditional methods. In Ref. [19], a cost/reliability evaluation for a stand-alone hybrid PV/battery/diesel system for urban electricity supply is presented using particle swarm algorithm. In Ref. [20] the optimal design of a hybrid PV/biomass system was investigated with minimization of cost of energy and considering the loss of power supply probability using a harmony search algorithm. In Ref. [21] designing of PV/diesel/battery system was presented with the objective of minimizing the total annual cost using a grey wolf optimizer algorithm in a case study for Algeria. In Ref. [22], an off-grid PV/wind/battery system was designed optimally in order to minimize levelized cost of electricity considering the full supply of the load using the firefly algorithm for a region in India. However, as the complexity of hybrid systems increases, these techniques may prone to fall into local optima [23, 24]. Therefore, researchers in recent years applied hybrid meta-heuristic optimization algorithms to solve one of those problems. Hybrid optimization algorithms, which is a combination of two or more different algorithms are suitable for problems that consider more than one object in the optimization problem Fig. 1.

Although the available recent review articles related to the area of sizing methodologies for hybrid renewable energy systems focused on single methods such as traditional methods, artificial intelligence methods, software tools [24–33]. Summary highlights of these studies are given in Table 1. These studies have to some extent neglected the discussion of hybrid optimization algorithms. Thus, there is a need for updated information on the hybrid algorithms and a need for up-to-date on the notion of the hybridization as well as an investigation on the effectiveness of techniques used. This paper first provides a comprehensive overview of hybrid optimization algorithms and prescribes the motivations of their developments, then discusses some drawbacks concerning hybrid meta-heuristics algorithm with a brief summary of hybridization technique. Available application of hybrid algorithm used to design hybrid renewable energy system components from the literature have been presented. Finally, some suggestions for future search were recommended that can be useful to overcome the limitations of hybrid algorithm for size optimization of renewable energy based hybrid systems.

2 Optimization Concept and Problem

Man seeks to improve his daily life, man loves perfection and without him realizing it, he tries to minimize his expenses, his rent or the consumption of his car, etc., he always tries to optimize that is to minimize his expenses and maximize his goods. The mathematician comes to concertize man’s wishes by modeling life problems under cost functions using different types of optimization.

Solving optimization problems has become a central topic in operational research, as the number of decision support
| S. No. | Ref.                | Year | Systems covered                                      | Topics covered                                                                 | Highlights                                                                                                                                 |
|-------|---------------------|------|-----------------------------------------------------|--------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| 1     | Banos et al. [25]   | 2011 | Includes all possible combinations of hybrid renewable energy systems | Reviewed single and multi-objective optimizations for renewable energy based hybrid systems  
Optimization techniques reviewed:  
- Traditional approaches  
- Heuristic optimization methods  
- Pareto-optimization techniques | Concludes that heuristic approaches, parallel processing, and Pareto front-based multi-objective optimization are most promising methods for solving hybrid system design problems |
| 2     | Fadae and Radzi [26] | 2012 | Review focused on different combinations of PV/wind/diesel/battery based hybrid systems | Studied multi-objective optimizations for hybrid renewable energy system  
Optimization techniques discussed:  
- Multi-objective evolutionary algorithms (MOEA) | Evolutionary algorithms such as GA and PSO are identified to be promising to find solution for many objective optimizations. |
| 3     | Khatib et al. [27]  | 2013 | Study concentrates on various combinations of on/off-grid PV/wind/diesel based hybrid systems | Reviewed size optimization methodologies for standalone PV systems:  
- Artificial intelligence methods  
- Intuitive approaches  
- Numerical approaches  
- Analytical approaches  
- Grid-connected sizing optimization techniques discussed are:  
- Artificial intelligence methods  
- Intuitive approaches  
- Numerical approaches  
- Software based approach: HOMER | Artificial intelligence methods are recommended to solve size optimization problem of renewable energy based hybrid system components |
| 4     | Sinha and Chandel [28] | 2014 | Review covers on various combinations PV/wind/battery based hybrid systems | Software tools reviewed are: HOMER, RETScreen, HYBRID2, iHOGA, NSEL, TRNSYS, IGRHYSO, HYBRIDS, RAPSIM, SOMES, SOLSTOR, HySim, HybSim, IPSYS, HySys, Dymola/Modelica, ARES, SOLSIM, and Hybrid Designer | Concludes HOMER as a faster, easier, and most widely used tool to evaluate the many possible system combinations. |
| 5     | Fathima and Palanisamy [29] | 2015 | Study concentrates mostly on PV, wind, diesel, and energy storage hybrid systems | Reviewed sizing objectives, control and energy management of renewable energy based hybrid systems  
Mathematical model for PV, wind, diesel generators, and energy storage systems are studied | Promising methods mentioned are: Tabu Search (TS), Honey Bee Mating Algorithm (HBMA), Multicriteria Decision Analysis Optimization (MDAO), Bacterial Foraging Algorithm (BFA), Biogeography based optimization (BBO) Artificial Immune System Algorithm (AISA), Firefly Algorithms (FA)  
PSO are suitable for high dimensional problems than GA |
| S. No. | Ref.             | Year     | Systems covered                               | Topics covered                                                                 | Highlights                                                                 |
|-------|------------------|----------|-----------------------------------------------|--------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| 6     | Khare et al. [30]| 2016     | Concentrated on PV/wind based hybrid systems  | Reviewed various sizing methodologies used:                                    | Iterative and artificial intelligence methods are useful for size optimization of PV-wind hybrid systems, but it requires to be improved |
|       |                  |          |                                               | Differential evolution (DE)                                                    |                                                                            |
|       |                  |          |                                               | Genetic algorithm (GA)                                                        |                                                                            |
|       |                  |          |                                               | Particle swarm optimization (PSO)                                              |                                                                            |
|       |                  |          |                                               | Simulated annealing (SA)                                                      |                                                                            |
|       |                  |          |                                               | Ant colony algorithm (ACS)                                                    |                                                                            |
|       |                  |          |                                               | Software based approach:                                                      |                                                                            |
|       |                  |          |                                               | HOMER                                                                         |                                                                            |
|       |                  |          |                                               | GAMS                                                                          |                                                                            |
|       |                  |          |                                               | HYBRID2                                                                       |                                                                            |
|       |                  |          |                                               | RETSCREEN                                                                     |                                                                            |
|       |                  |          |                                               | Discussed feasibility analysis, modeling, reliability issues, and control aspects of PV/wind based hybrid systems |                                                                            |
|       |                  |          |                                               | Optimization techniques reviewed are:                                        |                                                                            |
|       |                  |          |                                               | Genetic algorithm (GA)                                                       |                                                                            |
|       |                  |          |                                               | Particle swarm Optimization (PSO)                                             |                                                                            |
|       |                  |          |                                               | Fuzzy                                                                         |                                                                            |
|       |                  |          |                                               | Neural                                                                         |                                                                            |
|       |                  |          |                                               | Game theory                                                                   |                                                                            |
| 7     | Al-falahi et al. [31] | 2017   | Focused on standalone PV/wind based hybrid systems | Reviewed various PV/wind combinations and configurations for standalone application, design parameters, and evaluation criteria for power system reliability | Study suggests that artificial intelligence methods and hybrid algorithms provide more accurate optimization solutions than classical techniques |
|       |                  |          |                                               | Sizing methodologies reviewed are:                                            |                                                                            |
|       |                  |          |                                               | Classical techniques                                                         |                                                                            |
|       |                  |          |                                               | Artificial intelligence methods                                              |                                                                            |
|       |                  |          |                                               | Hybrid algorithms                                                             |                                                                            |
|       |                  |          |                                               | Software tools for hybrid PV/wind systems mentioned are:                     |                                                                            |
|       |                  |          |                                               | HOMER Pro                                                                     |                                                                            |
|       |                  |          |                                               | HOMER                                                                         |                                                                            |
|       |                  |          |                                               | iHOGA                                                                         |                                                                            |
| 8     | Anoune et al. [32]| 2018    | Focused only on standalone PV/wind based hybrid systems | Discussed different solar/wind combinations and configurations for standalone system, design parameters, and evaluation criteria | Artificial intelligence and heuristic approaches are most suitable and efficiency for solving hybrid renewable energy optimization problems |
|       |                  |          |                                               | Sizing methodologies reviewed are:                                            |                                                                            |
|       |                  |          |                                               | Classical techniques                                                         |                                                                            |
|       |                  |          |                                               | Artificial intelligence methods                                              |                                                                            |
|       |                  |          |                                               | Multi-objective approach                                                     |                                                                            |
|       |                  |          |                                               | Software based approach:                                                      |                                                                            |
|       |                  |          |                                               | HOMER, iHOGA, HYBRID2, TRNSYS, HYDROGEMS, INSEL, ARES, SOLSIM, SOMES, H2RES   |                                                                            |
| S. No. | Ref.       | Year | Systems covered                                      | Topics covered                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Highlights                                                                                                                                                                                                 |
|-------|------------|------|-----------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 9     | Lian et al. [24] | 2019 | Review covers all forms of renewable energy sources based hybrid systems | Reviewed various operating mode (Standalone, grid-connected), various structure of system (presence/absence of conventional source, presence/absence of storage, renewable energy used) and system performance indicators  
Sizing methodologies reviewed are: Analytical method, Probabilistic method, Iterative method, Numerical method, Graphic construction method, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Ant Colony Optimization (ACO), Artificial bee colony (ABC), Cuckoo search (CS), Hybrid methods  
Software tools reviewed are: HOMER, iHOGA, HYBRIDS, HYBRIDS2, HOMER, iHOGA, HYBRIDS, HYBRIDS2 | Hybrid optimization methods are recommended for hybrid renewable energy systems research to avoid the limitations of one methodology due to their greater adaptability and optimization performance |
| 10    | Emad et al. [33] | 2020 | Study covers PV/wind/battery system                 | Mathematical model for wind, solar, and energy storage systems are studied  
Discussed various architecture of power source configuration: DC, AC, and hybrid DC/AC coupled configurations  
Reviewed hybrid system Economical parameters: Net Present Cost (NPC), Life Cycle Cost (LCC), Total Annual Cost (TAC), and Cost of Energy (COE)  
Sizing methods reviewed are: Classical Techniques, Meta-heuristic Techniques, Classical and Meta-heuristic Techniques  
Software tool reviewed is: Homer | Article conclude that meta-heuristic optimization techniques are more accurate and required less computational time than classical techniques |
problems that can be formalized as an optimization problem is growing rapidly [34]. Problems such as learning neural networks [35], task planning [36] or identification [37] are, for example, common optimization problems.

In general, optimization problems are problems of searching for the minimum (or maximum) of a function of one or more variables subject or not to constraints. Mathematically, in the case of minimization, an optimization problem is presented as follows [38]:

\[
\begin{align*}
\text{Minimize} & \quad f(x) \\
\text{subject to} & \quad h_i(x) = 0, \quad i = 1, \ldots, m, \\
& \quad g_j(x) \leq 0, \quad j = 1, \ldots, k, \\
& \quad \mathbf{x_L} \leq x \leq \mathbf{x_U}
\end{align*}
\]

(1)

Here, \(x \in \mathbb{R}^d\) is the vector of the decision variables, \(f\) is the objective function, \(h_1, \ldots, h_m\) and \(g_1, \ldots, g_k\) are respectively the constraints of equality and inequality and \(x_L, x_U\) are respectively the lower and upper bounds of the search domain of the variables. This set defines the state space, while the set of points in the possible state space that best satisfies the constraints is given by:

\[
C = \{ x \in \mathbb{R}^d / h_i(x) = 0, \quad g_j(x) \leq 0 \text{ and } x_L \leq x \leq x_U \}
\]

(2)

It is possible to go from a maximization problem to a minimization problem, thanks to the following property:

\[
\max_{x \in C} f(x) = \min_{x \in C} -f(x)
\]

(3)

Depending on the nature of \(f(x)\), constraints \(g_j(x)\), and variables \(x\), the corresponding optimization problem may be classified in different ways based on several of criteria. For example, it is possible to classify optimization problems into two types deterministic or stochastic optimization depending on whether the data involved in the problem is definitely known or not; limited or unlimited optimization depending on whether limits exist; discrete (combinatorial), continuous or mixed optimization depending on deciding variables; uni or multimodal; with or without constraints; and single or multi-objective depending on the number of objective functions [39].

### 2.1 Multi-objective Optimization Problem: Brief Overview

Multi-objective optimization is a fundamental area of multi-criteria decision support, necessary for many scientific and industrial environments. Over the last two decades, a very large number of works, both theoretical and applied, have been published in this field. The resolution of a multi-objective optimization problem consists of determining the solution that best corresponds to the decision maker’s preferences among good compromise solutions [40]. One of the most difficult questions is therefore related to the identification of the optimal Pareto set, or an approximation of it for complex problems. In particular, many mechanical problems encountered in industry are multi-objective nature.

A multi-objective or multi-criteria problem can be defined as a problem where one seeks to optimize several components of the vectors of the objective function, while satisfying a set of constraints. Contrary to a single-objective problem, the solution is not unique but consists of a set of so-called optimal Pareto solutions [40].

The mathematical formulation of a multi-objective optimization problem is given as follows [41]:

\[
\begin{align*}
\text{Minimize} & \quad \mathbf{F}(x) = (f_1(x), \ldots, f_l(x))^T \\
\text{subject to} & \quad h_i(x) = 0, \quad i = 1, \ldots, m, \\
& \quad g_j(x) \leq 0, \quad j = 1, \ldots, k, \\
& \quad \mathbf{x_L} \leq x \leq \mathbf{x_U}
\end{align*}
\]

(4)

with \(x \in \mathbb{R}^d\) is the vector of decision variables, \(\{f_1, \ldots, f_l\}\) is the ensemble of objective functions.

The main difficulty of a multi-objective problem is that there is no definition of the optimal solution. The decision-maker may simply express the fact that one solution is better than another, but there is no one solution that is better than all the others [40]. Therefore, solving a multi-objective problem does not consist in searching for the optimal solution but for the set of satisfactory solutions for which a ranking operation cannot be performed. Multi-objective problem solving methods are therefore methods of decision support because the final choice will be left to the decision-maker.

To respond to this problem, the scientific community has adopted two types of behavior [41]:

- Transform a multi-objective problem to a single-objective problem;
- Attempt to provide answers to the problem by taking into consideration all the objective functions.

It is very difficult to recommend one behavior over the other. Either the decision-maker intervenes at the very beginning of the problem definition, by expressing his preferences, in order to transform a multi-objective problem into a single-objective problem. Or the decision-maker makes his choice from the set of solutions proposed by the multi-objective optimization method.

The main quality of a multi-objective optimization method is thus making decisions easier and less subjective.
2.2 Hybrid Renewable Energy System Optimization Problem

The optimization problem of the hybrid renewable energy systems can be categorized as non-linear, non-convex, multi-objective in nature consisting of discrete/integer variables and non-linear/linear constraints [63]. The modality of the HRES sizing problem is assumed to be multimodal and thus the global optimum solution is essential to investigate. The main objective when designing an HRES is to supply the load continuously with minimum possible cost while satisfying all imposed constraints. In order to design an HRES, there are four main perspectives to be identified: decision variables, objective function, constraints, and optimization techniques.

2.2.1 Decision Variables

Decision variables are a set of quantities needed to be identified in order to solve the problem. In fact, defining the decision variables of the problem is one of the hardest steps in formulating a problem. More specifically, in the HRES optimization various system combinations exist which comprises different numbers and types of components, as the distributed energy generators (e.g. PV, WT, Biomass, DG, ), the energy storage systems (e.g. battery and fuel cell), and the energy conversion devices (e.g. converter and inverter).

2.2.2 Objective Function

For an optimization problem, an objective function must be defined as the objective of the optimization. Finding the optimum sizes of HRES components is the key factor to reduce the cost with reliable and environmental accepted power supply. There are various indicators reported in literature to assess HRES which have a great influence on the system capacity. Existent evaluation indicators for design optimization include: reliability, economic, and environmental indicators which are summarized in Table 2. In addition to the above indicators, few studies have considered social assessments such job creation [64], human development index [65], social acceptance [66], portfolio risk [67], and social cost of carbon [56].

2.2.3 Constraints

A constraint is a logical relationship, a property that must be verified between different variables (design variables), each taking its values in a given set, called domain. When tackling a constrained optimization problem, the constraints have to be identified before applying the optimization algorithm to the problem. The set of constraints is in general a set of equalities or inequalities, linear (for example upper and lower bound for HRES optimization problem) or non-linear that the variables of the state space must satisfy. These constraints limit the search space [38]. In the HRES optimization, different constraints have been applied that include number/capacity/installation/area of hybrid system components (PV panels, wind turbines, batteries, inverter), PV tilt angle, wind turbine height, depth of discharge (DOD), state of charge (SOC) and renewable fraction (RF).

2.2.4 Optimization Techniques

Focusing on the size problem, due to the intermittent and limited nature of renewable sources as well as the significant variation in the electricity consumption of a home basing on the time of day and season, the problem of sizing hybrid renewable energy systems is crucial. Since the 1990s, several works have focused on this problem. The first methods (traditional methods) are based on the experience and the justification of the proposed practice. They are based on the statistical study of production deposit data (wind speed, sunshine, and ambient temperature) and consumption profile. The new methods (meta-heuristic methods) are rather based on dynamic simulations and have led to the realization of various software tools for sizing. A brief description of these tools have been enlisted in Table 3.

2.3 Meta-Heuristic Optimization Algorithms

Today’s managers and decision-makers are confronted daily with increasingly complex problems that arise in a wide variety of sectors especially the design of hybrid renewable energy systems. The problem to be solved can often be expressed in the general form of an optimization problem, in which one or more objective functions are defined that one seeks to minimize or maximize in relation to all the parameters concerned. The resolution of such a problem has led researchers to propose more and more efficient methods, including meta-heuristics, which are general research methods dedicated to difficult optimization problems.

Meta-heuristics optimization are general optimization algorithms applicable to a wide variety of problems. They appeared from the 1980s onwards, with the aim of solving optimization problems in the best possible manner. In most cases, three types of optimization problems are frequently encountered: combinatorial (discrete) problems, continuous (continuous variable) problems, and mixed problems. The most common example in combinatorial optimization is traveling salesman problem. In continuous optimization, a simple example is the search for the parameters of a numerical model in order to get as close as possible to real data. The last type is that of mixed problems, which involve both discrete and continuous variable. Meta-heuristics tries to solve any kind of optimization problem. They are characterized by...
their stochastic character, as well as by their discrete origin [68]. They are inspired by analogies with physics (simulated annealing), with biology (evolutionary algorithms) or ethology (ant colony, particle swarms). Their particularity lies in the fact that they are adaptable to a large number of problems without major changes in their algorithms, hence the qualifier “meta”. One of their advantages is their ability to optimize a problem from a minimal amount of information, however they offer no guarantee as to the optimality of the best solution found. Only an approximation of the global optimum is given. Meta-heuristics are methods that have an iterative behavior, i.e. the same pattern is reproduced a certain number of times during optimization, and they are direct, in the sense that they do not involve the calculation of the gradient of the function. The user is certainly needs fast and efficient methods, but he is also in demand for methods that are easy to use. A major challenge of meta-heuristics is therefore to facilitate the choice of methods and to simplify their settings, in order to adapt them to the problems posed. Meta-heuristics are constantly evolving. Numerous methods are proposed each year to improve the resolution of the most complex problems. As a result of this permanent activity, a significant number of classes of meta-heuristics currently exist.

Despite the remarkable success of meta-heuristic algorithms, they present difficulties that are faced by the user in the case of a concrete problem such as the choice of an efficient method to have an optimal solution and the setting of parameters that may be feasible in theory but not in practice. The researchers are aiming to overcome these difficulties by proposing techniques that of improvement of which we cite the hybridization of meta-heuristics. This hybridization exploits the power of several algorithms and combines them in a single meta-algorithm.

### 3 Hybrid Meta-Heuristic Optimization Algorithms

The appearance of meta-heuristic methods and the improvement of these with the combination of other methods allow the introduction of a so-called hybrid method, which uses the positive influence of these techniques to obtain an optimal result for a specific design problem. These methods are evolved and much more applied in the literature.

Taking into account information from the Web of Science database, one of the world’s leading academic literature databases, based on two specific keywords: hybrid algorithm and optimization. These keywords were applied to search in the titles, keywords, and abstracts of papers in the database between 2010 and 2020. Fig. 2 shows the published items about hybrid optimization algorithm in a period of 10 years. It can be observed that a greater number of researches related to optimization using hybrid algorithms has been conducted in the past years, with a continuing increase, and there is several countries such as India, China, Iran, and the USA have demonstrated more interest in hybrid optimization algorithm compared to other countries.

Hybridization is a trend observed in many works on meta-heuristic algorithms in the last ten years. It makes it possible to draw benefits from the cumulative advantages of different meta-heuristic algorithms to such an extent that the meta-heuristics that we have seen so far are no longer as frameworks, starting points, to begin to solve an optimization problem. Hybridization consists in combining the characteristics of two different methods to derive the benefits of both methods. The origins of hybrid meta-heuristic algorithms can be traced back to the work of Glover [69]. Each of them introduced a simple descent method to improve evolutionary research. But At that time, most researchers had little interest in it. Currently, hybrid

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**Fig. 2** Number of research papers (including review and research articles) per: a Years, b Countries

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## Table 2 Summary of economical, reliability and environmental indices for HRES

| S.No. | Indicators                                      | Description                                                                 | Formulae                                                                 | References |
|-------|------------------------------------------------|----------------------------------------------------------------------------|--------------------------------------------------------------------------|------------|
|       | **Economical indices**                          |                                                                            |                                                                          |            |
| 1     | Annualized cost of the system (ACS)/Total annual cost (TAC) | It is defined as the summation of annualized capital system cost, annualized operational and maintenance costs, and the annualized replacement cost. | $ACS = C_{acap} + C_{arep} + C_{amain}$<br>$C_{acap}$: the annual capital cost of the system.<br>$C_{arep}$: the annual replacement cost of the system.<br>$C_{amain}$: is annual maintenance cost of the system. | [42]       |
| 2     | Net present cost (NPC)/Net present value (NPV)  | It demonstrates the ratio of annual aggregate cost of the system to the yearly power Net Present Cost (NPC) conveyed by the system. It is complete estimation of cost including starting cost, replacement expense and upkeep cost of system. | $NPC = TAC/CRF$<br>$CRF$: the capital recovery factor.<br>$i$: the interest rate.<br>$y$: the lifespan of the system. | [39]       |
| 3     | Life cycle cost (LCC)                           | It is defined as the sum of the NPVs for all the total amount of the system costs such as capital costs, operation and maintenance costs, replacement costs. | $LCC = C_{cap} + C_{O&M} + R_{npv} - S_{npv}$<br>$C_{cap}$: the capital costs.<br>$C_{O&M}$: the net present value of operation and maintenance costs.<br>$R_{npv}$: the net present value of replacement costs.<br>$S_{npv}$: the net present value of salvage value. | [39]       |
| 4     | Levelized cost of energy (LCOE)                 | It is the ratio of the ACS to the total electricity generated by the system.  | $LCOE = TAC/E_{tot}$<br>$E_{tot}$: the total annual energy generated by the system. | [24]       |
|       | **Reliability indices**                          |                                                                            |                                                                          |            |
| 1     | Loss of power supply probability (LPSP)         | It is defined as the percentage of power supply that it is not able to satisfy the load demand. It indicates the reliability of power supply to load. | $LPSP = \sum_{t=1}^{8760} ES(t)/\sum_{t=1}^{8760} LD(t)$<br>$ES(t)$: the power shortage at t hour (kWh).<br>$LD(t)$: the load demand at t hour (kWh). | [43]       |
| 2     | Expected energy not supplied (EENS)             | It is the expected energy which is not provided to the load under the condition when the load exceeds the available generation capacity. | $EENS = \sum_{t=1}^{8760} E_{unserved}(t)/\sum_{t=1}^{8760} LD(t)$<br>$E_{unserved}(t)$: the amount of energy that will not be served at t hour of the year (kWh). | [42]       |
| 3     | Deficiency of power supply probability (DPSP)   | It is defined as the ratio of all (DPS(t)) values to the sum of the load demand for a given period, and it represents the possibility of an insufficient power supply situation when the hybrid system cannot meet the load demand. | $DPSP = \sum_{t=1}^{8760} DPS(t)/\sum_{t=1}^{8760} LD(t)$<br>DPS: (power supply fault) is a condition that occurs when the main power generation components and/or backup units of the HRES cannot meet the load demand. | [27]       |
| 4     | Loss of load expected (LOLE)                    | It represents the expected number of hours in a year when the load exceeds the available electric generation capacity (h/year). | $LOLE = \sum_{t=1}^{8760} \sum_{i\in S} P_i \times Ti$<br>$S$: the total loss of load states of the system.<br>$P_i$: the probability of the system encountering state $i$.<br>$Ti$: the time of a load exceeds the production capacity (hour). | [32]       |
| 5     | Level of autonomy (LA)                          | It is the time ratio which expressed the percentage of load covered based on the operational time of the system. | $LA = 1 + T_{lost} \times T_{Operation}$<br>$T_{lost}$: the total time load not supplied.<br>$T_{Operation}$: the total operation hour of the system. | [42]       |
|       | **Environmental indices**                       |                                                                            |                                                                          |            |
meta-heuristics have become more popular because the best results found for many combinatorial optimization problems have been obtained with hybrid algorithms. The hybridization of meta-heuristics can be divided into two main parts [70]:

(i) Hybridization of meta-heuristics with meta-heuristics
(ii) Hybridization of meta-heuristics with others (Exact methods or Soft computational techniques)

3.1 Meta-Heuristics-Meta-Heuristics Hybridization

According to the taxonomy presented by Talbi [71] the hybridization of meta-heuristics between them takes place in two main classifications. A hierarchical classification and a flat classification.

Hierarchical classification is based on the level (low or high) of the hybridization and the mode (relay or co-evolutionary). On one hand, low-level hybridization, a given component in a meta-heuristic (e.g., mutation in an evolutionary algorithm) is replaced by another meta-heuristic. In the high-level hybridization, the internal functioning of the meta-heuristics is not modified. Each level of hybridization generates two modes of cooperation, relay and co-evolutionary mode. In a relay mode, the meta-heuristics are launched one after the other, each taking as input the output produced by the previous one. In co-evolutionary mode, each algorithm uses a series of agents cooperating together. The combination of modes and levels results in four hybridization classes which are (a) low-level relay hybridization, (b) low-level co-evolutionary hybridization, (c) high-level relay hybridization and, (d) high-level co-evolutionary hybridization [70].

The flat classification of meta-heuristics is characterized by the type of hybrid methods, their field of application, and the nature of their functions. According to the type of hybridization, Hybridization is said homogeneous when the combined meta-heuristics are identical, otherwise it is heterogeneous. The field of application of hybridized meta-heuristics makes it possible to distinguish two main classes of hybridization, global hybridization, and partial hybridization. A global hybridization ensures that all meta-heuristics explore the whole solution space, if they are limited to subpart of the space, we speak of a partial hybridization. Depending on the problem treated, two types of hybridization are distinguished, a generalist hybridization and a specialist hybridization. Generalist hybridization is when all hybridized meta-heuristics deal with the same optimization problem. Conversely, specialist hybridization occur when each meta-heuristic treats a different problem [70].

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| S.No. | Indicators | Description | Formulae | References |
|-------|------------|-------------|----------|------------|
| 1     | Total CO₂ Emissions/Fuel emissions (E) | It evaluates the carbon dioxide emissions in a period of time. | \[ E = \sum_{t \in T} \sum_{n \in N} E_{g_{n t}} \] | [44] |
|       | En: the amount of CO₂ emission generated by the unit of type n in time period t (ton/MWh). gn_{nt}: the sum of the energy generated by a non-renewable generating n units in time period t (MWh). | \[ E_{g_{n t}} = 2 \times \text{energy consumption of non-renewable sources (MWh)} \times \text{CO₂ emission factor} \] | \[ E_{g_{n t}} = 2 \times 26.1 \times 1.3 \times A_{n_{t}} \] |
|       | Embodied Energy (EE) | It refers to the energy that a hybrid energy system does not consume during its use. It involves the production of components that consume non-renewable primary energy. In short, it is the energy required for all activities related to the production process. | \[ P_{V_EE} = 3.78 \times A_{p v}; \quad W_{T_EE} = 28.34 \times A_{w t}; \quad B_{at_EE} = 60 \times C_{n} \] | \[ P_{V_EE}, W_{T_EE}, B_{at_EE}: the primary embodied energy of PV panels, wind turbines and batteries respectively. A_{p v}, A_{w t}, C_{n}: the swept area of wind turbines (m²), the surface area of PV panels (m²), and the nominal capacity of batteries (Ah). \] | [45] |
Table 3  Summary of techniques used for sizing of renewable energy based hybrid systems

| S. No. | Optimization techniques | Description |
|--------|-------------------------|-------------|
| 1      | **Traditional methods** | Trade off method [46], Iterative approach [47], Probabilistic approach [48], Linear programming [49], Graphical construction technique [50], Direct algorithm [51] and Analytic method [52], Numerical method [53], Mixed integer linear programming [54] |
| 1      | **Traditional methods** | Trade off method [46], Iterative approach [47], Probabilistic approach [48], Linear programming [49], Graphical construction technique [50], Direct algorithm [51] and Analytic method [52], Numerical method [53], Mixed integer linear programming [54] |
| 2      | **Meta-heuristic algorithms** | Genetic Algorithm (GA) [55], Particle Swarm Optimization (PSO) [56], Simulated Annealing (SA) [57], Ant Colony Algorithms (ACA) [58], Artificial Bee Colony Algorithm (ABC) [59], Cuckoo Search (CS) [60], Bacterial Foraging Algorithm (BFA) [61]. |
| 3      | **Software tools** | [62] HOMER, iHOGA, HYBRID2, TRNSYS, HYDROGEMS, INSEL, ARES, SOLSIM, SOMES, H2RES |

Traditional methods are relatively simple to implement “by hand” or with spreadsheets. For this reason, a majority of PV system installers use them. However, compared to simulating the system with a software tool, such methods can take more time. Secondly, these methods do not take into account weather changes and the variation in the shape of the consumption profiles, which are based on daily average values and not instantaneous. Furthermore, these methods focus on minimizing economic cost and satisfying user demand. They do not integrate environmental concerns.

Known for many years for their efficiency, meta-heuristics are a family of stochastic methods that consist of solving optimization problems. They generally exploit random processes in the exploration of the research space to cope with the combinatorial explosion generated by the use of exact methods. On the other hand, they often prove to be efficient in very large problems and, moreover, can benefit from convergence theorems while providing good quality solutions in a reasonable time. The disadvantage of this type of method is the existence of parameters to be adjusted in order to obtain a satisfactory convergence.

Most of these tools are used to simulate a given system predefined by the user and are rather dedicated to evaluate a certain system configuration and manually visualize the effect of a change in its parameters. The degree of precision of the models that use these tools varies from one to another and do not integrate the primary energy contained in the system as an evaluation indicator, so that only the economic aspect is considered.
Hybridization of meta-heuristics with other techniques such as exact methods or soft computational techniques has been less common than meta-heuristic-meta-heuristic hybridization because most researchers considered it to be quite useless. Recently, this hybridization is beginning to spread and a large number of articles have been published concerning this study [70]. We can apply the hierarchical and flat classification that used meta-heuristic-meta-heuristic hybridization for this technique without considering homogeneous models, since meta-heuristics and exact methods are definitely different.

4 Hybrid Meta-Heuristic Algorithms Applied for Sizing HRES

This section is devoted to the description of hybrid meta-heuristic algorithms applied to solve optimization problems of sizing hybrid renewable energy systems components from the point of quality results and computational time is provided below.

4.1 Hybrid Meta-Heuristic Approaches for Mono-Objective Design

Gandomkar et al. [72] were the first to implement hybrid meta-heuristic algorithms to find components sizes of a hybrid renewable distributed energy generations (PV/wind/biomass) based on minimizing the power loss (PL). The authors used Glover work [69] to combine tabu search (TS) and genetic algorithm (GA) by implementing the neighbors of TS for generating part of a new generation in the GA process to improve their efficiency. The results indicated that the new method had much better solution accuracy and convergence process than the original GA.

Dufo-Lopez and Bernal-Agustin [73] used a hybrid genetic algorithms to obtain the optimal number of system elements for a standalone PV/diesel based hybrid system located in Zaragoza, Spain. This optimization problem based on the minimization of the total net present cost (NPC). The results obtained were compared with a commercial program for the optimization of hybrid systems, and it was found that the proposed method has better quality results and precise optimal values than HOMER. Additionally, The proposed algorithm is used in what is currently known as iHOGA software.

Dehghan et al. [74] proposed hybrid meta-heuristic algorithms in order to obtain system components sizes of hybrid renewable energy system. The authors combined a particle swarm optimization (PSO) and harmony search (HS) algorithms for size optimization of a standalone PV, wind, and fuel cell based hybrid system in the Northwest region of Iran. NPC parameter is employed to evaluate the system economically, and the energy not supply (ENS) parameter is used to evaluate the system’s reliability. The optimization results concluded that the proposed algorithm provided a high convergence rate with less consumed computational time than classical PSO.

Hybrid iterative based GA is presented by Khatib et al. [75] to find the optimal combinations of hybrid PV/wind/battery components based on minimizing the total cost (TC) for Kuala Terengganu, Malaysia. The proposed method is implemented by first generating a set of possible combinations for the proposed system using the iterative part and then employing GA for optimization results. Also, Using the iterative approach, the authors optimized the tilt angle for system’s location and inverter capacity so as to increase system efficiency and decrease the size of the PV array. The study found that the optimum sizing ratios of the PV array ($C_A$), wind turbine ($C_T$), and storage battery ($C_B$) are 1.1411, 0.7159, and 0.550, respectively.

Hong et al. [76] applied GA incorporated with the Markov models to derive the optimal combinations for a standalone PV, wind, and diesel system for a remote island in Taiwan based on minimizing the TC with environmental and reliability aspects ($CO_2$ emissions and loss of load probability (LLP)). The authors employed fuzzy-c-means to cluster the PV, wind and the load states of operation and model it by Markov model. Based on these model, GA is used to determine the optimal design for the system units. The Markov model-based GA method reduces computational time and provides better results.

Simulated annealing (SA) is a stochastic method that excels at gravitating towards the global optimum. However, SA needed more computational time in a given solution area to find the optimum. Therefore, Katsigianni et al. [77] proposed a combination between SA and the local search TS. The authors used the hybrid algorithm for optimum sizing of a hybrid PV-wind-diesel-biodiesel-FC-battery system for the Chania region in Greece. It was found that the new hybrid method enhanced the result quality, without dramatically raising the number of simulations required.

Lujano et al. [78] used an artificial neural network-based GA (ANN-GA) for optimum sizing of a PV-wind-diesel-battery based hybrid system located in Zaragoza, Spain. Based on NPC and ENS parameters, the system was evaluated economically and technically. The authors implemented monte carlo simulation (MCS) for wind speed and solar radiation time-series forecasting and then the ANN-GA for sizing of the system elements. The optimal size was achieved under conditions of complexity and particularly high reliability.

Teaching and learning based optimization (TLBO) algorithm is one of the popular meta-heuristic techniques.
to solve combinatorial complex optimization problems. Indeed, TLBO has excellent exploration capability but lacks in exploiting the solution space locally. Therefore, Garcia et al. [80] employed mutation operations of differential evolution (DE) algorithm into TLBO to create a third phase (Mutation Phase) and improve the exploitation capability. The new algorithm used to find the optimal number of DG units and their optimal locations, based on minimizing PL in a network. The results obtained were compared with the improved PSO algorithm. It was concluded that new TLBO results had greater quality than another algorithm.

Askarzadeh et al. [79] presented a discrete chaotic harmony search based simulated annealing algorithm (DCHSSA) method, which combines chaotic search (CS), HS, and SA to find the optimal configuration of a standalone PV, wind, and battery hybrid energy system in South-Central-Montana. The objective function based on minimizing the total annual cost (TAC) of the system. The energy balance between the generation and load are employed in the optimization to evaluate the system’s reliability. The optimal design is achieved with two wind turbines, two PV panels, and 58 batteries with a TAC of $9687.11.

A fuzzy-based adaptive genetic algorithm is applied by Abdelhak et al. [81] to size a standalone PV, wind, and battery hybrid system based on minimizing the total cost (TC) for Troyes-Barberey City in France. This approach is based on the use of long-term wind speed data and solar irradiation forecasts for the site. The proposed method provide better quality hybrid energy system optimal size results compared to standard GA.

Ant colony optimization (ACO) for continuous domains-based on integer programming was developed in [82] to determine the optimal size of a hybrid renewable energy system satisfying the lowest TC and best power quality of system generation. The hybrid renewable energy system is composed by PV and wind generation. The results are compared with the artificial bee colony (ABC), GA, and conventional optimization Branch and bound (B&B) methods, and It was noticed that the algorithm proposed had greater speed and accuracy of convergence.

Zhou et al. [83] implemented simulated annealing particle swarm optimization (SAPSO) hybrid algorithm for optimum sizing of a standalone hybrid PV-wind-battery-super-capacitor system. In this optimization the objective function based on minimizing the life cycle cost (LCC) of the system while the power balance between generation and load parameter is employed to evaluate the system’s reliability. The results showed that, relative to standard PSO, SAPSO had improved computing time and better performance.

Ahmadi et al. [84] adopted hybrid big bang-big crunch (HBB-BC) algorithm by combining big bang-big crunch (BB-BC) algorithm with PSO capacities and mutation operations of DE algorithm to enhance the exploration ability. The authors used HBB-BC method to determine the optimum sizing of a standalone hybrid PV/wind/battery system. The total present cost (TPC) is employed to evaluate the system economically and the ENS parameter is employed to evaluate the system’s reliability. Compared to discrete harmony search (DHS) and PSO, the proposed approaches had greater precision in determining a set of optimal solutions.

Maleki et al. [43] incorporated PSO with monte carlo simulation (MCS). The authors used the optimization method to find the optimal size combination for a standalone PV-wind-battery system based on minimizing the TAC for a remote area located in Rafsanjan, Iran. The reliability of the system is evaluated by ensuring the energy balance between the generation and load. The results showed that the optimal configuration is PV/wind/battery system which is followed by the wind-battery system.

Tito et al. [85] formulated a new optimization methodology using the exhaustive method and GA for optimum sizing of a standalone PV/wind/battery based hybrid system in New Zealand based on minimizing TC and loss of power supply probability (LPSP). In this optimization, the authors used GA to generate a set of possible combinations of hybrid energy system units, and an exhaustive method to then find the optimal combination among the set of combinations obtained from GA. The optimal solution is achieved with a less number of iterations than individual GA.

Maleki et al. [86] hybridized HS and CS algorithms to determine the optimum combination of a hybrid PV-wind-battery plant which can supply the electric demand for a reverse osmosis (RO) system in a reliable way and minimum costs. LCC parameter is used to evaluate the system economically while LPSP is employed to evaluate the system’s reliability. The authors applied the economics (ANN) for solar radiation and wind speed forecasting. The results showed that a hybrid PV-battery-RO system is capable of providing the full water requirement for the case study investigated with the lowest LCC at $6120.

As the HS algorithm has rapid convergence time in the neighborhood of optimal solutions and the SA algorithm has high performance in achieving the best solutions in a given neighborhood. The hybrid mixture of the advantages of both algorithms was used by Guangqian et [87] to optimize the size of a PV-wind-biodiesel-battery-based hybrid system for a remote area in Iran. LCC parameter is used to evaluate the economics of the system while the power balance between generation and demand is used to evaluate the system’s reliability. It was found that PV/biodiesel/battery system provides the lowest LCC at $20,534.

Peng et al. [88] proposed several combinations between CS, SA, HS, and improved harmony search (IHS) to optimize the size of a hybrid PV/wind/battery system with reverse osmosis (RO) for a remote area in Khorasan, Iran. The authors used ANN for solar radiation and wind speed...
forecasting and the proposed algorithm for the optimum sizing of the system components. In the optimization, he objective function based on minimizing the LCC of the system. The reliability indice employed is LPSP. It was found that the improved harmony search-based chaotic simulated annealing (IHSCSA) algorithm produces more beneficial results than the other combinations based on mean, as well as the highest and lowest cost.

Sizing and siting of PV/FC hybrid renewable energy distributed generator were done in [89] by hybrid Nelder-Mead based cuckoo search (HNMCS) algorithm to get the system minimum PL. The authors used the Nelder-Mead (NM) to identify the initial variables for the cuckoo search (CS) algorithm. The results obtained were compared with PSO, CS, and NM algorithms, and it was found that the new algorithm provided efficient results at rapid convergence than other algorithms.

Zhang et al. [90] proposed a new hybrid approach by combining CS, HS, and SA for optimum sizing of a hybrid PV/wind/hydrogen system for a remote area of Khorasan, in Iran. The authors used an artificial neural network (ANN) for solar radiation and wind speed forecasting and the proposed approach for the optimal sizing of hybrid system’s components. The objective function based on minimizing the total life cycle cost (TLCC) of the system. The reliability indice used is LPSP. The optimal solution is obtained using the forecasted data, as these increase the solutions quality of optimization.

Mellouk et al. [91] developed a parallel hybrid genetic algorithm-based particle swarm optimization algorithm (P-GA-PSO) to determine the optimal renewable mix for Laayoune City located in the south-west of Morocco which is characterized by high potential of solar energy during the whole year. The authors used the proposed algorithm to identify the appropriate combination of it based on comparative technical, economic, and environmental analysis. As a result, the P-GA-PSO algorithm found the optimal combination with a high convergence time and better solution quality compared with standard GA or PSO, besides, the cost of energy is around 0.17 US$/kWh.

Khan et al. [92] formulated two hybrid algorithms called enhanced evolutionary sizing algorithms (EESAs) by combining firstly TLBO algorithm with enhanced differential evolution (EDE) and secondly with the salp swarm algorithm (SSA) to determine the size of a standalone hybrid PV, wind and battery system in Rafsanjan, Iran. TAC indice is employed to evaluate the system economically while LPSP is employed to evaluate the reliability system. The key concept of merging TLBO with these two algorithms is to improve the exploration and exploitation of the search space. The authors found that the hybrid PV/wind/battery has the lowest TAC followed by the hybrid PV/battery system and the hybrid PV/wind system. However, the authors concluded that EESAs provided better quality results compared with TLBO, EDA, and SSA in hybrid energy system sizing.

Cai et al. [93] applied a hybrid method by combining IHS and SA to optimize the size of a hybrid PV/diesel/battery system in an eastern region of Iran. The authors used geographic information system (GIS) to identify the best location based on technical, economic, reliability, social, and environmental criteria and IHS-based SA for optimum sizing of hybrid system’s components. The objective function based on minimizing TLCC of the system. The results concluded that the new hybrid method improved the solution quality compared to the solutions provided by original IHS or original SA methods.

Khan et al. [94] implemented a combination between Jaya and TLBO to form a new algorithm called the JLBO algorithm. The new algorithm is used for optimum sizing of a standalone hybrid PV-wind-battery based on minimizing the TAC of the system. In this simulation, LPSP is employed to evaluate the reliability. The optimization results indicated that PV/wind/battery is the most cost effective system with TAC values of $66542, $60752, $50247, $43046, and $34464 at LPSP max values of 0, 0.3%, 1%, 2%, and 5%, respectively.

Jahannoosh et al. [95] proposed a hybrid grey wolf optimizer-sine cosine algorithm (HGWOSCA) to determine the optimal size of a standalone hybrid PV-wind-FC based hybrid system to supply the demand of residential commercial centers in Iran. In this study, the objective function based on minimizing the total lifespan cost of the hybrid system (LSCS). The reliability indice employed in this optimization is the load interruption probability (LIP). The main reason for combining grey wolf optimizer (GWO) and sine cosine algorithm (SCA) is to balance between exploration and exploitation phases. The results showed that HGWOSCA provided better quality cost (better LSCS) compared to SCA, GWO, and PSO.

The summary of these studies is presented in Table 4.

4.2 Hybrid Meta-Heuristic Approaches for Multi-objective Design

Multi-objective optimization of the renewable energy-based hybrid system design is a current field of scientific research. It tries to deal with complex multi-objective problems and solve them using simplified but robust methods. The field of application of structural optimization extends today to new and more interesting challenges. The determination of the optimal size of components is a problem of primary importance. Therefore, hybrid algorithms are more fitting to solve complex optimization problems of hybrid renewable energy systems sizing which has been proven in several articles, as summarized in Table 5.
### Table 4 Summary of studies based on single objective optimization

| S. No. | Author/Year         | System components       | Site     | Mode   | Combined methods                  | Proposed methods                      | Compared methods                  | Objective functions | Design constraints                                                                 |
|--------|---------------------|-------------------------|----------|--------|-----------------------------------|---------------------------------------|-----------------------------------|---------------------|-------------------------------------------------------------------------------------|
| 1      | Gandomkar et al. 2005 [72] | PV-wind-biomass        | Iran     | On-grid | Genetic Algorithm (GA) Tabu Search (TS) | Hybrid GA-based TS                    | Genetic Algorithm (GA)            | (−) PL               | Maximum number of DEG, current capacity limit, upper and lower voltage limit, total capacity of DEG at distribution network, and inequality constraint |
| 2      | Dufo-Lopez et al. 2005 [73] | PV-diesel              | Spain    | Off-grid | Genetic Algorithms (GAs)           | HOGA                                   | HOMER                             | (−) NPC             | Not specified                                                                                                                                         |
| 3      | Dehghan et al. 2009 [74] | PV-wind-FC             | Iran     | Off-grid | Particle Swarm Optimization (PSO) Harmony Search (HS) | Hybrid PSO-based HS                    | Particle swarm optimization (PSO) | (−) NPC             | The maximum permissible level of the Equivalent Loss Factor (ELF) index                                                                       |
| 4      | Khatib et al. 2012 [75] | PV-wind-battery        | Malaysia | Off-grid | Iterative Method Genetic Algorithm (GA) | Iterative-based GA                    | Not Specified                    | (−) TC              | Energy balance, loss of load probability (LLP) and capacity of PV array, wind and battery                                                 |
| 5      | Hong et al. 2012 [76] | PV-wind-diesel         | Taiwan   | Off-grid | Markov model Genetic Algorithm (GA) | Markov model-based GA                  | Chronology model-based GA          | (−) TC              | Number of PV panels, wind turbines, and diesel generators, LLP and CO2 emissions                                                          |
| 6      | Katsigiannis et al. 2012 [77] | PV-wind-diesel-bio-diesel-FC-battery | Greece   | Off-grid | Simulated Annealing (SA) Tabu Search (TS) | SA-based TS                           | Individual SA Individual TS        | (−) LCOE             | Initial cost, Unmet load, capacity storage, fuel consumption, renewable fraction and components size limitation |
| 7      | Lajano et al. 2013 [78] | PV-wind-diesel-battery | Spain    | Off-grid | Artificial Neural Network (ANN) Genetic Algorithm (GA) | ANN-based GA                          | Not Specified                    | (−) NPC             | Probability of energy not supply limit and NPC                                                                                   |
| 8      | Askarzadeh et al. 2013 [79] | PV-wind-battery        | USA      | Off-grid | Discrete Simulated Annealing (DSA) Chaotic Search (CS) Harmony Search (HS) | DHSSA and DCHSSA                      | Discrete Simulated Annealing (DSA) | (−) TAC              | Number of PV panels, wind turbines and batteries and maximum depth of discharge (DOD)                                                            |
| 9      | Garcia et al. 2014 [80] | Multiple DEG systems (Not specified) | Spain    | On-grid | Teaching Learning-Based Optimization (TLBO) Differential Evolution (DE) | Modified Teaching Learning-Based Optimization (MTLBO) | Improving Particle Swarm Optimization (IPSO) | (−) PL              | Inequality constraints                                                                                                                                 |

Note: DEG = Distributed Energy Generation, NPC = Net Present Cost, TC = Total Cost, PL = Present Load, NPC = Net Present Cost, LLP = Loss of Load Probability, ELF = Equivalent Loss Factor, LCOE = Levelized Cost of Energy, DOD = Depth of Discharge.
| S. No. | Author/Year | System components | Site       | Mode      | Combined methods | Proposed methods                     | Compared methods                          | Objective functions | Design constraints                                      |
|-------|-------------|--------------------|------------|-----------|------------------|--------------------------------------|-------------------------------------------|---------------------|--------------------------------------------------------|
| 10    | Abdelhak et al. 2014 [81] | PV-wind-battery | France     | Off-grid  | Genetic Algorithms (GA) Fuzzy Logic | Fuzzy-Adaptive Genetic Algorithm | Genetic Algorithm (GA) | (−) TC | Energy balance and state of charge (SOC) |
| 11    | Fetanat et al. 2015 [82] | PV-wind | Iran       | Off-grid  | Ant Colony Optimization for Continuous Domains (ACO_g) Integer Linear Programming (ILP) | ACO_g-based ILP | Artificial Bee Colony (ABC) Genetic Algorithm (GA) Conventional Optimization B&B method | (−) TC | Number of PV panels, wind turbines, batteries |
| 12    | Zhou et al. 2016 [83] | PV-wind-battery-super capacitor | China | Off-grid  | Particle Swarm optimization (PSO) Simulated Annealing (SA) | SAPSO | Particle Swarm optimization (PSO) | (−) LCC | Super capacitor charging and discharging, power surplus, and PL |
| 13    | Ahmadi et al. 2016 [84] | PV-wind-battery | Iran       | Off-grid  | Particle Swarm Optimization (PSO) Big Bang-Big Crunch (BB-BC) Differential Evolution mutation operators | HBB-BC algorithm | Particle Swarm Optimization (PSO) Discrete Harmony Search (DHS) | (−) TPC | Number of hybrid system components, ENS, and charge quality of the battery |
| 14    | Maleki et al. 2016 [43] | PV-wind-battery | Iran       | Off-grid  | Particle Swarm Optimization (PSO) Monte Carlo Simulation (MCS) | PSOMCS | Not Specified | (−) TAC | Number of PV panels, wind turbines, batteries and SOC |
| 15    | Tito et al. 2016 [85] | PV-wind-battery | New Zealand | Off-grid  | Exhaustive Search Method Genetic Algorithm (GA) | GA-based Exhaustive Search | Not Specified | (−) TC | Number of PV panels, wind turbines, and batteries |
| 16    | Maleki et al. 2016 [86] | PV-wind-battery | Iran       | Off-grid  | Harmony Search (HS) Chaotic Search (CS) | HSBCS | NHarmony search (HS) | (−) LCC | LPSP, swept area of wind turbine’s blades, total area occupied by PV panels and number of batteries |
| 17    | Guangqian et al. 2018 [87] | PV-wind-biodiesel-battery | Iran | On-grid  | Harmony Search (HS) Simulated Annealing (SA) | HHSSAA | Harmony Search (HS) Simulated Annealing (SA) | (−) LCC | Number of PV panels, wind turbines and batteries and DOD |
| S. No. | Author/Year   | System components | Site       | Mode     | Combined methods                                                                 | Proposed methods                   | Compared methods                                                                 | Objective functions | Design constraints |
|--------|---------------|-------------------|------------|----------|----------------------------------------------------------------------------------|-----------------------------------|----------------------------------------------------------------------------------|---------------------|--------------------|
| 18     | Peng et al. 2018 [88] | PV-wind-RO-battery | Iran       | Off-grid | Simulated annealing (SA) chaotic search (CS) Harmony search (HS) Improving Harmony search (IHS) | HSCS, IHSCS, HSSA, IHSSA, SACS, HSCSSA | Particle Swarm Optimization algorithm (PSO) Artificial Bee Swarm optimization (ABSO) Tabu Search (TS) Individual hybridization algorithm | (−) TLCC            | The maximum total area occupied by the PV arrays, the maximum total area swept by the wind turbine blades, the maximum number of batteries, LPSP and SOC. |
| 19     | Kumar et al. 2018 [89] | PV-FC            | India      | Off-grid | Cuckoo Search (CS) Nelder-Mead (NM) Algorithm                                      | Hybrid Nelder-Mead-based Cuckoo Search (HNMCS) Algorithm | Particle Swarm Optimization algorithm (PSO) Cuckoo Search (CS) Nelder-Mead (NM) Algorithm | (−) PL              | Power balance of the power flow equations |
| 20     | Zhang et al. 2019 [90] | PV-wind-hydrogen | Iran       | Off-grid | Chaotic Search (CS) Harmony Search (HS) Simulated Annealing (SA)                    | CS-HS-SA                          | Chaotic Search (CS) Harmony Search (HS) Simulated Annealing (SA)                   | (−) TLCC            | Number of hydrogen tank, PV surface area, and the area swept by the wind turbine blades, LPSP. |
| 21     | Mellouk et al. 2019 [91] | PV-wind-CSP-CPV-battery | Morocco   | On-grid | Genetic Algorithm (GA) Particle Swarm Optimization algorithm (PSO)                | P-GA-PSO                          | Genetic Algorithm (GA) Particle Swarm Optimization algorithm (PSO)                | (−) LCOE            | Energy balance, unmet load, and inequality constraints |
| 22     | Khan et al. 2019 [92]    | PV-wind-battery  | Iran       | Off-grid | Teaching Learning Based Optimization (TLBO) Enhanced Differential Evolution (EDE) Salp Swarm Algorithm (SSA) | Enhanced Evolutionary Sizing Algorithms (EESAs) | Teaching Learning-based optimization (TLBO) Enhanced Differential Evolution (EDE) Salp Swarm Algorithm (SSA) | (−) TAC             | Number of hybrid system components, LPSP and DOD |
| 23     | Cai et al. 2020 [93]     | PV-diesel-battery | Iran       | Off-grid | Simulated Annealing (SA) Improved Harmony Search (IHS)                           | IHS-based SA                      | Simulated Annealing (SA) Improved Harmony Search (IHS)                           | (−) TLCC            | Number of batteries, diesel generator fuel usage, and surface area of PVs |
For instance, Tahani et al. [96] proposed a hybrid flower pollination algorithm (FPA)-based simulated annealing (SA) algorithm to optimize the size of a hybrid PV/wind/battery system located in Tehran, Iran. Combining these two algorithms increase the global search and prevent the algorithm to be trapped in local optimum solutions. The reliability and economic objective functions based on minimizing LPSP and maximizing the cumulative savings of the system. The results concluded that the new method achieved the solution quality with 3.28% payback time and 0% LPSP.

Lan et al. [97] presented a new optimization methodology using multi-objective particle swarm optimization (MOPSO) with elitist non-dominated sorting genetic algorithm (NSGA-II) to optimize the size of hybrid PV, diesel, and battery in a standalone ship power system for a typical navigation route from Dalian in China to Aden in Yemen based on economic and environmental criteria. The economic and environmental objective functions based on minimizing TAC and CO2 emissions. The authors concluded that the hybrid PV-diesel-battery system provides the lowest TAC followed by the PV-diesel system.

Kefyat et al. [98] implemented a hybrid method by combining ant colony optimization (ACO) with artificial bee colony (ABC) algorithms for optimal sizing and placement of multiple renewable distributed energy generation units in terms of minimizing power losses, total electrical energy cost, total emissions, and improving the voltage stability. The main idea of hybridizing this two meta-heuristics algorithms is to produce a good initial solution and determine a good search direction using ABC to help ACO to find a good results. The results obtained were compared with another evolutionary optimization methods. The results showed the potential and effectiveness of ABC-ACO algorithm compared with other methods.

Khare et al. [99] developed hybrid many optimizing liaisons (MOL)-based TLBO to optimize the size of different components of a hybrid PV/wind/diesel/battery system based on minimizing the TAC. The environmental indice considered is CO2 emission while the reliability indice is LLP. Compared to SGA, PSO, TLBO, ITLBO, and MOL, hybrid MOL-based TLBO has been found to be good in finding the best solutions for complex problems as it has faster computation time. In addition, MOL-based TLBO offers improved solutions quality when it more effectively samples the search space and can thus be used to solve complex hybrid energy system sizing problems and provide appropriate optimal solutions.

Ma. et al. [100] used a combination between PSO with the selection operator of GA to create a new effective algorithm named natural selection particle swarm optimization (NSPSO). The proposed algorithm is employed to optimize the economical and reliability aspects of a hybrid energy system comprised of PV, wind, and battery. The economic
| S. No. | Author/Year | System components | Site       | Mode    | Hybrid Algorithm                                           | Novel Algorithm                  | Compared Methods                      | Objective function | Constraints                                                                 |
|--------|-------------|-------------------|------------|---------|----------------------------------------------------------|----------------------------------|--------------------------------------|-------------------|-----------------------------------------------------------------------------|
| 1      | Tahani et al. 2015 [96] | PV-wind-battery   | Iran       | Off-grid | Flower Pollination Algorithm (FPA) Simulated Annealing (SA) | FPA/SA                           | Genetic Algorithm (GA)              | (−) LPSP           | PV panel tilt angle, number of PV panels and number of batteries          |
| 2      | Lan et al. 2015 [97] | PV-diesel-battery | A Ship     | On-grid | Multi-Objective Particle Swarm Optimization (MOPSO) Non-dominated Sorting Genetic Algorithm (NSGA-II) | MOPSO/NSGA-II                     | Not Specified                       | (−) TC, (−) CO₂ emission | Number of hybrid system components, ENS and charge equality of the battery |
| 3      | Kefyat et al. 2015 [98] | Multiple renewable distributed energy generation units (not specified) | Iran       | Off-grid | Ant Colony Optimization (ACO) Artificial Bee Colony (ABC) | ACO-ABC                           | Artificial Bee Colony (ABC)         | (−) PL, (−) VSI, (−) GHG Emission, (−) CO₂ emission | Equality constraints |
| 4      | Khare et al. 2016 [99] | PV-wind-diesel-battery | Iran       | Off-grid | Many optimizing liaisons(MOL) Teaching learning based optimization (TLBO) | Hybrid MOL-TLBO                   | Simple genetic algorithm (SGA) Particleswarm optimization (PSO) Many optimizing liaison (MOL) Teaching learning based optimization (TLBO) Improved teaching learning based optimization (ITLBO) | (−) TAC, (−) LOLP, (−) CO₂ emission | Energy balance, number of wind turbines, PV panels, batteries and Diesel generators |
| 5      | Ma et al. 2016 [100] | PV-wind-battery   | China      | Off-grid | Particle swarm optimization (PSO) Genetic algorithm (GA) | Natural selectionparticle swarm optimization (NSPSO) Genetic algorithm (GA) | Genetic algorithm (GA)              | (−) LPSP, (−) LEP, (−) LCC, (−) K1 | Number of type 1 and 2 of PV panels, type 1 and type 2 of wind turbines and batteries |
| 6      | Dufo-Lopez et al. 2016 [65] | PV-wind-diesel-battery | Tindouf   | On-grid | Multi-objective evolution-ary algorithm (MOEA) Genetic algorithm (GA) | MOEA-based GA                     | Not Specified                       | (−) NPC, (−) HDI, (−) JC | Power balance, excess energy, and state of charge (SOC) |
| S. No. | Author/Year | System components | Site   | Mode   | Hybrid Algorithm | Novel Algorithm | Compared Methods | Objective function | Constraints |
|-------|-------------|--------------------|--------|--------|------------------|-----------------|------------------|-------------------|-------------|
| 7     | Cho et al. 2016 [101] | PV-wind-diesel-battery | South Korea | Off-grid | Teaching Learning-Based Optimization (TLBO) Clonal Selection Algorithm (CSA) | TLBO-CS | Particle Swarm Optimization (PSO) Genetic algorithm (GA) | (−) TAC (+) LPSP (+) Fuel cost | Number of PV panels, windturbines, batteries, and Diesel generators and charge value of the battery |
| 8     | Yammani et al. 2016 [102] | PV-wind-micro turbine-FC | India | On-grid | Shuffled frog-leap algorithm (SFLA) Bat algorithm (BAT) | Shuffled batalgorithm (ShBAT) | Genetic Algorithm (GA) Shuffled frog-leap algorithm (SFLA) Bat algorithm (BAT) | (−) PL (+) VSI (+) Lineflow-capacity index | Equality and Inequality constraints |
| 9     | Bakshi et al. 2017 [103] | PV-wind-battery | India | On-grid | Modified Human Opinion Dynamics (MHOD) Gravitational Search Algorithm (GSA) | MHODGSA | Gravitational Search Algorithm (GSA) | (−) PL (+) VSI | Power balance equality constraints of the power equations |
| 10    | Abdelshafy et al. 2018 [104] | PV-wind-hydrogen-diesel-battery | Egypt | On-grid | Particle Swarm Optimization (PSO) Grey Wolf Optimizer (GWO) | PSO|GWO | Classical Particle Swarm Optimization (PSO) Classical Grey Wolf Optimizer (GWO) | (−) TAC (−) CO2 emission | Number of hybrid system components, energy storage capacity of hydrogen tank, renewable fraction and DOD |
| 11    | Bhullar et al. 2018 [105] | Multiple renewable DEG units (not specified) | India | On-grid | Artificial Bee Colony (ABC) Cuckoo Search (CS) | ABC-CS | Genetic Algorithm (GA) Particle Swarm Optimization (PSO) Genetic algorithm (PSO) | (−) Power loss (+) Voltage profile | Bus voltages constraints and reactive power limits of generators |
| 12    | Senthil et al. 2018 [106] | PV-Wind-FC | India | | Particle Swarm Optimization algorithm (PSO) Nelder-Mead Algorithm (NM) | Hybrid Nelder-Mead-Particle Swarm Optimization (HNMPSO) | Genetic Algorithm (GA) Particle Swarm Optimization algorithm (PSO) | (−) Power Loss | Power balance constraints, bus voltage constraint, Bus voltage stability margin, and DG penetration constraint in network |
| 13    | Nowdeh et al. 2019 [107] | PV-wind | India | On-grid | Teaching-Learning Based Optimization (TLBO) Grey Wolf Optimizer (GWO) | MOHTILBOGWO | In comparison with each of the methods being used individually | (−) Power losses (−) ENS | Equilibrium power, bus volt-ages, DG generation limits and line capacity |
| S. No. | Author/Year | System components | Site       | Mode       | Hybrid Algorithm | Novel Algorithm | Compared Methods | Objective function | Constraints                        |
|-------|-------------|-------------------|------------|------------|------------------|-----------------|------------------|-------------------|------------------------------------|
| 14    | Sambaiah et al. 2019 [108] | PV-wind          | India      | On-grid    | Grey Wolf Optimizer(GWO) | Hybrid GWO | Particle Swarm Optimization (PSO) | (-) PL | (+) Voltage stability | Equality and inequality constraints |
|       |             |                   |            |            | Differential Evolution (DE) |         | (+) Network-security index |                  |                                    |
| 15    | Battapothula et al. 2019 [109] | Multiple distributed energy generation units (not specified) | India      | On-grid    | Shuffled Frog Leap Algorithm (SFLA) Teaching and Learning Based Optimization(TLBO) | SFL-TLBO | In comparison with each of the methods being used individually | (-) Voltage deviation | (-) PL | (-) DGs cost | Charging stations constraints and DG constraints |
|       |             |                   |            |            |                  |                 |                  | (-) The energy consumption of electric vehicle users |                                    |
| 16    | Radosavljević, et al. 2020 [110] | PV-wind          | Serbia     | On-grid    | Particle Swarm Optimization algorithm (PSO) Gravitation search algorithm (GSA) | PPSOGSA | ACO-ABC Modified teaching-learning based optimization (MTLBO) Symbiotic Organism search (SOS) | (-) Total energy loss | (+) Voltage profit | Power Flow Constraints, bus Voltage and Branch Load Constraints, and renewable distributed generation Capacity Constraints |
|       |             |                   |            |            |                  |                 |                  |                  |                                    |
| 17    | Rezaemozafar et al. 2020 [111] | Renewable resources, EV charging stations, and energy storagesystems | Iran       | On-grid    | Genetic Algorithm (GA) Particle Swarm Optimization (PSO) | GA-PSO | NSGA-II DE GA E-PSO | (-) PL | (-) Voltage fluctuations | Demand-Supply Balance, bus Voltage Limitations, line Current Constraint, and pricing Constraints |
|       |             |                   |            |            |                  |                 |                  | (-) Demand suppling costs |                                    |
| 18    | Abuelrub et al. 2020 [112] | PV-wind-battery | India      | On/Off-grid | Biogeography-based optimization (BBO) Particle Swarm Optimization algorithm (PSO) | GPSBBO | Non-dominated sorting genetic algorithm (NSGA-II) Multi-objective particle swarm optimization algorithm (MOPSO) | (-) TC | (-) System index of reliability | Power balance between the generated and consumed power |
| S. No. | Author/Year     | System components                  | Site      | Mode             | Hybrid Algorithm                      | Novel Algorithm                  | Compared Methods                  | Objective function | Constraints |
|-------|----------------|-----------------------------------|-----------|------------------|----------------------------------------|---------------------------------|-----------------------------------|-------------------|-------------|
| 19    | Sultan et al. 2021 [113] | PV-wind-FC                        | Egypt     | On/Off-grid      | Artificial Ecosystem Optimization (AEO) | Improved Artificial Ecosystem Optimization (IAEO) | Artificial Ecosystem Optimization (AEO) Particle Swarm Optimization (PSO) Salp Swarm Algorithm (SSA) Grey Wolf Optimizer (GWO) | (−) COE            | (−) LPSP     |
|       |                 |                                   |           |                  | Sine Cosine Algorithm (SCA)            |                                 |                                   | (−) Excess energy  |             |
| 20    | Suman et al. 2021 [114] | PV-wind-bio-generator-diesel-battery | India     | Off-grid         | Grey Wolf Optimizer (GWO) Particle Swarm Optimization (PSO) | Hybrid PSO-GWO | Ant Lion Optimisation (ALO) Teaching Learning Based Optimisation (TLBO) Whale optimisation algorithm (WOA) Cuckoo search algorithm (CSA) Artificial Bee Colony (ABC) | (−) COE            | (−) LPSP     |
|       |                 |                                   |           |                  |                                         |                                 |                                   | (−) Excess energy  |             |
| 21    | Aliabadi et al. 2021 [115] | PV-wind-battery                   | Iran      | On-grid          | Crow search algorithm (CSO) Particle Swarm Optimization algorithm (PSO) | Improved Crow search algorithm (ICS0) | Crow search algorithm (CSO) Particle Swarm Optimization algorithm (PSO) Manta ray foraging optimization (MRFO) | (−) Cost            | (−) Loss     |
|       |                 |                                   |           |                  |                                         |                                 |                                   | (−) Voltage profile |             |
|       |                 |                                   |           |                  |                                         |                                 |                                   |                   |             |

(−)-Minimize; (+)-Maximize
and reliability objective functions based on minimizing the loss of power supply probability (LPSP), loss of energy probability (LEP), life cycle cost (LCC), and energy fluctuation rate ($f_k$). The results obtained from the proposed approach were checked by the authors by comparing them with the results obtained by the original PSO. The results showed that NSPSO avoids premature convergence effectively. Therefore, the proposed method provided good promising results in terms of precision with less fitness function value relative to PSO.

In [65] a multi-objective evolutionary algorithm (MOEA) including GA was applied to find the optimal combination of PV, wind, diesel, and battery units for a small community in terms of social (HDI, JC), and economic (NPC) assessment parameters. The authors used MOEA for system’s component sizing based on maximizing JC and HDI and minimizing NPC, thereafter GA to obtain the control strategy based on NPC. It was found four possible solutions in which no solution is better than another one for all three objectives.

Cho et al. [101] used a hybrid TLBO-based clonal selection algorithm (CSA) to optimize the size of a PV-wind-diesel-battery hybrid system. TAC and fuel cost indices are employed to evaluate system economically while LPSP is employed to evaluate the reliability. The authors used the TLBO algorithm to search for a global “best solution” using the teacher and student phase, and CSA to then determine a better solution among the solution obtained from the TLBO algorithm. The optimal design is achieved with 22 wind turbines, 215 PV panels, 8 diesel generators, and 1 battery bank.

Bat algorithm (BAT) is a meta-heuristic population-based algorithm. It was applied by Yammani et al. [102] to form a new algorithm named Shuffled bat algorithm (ShBAT) by incorporating the exploitation property of the shuffled frog-leap algorithm (SFLA) and exploration features of BAT. The proposed algorithm is used to find the optimal location and sizing of several Distributed energy generation resources (PV, wind, fuel cell and micro turbine) with different load models in terms of minimizing power losses, distributed energy source cost and maximizing voltage profile. The results obtained were compared with GA, SFLA, and BAT, and it was found that ShBAT had better convergence speed and accuracy than other methods.

Durairasan et al. [116] proposed a hybrid meta-heuristic search algorithm between particle swarm optimization (PSO) and biography based optimization (BBO) algorithms to determine the optimal location and sizing of several distributed generation sources for radial distribution network. The algorithm is analyzed by considering the system loss diminution, feeder load balancing, and voltage profile improvement as objective functions. ANN is used to calculate the available capacity of distributed generation sources (wind and PV) for 24 hours. The results indicated the potential and effectiveness of the proposed algorithm in comparison with classical PSO and BBO.

Bakshi et al. [103] presented a hybrid method by combining modified human opinion dynamics (MHOD) algorithm and gravitational search algorithm (GSA) to determine the optimal number of distributed generation units and its optimal placement, based on minimizing power losses and improving the voltage profile. The purpose of this hybridization is to balance between exploration and exploitation of the two meta-heuristic methods. The authors state that the proposed algorithm results performed better than classical GSA in terms of convergence time and losses of the bus system.

An hybrid technique combining genetic algorithm (GA) and particle swarm optimization (PSO) algorithm is presented for sizing and optimal location of renewable energy sources and electric vehicles charging stations [117]. The objectives include minimizing power losses, voltage fluctuations, charging and demand supplying costs, and electric vehicle battery cost. The analysis demonstrates the potential and effectiveness of the multi-objective algorithm in comparison with other evolutionary optimization methods. The results are compared with the differential evolution algorithm in which GA-PSO algorithm demonstrates exceptional performance.

Abdelshafy et al. [104] proposed a new multi-objective hybrid particle swarm optimization-based grey wolf optimizer (PSO-GWO) method to find the optimal design of a grid-connected PV, wind, battery, diesel generator, battery, and fuel cell hybrid energy system. The main idea of combining these two algorithms is to improve the ability of exploitation in PSO with the ability of exploration in GWO. The economic and environmental objective functions of the optimization are to minimize the total investment cost and CO$_2$ emissions. The results concluded that the novel method achieved the solution quality with less computational time comparing with each of the methods being used individually.

Bhullar et al. [105] employed a hybrid ABC-CS algorithm by combining artificial bee colony (ABC) and cuckoo search (CS) algorithm to determine the optimal placement and size of a multiple distributed generations. The objective functions include the distributed generations cost, power losses, and voltage stability, which are, optimized subject to system technical and operational constraints. The authors concluded that the proposed method provided better performance in all aspects comparing to existing GA-PSO, PSO, and GA.

Senthil et al. [106] formulated a hybrid method by comprising nelder- mead (NM) and particle swarm optimization (PSO) algorithms to find the optimal size of renewable distributed generators in a 12-bus, 69-bus, and 84-bus radial distribution system network. The authors study diverse 24-hours load profiles: residential, commercial, constant, industrial and mixed load profiles. A triple multi-objective
function combination power loss, voltage profile, and stability improvement is used in this study. The results indicated that the proposed algorithm’s performance is better and more effective than original PSO and GA.

Nowdeh et al. [107] implemented a multi-objective hybrid teaching-learning based optimization-grey wolf optimizer (MOHTLBOGWO) in order to determine the optimal placement and size of distributed generation units (PV, wind) with the objective of minimizing the total power losses and energy not-supplied (ENS) in a 33 and 69 bus distribution systems. A single objective optimization is initially performed then a multi-objective optimization to optimize both objective functions. The comparison between the proposed algorithm, TLBO, and GWO for single and multi-objective optimization results indicates that the studied algorithm’s performance is better and more effective than both algorithms.

In [108], Sambaiah et al. enhanced the exploratory capability of grey wolf optimizer (GWO) algorithm by adding crossover and mutation operators of differential evolution (DE) algorithm. The authors used the hybrid algorithm to find optimal design of hybrid PV and wind system in a distribution network. The objective functions in the optimization of hybrid distributed renewable energy system are currently defined to minimize the power loss and to evaluate the corresponding voltage stability factor and network security index. The results obtained were compared with PSO, and it was found that the proposed algorithm performed better than other algorithm.

Battapothula et al. [109] adopted the shuffled frog leap algorithm (SFLA) to enhance the exploitation capability of TLBO and create a novel algorithm named shuffled frog leap-teaching and learning-based optimization (SFL-TLBO). The proposed algorithm is used to determine the optimal location and size of a hybrid distributed renewable energy system and electric vehicles charging station with the minimization of voltage deviation, distribution network power loss, distributed generations (DGs) cost, and the energy consumption of electric vehicle users as objectives. The results showed that SFL-TLBO improved the solution quality compared to the solutions provided by individual SFLA or individual TLBO methods.

Radosavljević et al. [110] used a hybrid meta-heuristic algorithm by combining particle swarm optimization algorithm (PSO) and gravitation search algorithm (GSA) to solve the optimal placement and sizing of distributed generation problem. The authors define the objective function of the optimization problem as a multi-objective function based on minimizing the total energy loss of a distribution network and maximizing the profit for renewable distributed generation owners. The proposed algorithm is adapted to the IEEE 69-bus radial network, taking into account the generic and controllable type of DG technology. The results of this study concluded that the new method provided better solutions and converges to an optimal solution with less number of iterations compared to standard PSO and GSA.

Rezaeimozafar et al. [111] formulated a hybrid method by incorporating PSO with GA to create a new algorithm more efficient and effective in order to determine the optimal siting and sizing of several distributed energy resources with electric vehicles charging stations and energy storage systems. The objective function to be minimized includes a the operation costs, voltage fluctuations, and power losses. The authors compared the performance of GA-PSO with other brute force methods including NSGA-II, DE, GA, and E-PSO. The proposed algorithm can find the optimal results with faster convergence time than the four others.

Abuclrub et al. [112] applied a hybrid method by combining BBO with PSO to optimize PV-wind-battery hybrid energy system combination in Irbid, Jordan. The system is considered in both standalone and grid-connected modes. The objective functions of the optimization are based on minimizing TC and system index of reliability. The study showed that GPSBBO provides better quality results compared with the non-dominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization algorithm (MOPSO).

Sultan et al. [113] developed a solution to a multi-objective optimization problem with the aim of minimizing COE, LPSP, and excess energy of a HRES of PV-wind-fuel cell system. With this aim, they developed an improved version of the artificial ecosystem optimization algorithm by integrating sine cosine algorithm operators. Result of this, the improved algorithm is a more efficient way to obtain good solutions close to global optimum, out forming several well-known optimization algorithms.

Suman et al. [114] used a hybrid grey wolf optimizer(GWO) and particle swarm algorithm (PSO) developed by Senel et al. [118] to optimize the size of a hybrid solar/wind/bio-generator/diesel/battery system for three locations in India. Compared with the previous hybrid version of Abdelshafy et al. [104], hybrid PSO-GWO algorithm has been developed without changing the general operation of the PSO and GWO algorithms, in fact, the GWO algorithm is utilized to support the PSO algorithm to reduce the possibility of falling into a local minimum. The authors used the weighted sum method to tackle the multi-objective optimization problem contained minimization COE and DPSP, and the energy generated from diesel generation units. The results of this study concluded that the hybrid algorithm outperforms well-established algorithms viz TLBO, ALO, WOA, PSO among others.

Aliabadi et al. [115] implemented an improved method for the design and placement of hybrid PV, wind, and battery systems. The objective function to be minimized includes active losses and voltage deviations of the networks
considering generation and load uncertainty as well as a hybrid system cost. The author integrate an improved version of the inertia weight strategy of PSO into the crow search algorithm to increase their exploration capabilities. In the study, the results showed the superiority of the proposed method compared with traditional CSA, PSO, and MRFO methods in reducing losses and voltage deviations of the networks.

5 Discussions and Future Directions

Many approaches and algorithms have been studied in optimization of hybrid renewable energy systems, with a particular focus on improving the reliability and reducing the computation time of the optimization models. The most common sizing methodologies reported in the literature are the traditional methods (the probabilistic methods, analytical methods, iterative optimization techniques), artificial intelligence methods (genetic algorithm, particle swarm algorithm), and software tools (HOMER, IHOGA). Once the uncertainties associated with distributed generation output, load, and constraint are incorporated, the system becomes more complex. As a consequence, a simple algorithm might not be capable of finding the desired solution and could fail to achieve a convenient solution. Therefore, developing a new method by combining the advantage of two or more methods may find the optimal sizing with higher accuracy and less computational time.

Based on Web of science database, since 2009 various framework and combinations of hybrid meta-heuristic algorithms such as SA-TS, PSO-GWO, and GA-PSO, etc. are being applied for optimal sizing of renewable energy based hybrid systems. Most of these papers are carried out based on single objective optimization (SOO), while there is an increase in using hybrid algorithms to solve multi-objective optimization (MOO) problems in the last five years as shown in Fig. 3. This number of published articles is small compared to other search area like, production planning, feature selection, project scheduling, graph coloring, mesh partitioning, and traveling salesman problems which are commonly known significant increase of application of hybrid meta-heuristic algorithms. Therefore, the use of new hybrid algorithm recently developed is recommended for finding the global optimum solution of a hybrid energy system sizing problem.

Hybrid energy system size optimization problems often need to consider more conflicting objectives. For example, total annual cost, CO₂ emissions and fuel cost minimization, job creation and human development index maximization. With the increase in the number of objectives, it is harder to reach the optimal Pareto front (PF). It is thus desirable to develop and investigate strong and effective algorithms for multi-objective optimization problems. Multi-objective hybrid meta-heuristic algorithms deal with the diversity of solutions, infeasible solutions and optimum separation of multi-objective optimization problems and provide better and accurate results.

The successful resolution of an optimization problem using a meta-heuristic technique depends on its ability to provide a good balance between exploration (diversification) and exploitation (intensification). Any optimization algorithm must use these two strategies to find the global optimum: exploration to search for unexplored regions of the search space and exploitation to exploit the knowledge acquired at points already visited and thus find better points. In this spirit, several types of hybridization are possible. As shown in Table 6 there is a huge concentration of using low-level co-evolutionary hybridization model to balance between exploration and exploitation capabilities.

In the low-level co-evolutionary hybridization model, other meta-heuristic component is embedded into population-based meta-heuristic algorithm in order to ensure that the optimization process does not stick in a local optima. According to Table 6 various meta-heuristic components have been utilized such as: crossover and mutation operators of genetic algorithm and differential evolution algorithm, updating operator of sine-cosine algorithm (SCA). The research work may further be extended in future by using these operators to increase the diversity of the population against premature convergence and enhancing the capability of jumping out of local optima for the recent population-based meta-heuristic algorithms.
Table 6 Annotated bibliography

| S.No. | Combined methods | Combination type | Hybrid model used | Objective | The performance of proposed method | References |
|-------|------------------|------------------|-------------------|-----------|-----------------------------------|------------|
| 1     | GA               | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Incorporate TS to guide GA for better local optima avoidance | GA-TS provided much better solution accuracy and convergence process than original GA | [72]       |
| 2     | GAs              | Meta-heuristics  | Low level co-evolutionary homogeneous hybrid model | Develop an efficient optimization algorithm | It provides better quality results and precise optimal values than HOMER | [73]       |
| 3     | PSO              | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Implement HS algorithm to make all the particles of PSO fly inside the variable boundaries and regenerate which fly outside the variables boundary then to check whether they violate the problem-specific constraints and get better solutions | Less computational time compared to PSO The effectiveness to manipulate the new particles fulfilling the problem constrains. | [74]       |
| 4     | GA               | Iterative method | High level relay heterogeneous hybrid model | Reduce computational time by minimizing the number of iterations | Less number of iterations with relatively less consumed time | [75]       |
| 5     | GA               | Markov model     | High level relay heterogeneous hybrid model | Minimize the long computational time required by GA | Markov mode-based GA produced high quality solutions It provides less consumed CPU time | [76]       |
| 6     | SA               | Meta-heuristic   | High level Relay heterogeneous hybrid model | SA is not especially fast at finding the optimum in a given solution region | The performance of the proposed algorithm is higher than standard SA and TS | [77]       |
| 7     | GA               | ANN              | High-level Relay heterogeneous hybrid model | Reduce the computational effort required | It provides the optimal size combination under conditions of uncertainty, in a reasonable manner | [78]       |
| 8     | SA               | CS               | Low level co-evolutionary heterogeneous hybrid model | Improve exploration and exploitation capabilities | The combination has showed better performance than other algorithms based on mean and worst values | [79]       |
| 9     | TLBO             | Fuzzy logic      | Low level co-evolutionary heterogeneous hybrid model | Increasing the diversity of the population | This combination has produced high quality solutions | [80]       |
| 10    | GA               | Soft computation | Low level co-evolutionary heterogeneous hybrid model | Reduce computational time and improve quality results | The proposed algorithm increased the quality of solutions compared to GA | [81]       |
| 11    | ACO              | Soft computation | Low level co-evolutionary heterogeneous hybrid model | Create an efficient optimization algorithm | The method has smaller convergence iterations and consumed time than ABC and GA | [82]       |
| 12    | PSO              | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Enhancing the capability of jumping out of local optimal optima | The proposed combination gives greater cost results in less calculation time than PSO | [83]       |
| 13    | PSO              | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Improve the exploration ability of the BB-BC algorithm and avoid local optima entrapment | Low standard deviation relative to PSO and DHS Higher quality results | [84]       |
| 14    | PSO              | Exact method     | Low level co-evolutionary heterogeneous hybrid model | Increase chance to find the optimal decision variables | It provides excellent solutions quality based on minimizing TAC | [43]       |
| S.No. | Combined methods | Combination type | Hybrid model used | Objective | The performance of proposed method | References |
|-------|------------------|------------------|------------------|-----------|-----------------------------------|------------|
| 15    | GA Exhaustive search | Meta-heuristic Exact method | High level relay heterogeneous hybrid model | Enables GA to avoid probably of trapping into local optima | Proposed method achieved the optimal solution with less number of iterations compared to classical GA | [85] |
| 16    | HS CS | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Escape from the local optimum | HSBCS yields better results than the standard HS | [86] |
| 17    | HS SA | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Balance exploration and exploitation capabilities | HHSSAA provided better quality results compared to individual HS or individual SA | [87] |
| 18    | CS SA IHS | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Balance exploration and exploitation capabilities | Better quality results | [88] |
| 19    | CS NMA | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Employ Nelder-Mead method to reduce the time taken for the search by ACO | The proposed combination improved convergence rate and reduced simulation time | [89] |
| 20    | CS HS SA | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Balanced exploration and exploitation capabilities | Better quality results | [90] |
| 21    | GA PSO | Meta-heuristic Meta-heuristic | High level co-evolutionary heterogeneous hybrid model | Develop an efficient optimization algorithm | Proposed method achieved search performance | [91] |
| 22    | TLBO SSA ED | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Better exploitation of the search space of the search space | Superior quality of solutions | [92] |
| 23    | SA IHA | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Increase the probability of finding the global solution for a complex optimization problem | Higher optimal solutions accuracy | [93] |
| 24    | Jaya TLBO | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Increase the search power around the global solution | JLBO provided more promising solutions quality in terms of minimizing TAC than GA | [94] |
| 25    | GWO SCA | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Improve the accuracy and speed of the GWO method by adding the updating operator of the SCA instead | The new algorithm has produced high quality results than PSO, GWO and GWO | [95] |
| **Multi-objective optimization** | | | | | | |
| 1     | FPA SA | Meta-heuristic Meta-heuristic | Low level co-evolutionary heterogeneous hybrid model | Increase the global search of FPA and prevent the algorithm to be trapped in local optimum solutions | Better results quality than GA Good solution precision than PSO Better performance with less run-time | [96] |
| 2     | MOPSO NSGA-II | Meta-heuristic Meta-heuristic | High level relay heterogeneous Hybrid model | Ameliorate quality results | It provides more promising solutions quality in terms of minimizing TC solutions quality in terms of minimizing TC | [97] |
| S.No. | Combined methods | Combination type | Hybrid model used | Objective | The performance of proposed method | References |
|-------|------------------|------------------|------------------|-----------|-----------------------------------|------------|
| 3     | ACO              | Meta-heuristic   | High level relay heterogeneous hybrid model | Help ACO by produce a good initial solution and determine a good search direction using ABC | ABC-ACO provided better quality results than original ACO | [98]       |
|       | ABC              | Meta-heuristic   |                   |           |                                   |            |
| 4     | MOL              | Meta-heuristic   | High level relay heterogeneous hybrid model | Enhance exploration and exploitation capabilities | It provides fast result convergence and lesser chances of local minima | [99]       |
|       | TLBO             | Meta-heuristic   |                   |           | It provides better results quality than SGA, PSO, TLBO, ITLBO and MOL |            |
| 5     | GA               | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Augment the computational efficiency because PSO can easily fall into a local optimal point prematurely. | The proposed algorithm provided more effective results with lower fitness function value | [100]      |
|       | PSO              | Meta-heuristic   |                   |           |                                   |            |
| 6     | MOEA             | Meta-heuristic   | Low level co-evolutionary heterogeneous Hybrid model | Reduce computational time and improve results quality | Optimum solution | [65]       |
|       | GA               | Meta-heuristic   |                   |           | Less computational time           |            |
| 7     | TLBO             | Meta-heuristic   | Low level co-evolutionary heterogeneous Hybrid model | Improve exploration and exploitation capabilities | New TLBO provided more promising solutions quality (better cost) than GA and PSO | [101]      |
|       | CSA              | Meta-heuristic   |                   |           |                                   |            |
| 8     | SFLA             | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Balanced trade-off between the exploration and exploitation | ShBAT gives best result compared with the GA, SFLA and BAT | [102]      |
|       | BAT              | Meta-heuristic   |                   |           |                                   |            |
| 9     | MHOD             | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Balance the exploratory behavior with exploitative behavior | The novel algorithm yields better result in terms of convergence time and losses of the bus compared to both algorithm individually | [103]      |
|       | GSA              | Meta-heuristic   |                   |           |                                   |            |
| 10    | PSO              | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Combine the ability of exploitation in PSO with the ability of exploration in GWO for better trade off between the exploration and exploitation in order to avoid high local optima | Hybrid PSO-GWO provided superiority results over the comparative algorithms in terms of reducing the computational time and achieving the best function values for both the single and the multi-objective problems | [104]      |
|       | GWO              | Meta-heuristic   |                   |           |                                   |            |
| 11    | ABC              | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Increase the efficiency of ABC | The proposed method provides better performance in than GA, PSO and hybrid GA-PSO | [105]      |
|       | CS               | Meta-heuristic   |                   |           |                                   |            |
| 12    | PSO              | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Improve the convergence rate of the optimal solution and help PSO with best start for faster convergence with global solution | It provides more accurate optimization results compared to PSO and GA | [106]      |
|       | NMA              | Meta-heuristic   |                   |           |                                   |            |
| S.No. | Combined methods | Combination type | Hybrid model used | Objective | The performance of proposed method | References |
|-------|------------------|------------------|-------------------|-----------|-----------------------------------|------------|
| 13    | TLBO GWO         | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Increase the global and local search capability as well as track the optimal answer of TLBO | The suggested algorithm has a better convergence speed in single objective problem solution and also in multi-objective optimization based on Pareto levels and achieving the less loss and more reliability than TLBO and GWO individually | [107] |
| 14    | GA GWO           | Meta-heuristic   | Low-level co-evolutionary heterogeneous hybrid model | Increase the exploration capability of GWO | The HGWO algorithm performs better than the PSO algorithm | [108] |
| 15    | SFL TLBO         | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Enhance the exploitation capability of TLBO algorithm | The combination offered higher quality solution compared to TLBO and SFL individually | [109] |
| 16    | PSO GSA          | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Combine the ability for social thinking in PSO with the local search capability of GSA | The hybrid PSOGSA algorithm provides an effective and robust high-quality solution. Hybrid PSOGSA are either better or comparable to those obtained using other techniques reported in the literature | [110] |
| 17    | GA PSO           | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | To avoid falling into the local optimum and to improve the quality of searching global optimum | GA-PSO operated faster and more accurately compared to NSGA-II, E-PSO, DE, and GA | [111] |
| 18    | BBO PSO          | Meta-heuristic   | High level co-evolutionary heterogeneous hybrid model | Improve exploration and exploitation capabilities | The proposed algorithm provided better results quality than NSGA-II and MOPSO | [112] |
| 19    | AEO SCA          | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Reduce the computational time and avoid falling into local optimum | Better quality results and higher convergence accuracy than standard AEO The proposed IAEO has the best performance among PSO, GWO, and SSA | [113] |
| 20    | GWO PSO          | Meta-heuristic   | High level relay heterogeneous hybrid model | Reduce the possibility of falling into a local minimum | Superior quality of solutions | [114] |
| 21    | CSO PSO          | Meta-heuristic   | Low level co-evolutionary heterogeneous hybrid model | Increase the exploration capabilities of CSA | Higher convergence accuracy | [115] |
Various combinations have been applied between PSO and other meta-heuristic algorithms to solve hybrid renewable energy sizing problems, for example, Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Gravitational Search Algorithm (GSA). These combinations seem very effective, able to avoid local optima entrapment and provide superior quality solutions. For future works, we recommend hybridizing PSO by using its exploitation ability with other meta-heuristic algorithms with strong exploration ability for further benefits to solve hybrid renewable energy optimization problems.

From the review, several local search algorithms have been incorporating with other evolutionary algorithms to overcome their shortage of trapping into local optimum such as tabu search (TS) and simulated annealing (SA). In these hybrid algorithms, the evolutionary algorithms were used to search the decision space by their global search capability, while local search algorithms were utilized to perform local search and avoid premature convergence. These hybrid approaches seem to provide better accuracy, with good convergence. Besides TS and SA, there are other local search techniques that can be incorporated, which may give good quality results. For example, chaotic maps (CS), sensitivity based clustering, ejection chain method based local search, hill-climbing, variable neighborhood search, alternate heuristic location-allocation algorithm, the exchange heuristic algorithm.

As can be noticed from this review, there is a huge interest of combining TLBO with other meta-heuristic techniques which provide better quality results. TLBO is a population-based optimization algorithm inspired by a teaching-learning process. Indeed, TLBO has excellent exploration capability but lacks in exploiting the solution space locally. As a result, most previous studies focused on enhancing exploitation ability of algorithm. Therefore, as part of future work, combining the previous-mentioned local search techniques with TLBO may give good quality results.

According to this compiled study’s, it is found that serial implementation has been mostly applied for SA and population-based meta-heuristic hybridization as shown in Table 6. Besides, the original SA has been widely used to enhance the exploitation of other algorithms. The capabilities to escape from trapping at local solutions helps population-based meta-heuristic algorithms to increase the explorative search ability. Thus, the algorithm can produce better optimal solutions than the original. On the other hand, SA was used in several studies as a component in the population-based meta-heuristics algorithm. It is used to search the neighborhood of the best search agent so far to ensure that it’s the local optima by using the low-level co-evolutionary hybridization technique. Future research can be focused on the application of the high-level relay hybridization technique by employing SA in a pipeline mode after the population-based meta-heuristic algorithm terminates to enhance the best-found solution [119].

One of the main findings of this study is related to the use of inertia weight strategy or an improved version of inertia weight strategy of PSO to improve the performance of other meta-heuristic algorithms in achieving the global optimal quickly and not being trapped in the local optimal. Therefore, it is recommended to explore the use of other meta-heuristic algorithms based inertia weight strategy to solve HRES problems as these improved versions provide better results compared to the standard algorithm.

As can be concluded from this review, there is a huge interest in the use of a combination between exact methods and meta-heuristic algorithms especially the genetic algorithm. These hybrid algorithms are suitable to solve single optimization hybrid renewable energy sizing problems instead there a major difficulty for applying meta-heuristic-exact hybridization method to solve multi-objective problems is that there are few exact methods that can treat the specificities of multi-objective optimization.

Many new algorithms have been developed in recent years. For example Water Wave Optimization (WWO) [120], Bird Swarm (BS) [121], Equilibrium Optimizer algorithm (EO) [122], Hydrological Cycle Algorithm (HCA) [123], Farmland Fertility (FF) [124], The Sailfish Optimize (TSO) [125], Heterogeneous Pigeon-Inspired Optimization (HPIO) [126], Harris Hawks Optimization (HHO) [127], Emperor Penguins Colony (EPC) [128], Political Optimizer(PO) [129], Slime Mould Algorithm (SMA) [130] and others. The list is quickly expanding. These algorithms may have entities and some novel features for hybridization that remain to be investigated in the near future. However, It should however be stressed that easy, random hybridization should not be encouraged.

### 6 Conclusion

This paper review and analyze the available research studies on the use of hybrid meta-heuristic algorithms to size and design hybrid renewable energy system components.

The first finding of this review is that although there are a large number of review articles related to the area of sizing methodologies for hybrid renewable energy systems, however a few of them have a flat discussed around size optimization of renewable energy based hybrid system by using hybrid meta-heuristic algorithms. The second finding is an indication of the fast and significant growth of using hybrid meta-heuristic algorithms for engineering problems. As we mentioned by considering multiple objective functions and constraints to improve solutions quality the complexity of the system increase, thus, there is a promising research area in finding solutions for multi-objective optimizations.
by hybrid meta-heuristics algorithm in a special place. The third finding is the good quality results and less computational time by combining the SA algorithm with population-based meta-heuristic algorithms.

Among various hybridization techniques, this review concludes that using a low-level co-evolutionary hybridization model to combine global search algorithm with local search techniques is the most useful and promising technique which can produce better optimal solutions than the individual methods. Future research needs to take into consideration larger problem scale, irregular objective space and uncertainty to develop strong and efficient hybrid algorithms capable to solve single and multi-objective hybrid energy system sizing problems.

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Declarations

Confict of interest The authors declare that they have no conflict of interest.

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