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REVIEW ARTICLE

Review on constraint handling techniques for microgrid energy/power management systems

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Abstract
Microgrid energy management system (EMS)/power management system (PMS) optimisation problems often have conflicting objectives subjected to nonlinear constraints. They are challenging to solve due to sources of discontinuity and non-convexity. However, the optimisation algorithms used to solve these problems are originally developed to solve unconstrained problems. Therefore, constraint handling techniques (CHTs) are integrated into these algorithms to solve constrained optimisation problems. The strategy of handling constraints contributes immensely toward the quality and accuracy of the solutions. Nonetheless, CHTs in solving microgrid EMS/PMS optimisation problems have received scant attention in the research. This study reviews the state-of-the-art CHTs through a four-step systematic framework. It identifies and screens the related research work, conducts an in-depth analysis on CHTs, scrutinises the nature of recurring constraints in EMS/PMS optimisation problems and critically analyses the findings. Based on the results of this review, three crucial factors in selecting an appropriate CHT were identified: (i) domain knowledge, which includes the nature of the problem (unimodality or multi-modality), the nature of the equality/inequality constraints (linearity or non-linearity), relationships among objective functions and constraints, number of constraints and their interdependencies, (ii) the area of feasible space defined by the constraints and (iii) the exploration and exploitation stages of the search algorithm. In addition, the need for more accurate and advanced CHTs to handle the constraints in microgrid EMS/PMS problems is emphasised. Moreover, conducting performance comparisons of CHTs in these problems would assure favourable upgrades in microgrid EMS/PMS.

Keywords Constraint handling techniques · Energy management system · Microgrids · Optimisation · Power management system · Renewable energy

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List of symbols

Abbreviations

BS	Battery storage
CEED	Combined economic emission dispatch
CHT	Constraint handling technique
DG	Diesel generator
DR	Demand response
EA	Evolutionary algorithm
ED	Economic Dispatch
EENS	Expected energy not supplied
EIR	Energy index of reliability
EL	Electrolyser
ELF	Equivalent loss factor
EMS	Energy management system
ENS	Energy not supplied
EPP	Efficient power plant
ESS	Energy storage system
FC	Fuel cell
GA	Genetic algorithm
GC	Grid connected
HSP	Health state probability
LLP	Loss of load probability
LOLP	Loss of load probability
LPSP	Loss of power supply probability
MO	Multi-objective
MOOP	Multi-objective optimisation problem
MT	Microturbine
NSGA II	Nondominated sorting genetic algorithm II
OPF	Optimal power flow
OR	Operating reserve
PF	Penalty factor
PMS	Power management system
PSO	Particle swarm optimisation
PV	Photovoltaic
RER	Renewable energy resource
RM	Reserve margin
RSP	Risk state probability
SOC	State of charge
SR	Stochastic ranking
UL	Unmet load
WT	Wind turbine

Symbols

a_k^l, a_k^u	Values defined for transformation repair
cp	Parameter controlling the speed of constraint relaxation

$C_j(x)$	j[th] PF for inequality constraints
$f(x)$	Objective function
f_{worst}	Worst feasible solution
$f_i(x)$	i[th] constraint violation
$g_j(x)$	j[th] inequality constraint
$h_i(x)$	i[th] equality constraint
K	Large constant used in death penalty
$K_i(x)$	i[th] PF for equality constraints
$l_k(x)$	Lower bound of x_k
m	Number of equality constraints
n	Number of decision variables
N	Number of constraint violations
p	Number of inequality constraints
$P(x)$	Penalty function
p_f	Control parameter to balance feasibility/infeasibility
p_o	Probability of an individual winning based on its objective function
p_s	Predefined probability
p_v	Probability of an individual winning based on its constraint violations
$r\left(x_k\right)$	Repaired k[th] decision variable
s	Number of satisfied constraints in death penalty
t	Iteration number
t_c	Predefined number of iterations
t_{max}	Maximum number of iterations
u	Random value used in ranking methods
$u_k(x)$	Upper bound of x_k
w_1, w_2	PFs used in co-evolutionary based penalty
x_k	k[th] decision variable
x_k^{best}	The current best solution
z	Number of objective functions

Greek letters

α, β, γ	Predefined constants in penalty methods
β_1, β_2	Predefined constants in self-adaptive penalty method
$\delta, \rho, \zeta,\ \eta, \sigma, \tau$	Values defined in repair methods
ε	Allowed tolerance for equality constraint conversion/constraint relaxation in ε-constrained method
$\varepsilon(0)$	Constraint violation at the top individual at initialisation
$\varepsilon(\mathrm{t})$	Evolution of ε at t[th] iteration
λ	Single PF used in static penalty
$\lambda(t)$	PF used in dynamic penalty
ξ	Random value used in repair methods
$\varphi(x)$	Revised objective function

1 Introduction

1.1 Background

Using renewable energy resources (RERs), such as wind, solar, biomass, hydro, tidal and wave energy, provides a promising alternative to ever increasing fossil fuel demand. Currently, microgrids integrated with RERs, conventional energy resources and energy buffers are often used to cater for the energy demand in islands and remote locations. Microgrids can be operated either in grid-connected mode or off-grid mode. However, the intermittency of RERs and the dynamic nature of demand make integration and management challenging [1]. This challenge can be handled by incorporating energy management systems (EMSs)/ power management systems (PMSs) [2, 3].

In recent literature, extensive research and development in EMS/PMS provide ample evidence of the benefits of integrating EMS/PMS in microgrids [4, 5]. EMS/PMS ensures power smoothing, maintains the safety of devices, enhances the system's reliability and optimises the microgrids' performance, lowering the operation cost with minimum emissions [6–8]. In this context, researchers have solved various optimisation problems to increase the RERs utilisation in microgrids. These optimisation problems are often complex with highly nonlinear constraints and demand more robust algorithms to solve. Therefore, to solve these problems, scholars have often used single or hybrid meta-heuristic optimisation algorithms [9–13].

There are a few key challenges in solving EMS/PMS optimisation problems. On the one hand, they usually have multiple local solutions within their feasible region, which make them multi-modal problems. On the other hand, constraint handling becomes challenging with higher penetration of RERs in microgrids [14]. Besides, when these problems are subjected to complex constraints, the feasible search space reduces drastically and becomes non-convex. Notably, equality constraints lessen the dimension of the search space [15, 16]. Thereby, these problems are usually represented as constrained non-convex, nonlinear mixed integer complex problems [17]. Furthermore, the complexity of algorithms used to solve these problems increase dramatically with increased constraints [14, 18]. This makes locating the global optimum solution even more challenging.

Moreover, the approach utilised in constraint handling greatly contributes to the quality and accuracy of the solutions [19, 20] and considerably influences the algorithm's performance [21]. However, the usual approach randomly integrates a simple constraint handling technique (CHT). According to the well-known 'no free lunch theorem' [22], the trial and error approach does not guarantee the best results. It highlights that while algorithm A outperforms algorithm B for some optimisation problems, B will outperform A for other problems. This theorem is equally applicable for CHTs because each optimisation problem and CHT are unique. Central to the entire discipline of optimisation is the concept of constraint handling. However, in the context of microgrid EMS/PMS problems, a systematic review on CHTs is still lacking. Moreover, research to date lacks the prospective approaches to selecting appropriate CHTs for microgrid EMS/PMS problems. This review is focused on filling in these research gaps.

1.2 Previous research work on CHTs in microgrid EMS/PMS optimisation

CHTs employed in optimisation problems are broadly classified into four categories: penalty methods (static, dynamic, self-adaptive, co-evolutionary and death), separatist methods (feasibility criteria, ε-constrained method, multi-objective (MO) based conversion, co-evolution based separation and ranking methods), repair methods and hybrid (ensemble) methods [23–25]. A more detailed account of each of these is given in Sects. 3 and 5.

The static penalty approach is widely used to eliminate objective functions violating any constraints of EMS/PMS and sizing optimisation problems [26–37]. Similarly, the death penalty is used to discard infeasible solutions [38–41]. These are the simplest CHTs among all types. However, static and death penalty approaches ignore valuable solution space information. Similarly, if randomly generated new solutions replace the infeasible solutions, the search process becomes inefficient. By identifying these limitations, scholars have attempted to use improved versions of the penalty approach. For example, EMS optimisation of microgrid considered in [42] used a dynamic penalty factor (PF) in fitness function evaluation. PF is increased during the optimisation search process if more constraint violations are observed in this case.

Researchers have employed other CHTs to solve microgrid EMS/PMS and sizing optimisation problems. For instance, feasibility criteria were utilised to handle the constraints in EMS studies on microgrids [43–47]. Furthermore, in [48], the ε-constrained method was used to handle constraints in sizing optimisation of a microgrid. In addition, repair methods were employed to solve a home EMS [49] and an islanded microgrid EMS [50] to satisfy the constraints. Moreover, a repair method was hybridised with feasibility criteria in [47] for a ship-integrated energy system. A hybrid CHT, which integrates stochastic ranking (SR) and feasibility criteria, was applied to handle constraints in the EMS optimisation of an industrial microgrid [51]. This CHT is employed in the differential evolutionary algorithm (EA) selection process to filter the feasible solutions.

Microgrid economic dispatch (ED) and combined economic emission dispatch (CEED) problems provide excellent learning opportunities for applying various CHTs. For instance, the authors in [52] utilised a multiple constraint ranking method to solve a CEED problem. In this approach, each constraint is ranked based on the objective value, the number of violated constraints and the individual constraint violation. Authors claimed the benefits of the CHT as no user-predefined parameters, less computational burden and easy implementation. In solving CEED problems, [19, 53, 54] used repair mechanisms to monitor the inequality constraint violations. In these, the infeasible coordinates are projected onto the violated bounds. The repair is extended for the equality constraints separately by selecting the generator units randomly. Further, a penalty is also applied to discard infeasible solutions after the repair process. A similar repair-based penalty approach was employed in [55] for an ED problem. In [56], the authors used a penalty function to handle equality constraints and a bound repair approach for inequality constraints of an ED problem. Moreover, a repair method integrated with genetic algorithm (GA) was proposed in [57] to handle the constraints in solving an ED problem. This approach repairs the mutated offsprings to return infeasible populations to the feasible region. The death penalty was imposed to discard infeasible solutions to a CEED problem in [58] while monitoring constraint violations. In [59, 60], feasibility criteria and a repair scheme were hybridised to effectively handle constraints in microgrid CEED problems.

Microgrid optimal power flow (OPF) problems are also solved using different CHTs. In [61], a repair-based CHT was coupled with the horse herd optimisation algorithm in integrating wind power in a power network. In this CHT, a predefined small value is reduced at each iteration from the existing control variable if the constraints violate the upper bounds and treated vice versa for lower bound violations. It returns to the previous feasible solution if the constraint violations do not eliminate after the repair process. Moreover, feasibility criteria and the ε-constrained method were used in [62, 63] respectively to solve OPF problems in microgrids.

While all research work in solving EMS/PMS optimisation problems must have employed various CHTs, only a few scholars have discussed using CHTs in their studies. Surprisingly enough, static/death penalty methods and feasibility criteria are widely used in solving microgrid EMS/PMS optimisation problems, which appear simpler in the application and easier to implement. Despite the importance of CHTs, their use has not been systematically investigated in this framework. Conclusively, the previous reviews on EMS/PMS of microgrids mainly focus on the control architectures, forecasting strategies, optimisation techniques, objective functions, constraints and integration of energy storage systems (ESSs) [1, 14, 64–69]. None of these reviews has critically analysed the importance of CHTs in solving EMS/PMS optimisation problems. A summary of previous work under the scope of this study is illustrated in Table 1.

1.3 Contributions and structure of this paper

Based on the previous literature and to the best of our knowledge, CHTs in solving microgrid EMS/PMS optimisation problems have received scant attention in the research. Intending to fill this research gap, the specific objective of this review is to investigate a large and growing body of literature to analyse various CHTs that could be applied to solve EMS/PMS optimisation problems in microgrids. Thereby, the contributions of this study are:

- Providing a comprehensive analysis of various CHTs which can be applied in solving microgrid EMS/PMS optimisation problems
- Investigating the holistic overview of microgrid EMS/PMS optimisation problems to analyse the nature of recurring constraints
- Identifying factors influencing the choice of appropriate CHTs for solving EMS/PMS optimisation problems in microgrids

Table 1 CHTs applied in microgrid EMS/PMS/Sizing/ED/CEED optimisation problems

CHT	Focus of the study in microgrids			
	EMS/PMS	Sizing	EMS/PMS & Sizing	ED/CEED/OPF
Penalty methods				
Static	[28, 33–35, 70]	[29, 30]	[26, 27, 32]	
Death	[38]	[37]	[36, 39, 40, 71]	[58]
Dynamic	[42]			
Self-adaptive				[72]
Separatist methods				
Feasibility criteria	[43–46]			[62, 73]
ε-constrained		[48]		[63, 74]
Ranking				[52]
Repair methods	[49, 50]			[19, 53–57, 61, 75–79]
Hybrid methods	[47, 51]			[59, 60]

- Delivering valuable insights for scholars on current challenges, opportunities and future directions on CHTs applicable for microgrid EMS/PMS studies

The rest of this paper is organised as follows. Section 2 presents the methodology, including the proposed framework developed for this study. Section 3 analyses various CHTs applicable in solving optimisation problems in microgrids. Section 4 covers the holistic overview and the nature of recurring constraints in EMS/PMS optimisation in microgrids. Moreover, this section summarises the use of CHTs in these problems. Section 5 critically analyses the findings of this review. Conclusions drawn from the study and the future directions are presented in Sect. 6.

2 Methodology and the proposed framework

Although extensive research has been carried out on microgrid EMS/PMS optimisation problems, relatively few have discussed integrated CHTs. Therefore, a systematic four-step framework was followed to achieve the objectives of this paper. Each step is linked into different sections, as illustrated in Fig. 1. The records were identified and screened in the first step. In the second step, the research trends were analysed. After that, with a preamble for the generalised constrained optimisation problem, various CHTs were examined based on the literature. In the third step, the CHTs in microgrid EMS/PMS application and the nature of recurring constraints were scrutinised. A holistic overview of microgrid EMS/PMS problems is also presented in this step. Finally, in the fourth step, the research findings were critically analysed. This includes the critical findings of this review, the merits/demerits of CHTs and the factors that need to be considered in selecting a CHT.

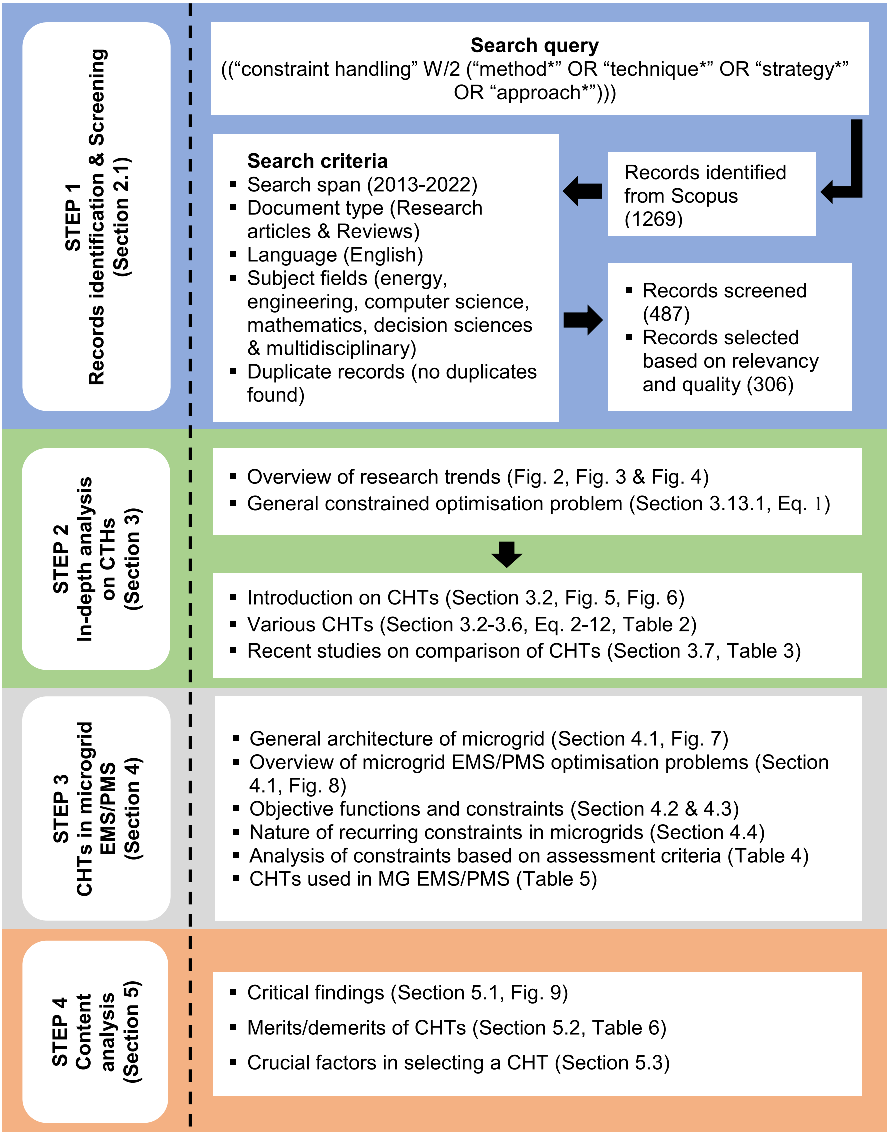

Fig. 1 Systematic four-step framework research methodology

2.1 Records identification and screening

The literature related to CHTs was identified through an exclusive search with relevant keywords. After that, systematic screening and quality assessment were performed to extract updated and quality data from the literature. The records identification and screening process is explained below in detail.

Firstly, a search strategy was developed to identify the most relevant literature discussing various CHTs. The focus was on the CHTs, which can be used with meta-heuristic algorithms and EAs to solve microgrid EMS/PMS optimisation problems. For this, the search strategy was tailored to the Scopus database on 05/05/2022. The following search query was used based on the title, abstract and keywords: ((“constraint handling W/2 (“method*” OR “technique*” OR “strateg*” OR “approach*”))), which resulted in a total of 1269 records. The search was mainly focused on mapping existing literature on CHTs; therefore, the search span was limited to the last 10 years (from 2013 to 2022). Thereby, we ensure that the updated knowledge is presented in this paper. The search was then narrowed down to the research articles and reviews in journals published in English. After that, the search was further restricted to energy, engineering, computer science, mathematics, decision sciences and multidisciplinary fields. There were 487 records in the search at this stage and no duplicate records were observed among these articles.

To ensure the relevancy and quality of the articles, the abstracts and contents of these articles were scrutinised. Finally, we selected 306 records based on the inclusion and exclusion criteria. These records were then imported to ‘VOSviewer’, a free software tool used to generate networks by importing bibliographic databases or reference manager files [80]. Then the generated maps were analysed based on a co-occurrence matrix table of all keywords in the articles, subjected to a minimum of 10 occurrences of a keyword. 84 keywords directly related to CHT studies met the threshold, and a detailed analysis of the generated visualisations is given in Sect. 3.

3 Analysis on CHTs

The yearly trend of publications and citations during the last decade is depicted in Fig. 2, which illustrates a positive trajectory in research on CHTs. However, it shows that there has been a slight fall in the number of publications in 2015 and 2021 in comparison with 2014 and 2020 respectively. The citations related to these publications have steadily risen during the last decade. The data for the year 2022 in Fig. 2 was extracted on 05/05/2022. Therefore, even though the figure shows a sharp decline this year, we can expect the continuation of the rising trend in the engagement of research on CHTs in future. Furthermore, keywords provide insight into a particular research area by representing essential elements in that field. Therefore, an analysis of keyword co-occurrence was conducted. Figure 3 highlights the overlay visualisation of the co-occurrence of keywords over the study period. It demonstrates the frequency of research related to constraint handling each year.

Co-occurrence analysis of the keywords is shown in Fig. 4. It provides a quick overview of CHT studies that appeared together with five working clusters shown by different coloured groups: constrained optimisation, constraint handling, multi-objective optimisation, optimisation algorithms and electric load dispatching. It also shows that the discussion on CHTs is often carried out with EAs, swarm intelligence, heuristic and meta-heuristic algorithms. The size of the nodes and the

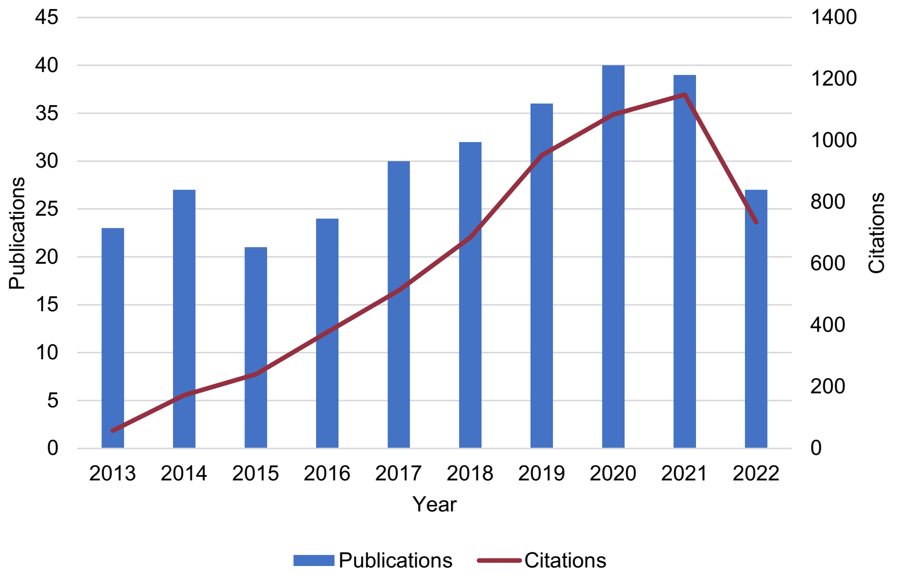

Fig. 2 Number of publications and citations for research on CHTs during 2013–2022

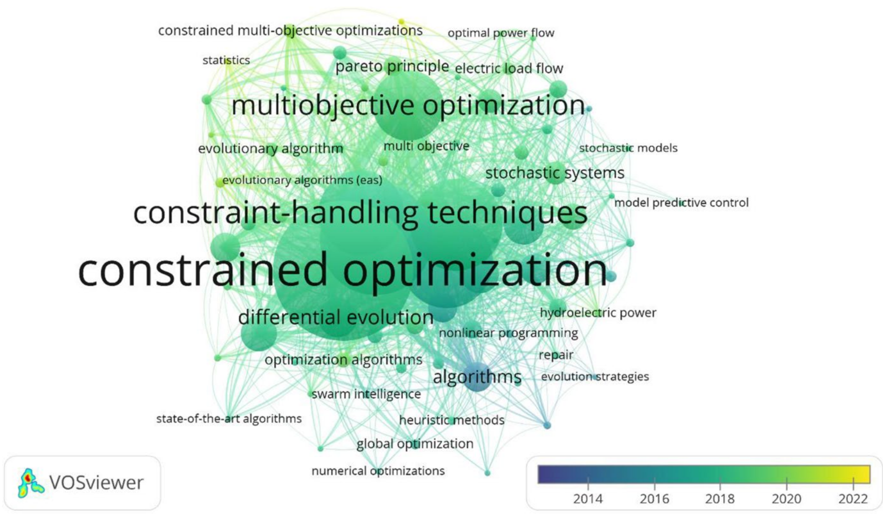

Fig. 3 Keyword co-occurrences (at least 10 occurrences) in articles on CHTs during 2013–2022

strength of the interconnecting lines in Fig. 4 interpret the frequency of occurrence and relationship among them. What stands out is the employment of GA, its variants and particle swarm optimisation (PSO) algorithm with CHTs by many researchers.

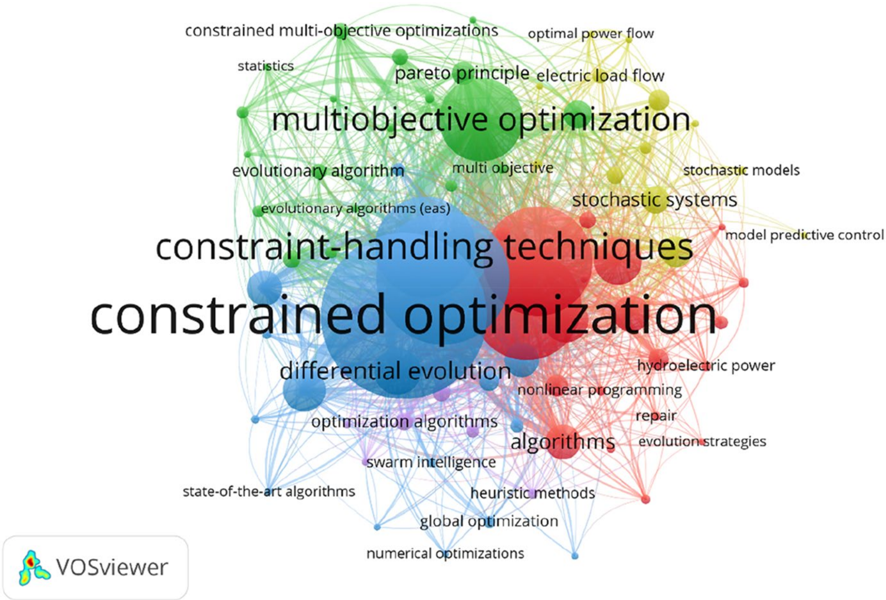

Fig. 4 Different research clusters based on keyword co-occurrences

3.1 General constrained EMS/PMS optimisation problem

Microgrid EMS/PMS optimisation problems have various constraints that drastically reduce the feasible search space. Moreover, the complexity of the feasibility region rises either from not having a closed form representation for a point in the feasibility region or from the computational complexity of determining the closed form. In solving microgrid EMS/PMS optimisation problems, researchers use meta-heuristic algorithms following swarm intelligence more frequently. These algorithms are originally developed to solve problems in unconstrained search spaces. Therefore, incorporating a suitable CHT in the search process is crucial. The easiest way is to discard the infeasible solutions. However, this approach may fail to reach any feasible solution when the search space is limited and discontinuous. Furthermore, the failure vulnerability is prominent because the search is stochastic. There are a few alternative approaches to handle this issue: applying predefined rules to filter the information from infeasible solutions, treating objective functions and constraints separately, and repairing infeasible solutions. Various CHTs have been devised based on these alternatives.

As a preliminary set up, a general constrained optimisation problem is defined in Eq. 1.

$$\text{Minimise}\, f(x) = \left[f_1(x), f_2(x), \ldots \ldots, f_z(x)\right], z = 1 \ldots \ldots n \tag{1}$$

$$\text{subject to} \qquad h_i(x) = 0, i = 1, \dots .m$$

$$g_j(x) \leq 0, j = 1, \dots .p$$

$$l_k(x) \leq x_k \leq u_k(x), k = 1 \dots .n$$

where $x = x_{1,}x_2, \dots ..x_n$ are n decision variables, $f(x)$ is the objective function (single objective when $z = 1$ or MO otherwise), $h_i(x)$ and $g_j(x)$ are m equality constraints and p inequality constraints. The objective function and all these constraints are linear or nonlinear real-valued functions. The upper and lower bounds of the k^{th} decision variable (x_k) are $u_k(x)$ and $l_k(x)$; those define the search space. The inequality and equality constraints define the feasible region within the search space. The parameters specified herewith are used in the sequel.

3.2 Introduction on CHTs

The solutions to constrained optimisation problems often fall outside the feasibility region. This issue can be fixed using an appropriate CHT because it either guides the population to the feasible region or repairs the infeasible population to find solutions. The primary purpose of a CHT is to balance feasibility and convergence [81]. This highlights the importance of using CHTs in solving constrained optimisation problems. In this review, we focused on the adaptable CHTs for meta-heuristic algorithms and EAs that could be used in solving constrained EMS/PMS optimisation problems in microgrids. These problems are hard to be solved by the traditional CHTs, such as the method of Lagrange multipliers, barrier functions and stack variables, which are extensively reviewed and, thus, were not included in our discussion. Even though the decoders [82, 83] and special operators [84, 85] are interesting CHTs, they are rarely used. This is because decoders demand higher computational costs to find the most efficient mapping [86], while special operators are developed to handle specific problems [87]. Therefore, these types were not analysed in this study. CHTs can be broadly classified as penalty methods, separatist methods, repair methods and hybrid methods [23–25], as illustrated in Fig. 5. With a brief introduction to each of these, we discuss their merits and demerits for the benefit of future research in EMS/PMS optimisation applications in microgrids.

The evolution of CHTs, except for the traditional methods, is illustrated in Fig. 6. In producing this figure, the timeline for CHTs was based on the first reported studies ascertained from the available literature. Thereby, the referred studies are: static penalty [88], dynamic penalty [89], self-adaptive penalty [90], co-evolutionary based penalty [91], death penalty [92], feasibility criteria [93], ε-constrained method [94], MO based conversion [95], co-evolution based separation [96], SR [97], repair methods [98], hybrid methods [99], special operators [100] and decoders [101]. Moreover, countless novel CHTs add to the evolution of CHTs, and it is difficult to

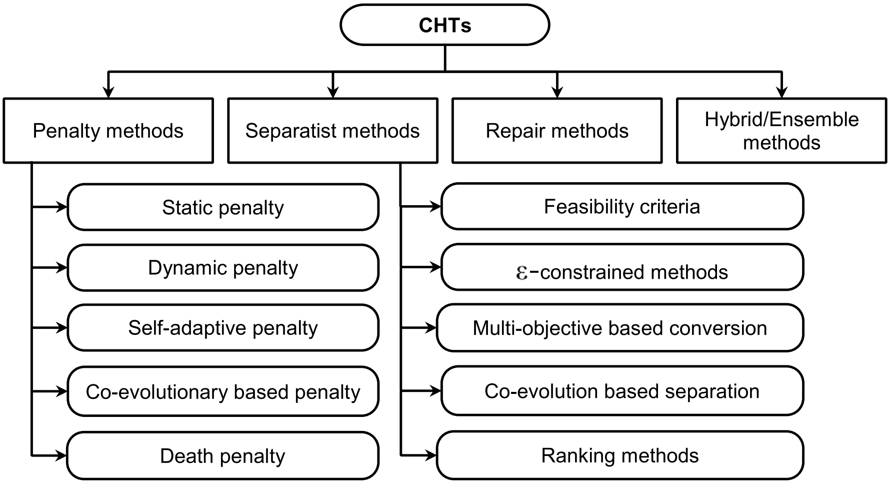

Fig. 5 Classification of CHTs

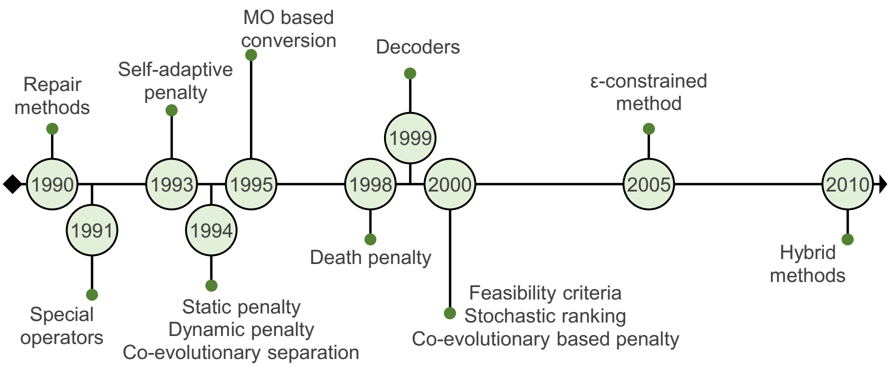

Fig. 6 Evolution of CHTs over two decades

determine the first reported novel CHT. Additionally, such novel CHTs are based on the core concept of one of the CHTs shown here and, thus, can be classified under them.

3.3 Penalty methods

The penalty methods are the most popular CHTs due to their easy implementation and lesser algorithm modifications. However, they do not use the linearity or nonlinearity of the constraints, and therefore the performance in most of the applications is uncertain. Penalty methods convert constrained optimisation problems to unconstrained ones by including the constraints in revised objective functions (φ(x)). The general form of the revised (penalised) objective function is given in Eq. 2 [25].

$$\varphi(x) = f(x) + P(x) \tag{2}$$

$$P(x) = \left[\sum_{i=1}^{m} K_i.\left|h_i(x)\right|^{\gamma} + \sum_{j=1}^{p} C_j.max\left\{0, g_j(x)\right\}^{\beta}\right] \tag{3}$$

$$P(x) = \lambda(t).\left[\sum_{i=1}^{m} \left|h_i(x)\right|^{\gamma} + \sum_{j=1}^{p} max\left\{0, g_j(x)\right\}^{\beta}\right] \tag{4}$$

$P(x)$ is the penalty function. All equality and inequality constraint violations are multiplied by the PFs to make $P(x)$. Various penalty methods are defined by using PFs (K_i and C_j) as given in Eq. 3 or by a single PF, $\lambda(t)$, for simplicity as in Eq. 4, where t denotes the iteration number. β and γ are generally used as 1 or 2, where β defines if the PF is exact (when β =1) or quadratic (when β =2) [102].

Converting an optimisation problem into an unconstrained one is advantageous because the search domain is specific, and easy to determine the optimal location. Nevertheless, assigning PFs is crucial and challenging [103]. Too low PFs can fail in finding the feasible region with a considerable search effort wasted in the infeasible region. In contrast, too high PFs converge the population to the feasible region instantly, thus failing to explore the valuable information in the infeasible region. Various penalty approaches have been developed based on assigning the PFs. They are static, dynamic, self-adaptive, co-evolutionary and death penalty methods [23].

3.3.1 Static penalty method

In this approach, the user must assign PFs, those are kept fixed during the evolution process. All equality constraints are converted to inequality constraints. i.e., $h_i(x) = 0$ is converted to $\left|h_i(x)\right| \leq \varepsilon$ where ε is the allowed tolerance. The revised objective function takes the form shown in Eq. 1 where, K_i, C_j and $\lambda(t)$ in Eqs. 3 or 4 are fixed. In this method, $\lambda(t) = \lambda$, which is independent of iteration (t) [25]. This approach may suffer the issue of converging either to a feasible or infeasible region depending on the assigned PF. There is no theoretical approach to assigning these values because it depends on the problem dynamics. However, most researchers adopt the static penalty method because of its easy implementation.

3.3.2 Dynamic penalty method

In the dynamic penalty method, the PFs are gradually increased during iterations by increasing $\lambda(t)$ in Eq. 4. $\lambda(t) = (\alpha t)^{\beta}$, where $\alpha = 0.5$ and $\beta = 1, 2$ are commonly used [104]. Therefore, the PFs significantly affect the objective function as they evolve with iterations. Some scholars argue that the dynamic penalty outperforms the static penalty approach. Annealing and adaptive penalty methods are also dynamic penalty approaches [105].

3.3.3 Self-adaptive penalty method

This is a further development of the dynamic penalty method. The PF ($\lambda(t)$ in Eq. 4) is adaptively changed to penalise infeasible solutions based on the information shared from the search process. If the search is dominated in the feasible region (case I in Eq. 5), the PF is reduced to increase exploration in the infeasible region. On the contrary, if the search is in the infeasible region (case II in Eq. 5), PF is increased because the best individual is never feasible. Doing so allows valuable information from the infeasible region to improve the final solution [25, 102].

$$\lambda(t+1) = \begin{cases} \dfrac{\lambda(t)}{\beta_1}, if\ Case\ I\ occurs \\ \beta_2.\lambda(t),\ if\ Case\ II\ occurs \\ \lambda(t),\ otherwise \end{cases} \tag{5}$$

where β_1 and β_1 are constants such that $\beta_1, \beta_2 > 1$ and $\beta_1 \neq \beta_2$.

3.3.4 Co-evolutionary based penalty method

This method divides the population into two groups with unique assignments. While the first group evolves possible solutions, the second group evolves PFs (w_1 and w_2) to derive the revised objective function shown in Eq. 6 [25, 91].

$$\varphi(x) = f(x) + w_1.\sum_{j=1}^{p} C_j.max\left\{0, g_j(x)\right\}^{\beta} + w_2.N \tag{6}$$

where N is the number of constraint violations. As in the static penalty method, all equality constraints are converted to inequality constraints. Moreover, in execution, this approach considers the scale of constraint violation as well as the number of violations in determining the PF.

3.3.5 Death penalty method

The death penalty method follows similar steps to the static penalty method. In this method, the PFs are all set to infinity or a very large constant to represent constraint violations [92, 105]. Thereby, the revised objective function is expressed as in Eq. 7 [21, 25, 106].

$$\varphi(x) = \begin{cases} f(x), \textit{if feasible} \\ K - \sum_{j=1}^{s} \frac{K}{m}, \textit{if infeasible} \end{cases} \tag{7}$$

where K is a very high value and s is the number of satisfied constraints. All the infeasible solutions are discarded without obtaining any information from the infeasible region, and the search process remains only in the feasible region. Despite being a simple approach, it is unsuitable for problems with discontinuous search spaces.

3.4 Separatist methods

Contrary to penalty methods, the separatist methods handle objective functions and constraints separately. Feasibility criteria, ε-constrained method, MO-based conversion, co-evolution based separation and ranking methods are evolved as separatist methods [23, 24].

3.4.1 Feasibility criteria

This method, proposed by [93], performs a pairwise comparison of two solutions by the following three rules:

(i) once two feasible solutions are compared, the one having better objective function is selected,
(ii) if one feasible and one infeasible solution are compared, the feasible solution is selected,
(iii) if two infeasible solutions are compared, the one having the lowest constraint violation is selected.

For rule (iii), all constraints are transformed into inequality constraints and the normalised constraints are summed up to the worst feasible solution (f_{worst}). Thereby, the objective function is evaluated by Eq. 8.

$$\varphi(x) = f_{worst} + P(x) \tag{8}$$

where, $P(x) = \left[\sum_{i=1}^{m} \left|h_i(x)\right|^{\gamma} + \sum_{j=1}^{p} max\left\{0, g_j(x)\right\}^{\beta}\right]$ is the total constraint violation. There are several unique advantages to this approach. Though this CHT follows the penalty approach, there is no requirement to assign PFs. Moreover, this method can be integrated with any population-based search method. Therefore, it is popular in solving constrained optimisation problems in meta-heuristic approaches [43, 44, 47, 107]. The authors in [106] integrated a modified version of feasibility criteria to handle constraints in comparing the performance of metaheuristic algorithms, which outperformed the standard feasibility criteria. They generated a new individual in the mid of two solutions violating the constraints. Then, this new solution was used in the third rule to compare infeasible solutions and was accepted only if it is better than the existing violations.

3.4.2 ε-constrained method

The ε-constrained method, proposed by [94], is a similar concept to the feasibility criteria. The uniqueness of this approach is in monitoring and relaxing the constraint violation during the early search process. The constraint violations dominate the objective function through ε level comparison based on lexicographic order [108]. Information obtained from the infeasible solutions is used effectively in the early stages of evolution until it reaches a set number of generations (t_c) as given in Eq. 9. After that, ε is set to zero. The search process from there follows the feasibility criteria.

$$\varepsilon(t) = \begin{cases} \varepsilon(0).\left(1 - \frac{t}{t_c}\right)^{cp}, & 0 < t < t_c \\ 0 & , t \geq t_c \end{cases} \tag{9}$$

Here, $\varepsilon(0)$ is the constraint violation at the top individual at initialisation and cp is a parameter, which controls the speed of reducing the constraint relaxation. $t_c \in [0.1t_{max}, 0.8t_{max}]$ and $cp \in [2, 10]$ are recommended [109, 110], where t_{max} is the maximum number of iterations. This method solves multi-modal problems in small feasible regions with equality constraints efficiently. In [24, 74, 111], the authors proposed improved versions of ε-constrained method by introducing a self-adaptive ε setting mechanism to enhance the convergence of the population to the feasible region. More recently, in [112], an improved ε-constrained method was applied in two search stages to solve constrained multi-objective optimisation problems (MOOPs). In the first stage, the population is pushed towards an unconstrained Pareto front, and in the second stage, the CHT is applied to pull the population towards a constrained Pareto front. Thereby, the computational burden is reduced while the information of the constraints is employed effectively.

3.4.3 Multi-objective (MO)-based conversion

Usually, MOOPs are transformed into single-objective problems to make them simple to solve. In contrast, this approach transforms a constrained optimisation problem (as defined in Eq. 1) into an unconstrained MOOP by incorporating all constraints into objective functions as shown in Eq. 10 [102, 113].

$$\varphi(x) = [f(x), f_1(x), \ldots ., f_i(x), \ldots f_{m+p}(x)] \tag{10}$$

$f_i(x)$ represents the amount of i th constraint violation (for $i = 1, \ldots .m + p$). Problem-solving becomes more complex and computationally expensive [24].

3.4.4 Co-evolution based separation

Like the co-evolutionary based penalty approach, the population is split into two groups to allocate constraints and fitness functions [25]. The selection pressure correlates with the populations of these groups [96]. Algorithm 1 describes the basic steps of this approach.

Algorithm 1: Pseudocode for co-evolution based separation [96]

```
Do (for specified number of times)
        sol:=SELECT(sol-pop)
        constr= SELECT(constr-pop)
        res:=ENCOUNTER(sol, constr)
        UPDATE-HISTORY-AND-FITNESS(sol, res); % [res=1]
        UPDATE-HISTORY-AND-FITNESS(constr, -res)
End (for loop)
sol1:=SELECT(sol-pop);parent1
sol2:=SELECT(sol-pop);parent2
child:=MUTATE-CROSSOVER(sol1,sol2)
f:=FITNESS(child)
INSERT(child, f, sol-pop)
```

In this, a specified task is assigned to each function: 'SELECT' chooses the high-ranked individuals, 'ENCOUNTER' returns 1 if the solution satisfies constraints or -1 if constraints are violated, 'UPDATE-HISTORY-AND-FITNESS' updates the histories of solution and constraints, 'MUTATE-CROSSOVER' performs standard mutate and crossover operations, 'FITNESS' calculates the initial fitness of the child and 'INSERT' places the child into appropriate rank in the population. After executing a specified number of encounters, based on the updated history and fitness, two parent solutions are selected for reproduction.

In [114], the authors devised a co-evolutionary based CHT, which divides the initial population into two: feasible (in the objective space) and infeasible (in the constraint space). Each infeasible solution that evolves into a feasible one is migrated to the feasible region during the evolution process. Recently, in [115], authors stated that, in the previous studies, the strong cooperation between populations restricts converged and distributed feasible solutions. Thereby, their proposed framework follows weak cooperation between populations. The authors claim the approach to be simple, flexible and has the potential for broader applicability. Several scholars recently proposed different CHTs based on the core concept of this method to handle constraints effectively [81, 116].

3.4.5 Ranking methods

Ranked-based CHTs obtain a balance between objective and constraints. These CHTs emerged with the SR method [97]. It compares the adjacent solutions and ranks them based on the objective function and the constraint violations. Therefore, PFs are not required to be defined. Instead, a control parameter (p_f) is defined to balance feasibility and infeasibility. A uniformly distributed random value (u), between

0 and 1, is compared with the predefined p_f. Ranking is performed as shown in algorithm 2 [102, 104, 108] with the probability of p_s given by Eq. 11:

Algorithm 2: Pseudocode for SR
if both solutions are feasible or $u < p_f$
rank based on the objective function value only
else
rank based on constraint violation only
end

$$p_s = p_0 p_f + p_v (1 - p_f) \tag{11}$$

where p_0 and p_v are the probabilities of an individual winning based on its objective function and constraint violations respectively. The originators have suggested using $p_f = 0.425$ for a better outcome.

Scholars have proposed various ranking methods to handle constraints in different optimisation problems. For instance, in [117], the authors proposed a balanced ranking method. In this, fitness function evaluation is based on two ranks of feasible and infeasible solutions. The first rank considers only the feasible solutions and sorts them based on the objective function. In contrast, the second rank considers the infeasible solutions and sorts them based on their objective function and constraint violations. More recently, an improved SR method was integrated with a surrogate model to handle constraints [118]. In that, convergence and diversity are considered to improve the quality of solutions.

3.5 Repair methods

Real-world problems usually have discontinuities in feasible spaces. To handle such problems, repair methods are effective CHTs. These infeasible solutions are repaired and returned to the feasible region [23, 119]. Usually, the repairing priority is given to the solutions that dominate feasible individuals in the current population or solutions with the lowest constraint violation [119]. Repair methods applicable to the bound constraints are reinitialization, projection, reflection, wrapping, transformation, evolutionary, random and projection to midpoint [120, 121]. These methods are summarised in Table 2. To recall, the upper and lower bounds of the kth decision variable (x_k) are $u_k(x)$ and $l_k(x)$ as illustrated in Eq. 1. (Note that u_k and l_k are used to denote $u_k(x)$ and $l_k(x)$ in the table for simplicity). If x_k violates a bound, one of the following approaches can be used to map it back to the feasible region. Recently, a new repair-based approach was proposed in [122] to handle bound constraints, which promotes the repair methods over penalty methods and other CHTs.

Table 2 Repair methods for bound constraints

Repair method	Description	Formulation for repaired decision variable $r(x_k)$	Remarks
Reinitialisation	Infeasible x_k is replaced by a random value (ξ)	$r(x_k) = \begin{cases} x_k, l_k \le x_k \le u_k \\ \xi, x_k < l_k or x_k > u_k \end{cases}$	For ξ, usually a uniform distribution in the interval $[l_k, u_k]$ is used
Projection	Infeasible x_k is projected on to the violated bound	$r(x_k) = \begin{cases} x_k, l_k \le x_k \le u_k \\ l_k, x_k < l_k \\ u_k, x_k > u_k \end{cases}$	
Reflection	Infeasible x_k is reflected from the exceeded boundary value	$r(x_k) = \begin{cases} x_k, l_k \le x_k \le u_k \\ 2l_k - x_k, x_k < l_k \\ 2u_k - x_k, x_k > u_k \end{cases}$	
Wrapping	Infeasible x_k is shifted by the feasible interval (δ).	$r(x_k) = \begin{cases} x_k, l_k \le x_k \le u_k \\ x_k + \delta, x_k < l_k \\ x_k - \delta, x_k > u_k \end{cases}$	$\delta = u_k - l_k$
Transformation	x_k is transformed before it reaches the bound	$r(x_k) = \begin{cases} x_k, l_k + a_k^l \le x_k \le u_k - a_k^u \\ l_k + \rho, l_k - a_k^l \le x_k < l_k + a_k^l \\ u_k - \tau, u_k - a_k^u < x_k \le u_k + a_k^u \end{cases}$	[a]Refer the note below
Evolutionary	x_k is replaced with a random value between the bounds and the current best solution	$r(x_k) = \begin{cases} \zeta l_k + (1-\zeta) x_k^{best}, x_k < l_k \\ \eta u_k + (1-\eta) x_k^{best}, x_k > u_k \end{cases}$	x_k^{best} is the current best solution and ζ, η are real numbers [0,1]
Random	x_k is replaced with a random value within the bounds	$r(x_k) = l_k + rand(0,1).(u_k - l_k)$	$rand(0,1)$ returns a real value
Projection to mid-point	Coordinate-wise repair is not done. Infeasible vector is projected onto the boundary along the direction going through the midpoint of the feasible area by $r(x) = (1-\sigma)(l+u)/2 + \sigma x$ where σ is the maximum value for which $l_k \le r(x_k) \le u_k$ for all $k = 1 \ldots .n$		

[a]In the transformation method, $\rho = \frac{(x_k - (l_k - a_k^l))^2}{4a_k^l}$, $\tau = \frac{(x_k - (u_k + a_k^u))^2}{4a_k^u}$, $a_k^l = \min\left(\frac{(u_k - l_k)}{2}, \frac{(1+|l_k|)}{20}\right)$, $a_k^u = \min\left(\frac{(u_k - l_k)}{2}, \frac{(1+|u_k|)}{20}\right)$

3.6 Hybrid method (Ensemble CHT)

As explained in the introduction, EAs and meta-heuristic algorithms are stochastic, and the search process has different stages. They follow the 'no free lunch theorem'. This is equally applicable for CHTs, because each CHT treats constraints differently and each optimisation problem is unique. In some problems, a single CHT might not handle constraints effectively. In such cases, using several CHTs at different stages of the evolution process or hybridising CHTs to extract the mutual benefits of each CHT is a promising approach [123–125]. However, improper integration may cause lower convergence speed.

As hybridisation can be devised with any CHTs, a specific methodology cannot be outlined. Therefore, the hybrid CHT proposed in [125] is illustrated here as an example. The feasibility criteria and ε-constrained method (referred as 'α-constrained method' in [126]) are hybridised for the local and global search respectively, as illustrated in Eqs. 12 and 9.

$$\varphi(x) = \begin{cases} f(x_1) \prec f(x_2), P(x_1), P(x_2) = 0 \\ f(x_1) \prec f(x_2), P(x_1) = P(x_2) \\ P(x_1) \prec P(x_2) \ otherwise \end{cases} \tag{12}$$

In this, following the feasibility criteria, two sets of solutions x_1 and x_2 are compared and ranked by objective function ($f(x)$) and constraint violation ($P(x)$) in the local search model. To accelerate the convergence rate and to obtain a distributed Pareto front, ε-constrained method is combined with crowding distance calculation as in [127].

Previous studies also demonstrate the superiority of hybrid CHT methods over single CHTs. For instance, in [128], the authors demonstrated the superior performance of a hybrid CHT over individual CHT, using three different CHTs: self-adaptive penalty, feasibility criteria and ε-constrained method. A recent work demonstrated the superiority of combining the gradient-based repair method with six other CHTs separately [129]. One of their main findings was that the hybridisation of CHTs with gradient-based repair methods is particularly beneficial to solving problems with narrow feasible regions. Moreover, in [123], the authors divided the main problem into several sub-problems. They proposed a hybrid CHT, which combines unconstrained and constrained search modes to balance the convergence and feasibility of each sub-problem.

3.7 Comparison of CHTs

The superiority of CHTs cannot be compared in general terms because it is problem specific, and the performance of each technique differs in terms of different aspects. This was notably illustrated in [108], where the authors compared static penalty, feasibility criteria, ε-constrained and SR methods in dynamic constrained optimisation problems. They concluded that none of the considered CHTs could be the best technique in all aspects. However, the authors have shown the superiority of each CHT in different aspects such as the accuracy and reliability of solutions, and convergence rate. In [130], the authors investigated the effect of three CHTs based on the shape of Pareto front, dimension of the decision vector and size of the feasible region by combining them with nondominated sorting genetic algorithm II (NSGA II). Each CHT has shown competitive performance in different aspects. Another study [104] compared CHTs by applying them to the pressure vessel design problem. They ranked SR and ε-constrained method as the most effective approaches over penalty, barrier function and feasibility criteria. The authors in [131] evaluated the relative effectiveness of feasibility criteria, ε-constrained and adaptive penalty methods by using the problem suite defined in [132]. Based on their results, none of the CHTs displayed exceptional performance; therefore, the authors suggested using hybrid CHT for further performance improvement. Furthermore, in [133], while showcasing the superiority of hybrid methods over single CHTs in solving an OPF problem, the authors stated that the hybrid methods do not guarantee the optimal solution and fast convergence.

More recently, in [134], the author assessed the performance of five CHTs integrated with PSO based on evaluating the problem suite defined in [132]. This study introduces a mechanism to switch among the CHTs during the search. The results show each CHT outperforms at different instances. Interestingly, the switching mechanism demonstrates better performance over individual CHT in this case. Another recent study compared the influence of six versions of penalty methods on the performance of PSO based on the best, mean and standard deviation of solutions [21].

A significant interest in developing novel CHTs and comparing their performance with the established CHTs is apparent [135–141]. For instance, an indicator-based EA was designed to solve constrained MOOPs and compared with six state-of-the-art constrained EAs in [142], which displayed superior performance of the proposed CHT. Table 3 summarises some recent comparison studies on CHTs in different applications. However, such comparisons related to microgrid EMS/PMS optimisation were not revealed.

Besides, a growing interest in the necessity of using revised benchmarks to compare the performance of CHTs was observed recently. As highlighted by [146], constrained MOOPs included in the current benchmarks have a couple of drawbacks: they are too simple and do not reflect real-world problems, offer limited scalability of search space and the number of objectives, limited to a maximum of two inequality constraints, and inability to adjust in terms of the complexity of the constraints. The authors presented 20 test problems with a specific focus on constraints that could be useful for future studies. Moreover, a new benchmark for equality-constrained MOOP was proposed in [16] because none of the earlier benchmarks contains equality constraints.

Table 3 Recent studies on comparison of CHTs

Application	Algorithm used	Compared CHTs	Evaluation criteria	References
Test problems defined in [143]	NSGA II	Feasibility criteria, self-adaptive penalty and adaptive trade off model	Influence of shape of pareto front, dimension of decision vector and size of feasible region on performance of CHT	[130]
Fourteen constrained problems defined in [144]	Differential evolution	Static penalty, feasibility criteria, ε-constrained and SR	Modified offline error, feasibility ratio, success ratio, average evaluations, convergence score and progress ratio	[108]
Pressure vessel design	Flower pollination algorithm	Static & dynamic penalty, barrier functions, ε-constrained, feasibility criteria and SR	Mean error of objective function value and number of iterations	[104]
Problem suite defined in [132]	PSO	No CHT, death penalty, MO-based conversion, feasibility criteria and ε-constrained	Criteria defined in [132]	[134]
Selected 12 benchmarks	PSO	Six versions of penalty methods	Best, mean and standard deviation of solutions	[21]
Problem suite defined in [132]	Covariance Matrix adaptation EA	ε-constrained, feasibility criteria and adaptive penalty method	Relative effectiveness	[131]
OPF	Differential evolution	ε-constrained, feasibility criteria and hybridised CHT with these two	Best, worst, mean and standard deviation of solutions	[133]
Benchmark constrained problems	Differential evolution	Gradient-based repair method hybridised with six other CHTs separately	Mean and standard deviation of solutions, and computational efficiency	[129]
Tourist trip design	GA	Penalty, repair and decoders	Signal-to-noise ratio and computational efficiency	[103]
Structural optimisation	Harmony search algorithm	Death penalty, feasibility criteria, filter method and mapping method	Search capability, stability and computational efficiency	[145]
Constrained MOOP	Surrogate-assisted EA	Improved SR, original SR, SR with adaptive selection and SR with fitness mechanism	Hypervolume and inverted generational distance	[118]

4 Application of CHTs in microgrid EMS/PMS optimisation

4.1 General architecture/the holistic overview of microgrid EMS/PMS optimisation

Microgrids provide an opportunity to integrate RERs with energy buffers in remote locations and usually comprise conventional energy sources such as diesel generators (DGs), as shown in Fig. 7. The main concerns of microgrids development are the high investment cost, control mechanism, the safety of RERs and energy buffers, and emissions from the DGs. Moreover, with increased utilisation of RERs in microgrids, sustaining a reliable and smooth power supply is desired. As previously stated, EMS/PMS optimisation plays a significant role in addressing these challenges.

The holistic overview of EMS/PMS optimisation in microgrids is given in Fig. 8. In a broad sense, input data are used in an algorithm to optimise the objective function subject to constraints defined according to the problem formulation. Usually, the outputs from EMS/PMS optimisation problems are optimum cost, minimum environmental impact, maximum reliability of power supply and social benefits. Objective functions and constraints in these problems are evaluated based on different criteria. They can be classified into economic, reliability, environmental, social, technical, policy and demand side assessment parameters.

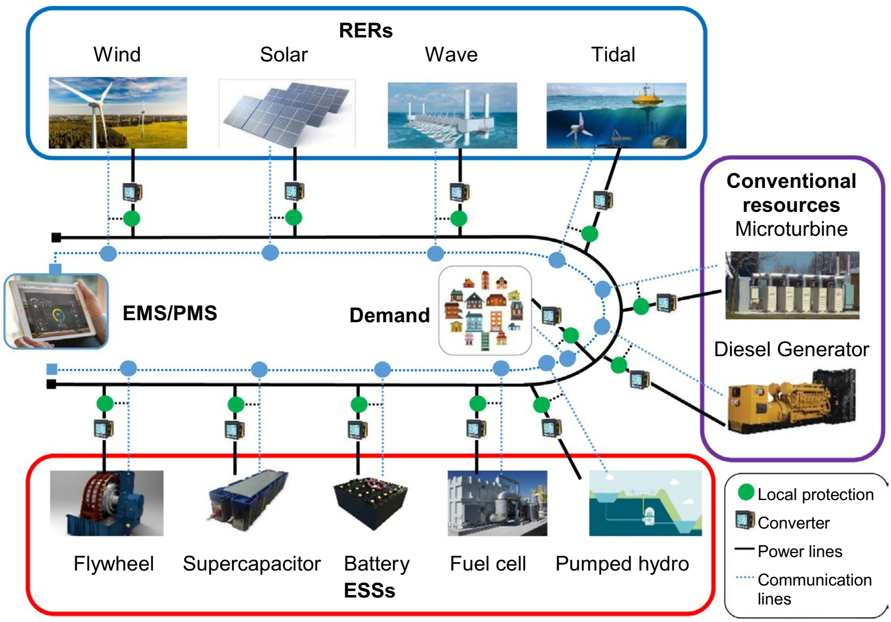

Fig. 7 General architecture of a microgrid

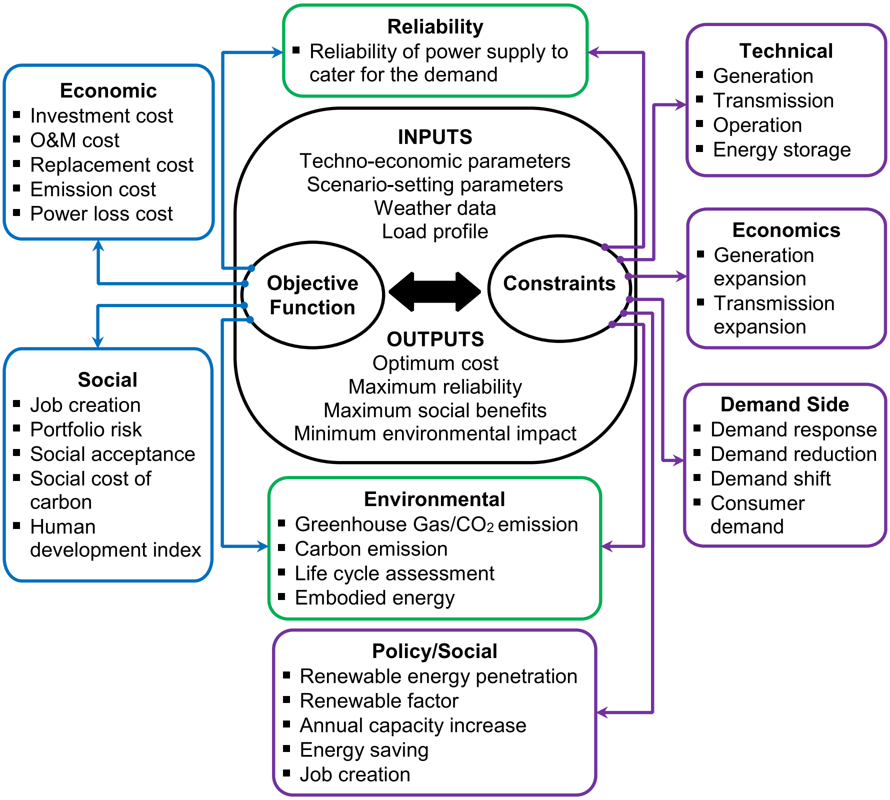

Fig. 8 Holistic overview of microgrid EMS/PMS optimisation

4.2 Objective functions

Optimisation problems are formulated either as a single objective or MO evaluation. The single objective EMS/PMS optimisation problems usually conduct an economic assessment [11, 26, 27] whereas, in a MOOP scenario, economic assessment is combined with other environmental, reliability or social criteria [47, 147–149]. Economic estimations include combinations of the cost involved in investment, operation and maintenance, replacement, emission and power losses. Optimised use of RERs in microgrids supports reducing the potentially harmful emissions by limiting the excessive use of fossil fuels in catering for the energy demand. Therefore, one of the objectives of microgrid optimisation is to minimise the environmental impacts by assessing harmful emissions [29, 34, 47, 59]. Moreover, the life cycle assessments and embodied energy on production and plant manufacturing are considered to minimise the environmental impacts [150]. The reliability criteria are used to evaluate the reliability of power supply to cater for the demand; those are measured through many indices [10, 151–154]. As shown in Fig. 8, environmental and reliability criteria are used as objective functions or constraints. The social criterion is also considered in some studies as an objective [147, 152]. It is an important parameter that measures the benefits to society from implementing microgrids. For this, indices such as the human development index, job creation and social cost of carbon are used.

4.3 Constraints

Based on the existing literature, we classified constraints into six broad areas as illustrated in Fig. 8: economic, technical, environmental, reliability, demand side, policy and social. A detailed description of each, including the constraint formulation, is presented in Table 4. Depending on the application, the parameters clustered under these groups might be treated differently concerning the common attributes of the constraints. For instance, while we cluster operating reserve (OR) under the techno-operational group, it can also be considered a reliability constraint because it assures the continuous power supply. Additionally, the constraints that define a peculiar context were not listed here. For example, in [155], the authors used interconnection constraints to cater for the protocols of electricity exchange with nearby countries.

4.3.1 Economic constraints

Economic constraints usually include investment limitations for generation and transmission expansions. These limits are stipulated in the long-term generation and transmission plans in a country that consider annual commissioning and retiring plant capacities [156–158]. In line with the country's energy policy, generation expansions can include a certain percentage of RER and conventional generation technologies. Some studies also have these constraints as budget constraints, limiting the installation cost below the annual allocated budget [159]. Additionally, some authors use the investment for ESSs as an economic constraint [160].

4.3.2 Technical constraints

The technical assessment criteria impose limitations on generation, transmission, operation and energy storage in microgrids to ensure the safety of the devices and smooth power supply. The generation constraints ensure that the power limits of dispatchable and non-dispatchable generators are not exceeded [26]. Safe voltage limits of the generators are also used in some studies [40, 41, 45]. Transmission constraints are used to evaluate interregional power grids, and they limit power below the maximum transmission capacity of the transmission channels [156, 161].

The operational constraints are another cluster of technical constraints in microgrids. They include power balance, reserve limits, fuel usage and limits of ESSs to sustain uninterrupted power supply and safety of the devices. Power balance constraint is the primary prerequisite of any power system and therefore, it is used in almost all studies. It ensures the power balance between supply and demand by considering all dispatchable and non-dispatchable generators and ESSs on the supply

Table 4 Analysis of constraints based on assessment criteria

Constraints	Constraint formulation	References
Economic		
Generation expansion	$(Total\ annual\ commissioned\ capacity - Total\ annual\ retired\ capacity) * Installation\ cost\ per\ unit\ capacity \leq Max\ investment\ limit\ on\ generation\ expansion$ $Initial\ installation\ cost \leq Max\ allowable\ initial\ cost\ of\ the\ system$	[156, 157]
Transmission expansion	$Total\ annual\ transmitted\ capacity * Installation\ cost\ per\ unit\ capacity \leq Max\ investment\ limit\ on\ transmission\ expansion$	[156, 158]
Technical		
Generation		
Generation capacity	$Min\ producible\ power\ of\ RER \leq Power\ output\ of\ RER \leq Max\ producible\ power\ of\ RER$	[151, 162, 177]
Voltage limits of generator	$Min\ voltage\ of\ RER \leq Voltage\ of\ RER \leq Max\ voltage\ of\ RER$	[40, 41, 45]
Transmission		
Transmission capacity	$Total\ transmission\ capacity \leq Max\ technological\ \&\ constructional\ limit$ $0 \leq Annual\ transmission\ capacity\ increase \leq Max\ growth\ potential\ of\ transmission\ channel.$	[156, 161]
Power/Electricity transmission	$Total\ power\ transmission \leq Capacity\ of\ grid$ $Annual\ electricity\ transmission \leq Capacity\ of\ grid * Annual\ \max\ utilisation\ hour$	[156]
Operational		
Power balance	$Total\ generation\ power + Total\ stored\ power\ in\ ESSs = Total\ power\ demand$	Most refs
OR	$Max\ generation\ power + Max\ stored\ power\ in\ ESSs - Max\ power\ demand \geq OR$	[26, 162]
Capacity shortage	$\frac{Annual\ capacity\ shortage}{Annual\ demand} \leq Max\ allowable\ annual\ capacity\ shortage\ fraction$	[157]
RM	$Min\ RM \leq \frac{Total\ generation\ capacity - Peak\ demand}{Peak\ demand} \leq Max\ RM$	[163]
Unit commitment	$(Unit\ turn\ on\ period - Min\ uptime\ of\ unit).(on/off\ status\ of\ unit) \geq 0$ $(-Unit\ turn\ on\ period - Min\ downtime\ of\ unit).(on/off\ status\ of\ unit) \geq 0$	[9, 47, 177]
Ramp rate	$(Power\ generated\ by\ unit\ at\ time\ t - Power\ generated\ by\ unit\ at\ time\ t-1) \leq Max\ generation\ of\ generation\ unit$	[9, 47, 173, 177]
Fuel consumption	$Annual\ generator\ fuel\ consumption \leq Max\ allowable\ annual\ fuel\ consumption$	[157]
Energy storage		

Table 4 (continued)

Constraints	Constraint formulation	References
Charge/discharge power	$Min\ power\ of\ ESS \leq Power\ output\ of\ ESS \leq Max\ power\ of\ ESS$ $0 \leq \frac{Charging\ power\ of\ ESS}{Charging\ efficiency\ of\ ESS} \leq Max\ charging\ power\ of\ ESS$ $0 \leq Discharging\ power\ of\ ESS * Discharging\ efficiency\ of\ ESS \leq Max\ charging\ power\ of\ ESS$	[26, 164]
Energy	$Min\ capacity\ of\ ESS \leq Energy\ stored\ in\ ESS\ at\ time\ t \leq Max\ capacity\ of\ ESS$	[26, 162]
SOC	$MinSOC\ of\ ESS \leq SOC\ of\ ESS \leq Max\ SOC\ of\ ESS$	[47, 151, 177]
Environmental		
Green House Gas emissions	$CO_2\ emissions + SO_x\ emissions + NO_x\ emissions \leq Max\ allowable\ total\ emissions$ $Generation\ from\ fuel * Fuel\ consumption\ rate * Pollutant\ emission\ factor \leq Total\ emissions * (1 - mitigation\ target)$	[148, 156, 161, 164]
CO_2 emissions	$Total\ CO_2\ emissions \leq Max\ allowable\ CO_2\ emissions$	[8, 156, 165, 166, 178]
Reliability		
LPSP	$0 \leq \frac{(Total\ annual\ demand\ served - Total\ annual\ energy\ generated)}{Total\ annual\ demand\ served} \leq Max\ allowable\ LPSP$	[10, 151, 153]
LOLP, LLP	$0 \leq \frac{Total\ power\ failure\ time}{Total\ operating\ time\ of\ the\ hybrid\ ststem} \leq Max\ allowable\ LOLP$ $0 \leq \frac{Total\ energy\ deficit}{Total\ energy\ demand} \leq Max\ allowable\ LLP$	[13, 154]
UL	$0 \leq \frac{Total\ annual\ power\ failure}{Total\ annual\ demand\ served} \leq Max\ allowable\ UL$ $AnnualUL = \sum Annualloaddemand - Annualservedload = 0$	[71, 157]
ENS	$\frac{(Total\ annual\ energy\ not\ supplied)}{Total\ annual\ demand\ served} \leq Max\ allowable\ ENS$	[30, 160, 168]
EIR	$1 - \frac{Expected\ energy\ not\ served}{Total\ annual\ energy\ demand} \geq Max\ allowable\ EIR$	[171]
EENS	$EENS \leq Max\ EENS$	[169]
RSP	$\frac{Total\ hours\ of\ inadquate\ power\ supply}{Total\ hours\ in\ study\ period} \leq Max\ permissible\ RSP$	[152]
HSP	$\frac{Total\ hours\ of\ adquate\ power\ supply}{Total\ hours\ in\ study\ period} \geq Min\ permissible\ HSP$	[152]
Blackout prevention	$Max\ generation\ power + Max\ stored\ power\ in\ ESSs - Max\ power\ demand \geq 0$	[164]
ELF	$\frac{1}{Total\ time} * \sum_{h=1}^{h=Total\ time} \frac{Loss\ of\ load\ at\ time\ h}{Demand\ at\ time\ h} \leq Max\ allowable\ ELF$	[8, 29]

Table 4 (continued)

Constraints	Constraint formulation	References
Demand side		
DR	$0 \le \textit{Annual DR capacity} \le \textit{Max potential capacity of DR}$	[49, 50, 156]
Demand reduction	$\textit{Total planned hourly demand reduction from consumers} \le \textit{Max planned hourly demand reduction}$	[148, 169]
Demand shift	$\textit{Demand reduction} \ge -\textit{Electricity demand}*\%\ \textit{demand reduction potential}$ $\textit{Total short term demand recovery within recovery time} \ge 0$ $\textit{Total long term demand recovery within recovery time} = 0$	[172, 174]
Consumer energy demand	$(\textit{Annual energy usage} - \textit{Energy export} + \textit{Energy import}*\textit{Line loss rate}) \ge \textit{Annual demand forecast} - \textit{Energy saving from EPP}$	[156]
Policy/Social		
Renewable factor, Renewable energy fraction	$1 - \frac{\textit{Total annual diesel generator output power}}{\textit{Total annual renewable generation output power}} \le \textit{Max allowed RER limit}$ $\frac{\textit{Total annual energy generation of the system}}{\textit{Total annual renewable generation output power}} \ge \textit{Min allowed RER limit}$	[10, 31, 157]
Renewable energy penetration	$\frac{\textit{Total energy generated from RER}}{\textit{Total conventional energy generation}} \ge \textit{Renewable energy penetration target}$	[149]
Annual national capacity increase	$\textit{Annual new built capacities} \le \textit{Max annual national capacity increase limit}$	[161]
Efficient power plant (EPP) capacity	$0 \le \textit{Annual EPP capacity increase} \le \textit{Max growth potential of EPP}$	[156]
Energy saving	$\frac{\textit{Energy saving from EPP}}{\textit{Annual demand forecast}} \ge \textit{Target EPP ratio}$	[156, 161]
Job creation	$\textit{Rate of jobs created by each RER technology per unit capacity}*\textit{Accumulated new capacity} \ge \textit{Job creation target}$	[155]

side. The OR and reserve margin (RM) constraints are contingency reserves used to meet the demand in case of an unexpected generator failure, thus ensuring a reliable power supply [26, 159, 162, 163]. The unit commitment is another crucial operational constraint for optimising the use of generators in microgrids. It decides on the committed or de-committed units over a period considering the demand and RM [26, 47]. The ramp rate constraint limits the power fluctuations at consecutive time steps during generator operation resulting in smooth power output in the dispatchable generators [9, 47]. Moreover, the fuel consumption constraint restricts annual fossil fuel usage. This promotes energy efficiency improvements of generators, allows penetration of RER in microgrids and restricts harmful emissions [157]. ESS constraints are used for the safety of microgrid ESSs and cover the limits of power, energy and state of charge (SOC) of ESSs [26, 162, 164].

4.3.3 Environmental constraints

With the increasing global concerns about climate change, environmental impact assessments in microgrids became apparent. The environmental constraints control harmful emissions by limiting the use of fossil fuels and thereby promoting sustainable energy systems [161, 165, 166]. These harmful emissions include carbon dioxide, sulfur oxides and nitrogen oxides [72]. Emissions are usually estimated by multiplying the electricity generated by conventional generators, the fuel consumption rate and the pollution emission factor (per unit fuel consumption) [72, 161, 167]. Some researchers include these constraints to offset the operational emissions as well as the avoided emissions [8]. Avoided emissions are related to RER penetrations in a microgrid.

4.3.4 Reliability constraints

The reliability constraints evaluate the ability of a microgrid to cater for the demand by restricting the power failure time or energy deficit [10, 29, 157, 168, 169]. These are applied frequently using various indices such as loss of power supply probability (LPSP) [10, 151, 153], loss of load probability (LOLP, LLP) [13, 154], unmet load (UL) [71, 157], energy not supplied (ENS) [30, 168, 170], energy index of reliability (EIR) [171], expected energy not supplied (EENS) [169], risk state probability (RSP) [152], health state probability (HSP) [152], equivalent loss factor (ELF) [29] and blackout prevention [164]. Reliability indices such as the system average interruption frequency index and system average interruption duration index are rarely used by scholars to enhance the reliability of microgrids [160, 170].

4.3.5 Demand side constraints

Another cluster of constraints includes the demand side constraints to evaluate the potential savings from energy users (residential, commercial and industrial). For instance, demand response (DR) encourages users to change their consumption patterns in response to incentives and pricing tariffs [148, 156, 167]. DR provides short-term flexibility by controlling power consumption. This is achieved either by reducing or shifting the demand from peak to off-peak hours. Thereby, these constraints reflect the participation of consumers in energy and reserve scheduling [172]. In [172, 173], up and down reserves are defined such that the customers are committed to decreasing and increasing their consumption accordingly. In addition to DR, the indices such as demand reduction, demand shift and consumer energy demand are used to enforce demand side constraints [148, 169, 174]. However, it is observed that most scholars have not considered these constraints because of the unpredictable consumption behaviour of the consumers.

4.3.6 Policy and social constraints

Apart from the above constraints, microgrids are governed by the stipulated energy policies of a country. These policies limit renewable energy presence in microgrids and promote energy-efficient power plants and potential energy savings [10, 149, 157, 161]. While the social aspects are mostly treated as objective functions in the studies, some consider them constraints [155]. Expansion and development of microgrids with RER technologies open opportunities for employment, and access to electricity improves the quality of life [155]. These are factors assessed either through policy or social constraints.

4.4 Nature of recurring constraints in microgrid EMS/PMS problems

This analysis shows that microgrids' EMS/PMS optimisation problems are formulated with various constraints. These constraints uniquely represent the microgrid structure through diverse aspects, as discussed in Sect. 4.3. The linearity or non-linearity of these constraints depends on the decision variables and the problem formulation. Moreover, microgrids have unique dynamics with higher penetration of RERs, varying loads and charging/discharging of ESSs. Therefore, the presence of constraints may constantly change. This could lead to changes in the feasibility and infeasibility regions in terms of shape, percentage or structure [175, 176]. Ultimately, the search space can have multiple disconnected and dispersed feasible regions, which makes it challenging to locate the global optimum solution.

In addition, these constraints often have interdependencies among them. For example, the energy and SOC of ESSs depend on their power level. When dealing with such interdependent constraints, certain CHTs may not be effective. Therefore, adding the constraint violations together or direct comparisons of constraint violations, as performed in the penalty methods and feasibility criteria, would not guarantee the fairness of feasibility evaluation [176]. Therefore, a thorough assessment of the constraints and their interdependencies is crucial.

Another significant aspect of the constraints in microgrids is their relationship with the competing objective functions. Managing these relationships also poses challenges in handling constraints [135]. However, scholars usually ignore the influence caused by the interactions among objective functions and constraints. Moreover, unintentional approximations in problem formulations can misrepresent the real problem for the analysis. These can yield inferior results.

Therefore, these facts demand proper management of constraints in this context. Based on the analysis of CHTs in microgrid EMS/PMS studies depicted in Table 5, static/death penalty and feasibility criteria are often employed. However, as highlighted by [139], these approaches may have two significant issues: stagnating the search in a feasible sub-region or leading the search into infeasible regions if the overall constraint violation has multiple nonzero local minimum values. When the search process stagnates in one of these regions, comparisons of individuals are made among the others in the same region, which can lead to unfavoured solutions. Moreover, the critical information available in the infeasible region can be inevitably lost by employing standard penalty methods. Despite all these discussed facts and characteristics of the constraints of microgrid EMS/PMS optimisation problems, none of the studies has assessed the quality, accuracy of solutions and limitations in using them in solving these complex problems.

5 Discussion

5.1 Critical findings

Based on the comprehensive review presented in this paper, the following critical findings are outlined:

- Microgrid EMS/PMS optimisation problems are usually represented as multimodal, nonlinear, constrained, non-convex, mixed integer complex problems. They have various competing objectives and constraints, which produce highly complex search spaces. However, these problems are mostly solved using EAs or meta-heuristic algorithms, primarily developed to solve unconstrained problems. Therefore, converging on a feasible solution is challenging.
- Higher penetration of RERs in microgrids, varying load conditions, and management of ESSs contribute to dynamic operating conditions. Consequently, the parameters and the presence of constraints may constantly change. Additionally, the constraints may have interdependencies coupled with the decision variables. Thereby, the feasible regions may be unevenly distributed in the search space. These challenges make it difficult to compare the constraint violations directly. Therefore, using appropriate CHTs in these problems is crucial for the quality and accuracy of the solution.
- The constraints in microgrids have relationships with the competing objective functions. These relationships directly affect convergence. However, scholars

Table 5 CHTs used in solving EMS/PMS optimisation problems in microgrids

Microgrid system	Meta-heuristic approach used	Objective function/s	Constraints	CHT	References
Penalty methods					
WT/PV/MT/BS/Thermal ESS/Gas boiler	Evolutionary PSO	Min total annual cost	LPSP, ESS SOCs, thermal power	Static penalty	[27]
WT/PV/FC/EL	Imperial competitive algorithm	Min net present cost, CO_2 emission	ELF, installation angle of PV array	Static penalty	[29]
WT/PV/BS	Hybrid Big bang-big crunch algorithm	Min total system cost	Number of hybrid system components, energy not supplied, BS limits	Static penalty	[30]
WT/PV/MT/BS/FC	PSO	Min total operating cost	Power balance, generator limits, ramp limits, BS SOC	Static penalty	[28]
WT/PV/MT/BS/FC	Cuckoo search algorithm	Min total operation cost	Power balance, generator limits, BS limits	Static penalty	[35]
WT/PV/DG/BS	Flower pollination algorithm	Min operating costs and emission	Power balance, generator limits, BS limits	Static penalty	[34]
WT/PV/DG/BS	PSO	Min cost of electricity and LPSP	Renewable factor, power balance, BS charge/discharge	Static penalty	[31]
PV/FC/EL (GC)	Artificial bee colony/ PSO	Min LCOE and LPSP	Rating limits of PV panels, FC, EL and hydrogen tank	Static penalty	[32]
WT/PV/Combined heat & power system (GC)	Memory-based GA	Min generation cost	Power balance	Static penalty	[33]
WT/PV/MT/BS	Enhanced Bee Colony optimisation	Min total operating cost	Power balance, generator limits, minimum up/down times, ramp rates, interchange with utility constraints, BS capacity limits	Dynamic penalty	[42]
WT/PV/DG/BS/Fuel tank	PSO/Differential evolution/ Water cycle algorithm/ Grey wolf algorithm	Min LCOE	Power balance, generator limits, OR and BS constraints	Death penalty	[37]

Table 5 (continued)

Microgrid system	Meta-heuristic approach used	Objective function/s	Constraints	CHT	References
WT/PV/BS/FC	GA	Min overall cost of energy	Power balance, state variable constraints, manipulated variable constraints, operation constraints, BS constraints	Death penalty	[36]
Fast charging electric urban bus/BS/SC	Hybrid fuzzy/GA	Min demand energy, demand power gradient and total cost of energy	SOC, current limits of BS and SC, control solution space constraint	Death penalty	[38]
WT/PV/MT/ BS/FC (GC)	Hybrid rule-based/Bat algorithm	Max profit from microgrid	Grid limits, generator limits, ESS SOC and power, bus voltage, power flow limits, transformer limits,	Death penalty	[39]
Case I—WT/BS Case II—PV/BS/ Capacitor (GC)	Dynamic programming	Min overall cost of energy import	Limits of power line, load, generator, ESS, point of common coupling	Death penalty	[41]
WT/PV/MT/ BS/FC (GC)	Enhanced JAYA algorithm	Min operational cost	BS power and energy limits, generator limits, power flow limits, voltage and line power limits	Death penalty	[40]
PV/BS/FC	Model predictive control	Min cost of energy	Annual UL, Power limits of PV/FC/BS and power balance	Death penalty	[71]
Separatist methods					
WT/PV/DG/FC	NSGA II	Min fuel cost and line losses	Power balance, bus voltage, generator limits, ESS capacity	Feasibility criteria	[43]
WT/PV/DG	Interior search algorithm	Min fuel cost, emissions	Power balance, generator limits	Feasibility criteria	[44]

Table 5 (continued)

Microgrid system	Meta-heuristic approach used	Objective function/s	Constraints	CHT	References
PV/MT/DG/BS/FC (GC)	NSGA II	Min total operation cost, emissions	Power balance, generator limits, ramp rate, ESS capacity and SOC	Modified feasibility criteria	[46]
WT/PV/thermal generator	PSO	Min system cost	Active and reactive power balance, generator power and voltage limits, line thermal limits, bus voltage limit	Feasibility criteria	[45]
WT/PV/DG/BS	NSGA II	Min annualized system cost, LPSP	Height of WT, PV installation angle, number of hybrid system components,	ε-constrained method	[48]
Repair methods					
WT/PV/Tidal/DG/BS	Hybrid Fuzzy logic/ Grey wolf algorithm	Min levelised cost of electricity	Power balance, generator limits, OR and BS constraints	Repair method	[26]
Home energy system with PV/BS	PSO	Min electricity cost	Power balance, battery power and SOC, constraints of appliances	Gradient-based repair method	[49]
WT/PV/MT/BS	Hybrid Artificial bee colony/ Markov chain	Min cost of electricity	Power balance, power generator limits of RESs/MT, ramp rate, SOC, power, energy, energy balance of BS, demand response	Repair method	[50]
Hybrid methods					
WT/PV/MT/BS/FC (GC)	NSGA II	Min total operating cost and emissions	Electricity/Heat power balance, generator limits, BS charge/discharge power and SOC, ramp rates	Modified feasibility criteria/ Repair	[59]

Table 5 (continued)

Microgrid system	Meta-heuristic approach used	Objective function/s	Constraints	CHT	References
PV/BS (GC)	Differential evolution	Min total operational cost	Power balance, BS limits, demand side constraints	SR/feasibility criteria	[51]
Ship integrated with DG/WT/ESS	NSGA II	Min total operation cost and air pollution	Power balance, generator limits, SOC of BS, ramp rate, minimum on/off time limits	Feasibility criteria/Repair	[47]

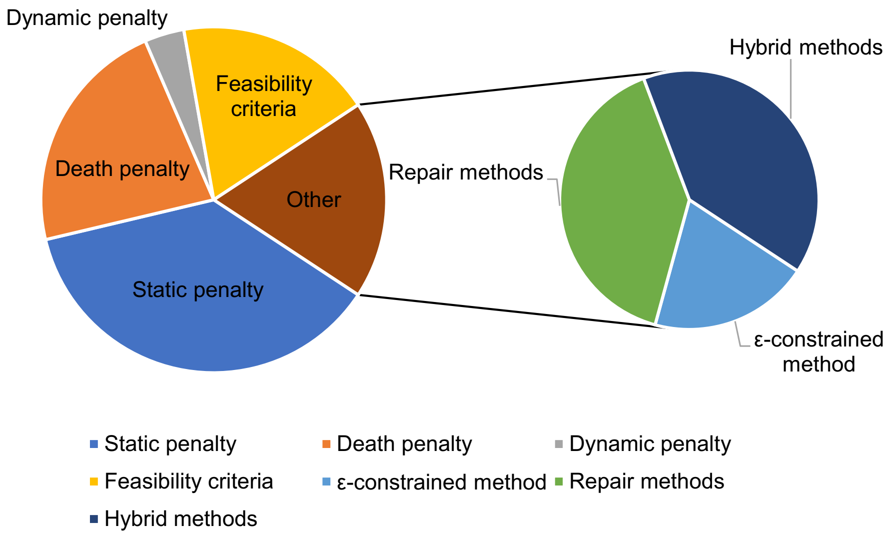

Fig. 9 Analysis of the popularity of CHTs in EMS/PMS studies

usually ignore the influence on the interactions among objective functions and constraints, which can yield inferior results.

- Four broad categories of CHTs are employed in solving constrained optimisation problems: penalty methods (static, dynamic, self-adaptive, co-evolutionary and death), separatist methods (feasibility criteria, ε-constrained method, MO-based conversion, co-evolution based separation and SR), repair methods and hybrid methods.
- A few researchers have discussed the CHTs employed in solving microgrid EMS/PMS optimisation problems. As illustrated in Fig. 9, within the limited literature evidence, well over 80% of studies have utilised penalty methods and feasibility criteria, which appear simpler in the application and easier to implement. In contrast, the other techniques are rarely used or hardly discussed in these applications.
- This review also brought in the scattered knowledge on CHTs from various disciplines to benefit the researchers working on microgrid EMS/PMS studies. In doing so, the merits/demerits of all CHTs were gathered (as summarised in Sect. 5.2) and a few crucial factors were identified in selecting a CHT (discussed in Sect. 5.3). These could also be applied to any other optimisation work, with a broad understanding of the problem domain.
- This review shows that single CHTs have provided promising results in solving microgrid EMS/PMS optimisation problems, whereas hybrid and modified CHTs have performed better with more favourable results. However, using hybrid or modified CHTs in microgrid EMS/PMS studies is rare.

- The choice of the optimisation algorithm and CHT play crucial roles in determining the global optimum solution. Surprisingly, the research efforts on developing efficient and effective CHTs are minimal compared to developing novel meta-heuristic algorithms and EAs. Thereby, the lack of novel CHTs is prominent in this area of research.
- Each CHT treats constraints differently, and each optimisation problem is unique. Besides, all the EAs and meta-heuristic algorithms are stochastic, and the search process has different stages. Therefore, the performance of each CHT integrated with these algorithms is unique and problem specific. This restricts the ability to rank them based on the best-to-worst scale in general terms. However, the performance of each technique can be evaluated based on different aspects. Scholars have not attempted such comparisons of CHTs in solving microgrid EMS/PMS optimisation problems. It is noteworthy that the solutions' accuracy remains questionable unless the performance of integrated CHT is evaluated.

5.2 Merits and demerits of CHTs

The merits and demerits of each CHT are summarised in Table 6. These can guide selecting an appropriate CHT for solving microgrid EMS/PMS optimisation problems. However, it is to be noted that the merits and demerits should not be used exclusively as a guide in employing a CHT in a problem. The user's expertise, the available resources such as computational cost and the availability of software count considerably in selecting an appropriate CHT. A few crucial factors in choosing a CHT, identified through this review, are discussed in Sect. 5.3.

5.3 Crucial factors in selecting an appropriate CHT

CHT is vital in converging to feasible and realistic solutions in microgrid EMS/PMS optimisation problems. In solving constrained optimisation problems, the general approach uses trial and error attempts, which is an inefficient way to find a suitable CHT. Through this extensive review, we have identified several factors, discussed below, that influence selecting an appropriate CHT.

- Domain knowledge—the user must have domain knowledge specifically on the problem, including the nature of the constraint functions. This is crucial in multi-modal problems over unimodal ones concerning constraint handling. For instance, simple CHTs can quickly solve unimodal problems with a lesser computational burden. However, the CHT employed may cause premature convergence to a local solution in multi-modal problems if the user is unaware of the problem domain. Moreover, the linearity or nonlinearity of equality/inequality constraints, relationships among objective functions and constraints, the number of constraints and their interdependencies also contribute to the complexity of the problem. Therefore, a thorough knowledge of each of these contributes substantially to selecting a suitable CHT.

Table 6 Merits and demerits of various CHTs

CHT	Core concept	Merits	Demerits
Penalty methods			
Static penalty	Keep PF fixed during evolution process	Simple and easy to implement	Outcome is highly dependent on user assigned PF Keeping a fixed PF along the entire evolution may affect badly
Dynamic penalty	Gradually increase PF during iterations	Good for optimisation problems having arbitrary constraints Easy to implement as no feasible starting point is required	Challenging to derive effective dynamic PF May cause premature convergence
Self-adaptive penalty	Update PF adaptively based on the feedback from search process	PF regulation follows an 'intelligent' path Avoids all-feasible and all-infeasible populations	Difficult to set parameters
Co-evolutionary penalty	Co-evolve PFs by two populations for solutions and PFs	Easy to implement for non-convex search spaces	For limited feasible region, generating initial feasible point is challenging
Death penalty	Discard all infeasible solutions	No parameters Simple and easy to implement	Valuable data from the infeasible region is not taken Search may stagnate in narrow search spaces
Separatist methods			
Feasibility criteria	Pairwise comparison based on three criteria	No parameters Simple and easy to implement Explores infeasible region	May cause premature convergence with the priority given for feasible region
ε-constraint method	Monitor and relax constraint violation during early search process	Solves the multi-modal problems with equality constraints efficiently Robust and competitive performance No premature convergence	Need to assign extra parameters Occasional pre-mature convergence is reported
MO-based method	Redefine a constrained optimisation problem as an unconstrained one		Problem solving becomes difficult with MOs Computationally expensive
Co-evolution based separation	Split population into two groups to handle constraints and objective functions	Suitable for non-convex search spaces	For limited feasible region, generating initial feasible point is challenging

Table 6 (continued)

CHT	Core concept	Merits	Demerits
Ranking methods	Ranking process based on objective function and constraint violations	Easy implementation Static constraints are handled efficiently	Complex in solving MOOPs Not suitable to handle dynamic constraints
Repair methods	Transform infeasible solutions to feasible solutions	Effectively handles problems with discontinuities in feasible search space	Approach is problem-dependent and needs to be designed for each problem In some cases, the repair operators may harm the evolution process
Hybrid methods	Combine two or more CHTs based on constraint types	Mostly outperforms single CHTs	Improper integration may cause lower convergence speed Need to assign extra parameters Comparatively complex than single CHTs

- Area of the feasible search space defined by the constraints—this is crucial when dealing with these real-world constrained problems having nonlinear and complex constraints. Discontinued or non-convex search spaces are more challenging to handle in terms of converging to a feasible solution. For instance, discarding all infeasible solutions by using the static or death penalty approach in a restricted search space might trap the solution in one of the local optimums or even fail to find a feasible solution. Alternatively, the appropriate use of other approaches discussed in Sect. 3 would be more effective.
- Exploration and exploitation stages of the search algorithm—the search process in each algorithm is unique. Users adopt different algorithms in solving optimisation problems. A broad understanding of the exploration and exploitation stages of the used algorithm allows the user to activate the CHT appropriately. Besides, due to the stochastic nature of the algorithms, the search process follows different search paths in each run, even when solving one problem with one algorithm. CHT alters the original search pattern of the optimisation algorithm. Therefore, merging a CHT in an algorithm may assist or disrupt the performance of the CHT or the search algorithm itself. As previously stated, the search space can have multiple disconnected and dispersed feasible regions. Unless the user pays attention to different stages of the search algorithm, the search process could yield inferior results.

6 Conclusion and future directions

This paper comprehensively reviews various CHTs suitable for solving EMS/PMS optimisation problems. Following a systematic analysis, the state-of-the-art CHTs are extensively reviewed. Together, this study provides important insights into the significance of CHTs on the quality and accuracy of results, classification, merits/demerits, and crucial factors in selecting CHTs. Additionally, the nature of recurring constraints in microgrid EMS/PMS problems is analysed based on a holistic overview.

The microgrid control architectures and EMS/PMS are evolving rapidly. EMS/PMS plays a significant role in microgrids in terms of stability, security and reliability of power supply. Therefore, the accuracy and quality of the results are vital. Microgrid EMS/PMS optimisation problems have various dynamic constraints. This makes it difficult to compare the constraint violations directly, as done in the feasibility criteria approach. Besides, the nature of these problems brings in a limited non-convex search space and converging to a feasible solution is challenging. Therefore, the CHTs widely used in this application may not always be qualified to produce accurate results. Owing to this, despite the promising results scholars claim, the fairness of these evaluations remains questionable. On that account, there is a need for more accurate and advanced CHTs to handle the constraints in microgrid EMS/PMS problems. Scholars in several other disciplines have achieved promising results by employing hybrid and modified

CHTs. These could be inspirations for future research in this area. Moreover, this study revealed the necessity of conducting performance comparisons of the CHTs by integrating them into microgrid EMS/PMS optimisation problems. This study has raised vital questions about the accuracy and quality of the results of microgrid EMS/PMS optimisation problems and suggests using advanced CHTs by researchers in their future studies. Taken together, these findings have significant industrial implications for the continued interest in upgrading microgrid EMS/PMS, and in particular the emerging field of renewable.

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Declarations

Conflict of Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Villanueva-Rosario, J.A., et al.: Coordinated ancillary services, market participation and communication of multi-microgrids: a review. Appl. Energy **308**, 118332 (2022)
2. Meng, L., et al.: Microgrid supervisory controllers and energy management systems: a literature review. Renew. Sustain. Energy Rev. **60**, 1263–1273 (2016)
3. Ghosh, B.K., Sen, S., Chanda, S.: Intelligent energy management systems for optimal techno-commercial benefit in DC micro-grids: a review. In: 2020 IEEE VLSI DEVICE CIRCUIT AND SYSTEM (VLSI DCS) (2020)
4. Elmouatamid, A., et al.: Review of Control and energy management approaches in micro-grid systems. Energies **14**(1), 168 (2021)
5. Iovine, A., et al.: Power management for a DC MicroGrid integrating renewables and storages. Control. Eng. Pract. **85**, 59–79 (2019)
6. López-Flores, D.R., Durán-Gómez, J.l.: Control and energy management system techniques in renewable sources: a brief review. In: 2018 14th International conference on power electronics (CIEP), pp. 139–145 (2018)
7. Zia, M.F., Elbouchikhi, E., Benbouzid, M.: Microgrids energy management systems: a critical review on methods, solutions, and prospects. Appl. Energy **222**, 1033–1055 (2018)
8. Azimian, M., Amir, V., Javadi, S.: Economic and environmental policy analysis for emission-neutral multi-carrier microgrid deployment. Appl. Energy **277**, 115609 (2020)
9. Marzband, M., et al.: Real time experimental implementation of optimum energy management system in standalone Microgrid by using multi-layer ant colony optimization. Int. J. Electr. Power Energy Syst. **75**, 265–274 (2016)
10. Suresh, M., Meenakumari, R.: An improved genetic algorithm-based optimal sizing of solar photovoltaic/wind turbine generator/diesel generator/battery connected hybrid energy systems for standalone applications. Int. J. Ambient Energy **42**, 1136–1143 (2019)
11. Marocco, P., et al.: Optimal design of stand-alone solutions based on RES + hydrogen storage feeding off-grid communities. Energy Convers. Manag. **238**, 114147 (2021)

12. Al-falahi, M.D.A., Jayasinghe, S.D.G., Enshaei, H.: A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system. Energy Convers. Manag. **143**, 252–274 (2017)
13. Sinha, S., Chandel, S.S.: Review of recent trends in optimization techniques for solar photovoltaic–wind based hybrid energy systems. Renew. Sustain. Energy Rev. **50**, 755–769 (2015)
14. Dkhili, N., et al.: A survey of modelling and smart management tools for power grids with prolific distributed generation. Sustain. Energy Grids Netw. **21**, 100284 (2020)
15. Cuate, O., et al.: A new hybrid evolutionary algorithm for the treatment of equality constrained MOPs. Mathematics **8**(1), 7 (2020)
16. Cuate, O., et al.: A benchmark for equality constrained multi-objective optimization. Swarm Evol. Comput. **52**, 100619 (2020)
17. Rezaei, N., et al.: A new stochastic gain adaptive energy management system for smart microgrids considering frequency responsive loads. Energy Rep. **6**, 914–932 (2020)
18. Leonori, S., et al.: Microgrid energy management systems design by computational intelligence techniques. Appl. Energy **277**, 115524 (2020)
19. Sundaram, A.: Multiobjective multi-verse optimization algorithm to solve combined economic, heat and power emission dispatch problems. Appl. Soft Comput. **91**, 106195 (2020)
20. Kaul, S., Kumar, Y.: Nature-inspired metaheuristic algorithms for constraint handling: challenges, issues, and research perspective. In: Kulkarni, A.J., et al. (eds.) Constraint Handling in Metaheuristics and Applications, pp. 55–80. Springer Singapore, Singapore (2021)
21. Rostamian, M., et al.: Experimental comparison of constraint handling schemes in particle swarm optimization. In: Kulkarni, A.J., et al. (eds.) Constraint Handling in Metaheuristics and Applications, pp. 81–99. Springer Singapore, Singapore (2021)
22. Wolpert, D.H., Macready, W.G.: No free lunch theorems for optimization. IEEE Trans. Evol. Comput. **1**(1), 67–82 (1997)
23. Yu, K., et al.: Purpose-directed two-phase multiobjective differential evolution for constrained multiobjective optimization. Swarm Evol. Comput. **60**, 100799 (2021)
24. Yang, Y., Liu, J., Tan, S.: A constrained multi-objective evolutionary algorithm based on decomposition and dynamic constraint-handling mechanism. Appl. Soft Comput. **89**, 106104 (2020)
25. Jordehi, A.R.: A review on constraint handling strategies in particle swarm optimisation. Neural Comput. Appl. **26**(6), 1265–1275 (2015)
26. El-Bidairi, K.S., et al.: A hybrid energy management and battery size optimization for standalone microgrids: a case study for Flinders Island, Australia. Energy Convers. Manag. **175**, 192–212 (2018)
27. Lorestani, A., Gharehpetian, G.B., Nazari, M.H.: Optimal sizing and techno-economic analysis of energy- and cost-efficient standalone multi-carrier microgrid. Energy **178**, 751–764 (2019)
28. Nikmehr, N., Najafi-Ravadanegh, S., Khodaei, A.: Probabilistic optimal scheduling of networked microgrids considering time-based demand response programs under uncertainty. Appl. Energy **198**, 267–279 (2017)
29. Gharavi, H., Ardehali, M.M., Ghanbari-Tichi, S.: Imperial competitive algorithm optimization of fuzzy multi-objective design of a hybrid green power system with considerations for economics, reliability, and environmental emissions. Renew. Energy **78**, 427–437 (2015)
30. Ahmadi, S., Abdi, S.: Application of the Hybrid Big Bang-Big Crunch algorithm for optimal sizing of a stand-alone hybrid PV/wind/battery system. Sol. Energy **134**, 366–374 (2016)
31. Borhanazad, H., et al.: Optimization of micro-grid system using MOPSO. Renew. Energy **71**, 295–306 (2014)
32. Singh, S., Chauhan, P., Singh, N.: Capacity optimization of grid connected solar/fuel cell energy system using hybrid ABC-PSO algorithm. Int. J. Hydrogen Energy **45**(16), 10070–10088 (2020)
33. Askarzadeh, A.: A memory-based genetic algorithm for optimization of power generation in a microgrid. IEEE Trans. Sustain. Energy **9**(3), 1081–1089 (2018)
34. De, M., Das, G., Mandal, K.K.: An effective energy flow management in grid-connected solar–wind-microgrid system incorporating economic and environmental generation scheduling using a meta-dynamic approach-based multiobjective flower pollination algorithm. Energy Rep. **7**, 2711–2726 (2021)
35. De, M., et al.: A reliable energy management and generation scheduling model in microgrids using modified cuckoo search algorithm. I:n 2018 Emerging Trends in Electronic Devices and Computational Techniques (EDCT) (2018)

36. Rullo, P., et al.: Integration of sizing and energy management based on economic predictive control for standalone hybrid renewable energy systems. Renew. Energy **140**, 436–451 (2019)
37. Fathi, M., et al.: Comparative study of metaheuristic algorithms for optimal sizing of standalone microgrids in a remote area community. Neural Comput. Appl. **34**(7), 5181–5199 (2022)
38. Yu, H., et al.: Real time energy management strategy for a fast charging electric urban bus powered by hybrid energy storage system. Energy **112**, 322–331 (2016)
39. Elgamal, M., et al.: A framework for profit maximization in a grid-connected microgrid with hybrid resources using a novel rule base-BAT algorithm. IEEE Access **8**, 71460–71474 (2020)
40. Javidsharifi, M., et al.: Probabilistic model for microgrids optimal energy management considering AC network constraints. IEEE Syst. J. **14**(2), 2703–2712 (2020)
41. Levron, Y., Guerrero, J.M., Beck, Y.: Optimal power flow in microgrids with energy storage. IEEE Trans. Power Syst. **28**(3), 3226–3234 (2013)
42. Whei-Min, L., Chia-Sheng, T., Ming-Tang, T.: Energy management strategy for microgrids by using enhanced bee colony optimization. Energies (19961073) **9**(1), 5 (2016)
43. Beshr, E.H., Abdelghany, H., Eteiba, M.: Novel optimization technique of isolated microgrid with hydrogen energy storage. PLoS ONE **13**(2), e0193224 (2018)
44. Trivedi, I.N., et al.: An economic load dispatch and multiple environmental dispatch problem solution with microgrids using interior search algorithm. Neural Comput. Appl. **30**(7), 2173–2189 (2018)
45. Ilyas, M.A., et al.: (DA-DOPF): a day-ahead dynamic optimal power flow with renewable energy integration in smart grids. Front .Energy Res., **9** (2021)
46. Li, X., Xia, R.: A dynamic multi-constraints handling strategy for multi-objective energy management of microgrid based on MOEA. IEEE Access **7**, 138732–138744 (2019)
47. An, Q., et al.: A Two-stage offline-to-online multiobjective optimization strategy for ship integrated energy system economical/ environmental scheduling problem. Complexity **2021**, 6686563 (2021)
48. Chen, Y., et al.: Constraint multi-objective optimal design of hybrid renewable energy system considering load characteristics. Complex Intell. Syst. **8**(2), 803–817 (2022)
49. Huang, Y., Tian, H., Wang, L.: Demand response for home energy management system. Int. J. Electr. Power Energy Syst. **73**, 448–455 (2015)
50. Marzband, M., et al.: An optimal energy management system for islanded microgrids based on multiperiod artificial bee colony combined with Markov chain. IEEE Syst. J. **11**(3), 1712–1722 (2017)
51. Huang, C., et al.: Demand response for industrial micro-grid considering photovoltaic power uncertainty and battery operational cost. IEEE Trans. Smart Grid **12**(4), 3043–3055 (2021)
52. Nourianfar, H., Abdi, H.: Environmental/economic dispatch using a new hybridizing algorithm integrated with an effective constraint handling technique. Sustainability **14**(6), 3173 (2022)
53. Kansal, V., Dhillon, J.S.: Emended salp swarm algorithm for multiobjective electric power dispatch problem. Appl. Soft Comput. **90**, 106172 (2020)
54. Nourianfar, H., Abdi, H.: Solving power systems optimization problems in the presence of renewable energy sources using modified exchange market algorithm. Sustain. Energy Grids Netw. **26**, 100449 (2021)
55. Lin, J., Wang, Z.-J.: Multi-area economic dispatch using an improved stochastic fractal search algorithm. Energy **166**, 47–58 (2019)
56. Hosseini-Hemati, S., et al.: Society-based Grey Wolf Optimizer for large scale Combined Heat and Power Economic Dispatch problem considering power losses. Appl. Soft Comput. **117**, 108351 (2022)
57. Zou, D., et al.: Solving the combined heat and power economic dispatch problems by an improved genetic algorithm and a new constraint handling strategy. Appl. Energy **237**, 646–670 (2019)
58. Goudarzi, A., Li, Y., Xiang, J.: A hybrid non-linear time-varying double-weighted particle swarm optimization for solving non-convex combined environmental economic dispatch problem. Appl. Soft Comput. **86**, 105894 (2020)
59. Li, X., Lai, J., Tang, R.: A hybrid constraints handling strategy for multiconstrained multiobjective optimization problem of microgrid economical/environmental dispatch. Complexity **2017** (2017)
60. Sakthivel, V.P., Suman, M., Sathya, P.D.: Combined economic and emission power dispatch problems through multi-objective squirrel search algorithm. Appl. Soft Comput. **100**, 106950 (2021)

61. Ida Evangeline, S., Rathika, P.: Wind farm incorporated optimal power flow solutions through multi-objective horse herd optimization with a novel constraint handling technique. Expert Syst. Appl. **194**, 116544 (2022)
62. Luo, J., Shi, L., Ni, Y.: A solution of optimal power flow incorporating wind generation and power grid uncertainties. IEEE Access **6**, 19681–19690 (2018)
63. Kumar, A., et al.: Power flow analysis of islanded microgrids: a differential evolution approach. IEEE Access **9**, 61721–61738 (2021)
64. Espín-Sarzosa, D., Palma-Behnke, R., Núñez-Mata, O.: Energy management systems for micro-grids: main existing trends in centralized control architectures. Energies **13**(3), 547 (2020)
65. Hossein, S., et al.: A survey on microgrid energy management considering flexible energy sources. Energies **12**(11), 2156–2156 (2019)
66. Ouassima, B., et al.: Microgrid energy management system: a state-of-the-art review. J. Electr. Syst. **15**(1), 53–67 (2019)
67. Yimy, E.G.V., Rodolfo, D.-L., José, L.B.-A.: Energy management in microgrids with renewable energy sources: a literature review. Appl. Sci. **9**(18), 3854–3854 (2019)
68. Anderson, A.A., Suryanarayanan, S.: Review of energy management and planning of islanded microgrids. CSEE J. Power Energy Syst. **6**(2), 329–343 (2019)
69. Jamal, S., Tan, N.M.L., Pasupuleti, J.: A review of energy management and power management systems for microgrid and nanogrid applications. Sustainability **13**(18), 10331 (2021)
70. Zhang, Q., et al.: Multi-agent safe policy learning for power management of networked microgrids. IEEE Trans. Smart Grid **12**(2), 1048–1062 (2021)
71. Xie, Y., Ueda, Y., Sugiyama, M.: Greedy energy management strategy and sizing method for a stand-alone microgrid with hydrogen storage. J. Energy Storage **44**, 103406 (2021)
72. Goudarzi, A., et al.: A game theory-based interactive demand response for handling dynamic prices in security-constrained electricity markets. Sustain. Cities Soc. **72**, 103073 (2021)
73. Chen, M.-R., Zeng, G.-Q., Lu, K.-D.: Constrained multi-objective population extremal optimization based economic-emission dispatch incorporating renewable energy resources. Renew. Energy **143**, 277–294 (2019)
74. Li, B., Wang, J., Xia, N.: Optimal scheduling of a microgrid using multiobjective biogeography-based optimization model and algorithm with adaptive migration. Math. Prob. Eng. **2020**, 7120352 (2020)
75. Dong, R., Wang, S.: New optimization algorithm inspired by kernel tricks for the economic emission dispatch problem with valve point. IEEE Access **8**, 16584–16594 (2020)
76. Mahmoud, K., et al.: Improved salp-swarm optimizer and accurate forecasting model for dynamic economic dispatch in sustainable power systems. Sustainability **12**(2), 576 (2020)
77. Yi, L., et al.: Optimal scheduling of residential houses with optimal photovoltaic energy utilization strategy using improved multi-objective equilibrium optimizer algorithm. J. Build. Eng. **59**, 105102 (2022)
78. Goni, M.O.F., et al.: Integration of machine learning with economic energy scheduling. Int. J. Electr. Power Energy Syst. **142**, 108343 (2022)
79. Singh, M., Dhillon, J.S.: Multiobjective thermal power dispatch using opposition-based greedy heuristic search. Int. J. Electr. Power Energy Syst. **82**, 339–353 (2016)
80. van Eck, N.J., Waltman, L.: Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics **84**(2), 523–538 (2010)
81. Wang, J., et al.: Cooperative multiobjective evolutionary algorithm with propulsive population for constrained multiobjective optimization. IEEE Trans. Syst. Man Cybern. Syst. **52**(6), 3476–3491 (2022)
82. Kim, D.G., Husbands, P.: Landscape changes and the performance of Mapping Based Constraint handling methods. In: Eiben, A.E., Bäck, T., Schoenauer, M., Schwefel, H.P. (eds.) Parallel Problem Solving from Nature—PPSN V. Springer, Berlin, Heidelberg (1998)
83. Koziel, S., Michalewicz, Z.: A decoder-based evolutionary algorithm for constrained parameter optimization problems. In: Eiben, A.E., Bäck, T., Schoenauer, M., Schwefel, H.P. (eds.) Parallel Problem Solving from Nature—PPSN V. Springer, Berlin, Heidelberg (1998)
84. Schoenauer, M., Michalewicz, Z.: Evolutionary computation at the edge of feasibility. In: Voigt, H.M., Ebeling, W., Rechenberg, I., Schwefel, H.P. (eds.) Parallel Problem Solving from Nature—PPSN IV. Springer, Berlin, Heidelberg (1996)
85. Schoenauer, M., Michalewicz, Z.: Boundary operators for constrained parameter optimization problems. In: ICGA, pp. 322–329 (1997)

86. Kieffer, E., et al.: A new Co-evolutionary Algorithm Based on Constraint Decomposition. In: 2017 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW) (2017)
87. Coello, C.A.C.: Constraint-handling techniques used with evolutionary algorithms. In: Proceedings of the Genetic and Evolutionary Computation Conference Companion (2022)
88. Homaifar, A., Qi, C.X., Lai, S.H.: Constrained optimization via genetic algorithms. SIMULATION **62**(4), 242–253 (1994)
89. Jeffrey, A., Christopher, R.: On the Use of Non-stationary Penalty Functions to Solve Nonlinear Constrained Optimization Problems with GAs, pp. 27695–27906. Department of Industrial Engineering North Carolina State University (1994)
90. Bean, J.C., Hadj-Alouane, A.B.: A dual genetic algorithm for bounded integer programs James C. Bean. Atidel Ben Hadj-Alouane (1993)
91. Coello Coello, C.A.: Use of a self-adaptive penalty approach for engineering optimization problems. Comput. Ind. **41**(2), 113–127 (2000)
92. Morales, A.K., Quezada, C.V.: A universal eclectic genetic algorithm for constrained optimization. In: Proceedings of the 6th European Congress on Intelligent Techniques and Soft Computing (1998)
93. Deb, K.: An efficient constraint handling method for genetic algorithms. Comput. Methods Appl. Mech. Eng. **186**(2), 311–338 (2000)
94. Takahama, T., Sakai, S., Iwane, N.: Constrained optimization by the ε constrained hybrid algorithm of particle swarm optimization and genetic algorithm. In: AI 2005: Advances in Artificial Intelligence. Berlin, Heidelberg: Springer Berlin Heidelberg (2005)
95. Surry, P.D., Radcliffe, N.J., Boyd, I.D.: A multi-objective approach to constrained optimisation of gas supply networks: the COMOGA Method. In: AISB Workshop on Evolutionary Computing. Springer (1995)
96. Paredis, J.: Co-evolutionary constraint satisfaction. In: International Conference on Parallel Problem Solving from Nature. Springer (1994)
97. Runarsson, T.P., Xin, Y.: Stochastic ranking for constrained evolutionary optimization. IEEE Trans. Evol. Comput. **4**(3), 284–294 (2000)
98. Liepins, G.E., Vose, M.D.: Representational issues in genetic optimization. J. Exp. Theor. Artif. Intell. **2**(2), 101–115 (1990)
99. Mallipeddi, R., Suganthan, P.N.: Ensemble of constraint handling techniques. IEEE Trans. Evol. Comput. **14**(4), 561–579 (2010)
100. Davidor, Y.: A genetic algorithm applied to robot trajectory generation. In: Handbook of Genetic Algorithms. Van Nostrand Reinhold, pp. 144–165 (1991)
101. Raidl, G.R., Gottlieb, J.: On the importance of phenotypic duplicate elimination in decoder-based evolutionary algorithms. In: Late Breaking Papers at the 1999 Genetic and Evolutionary Computation Conference. Citeseer, pp. 204–211 (1999)
102. Huang, P., Wang, H.: Comparative empirical study on constraint handling in offline data-driven evolutionary optimization. Appl. Soft Comput. **110**, 107603 (2021)
103. Lopez-Sanchez, M., Cosío-León, M.A., Martínez-Vargas, A.: Comparative analysis of constraint handling techniques based on taguchi design of experiments. In: Kulkarni, A.J., et al. (eds.) Constraint Handling in Metaheuristics and Applications, pp. 285–315. Springer Singapore, Singapore (2021)
104. He, X.S., et al.: Comparison of constraint-handling techniques for metaheuristic optimization. In: J.M.F. Rodrigues, et al., (eds.) 19th International Conference on Computational Science, ICCS 2019, 2019, Springer Verlag. p. 357–366 (2019)
105. Coello Coello, C.A.: Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art. Comput. Methods Appl. Mech. Eng. **191**(11), 1245–1287 (2002)
106. Cimen, M.E., Garip, Z., Boz, A.F.: Comparison of metaheuristic optimization algorithms with a new modified deb feasibility constraint handling technique. Turk. J. Electr. Eng. Comput. Sci. **29**(7), 3270–3289 (2021)
107. Biswas, P.P., Suganthan, P.N., Amaratunga, G.A.J.: Optimal power flow solutions incorporating stochastic wind and solar power. Energy Convers. Manag. **148**, 1194–1207 (2017)
108. Ameca-Alducin, M.Y., et al.: A comparison of constraint handling techniques for dynamic constrained optimization problems. In: 2018 IEEE Congress on Evolutionary Computation, CEC 2018. 2018. Institute of Electrical and Electronics Engineers Inc (2018)

109. Takahama, T., Sakai, S.: Constrained optimization by the ε constrained differential evolution with gradient-based mutation and feasible elites. In: 2006 IEEE International Conference on Evolutionary Computation (2006)
110. Mallipeddi, R., Suganthan, P.N.: Differential evolution with ensemble of constraint handling techniques for solving CEC 2010 benchmark problems. In: IEEE Congress on Evolutionary Computation (2010)
111. Fan, Z., et al.: An improved epsilon constraint handling method embedded in MOEA/D for constrained multi-objective optimization problems. In: 2016 IEEE Symposium Series on Computational Intelligence (SSCI) (2016)
112. Fan, Z., et al.: Push and pull search embedded in an M2M framework for solving constrained multi-objective optimization problems. Swarm Evol. Comput. **54**, 100651 (2020)
113. Li, L.D., Xiaodong, L., Xinghuo, Y.: A multi-objective constraint-handling method with PSO algorithm for constrained engineering optimization problems. In: 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence), pp. 1528–1535 (2008)
114. Ebrahim Sorkhabi, A., Deljavan Amiri, M., Khanteymoori, A.R.: Duality evolution: an efficient approach to constraint handling in multi-objective particle swarm optimization. Soft Comput. **21**(24), 7251–7267 (2017)
115. Tian, Y., et al.: A coevolutionary framework for constrained multiobjective optimization problems. IEEE Trans. Evol. Comput. **25**(1), 102–116 (2021)
116. Liu, Z.Z., Wang, B.C., Tang, K.: Handling constrained multiobjective optimization problems via bidirectional coevolution. IEEE Trans. Cybern., pp. 1–14 (2021)
117. Rodrigues, M.D.C., de Lima, B.S.L.P., Guimarães, S.: Balanced ranking method for constrained optimization problems using evolutionary algorithms. Inf. Sci. **327**, 71–90 (2016)
118. Gu, Q., et al.: Surrogate-assisted evolutionary algorithm for expensive constrained multi-objective discrete optimization problems. Complex Intell. Syst. **8**(4), 2699–2718 (2022)
119. Samanipour, F., Jelovica, J.: Adaptive repair method for constraint handling in multi-objective genetic algorithm based on relationship between constraints and variables. Appl. Soft Comput. **90**, 106143 (2020)
120. Biedrzycki, R.: Handling bound constraints in CMA-ES: an experimental study. Swarm Evol. Comput. **52**, 100627 (2020)
121. Juárez-Castillo, E., Acosta-Mesa, H.-G., Mezura-Montes, E.: Adaptive boundary constraint-handling scheme for constrained optimization. Soft. Comput. **23**(17), 8247–8280 (2019)
122. Gandomi, A.H., Deb, K.: Implicit constraints handling for efficient search of feasible solutions. Comput. Methods Appl. Mech. Eng. **363**, 112917 (2020)
123. Yang, Y., Liu, J., Tan, S.: A partition-based constrained multi-objective evolutionary algorithm. Swarm Evol. Comput. **66**, 100940 (2021)
124. Vodopija, A., Oyama, A., Filipič, B.: Ensemble-based constraint handling in multiobjective optimization. In: Proceedings of the Genetic and Evolutionary Computation Conference Companion, pp. 2072–2075 (2019)
125. Lin, Y., Du, W., Du, W.: Multi-objective differential evolution with dynamic hybrid constraint handling mechanism. Soft. Comput. **23**(12), 4341–4355 (2019)
126. Qian, F., et al.: Self-adaptive differential evolution algorithm with α-constrained-domination principle for constrained multi-objective optimization. Soft. Comput. **16**(8), 1353–1372 (2012)
127. Deb, K., et al.: A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. **6**(2), 182–197 (2002)
128. Qu, B.Y., Suganthan, P.N.: Constrained multi-objective optimization algorithm with an ensemble of constraint handling methods. Eng. Optim. **43**(4), 403–416 (2011)
129. Cantú, V.H., Ponsich, A., Azzaro-Pantel, C.: On the use of gradient-based repair method for solving constrained multiobjective optimization problems—a comparative study. In: Kulkarni, A.J., et al. (eds.) Constraint Handling in Metaheuristics and Applications, pp. 119–149. Springer Singapore, Singapore (2021)
130. Li, J.P., et al.: A comparative study of constraint-handling techniques in evolutionary constrained multiobjective optimization. In: 2016 IEEE Congress on Evolutionary Computation (CEC), pp. 4175–4182 (2016)
131. Jamal, M.B., Ming, F., Zhengang, J.: Solving constrained optimization problems by using covariance matrix adaptation evolutionary strategy with constraint handling methods. In: Proceedings of the 2nd International Conference on Innovation in Artificial Intelligence. Association for Computing Machinery, Shanghai, China, pp. 6–15 (2018)

132. Mallipeddi, R., Suganthan, P.N.: Problem Definitions and Evaluation Criteria for the CEC 2010 Competition on Constrained real-Parameter Optimization, p. 24. Nanyang Technological University, Singapore (2020)
133. Biswas, P.P., et al.: Optimal power flow solutions using differential evolution algorithm integrated with effective constraint handling techniques. Eng. Appl. Artif. Intell. **68**, 81–100 (2018)
134. Malan, K.M.: Online landscape analysis for guiding constraint handling in particle swarm optimisation. In: Kulkarni, A.J., et al. (eds.) Constraint Handling in Metaheuristics and Applications, pp. 101–118. Springer Singapore, Singapore (2021)
135. Wang, H., et al.: Constraint handling technique based on Lebesgue measure for constrained multiobjective particle swarm optimization algorithm. Knowl.-Based Syst. **227**, 107131 (2021)
136. Ma, H., et al.: A multi-stage evolutionary algorithm for multi-objective optimization with complex constraints. Inf. Sci. **560**, 68–91 (2021)
137. Tian, Y., et al.: Balancing objective optimization and constraint satisfaction in constrained evolutionary multiobjective optimization. IEEE Trans. Cybern. **52**(9), 9559–9572 (2022)
138. Zapotecas-Martínez, S., Ponsich, A.: Constraint handling within MOEA/D through an additional scalarizing function. In: Proceedings of the 2020 Genetic and Evolutionary Computation Conference. Association for Computing Machinery, Cancún, Mexico, pp. 595–602 (2020)
139. Zhu, Q., Zhang, Q., Lin, Q.: A Constrained multiobjective evolutionary algorithm with detect-and-escape strategy. IEEE Trans. Evol. Comput. **24**(5), 938–947 (2020)
140. Peng, C., Liu, H.-L., Goodman, E.D.: Handling multi-objective optimization problems with unbalanced constraints and their effects on evolutionary algorithm performance. Swarm Evol. Comput. **55**, 100676 (2020)
141. Liu, Z.Z., Wang, Y., Wang, B.C.: Indicator-based constrained multiobjective evolutionary algorithms. IEEE Trans. Syst. Man Cybern. Syst. **51**(9), 5414–5426 (2021)
142. Yuan, J., et al.: Indicator-based evolutionary algorithm for solving constrained multiobjective optimization problems. IEEE Trans. Evol. Comput. **26**(2), 379–391 (2022)
143. Deb, K., Pratap, A., Meyarivan, T.: Constrained test problems for multi-objective evolutionary optimization. In: Zitzler, E., Thiele, L., Deb, K., Coello Coello, C.A., Corne, D. (eds.) Evolutionary Multi-Criterion Optimization. Springer, Berlin, Heidelberg (2001)
144. Nguyen, T.T., Yao, X.: Continuous dynamic constrained optimization—the challenges. IEEE Trans. Evol. Comput. **16**(6), 769–786 (2012)
145. Cao, H., et al.: Comparative study of four penalty-free constraint-handling techniques in structural optimization using harmony search. Eng. Comput. **38**(1), 561–581 (2022)
146. Picard, C., Schiffmann, J.: Realistic constrained multiobjective optimization benchmark problems from design. IEEE Trans. Evol. Comput. **25**(2), 234–246 (2021)
147. Dufo-López, R., Cristóbal-Monreal, I.R., Yusta, J.M.: Optimisation of PV-wind-diesel-battery stand-alone systems to minimise cost and maximise human development index and job creation. Renew. Energy **94**, 280–293 (2016)
148. Aghajani, G.R., Shayanfar, H.A., Shayeghi, H.: Demand side management in a smart micro-grid in the presence of renewable generation and demand response. Energy **126**, 622–637 (2017)
149. Quitoras, M.R., Campana, P.E., Crawford, C.: Exploring electricity generation alternatives for Canadian Arctic communities using a multi-objective genetic algorithm approach. Energy Convers. Manag. **210**, 112471 (2020)
150. Abbes, D., Martinez, A., Champenois, G.: Life cycle cost, embodied energy and loss of power supply probability for the optimal design of hybrid power systems. Math. Comput. Simul. **98**, 46–62 (2014)
151. Abdelkader, A., et al.: Multi-objective genetic algorithm based sizing optimization of a stand-alone wind/PV power supply system with enhanced battery/supercapacitor hybrid energy storage. Energy **163**, 351–363 (2018)
152. Paliwal, P., Patidar, N.P., Nema, R.K.: Determination of reliability constrained optimal resource mix for an autonomous hybrid power system using Particle Swarm Optimization. Renew. Energy **63**, 194–204 (2014)
153. Samy, M.M., Barakat, S., Ramadan, H.S.: A flower pollination optimization algorithm for an off-grid PV-Fuel cell hybrid renewable system. Int. J. Hydrogen Energy **44**(4), 2141–2152 (2019)
154. Khatib, T., et al.: Optimal sizing of hybrid pv/wind systems for Malaysia using loss of load probability. Energy Sources Part A Recov. Util. Environ. Effects **37**(7), 687–695 (2015)
155. Dhakouani, A., et al.: Long-term optimisation model of the Tunisian power system. Energy **141**, 550–562 (2017)

156. Zhang, N., et al.: An integrated source-grid-load planning model at the macro level: case study for China's power sector. Energy **126**, 231–246 (2017)
157. Katsigiannis, Y.A., Georgilakis, P.S., Karapidakis, E.S.: Hybrid Simulated Annealing-Tabu Search Method for Optimal Sizing of Autonomous Power Systems With Renewables. IEEE Trans. Sustain. Energy **3**(3), 330–338 (2012)
158. Caunhye, A.M., Cardin, M.-A.: Towards more resilient integrated power grid capacity expansion: a robust optimization approach with operational flexibility. Energy Econ. **72**, 20–34 (2018)
159. Alharbi, H., Bhattacharya, K.: Stochastic optimal planning of battery energy storage systems for isolated microgrids. IEEE Trans. Sustain. Energy **9**(1), 211–227 (2018)
160. Abdulgalil, M.A., et al.: Sizing of energy storage systems to enhance microgrid reliability. In: 2018 IEEE International Conference on Industrial Technology (ICIT), pp. 1302–1307 (2018)
161. Hui, J., et al.: Analyzing the penetration barriers of clean generation technologies in China's power sector using a multi-region optimization model. Appl. Energy **185**, 1809–1820 (2017)
162. Bahmani-Firouzi, B., Azizipanah-Abarghooee, R.: Optimal sizing of battery energy storage for micro-grid operation management using a new improved bat algorithm. Int. J. Electr. Power Energy Syst. **56**, 42–54 (2014)
163. Tabar, V.S., Jirdehi, M.A., Hemmati, R.: Energy management in microgrid based on the multi objective stochastic programming incorporating portable renewable energy resource as demand response option. Energy **118**, 827–839 (2017)
164. Al-Falahi, M.D.A., et al.: Power management optimization of hybrid power systems in electric ferries. Energy Convers. Manage. **172**, 50–66 (2018)
165. Abdel-hamed, A.M., et al.: Optimal Sizing and Design of Isolated Micro-Grid systems. Int. J. Environ. Sci. Sustain. Dev. **4**(3), 19 (2019)
166. Hong, Y., Lian, R.: optimal sizing of hybrid wind/pv/diesel generation in a stand-alone power system using markov-based genetic algorithm. IEEE Trans. Power Delivery **27**(2), 640–647 (2012)
167. Rezaei, N., Pezhmani, Y., Khazali, A.: Economic-environmental risk-averse optimal heat and power energy management of a grid-connected multi microgrid system considering demand response and bidding strategy. Energy **240**, 122844 (2022)
168. Lujano-Rojas, J.M., Dufo-López, R., Bernal-Agustín, J.L.: Probabilistic modelling and analysis of stand-alone hybrid power systems. Energy **63**, 19–27 (2013)
169. Fattahi, A., Nahavandi, A., Jokarzadeh, M.: A comprehensive reserve allocation method in a micro-grid considering renewable generation intermittency and demand side participation. Energy **155**, 678–689 (2018)
170. Yahaya, A.A., AlMuhaini, M., Heydt, G.T.: Optimal design of hybrid DG systems for microgrid reliability enhancement. IET Gener. Transm. Distrib. **14**(5), 816–823 (2020)
171. Amereh, M., Khozani, Z.S., Kazemi, A.: Multi objective design of stand-alone PV/wind energy system by using hybrid GA and PSO. In: 2014 22nd Iranian Conference on Electrical Engineering (ICEE), pp. 695–699 (2014)
172. Vahedipour-Dahraie, M., et al.: Stochastic security and risk-constrained scheduling for an autonomous microgrid with demand response and renewable energy resources. IET Renew. Power Gener. **11**(14), 1812–1821 (2017)
173. Vahedipour-Dahraie, M., et al.: Study of the effect of time-based rate demand response programs on stochastic day-ahead energy and reserve scheduling in islanded residential microgrids. Appl. Sci. **7**(4), 378 (2017)
174. Roos, A., Bolkesjø, T.F.: Value of demand flexibility on spot and reserve electricity markets in future power system with increased shares of variable renewable energy. Energy **144**, 207–217 (2018)
175. Bu, C., Luo, W., Yue, L.: Continuous dynamic constrained optimization with ensemble of locating and tracking feasible regions strategies. IEEE Trans. Evol. Comput. **21**(1), 14–33 (2017)
176. Li, X., et al.: A novel two-stage constraints handling framework for real-world multi-constrained multi-objective optimization problem based on evolutionary algorithm. Appl. Intell. **51**(11), 8212–8229 (2021)
177. Marzband, M., et al.: Optimal energy management system based on stochastic approach for a home Microgrid with integrated responsive load demand and energy storage. Sustain. Cities Soc. **28**, 256–264 (2017)
178. Zhao, S., et al.: Genetic algorithm based economic optimization of microgrid including multi-energy supply system. J. Phys: Conf. Ser. **1072**, 012017 (2018)

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