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Metaheuristic search in smart grid: A review with emphasis on planning, scheduling and power flow optimization applications

M. Papadimitrakis [a], N. Giamarelos [a], M. Stogiannos [a], E.N. Zois [a], N.A.-I. Livanos [b], A. Alexandridis [a,*]

[a] Department of Electrical and Electronic Engineering, University of West Attica, Thivon 250, Aigaleo, 12241, Greece
[b] EMTECH SPACE P.C., Korinthou 32 & S. Davaki, Metamorfosi 144 51, Athens, Greece

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ABSTRACT

A multitude of optimization tasks ensue in the context of the smart grid, often exhibiting undesirable characteristics like non-convexity, mixed types of design variables and multiple - and often conflicting - objectives. These tasks can be broadly categorized into three classes of problems, namely optimal power flow (OPF), scheduling and planning. Metaheuristic search methods form a generic class of optimization techniques, that have been shown to work successfully for complex problems. Not surprisingly, they have been widely applied in the smart grid, their use spanning almost every smart grid-related optimization task. In this work, we review the use of metaheuristic search for OPF, scheduling and planning through a unified approach, keeping in mind that these problems share many common challenges and objectives. The use of different metaheuristic methods is discussed extensively with regard to problem handling, multi-objective optimization performance and method accuracy in relation to computational complexity. An attempt to arrive at quantitative conclusions is also being made, by compiling tables which present collective results on common test grids. Lastly, the paper identifies promising directions for future research, concerning metaheuristic search application practices, method development and new challenges that we believe will shape the future of smart grid optimization.

1. Introduction

Electricity generation and distribution has undergone a major development in the last decades, moving from a conventional centralized generation towards a distributed, small-scale, producer-consumer (prosumer) model, connected to the distribution network [1]. This evolution has been made possible by the development of a reliable information and communication infrastructure, but it also gave rise to certain challenges, which were met through the emergence of the smart grid [2]. The technological framework defined by the smart grid enables a more reliable, more efficient and more economical operation, capable of accommodating increased utilization of renewable energy sources (RES) and energy storage systems (ESS). On the one hand, system operators now have an abundance of incoming information and available control decisions at their disposal in order to control critical network state variables. On the other hand, they must deal with modern challenges in grid operation that arise from distributed generation and storage, as well as RES stochasticity [1]. From an optimization perspective, this new paradigm offers significant potential for the application of new methods, capable of handling the aforementioned challenges. These methods must be able to cope with a larger amount of design variables (DVs) of diverse nature, while taking into account a significant number of incoming state measurements from the grid. In addition, they must provide satisfactory solution accuracy combined with reasonable computational complexity, even when applied to multiple optimization objectives. These objectives vary according to the network and time horizon specifications; Table 1 summarizes the most common ones.

Optimization tasks formed in the context of power grids can be categorized into three major classes, namely the optimal power flow (OPF) [3], scheduling [4] and planning problems [5,6]. OPF describes a broader set of optimization objectives that apply to the efficient operation of the smart grid bounded by a number of operational constraints. This amounts to the grid meeting the short-term active and reactive power needs of the load buses in an efficient manner. In tasks pertaining to generation scheduling and planning, the network operators set up power source scheduling plans, based on the total expected active and

* Corresponding author.
E-mail address: alexx@uniwa.gr (A. Alexandridis).

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List of abbreviations

ABC	artificial bee colony
ACO	ant colony optimization
AIS	artificial immune systems
ALO	ant-lion optimization
BFA	bacteria foraging algorithm
CHP	combined heat and power
COA	coyote optimization algorithm
CP	contingency planning
CS	cuckoo search
CSA	crow search algorithm
DE	differential evolution
DERMS	distributed energy resources management systems
DERs	distributed energy resources
DG	distributed generation
DSM	demand side management
DVs	design variables
EC	evolutionary computation
ED	economic dispatch
EM	emissions
EMA	exchange market algorithm
ESS	energy storage systems
FA	firefly algorithm
GA	genetic algorithm
GC	generation cost
GR	grid resiliency
GSA	gravitational search algorithm
GWO	grey wolf optimization
HSA	harmony search algorithm
ICA	imperialist competitive algorithm
LB	load balance
LP	linear programming
MG	micro grid
MINLP	mixed integer nonlinear programming
MOO	multi-objective optimization
NRP	network reconfiguration problem
NSGA-II	non-dominated sorting genetic algorithm
OF	objective function
OPF	optimal power flow
PSO	particle swarm optimization
PV	photovoltaic
RES	renewable energy sources
RPL	real power losses
SA	simulated annealing
SI	swarm intelligence
TLBO	teaching-learning based method
TST	transient stability
TS	tabu search
TSA	tree seed algorithm
UC	unit commitment
VNS	variable neighborhood search
VPI	voltage profile improvement
WOA	whale optimization algorithm

Table 1
Most common optimization objectives.

Optimization objective	Description
Generation cost (GC)	Minimization of the total generation cost
Real power losses (RPL)	Minimization of power losses
Transient stability (TST)	Maximization of grid stability against transient effects
Voltage profile improvement (VPI)	Minimization of voltage-related indices
Emissions (EM)	Minimization of emissions
Grid resiliency (GR)	Minimization of grid-contingency-related indices

reactive power demand. While these two problems share similar objectives, they refer to different horizons; scheduling is oriented towards addressing the load demand using the currently available resources, while planning forms strategic solutions in order to cope with expected demands in the far future by investing in expandability, capacity and emissions control. The three problems typically span different time horizons, as shown in Fig. 1; however, latest developments on distributed energy resources management systems (DERMS) technology [7] challenge this paradigm. In particular, DERMS functionalities allow for the automation of some of the smart grid tasks, thus obscuring their discrete horizon boundaries, as will be discussed later.

The extensive arsenal of mathematical programming tools has been put to use against some of the most challenging grid optimization problems before the smart-grid era has emerged. Indeed, standard mathematical optimization methods have been implemented successfully, including Newton, generalized reduced gradient, simplex and interior point methods [8–10]. However, most of these methods come with three inherent disadvantages, namely (a) poor performance on non-convex optimization problems, (b) inability to handle discrete design variables and (c) unsuitability for multi-objective problems, as

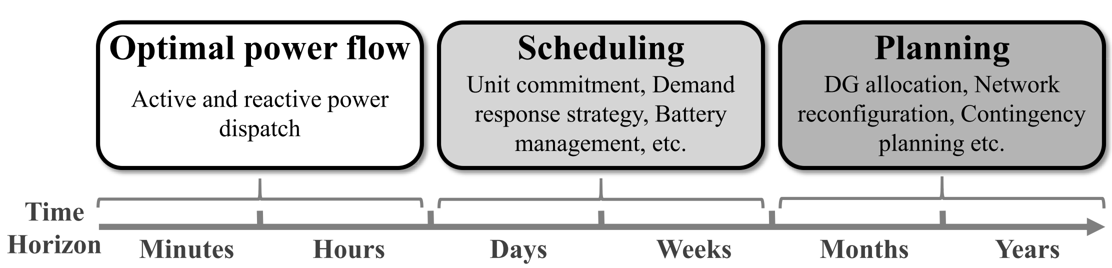

Fig. 1. The current paradigm in smart grid optimization; the three optimization problems span discrete horizon boundaries.

they cannot easily deal with discontinuous or concave Pareto fronts [11]. Unfortunately, a significant portion of the smart grid-related optimization problems are non-convex, multi-objective in nature and contain mixed integer and continuous design variables. Thus, it is easily understood that nowadays, the aforementioned methods may not be the best choice at hand.

Metaheuristic methods on the other hand constitute a class of optimization algorithms that are in principle better equipped to overcome the difficulties commonly encountered in smart grid optimization and provide better quality solutions than traditional approaches. By relying on stochastic search, they reduce the risk of getting trapped in local minima, while the generation and evolution of multiple solutions employed by most of metaheuristic methods bestows increased exploration capabilities. In addition, they can handle non-continuous and concave Pareto fronts and the population-based ones can generate several elements of the Pareto optimal set in a single evaluation.

Metaheuristic methods do come with disadvantages as well. The first is their overall higher computational burden, which is very important in the OPF problem solution since they usually require many more function evaluations than standard mathematical optimization approaches. The second is the absence of convergence proof for most problems. The third and most persistent, is the need of complex parameter tuning; speed of convergence is sensitive to tuning and may require tedious trial-and-error runs in order to evaluate the optimal parameter set.

Notwithstanding their disadvantages (which, as will be discussed in section 6 can be often mitigated in practice), metaheuristic optimization methods have been widely employed in the smart grid. Indeed, a plethora of successful applications have been reported in all three optimization problems depicted in Fig. 1. As a response to the growing research on the application of metaheuristics, a number of survey and review papers appeared, focusing on the use of these methods on the individual tasks of OPF [12–15], scheduling [16,17], or planning [18–20]. These reviews thoroughly cover the literature up to their respective publication dates and do produce interesting discussions. Surprisingly though, little attempt is being made to compare the reviewed techniques using the reported results on common benchmark test grids. Moreover, most reviews rarely touch upon the subject of computational complexity, which is of great practical importance, especially for real-time OPF implementations.

This paper reviews the latest applications of metaheuristic optimization in the optimal power flow, scheduling and planning problems. The contributions of this work to the existing reviewing literature are as follows:

- We extend the literature review with respect to the application of metaheuristic search methods on the individual problems of OPF, scheduling and planning during the last few years. More importantly, we approach smart grid optimization as a whole, recognizing that these three problems share a number of common challenges and objectives. Our approach is supported by the recent developments on DERMS and microgrid technology [21,22], which lead grid operators to consider these three problems under more flexible horizon boundaries and in intertwined formulations. Thus, by providing a total perspective of smart grid optimization problems, we draw conclusions of universal applicability regarding the effectiveness of different metaheuristic optimization methods.
- We provide a comparison of the single-objective and multi-objective optimization accuracy of the reviewed metaheuristic methods based on the reported results on common testbeds such as the IEEE-30, or the 10–100 generator test grids, wherever possible. Even though limited comparisons are common in individual research papers, to the authors' best knowledge, very few papers in the reviewing literature have reported them collectively, much less used them to draw qualitative conclusions of universal nature for the problems at hand.
- Furthermore, we provide a summary of the reviewed techniques in terms of computational complexity. The commonly reported metric of execution time is supplanted by the total objective function (OF) evaluations until convergence. This metric, which, to the authors' best knowledge has not been used by other reviews in the smart grid domain up to now, enables a more objective comparison. At the same time, it allows conclusions to be drawn independently from factors such as type of computing platform, software and special conditions under which each method was run.
- We identify promising directions for future research on the development and use of metaheuristic search methods for the optimization problems encountered in the context of the smart grid. These directions include improving the practices of metaheuristic search application, intensifying method development towards specific directions and identifying emerging smart grid challenges that befit the use of metaheuristics.

The structure of this work is as follows: Section 2 introduces some of the most popular metaheuristic search methodologies that have been applied in smart grid optimization. The literature review for the OPF, scheduling and planning problems is presented in sections 3-5, respectively. Section 6 contains a discussion on the literature review given in the previous sections and presents qualitative and - wherever possible - quantitative conclusions regarding the performance of metaheuristic methods. The paper concludes by identifying promising avenues for future research.

2. Metaheuristic search methods

Metaheuristic search algorithms form a broad category of optimization techniques, which usually receive inspiration from natural, or man-made processes. Though some of the early methods for metaheuristic search appeared near the middle of the 20th century, the last decades have been an era of overproduction of related works; this can be attributed to the ever-growing usage and capabilities of computing systems. On the other hand, the proliferation of related papers is not without its critics [23], who mainly focus on the absence of novelty for some of the works that rely too much on the biological metaphor, while neglecting the true mechanics underlying the search process.

This section provides a brief overview of the most influential metaheuristic search methods, outlines their strengths and weaknesses and paves the way for the literature review on their applications in smart grid optimization tasks.

2.1. Evolutionary computation

Evolutionary computation (EC) is a widely used computer science discipline comprising methods that simulate the evolution of members of a population which are regarded as possible solutions to the optimization problem. Genetic algorithms (GAs) [24] and differential evolution (DE) [25] comprise the two most distinctive representatives of EC, albeit a number of other EC techniques have also been proposed [26].

GAs are able to perform reliably and can easily collaborate with existing models and systems [27], as well as integrate into hybrid approaches [28]. Additionally, they are easily scalable with parallel implementation abilities [29,30] and they impose no restrictions on the functions they process. Their disadvantages include increased difficulty in encoding the optimization problem, as well as sensitivity to tuning parameters.

Differential evolution [31] was developed in an attempt to improve the slow convergence of GAs. The key difference is the use of the self-referential mutation technique which essentially improves exploration over GAs, based on the differences between random solution pairs. Over the past twenty years, DE has been thoroughly studied and applied to problems of constrained optimization, parallel computation [32] and multi-objective optimization (MOO) [25,33]. DE is robust, easy to use and requires relatively few control variables. One major disadvantage is the fact that the algorithm heavily relies on the tuning parameters in order to converge efficiently.

2.2. Swarm intelligence

Swarm intelligence (SI) methods exhibit characteristics found in decentralized, self-organized groups of biological organisms. SI systems typically consist of a population of simple agents that interact locally with each other, as well as with their environment; these interactions, albeit local, aim to lead to the emergence of a "smart" global behavior. Examples of SI methods inspired by nature include ant colonies [34], bird flocking [35], herd farming [36], beehives [37], bacterial growth [38], whale hunting [39], dragonfly swarming [40] and the relation between trees and their seeds [41], while many other metaphors are used, like the harmony search algorithm (HSA) which models the process of musical improvisation [42].

Particle swarm optimization (PSO) [43] comprises one of the most important SI methodologies. PSO requires no special encoding, thus enjoying an advantage over methods like GAs in terms of easiness to use. Its simplicity, combined with effectiveness and speed, makes PSO ideal for use in applications where computational cost is a critical parameter. Due to these merits, PSO has been widely used, while various modifications were proposed [35,44], aiming to cure its defects, which are mainly associated with premature convergence.

A different popular SI method is the ant colony optimization (ACO). ACO has proven to be effective in solving combinatorial optimization (CO) problems and has found application in a number of fields in industry [45], but presents some limitations in dealing with continuous design variables. Various modifications of the original algorithm have been reported in the literature [45–47].

2.3. Artificial immune systems

Artificial immune systems (AIS) are inspired by theoretical immunology, simulating the processes used by the biological immune system to respond to external threats. AIS follow a distributed model with an absence of any point of total control, using exclusively local information. Due to their inherent decentralized nature, AIS require minimal CPU and memory resources, in contrast to population-based techniques. On the other hand, AIS may require customization in order to solve optimization problems, unlike the rest of the methods presented in this section. AIS-based techniques have been extensively studied and applied to many engineering fields [48], including power grid applications [49,50]. They provide inspiration for hybrid methodologies with remarkable characteristics [51].

2.4. Non population-based metaheuristics

Unlike the previously mentioned categories, which evolve a population or swarm of solutions, some of the early metaheuristic methods were based on modifying a single solution, the most prominent being simulated annealing (SA) [52] and tabu search (TS) [53]. SA draws inspiration from the search of a minimum energy state which occurs during the process of annealing in metallurgy. Its distinct characteristic is that it allows for temporarily accepting a worse solution with a probability, which becomes smaller as the iterations progress. SA tuning involves only a few parameters while an obvious advantage involves the significantly reduced computational cost as a result of operating on a single solution. On the other hand, accuracy is usually inferior compared to population-based methods. Recent advances and SA modifications are reported in [52].

Tabu search owes its name to the so-called tabu lists, that record the search history in order to avoid cycling, i.e. revisiting previously found solutions. The basic idea behind TS has been subjected to a number of modifications, which improve the algorithm's efficiency [54,55]. TS is suitable for large-scale optimization problems as it combines the significant advantage of reduced computational complexity with reasonable performance in terms of accuracy, albeit it cannot compete with population-based methods in that respect.

3. Optimal power flow

3.1. Problem formulation

The OPF problem, in its generic form, is a large-scale, non-convex, mixed integer nonlinear programming (MINLP) optimization problem, belonging to the NP-hard class. This is partly owed to the nature of the design variables, which may be discrete, and to the non-continuity, non-differentiability and non-convexity of the objective function. Since the mathematical formulation of the OPF is extensively presented in the literature [3], this work will be confided to a brief descriptive introduction.

The OPF problem takes into account operational variables of the grid (such as voltage magnitudes and angles at every node). The design variables generally include active and reactive power generation levels of the node, transformer tap positions, capacitor bank switch positions, etc. The problem includes equality constraints, which describe the power flow equations and inequality constraints, corresponding to the operational and safety constraints of the system. Several techniques can be applied to ease the optimization problem, such as conic relaxations, or assumptions on the differentiability and continuity of the objective function, e.g. ignoring valve-point effects of thermal generators [56], or rounding values of reactive compensation devices to the nearest integer [57].

3.2. Metaheuristic methods for OPF

3.2.1. Swarm intelligence

The first application of a PSO method in OPF takes place in [35], reporting result insensitivity to different numbers of particles. The robustness of PSO-based methods to suboptimal hyperparameter tuning is also demonstrated in [58]. In [59], a PSO method equipped with a multi-stage penalty function for the incorporation of state variable constraints is presented. In [60] a faster-converging "coordinate aggregation" PSO is presented, where the new speed vector of each particle is computed using the best-performing particle of the previous iteration. Convergence acceleration ideas have also been developed for the ACO method, such as the decomposition of the constraints to active and non-active sets [47], or the replacement of ill-performing solutions with a recombination of the best-performing ones using a GA scheme [46].

In [61,62] PSO-based methods are presented, capable of honoring transient stability constraints described as sets of differential and algebraic equations. Their novelty resides in dynamic inertia weights and in the addition of a stochastic term for toggling between exploration and exploitation. The same strategy is used in [63] for a stability-oriented PSO where the weights are updated according to a stability condition. In [39], the weights of a whale optimization algorithm (WOA) are updated according to chaotic maps. Dynamic weights are also used in [64] through an uncertainty-oriented fuzzy PSO approach. Another enhanced PSO algorithm capable of handling RES uncertainty is presented in [65], which utilizes inverter-based reactive power injections as a design variable; this is oriented to real time applications. Uncertainty-oriented methods have also been developed on bacteria foraging algorithm (BFA) [66], in order to deal with time-varying loads and wind power uncertainties. In addition, a dragonfly algorithm (DFA) is used for multi-objective OPF to a RES-heavy grid [67]. In [68] PSO-based method is applied to congested transmission grids taking into account energy pricing schemes while honoring transmission system constraints. Lastly, a more realistic modelling of a microgrids' slack bus characteristics occurs in [69] and the OPF problem is solved using a PSO-based algorithm.

Swarm-based techniques that accommodate for reactive power compensation variables include a variation of the original BFA that directly handles taps [70], or a WOA variant that optimizes shunt compensator values in large-scale systems [71]. A variant of the water cycle algorithm is employed for reactive power dispatch [72], that employs a Gaussian solution mutation mechanism in order to dynamically manage the trade-off between exploitation and exploration. In [73] an imperialist competitive algorithm's (ICA) solution initializes a classic sequential quadratic programming method, resulting in enhanced domain exploration; a tree seed algorithm (TSA) tailored towards the same end, is presented in [41]. Lastly, a moth swarm algorithm (MSA) and a gravitational search algorithm (GSA) are presented in [74,75] respectively, oriented towards the ED of combined heat-power (CHP) plants. The two methods prove to be especially adept at handling the mathematical adversity of the valve-point effect, entailed in the modelling of CHP plants.

3.2.2. Evolutionary computation

In [76] a large-scale-system variant of the GA method is presented. The design variables are 4-bit coded and the algorithm employs an extra search level whenever finer resolution is required. The convergence speed of the standard GA can be increased either by initializing a feasible point [77], or by adaptively changing crossover and mutation probabilities according to the population diversity [78]. Due to the inherent parallelization of solutions in the DE, different transient responses of the system can be evaluated at the same time, thus confirming the suitability for TS-OPF [32].

In addition, DE algorithms have been found to be applicable to a number of multi-objective problems [25,33]. A notable multi-objective DE algorithm is proposed in [79], where each ε-level of the ε-constraint method is forcedly initialized using the best previous solutions, resulting in less OF evaluations. In [80] a success-history-based adaptive DE (SHADE) adaptively changes its hyper-parameters based on a historical memory of successful past tunings. The method is applied for multi-objective OPF in the face of grid uncertainties.

3.2.3. Artificial immune systems

AIS methods are useful candidates for OPF applications, mainly due to their low computational complexity. An AIS method with adaptive crossover rates that toggle between exploration and exploitation is provided in [81], while in [51] an AIS algorithm uses the Jacobian of the power flow equations in order to improve candidate solution mutation. In [82] a variant of the aforementioned approach, which is oriented for large systems is presented. The method rejects clusters of individuals that converge on similar local optima from participating in mutation.

3.2.4. Non-population based metaheuristics

A standard TS algorithm application takes place in [54], with both real and discrete design variables, while in [83] a version with an adaptive TS length, capable of handling polar constraints is presented.

4. Optimal network scheduling

4.1. Problem formulation

The main operational goal during power generation scheduling is the continuous satisfaction of load demand without interruptions. To this end, several scheduling tasks have been established, namely unit commitment (UC), economic dispatch (ED) and demand side management (DSM). In order to achieve a reliable, as well as economic power supply, power system scheduling is based on the following decision-making processes. Initially, the unit commitment process takes place, which is responsible for the minimization of both fuel and start-up cost [84]. The operational constraints comprise of: (a) system power balance, (b) spinning reserve requirements, (c) unit minimum up and down time and (d) unit generation limits. Another decision to be made, known as the ED problem, involves allocating power demand to the committed units. For this to be accomplished in an efficient way, ED is carried out for day ahead horizon with hourly intervals. The objective function aims to minimize the total fuel cost as described in [16]. ED shares constraints (a) - (c) with the UC problem, using additionally the ramp rate limits.

The aforementioned problems are formulated using as design variables the generated power, the commitment state and the on/off-service time of units. The objective is to minimize the power system operating cost, as well as the environmental cost. Other common scheduling targets include voltage balance, storage operations scheduling and DSM. This last procedure is achieved by allocation of shifting loads, peak demand management and more recently, improvement of intermittent generation balancing [85].

Due to multiple requirements regarding power systems operation, the objectives are either extended to minimization of power losses, congestion cost and ESS cost [86], or multi-objective formulation is applied [37,87]. Recently, the increasing integration of distributed energy resources (DERs) in power grids has led to the search of new techniques for centralized management, i.e. DERMS and virtual power plants (VPPs) [88,89]. The introduction of additional variables such as the status of switches, amount of branch currents, reactive power of generators, or reliability indices is frequently necessary, leading to a combinatorial optimization problem [90,91]. The set of constraints may also be related to the specific elements of a distribution grid such as ESS, RES, electric vehicles (EVs), etc. [44].

4.2. Metaheuristic methods for scheduling

4.2.1. Swarm intelligence

Over the last decade, SI algorithms and especially PSO, have gained great appeal in distributed networks scheduling. The problems of ED [44,92] and unit commitment [93] for micro grids (MGs) in presence of uncertainties from wind and solar energy, were dealt using standard PSO and recently, hybrid DE-PSO algorithms [94]. In this context, congestion management [86] and ED [90] are addressed by conventional PSO, thus achieving significant gains in ESS cost reduction and improvements in load profile. Premature convergence is avoided either by randomization of particle velocity [95], or by incorporation of the GA mutation process [96]. The economic dispatch of an MG in the presence of demand response programs is dealt with PSO in [97], considering CHP generation units as a way to increase the efficiency of the operating system. A multi-objective PSO approach is applied in [98] for a joint ED-emissions optimization, underlying the beneficial contribution of dual-mode CHP units from economical, as well as environmental aspect. Other PSO enhancements include: (a) altering the cost function to better model the battery charging/discharging operations [99], (b) updating particle speed through quantum bit logic, thus achieving quicker convergence [100] and (c) using Gaussian mutation for the strategic parameters and self-parameterization of the maximum and minimum particle velocities [101]. These works aim to minimize the total costs subject to several constraints regarding the operation of the system, units and battery.

Bio-inspired metaheuristics modified BFA [38,102] and cat swarm optimization (CSO) [103], have been proposed for solving the scheduling problem of distributed energy resources. According to Refs. [34,45], ACO manages to deal with DSM and optimal storage operations scheduling based on load and renewable production forecast, respectively. The problem of ED in microgrid scale is formulated as linear programming (LP) in Refs. [104,105]. A great reduction of the total generation cost and computation time is obtained by the so-called ant-lion optimization (ALO) and HSA methods, respectively. DSM [91] and ED [106] are addressed by artificial bee colony (ABC) and multi-dimension ICA optimizers, respectively, aiming to market clearing price minimization. Unit commitment as well as demand participation are investigated through shuffled frog leaping algorithm (SFLA) [107] and modified SFLA [108], allowing for the direct accommodation of minimum up/downtime constraints during generating feasible solutions. In [109], the ED optimization problem considering contingency issues is decomposed and the binary/continuous variables are handled by different versions of the firefly algorithm (FA). The same problem is examined using grey wolf optimization (GWO) subject to emissions minimization [110], exhibiting notable performance and easiness of ramp-rate constraint handling. In a recent work [111] GWO is utilized for voltage control through minimization of transformer tap movements, photovoltaic (PV) power curtailment and voltage rise/drop violations. Other multi-objective swarm-based techniques that treat the aforementioned objectives while accommodating for generation stochasticity include a PSO-based method [112] and binary/real coded ABC [37]. Integrated approaches based on a modified dragonfly method [40] and a natural aggregation algorithm (NAA) [113] are used to minimize the total system cost and the generation cost respectively. The optimal energy management is attempted through an enhanced version of the most valuable player algorithm (MVPA) [114], considering CHP units into a microgrid scale.

4.2.2. Evolutionary computation

A standard EC algorithm implementation for UC problem can be found in [115] and an evolutionary lightning flash algorithm is presented in [87], involving non-convex and nonlinear characteristics of the objective function. DE algorithms have been applied extensively featuring single-objective [116] and multi-objective [117] DSM optimization, as well as ESSM under uncertainties of RES supply and load demand [118]. Variant approaches addressing ED were also developed, enhanced either by sequence-based mathematical-programming-based initialization [88], or by introducing a series of operations into DE algorithm, such as individual ranking, population dividing and population restructuring [119]. More recently, variants of EC inspired from quantum bits (q-bits) have emerged, allowing the coding of all binary states in a single solution vector [120,121]. The large-scale energy resource scheduling problem is addressed by hybrid-adaptive differential evolution with decay function (HyDE-DF) [122], featuring the ability of self-tuning of parameters and fast convergence capabilities. Other EC techniques incorporate local search optimizers to enhance exploitation capabilities, forming memetic evolutionary algorithms [123,124].

GA is intrinsically suited to solve specific classes of scheduling problems like UC, as it allows for simple solution coding for binary variables [125]. A memory-based genetic algorithm (MGA) featuring improved search capability is utilized in [24], whereas in Refs. [126,127], two dynamic pricing schemes are introduced for minimization of the energy production cost. Advanced GAs have been reported to be effective in dealing with the UC problem, such as the hybridized GA-TS employed in [28]. A GA is applied in [57] considering interruptive loads with uncertainties. The minimization of both operating cost and voltage stability index is achieved by employing a multi-objective GA [128].

4.2.3. Artificial immune systems

An efficient and complex combinatorial wind–thermal scheduling problem formulation is presented in [56]. This formulation features a reduced number of binary string variables for modelling the start-up/shut-down status and ramp rate limits of thermal units. The maximization of profit is achieved by an AIS algorithm.

4.2.4. Non-population based metaheuristics

A TS based algorithm is proposed in [53] for day-ahead energy consumption profile scheduling. This methodology achieves a considerable reduction in the computational complexity as compared to energy consumption scheduling (ECS) algorithms. In [52], an SA method that generates only feasible neighboring solutions, thus greatly accelerating UC optimization, is presented. Finally, the improved variable neighborhood search (IVNS) algorithm, proposed in [129] for DER scheduling including DR, appears to perform better than standard VNS and PSO variants.

5. Optimal network planning

5.1. Problem formulation

Planning of power systems is a complex process due to existing alternatives, goals, constraints and uncertainties. Typical planning issues encountered are:

- *Power generation mix selection and sizing:* the aim of this task is to achieve high cost-effectiveness, low environmental impact and high reliability.
- *Siting problem:* covers power sources allocation and power lines layout in order to keep quality constraints; the objective of low power losses is also introduced.
- *Reconfiguration:* this procedure is primarily performed to minimize losses, as well as load imbalances, ensuring at the same time a satisfactory voltage profile across the system.

It should be stressed that simultaneous network reconfiguration and sizing of the distributed generation (DG) produces better results compared to the single approach in terms of real power losses (RPL) [130,131] and voltage profile improvement (VPI) [132]. As it can be seen, network scheduling and planning share common aspects, both in terms of optimization tasks (coordination of generating units, demand participation) and objectives (cost, losses, emission minimization). Nevertheless, due to its intrinsic characteristics, planning is sometimes oriented to long-term optimization, as it involves procedures related to network topology and structure, like network expansion [133] and equipment maintenance.

Network planning can be formulated as a single or multi-objective problem. However, active power loss minimization is traditionally considered, under the following constraints: (a) distributed generation limits, (b) power injection limits, (c) power balance, (d) node voltage limits, (e) line current limits and (f) radiality. This problem is mathematically formulated as in [18]. Numerous decision variables at the disposal of the network operator participate in the problem formulation, such as: (a) real and reactive power injected by DGs, (b) voltage at generation buses, (c) power imported/exported from/to the main grid, (d) load shedding values, (e) DG size and location, (f) investment costs and (g) technology assets (storage, dispatchable loads, capacitors etc.)

5.2. Metaheuristic methods for planning

5.2.1. Swarm intelligence

The mainstream of research efforts on smart grid planning deals with issues like optimal sizing, location, number and replacement of units, as well as their combinations. Similar problems are formulated as LP, or MINLP and addressed using conventional PSO, or its variants, in Refs. [134–136]; satisfactory results are reported regarding convergence speed, robustness and computational effort. A two-stage method is described in [137], which initially combines binary PSO together with an optimal power flow algorithm to find a feasible reconfiguration set. Then, the method dispatches reactive power by switching already-installed capacitors to minimize their losses. Traditional PSO and several modified approaches are introduced for network reconfiguration along DG installation [132,138,139], or plain reconfiguration [140,141]. According to [142], the hybrid crow search algorithm (CSA)-PSO is more efficient in dealing with the above issues.

Although PSO still remains the most popular among them, the list of SI algorithms employed for planning is constantly growing. Coyote optimization algorithm (COA) [143] and GWO [144] are applied in DER planning, presenting greater power losses reduction compared to other methods such as GA and PSO. Stud krill herd algorithm (SKH) [36], as well as the exchange market algorithm (EMA) [145], are addressing the problem of multiple DG allocation and sizing in radial distribution networks. Two bioinspired metaheuristics, FA and cuckoo search (CS)

Table 2
Summary of papers on optimal power flow.

#	Method	Objective	Discrete DVs	DVs (max)	Complexity (CPU/time, comments)	CPU time/iteration (s)	OF evaluations[a]	Systems tested on (system, buses)	Methods compared to	Population size
[35]	PSO	GC, VPI	N	25	Pentium I 166MHz/-	–	5000	IEEE 30	GA, Gradient projection	50
[59]	PSO	GC, VPI	N	25	Pentium IV 2GHz/16.72s	0.417	2000	IEEE 30	GA, Simplex	50
[60]	CA-PSO	RPL, VPI	N	75	Pentium V 1.4 GHz/20s, IEEE 118	0.25	1600	IEEE 30, IEEE 118	GA, PSO, IPM	20
[61]	TS-PSO	GC, TS	Y	25	Pentium V 1.8 GHz/576s, IEEE 30	28.8	600	IEEE 30, 39 bus	GA	30
[62]	EPSO	GC, TS	Y	60	10x Core2 3.2 GHz/140s, 39 bus	1.4	2000	IEEE 145, 39 bus	Multiple PSO	20
[64]	MF-APSO	RPL, VPI	N	8	i7 3.6 GHz/136s	2.26	480	24 Bus w/8 PV gen.	PSO	8
[63]	PSO	RPL	N	–	i7 3.4GHz/-	–	5000	IEEE 30, 183 bus	–	50
[58]	PSO–SSO	GC, EM, RPL, VPI	Y	75	−/−, IEEE 30	–	4500	IEEE 30, IEEE 57, IEEE 118	WOA, PSO, etc.	30
[65]	PPSOGSA	GC, RPL, VPI	Y	25	−/−, IEEE 30	–	5000	IEEE 30	PSO, GA, DE, etc.	50
[47]	ACO	GC, VPI	Y	6	Pentium IV 1.4 GHz/20s	–	–	IEEE 30	GA, evolutionary programming	20
[46]	ACO	GC, EM	N	6	Dual core (2014)/-	–	–	IEEE 30	NSGA, GA	100
[70]	BFA	RPL, VPI	Y	14	−/−	–	1000	39 bus	SQP-IPM	–
[76]	IGA	GC	Y	25	50MHz/5.25min	–	–	IEEE 30	Gradient-based method	50
[77]	GA	GC	Y	150	Athlon 1.8 MHz/106s, IEEE RTS96	0.424	20,000	IEEE 30, IEEE 118, IEEE RTS96	GA	80
[78]	EGA-DQLF	GC, RPL, VPI	Y	24	−/−	–	–	IEEE 30	PSO-fuzzy	200
[32]	DE	TS, GC	N	33	61x Xeon 2.66 GHz/195s, 162 bus	1.95	12,000	9, 39, 162 bus	–	120
[33]	MODE	GC, RPL, VPI, EM	Y	34	−/−	–	–	IEEE 30	KHA, ICA	50
[25]	ESDE	GC, RPL, VPI, EM	Y	34	i3 2.2 GHz/130s, IEEE 57	–	18,000	IEEE 30, IEEE 57, 59 bus	DE, Tent map, Sine map etc.	–
[80]	DE	VPI, RPL	Y	27	i5 2.7 GHz/148s, IEEE 30	1.783	5000	IEEE 30, IEEE 57	–	60
[79]	MODEA	VPI, GC, RPL	Y	27	−/−	–	10,000	IEEE 30, IEEE 57	PSO, DE	50
[81]	MOAIA	VPI	Y	12	Celeron 633MHz/-	–	1000	IEEE 30	Immune GA	100
[82]	CGbAIS	GC, VPI	Y	65	Core2 2.4 GHz/105s, 325 buses	–	–	IEEE 118, 325 bus	DE, evolutionary PSO	50
[54]	TS	GC, VPI	Y	16	/-	–	–	IEEE 30	Evolutionary programming	–
[83]	RTS	GC, EM	N	6	-/200s	–	–	IEEE 30	TS, Simplex	–
[73]	HMICA-SQP	GC, RPL, RESP	Y	130	-/28.74s, IEEE 30	–	–	IEEE 118, IEEE 30, IEEE 57	ICA, GA, EA	–
[41]	TSA	GC, RPL	Y	55	i7 2.4 GHz/309s, IEEE 300	0.618	6000	IEEE 57, IEEE 300	PSO, ABC, Moth swarm	12
[39]	CWOA	TS, GC	Y	21	Pentium IV 2.3 GHz/112s, 162 bus	2.8	2000	39 bus, 162 bus	WOA, DE	50
[71]	WOA	VPI, RPL	Y	39	i7 2.9GHz/-, 114 bus	–	900	IEEE 14, IEEE 30, 113 bus	PSO	30
[72]	NGBWCA	VPI, RPL	Y	75	Pentium IV/-, 118 bus	–	50,000	IEEE 30, IEEE 57, IEEE 118	GA, PSO, DE, etc.	50

[a] Values refer to the same tested system that is mentioned in the “Complexity” column.

algorithm, are combined in [146] for multi-objective planning, producing a technique that has proven useful in assessing the dynamic stability of the power system. Multi-objective allocation and sizing of DG is investigated by (a) a CS algorithm that demonstrates superior convergence speed [147], (b) an ALO with loss sensitivity factors capable of handling large-scale distribution systems [148] and (c) an HSA capable of generating a more converged Pareto front approximation than a non-dominated sorting genetic algorithm (NSGA-II) [149]. The minimization of both overloads and voltage deviations is combined in a multi-objective framework presented in [150], where ICA is employed for solving the flexible alternating current transmission systems (FACTS) allocation problem. Satisfactory results are obtained by NAA [151] and SEUMRE [152] when applied to energy storage system management (ESSM) and ESSM-DSM, respectively, considering distributed generation. The problem of optimal DG [153] along with ESS [154] placement and sizing is dealt with dominated groups search optimization (DGSO) and inherited competitive swarm optimization (ICSO), respectively.

5.2.2. Evolutionary computation

Evolutionary optimization approaches have been used to explore RPL minimization through optimal placement and sizing of DG [155]. RPL problem is addressed in a single [26] or multi-objective optimization framework [131], using different evolutionary algorithms, namely GOMEA and SPEA2, respectively. Fuzzy set theory is used to select the best compromise solution in case of multiple objectives.

A probabilistic formulation of shunt capacitor placement problem in distribution networks is followed in [156] and dealt with a GA. The

Table 3
Summary of papers on scheduling optimization.

#	Method	Objectives/ Tasks	Complexity (CPU/time, comments)	CPU time/ iteration (s)	OF evaluations[a]	Systems tested on	Methods compared to	Population size
[86]	PSO	ESSM	–/–	–	15,000	IEEE 24	–	300
[101]	Mut-PSO	DSM	-/68s	0.618	2200	937 bus	PSO, EPSO	20
[95]	PSO	ED, EM	Core 3.4 GHz/7862s, 100 units	7.862	200,000	10–100 units	NSGA, GA, BFA, EA, etc.	200
[97]	PSO	ED, DSM	–/–	–	–	33 bus MG	–	–
[98]	PSO	ED, EM	Pentium IV 1.66 GHz/-, 40 units	–	18,000	10–40 units	PSO, LR, ESA	30
[99]	PSO	ED	–/–	–	5000	11 units	–	50
[100]	PSO	ED	Pentium IV 2 GHz/158s, 40 units	0.527	9000	10–100 units	–	30
[104]	ALO	ED	-/1.69s	0.042	400	5 units	GA, ABC, BFA	10
[107]	SFLA	ED	Pentium IV 2 GHz/1430s, 100 units	28.6	10,000	10–100 units	LR, BFA, GA, PSO	200
[108]	MSFLA	ED	–/–	–	–	32 bus MG	GA, PSO, DE, ICA, SFLA	–
[109]	FFA	ED, CP	Pentium IV 3.2 GHz/945s, 100 units	1.89	50,000	IEEE 24, IEEE 118, 38, 100 units	EP, PSO, GA, etc.	100
[114]	MVPA	ED	i7 2.50 GHz/-	–	1000	3 MGs	GA, PSO, BH, ABC, EM	100
[75]	GSA	ED	Pentium 2 GHz/43.2s, 48 units	8.64	500	5, 7, 24, 48 units	PSO, EP, DE, RCGA, BCO, etc	100
[116]	EC	DSM	–/–	–	60,000	smart grid	–	200
[110]	GWO	ED, EM, CP	i3 2.2GHz/-, 10 units	–	5000	10–100 units, 38 units	BFA, GA, EP, FLA, SA, etc.	50
[112]	FS-MOPSO	UC	i7-4790 3.6GHz/2490.3s	3.11	48,000	26 units	MOPSO, TV-MOPSO	60
[37]	BRABC	UC	Pentium IV 3.2GHz/14.02s, 40 units	0.028	100,000	6, 10, 40 units, IEEE 30	PSO, EP, GA, etc.	200
[40]	ANFMDA	ED	Core i5/34.8s	0.87	8000	3 units	DA, ABC, WOA, HOMER	200
[115]	EP	ED	-/1 h 42 m, 100 units	1.224	250,000	10–100 units	LR, GA, EP	50
[88]	SDE	ED	Core i7 3.6 GHz/2.37s	0.024	331,100	6 units	PSO, PSOw, CBA, MFA	3311
[119]	CDE	ED	–/–	–	90,000	7 bus	DE, PSO	400
[87]	LFA	ED, EM	-/2.90s, IEEE 10	0.58	50	IEEE 10, 14, 30, 40, 160	EP, PSO, HS	10
[92]	PSO	ED	–/–	–	125,000	3 MGs	–	250
[120]	IQEA	ED	Core2 Duo 2.66 GHz/292s, 100 units	0.73	7200	10–100 units	LR, GA, EP, PSO, etc.	18
[121]	QEA	ED	Core 2.39 GHz/80s, 100 units	0.4	3600	10–100 units	GA, SA, PSO, LR etc.	18
[122]	HyDE-DF		Xeon E5-2620 v2/326.79s	0.817	2000	201 bus	DE, PSO, Vortex, HyDE	5
[123]	DE	ED	Core i5-2410 M 2.3GHz/ 11.82s, 100 units	0.118	3000	10–100 units	PSO, GA, ACO, ICA etc	30
[124]	NSGA-II	ED, EM	Core i5 3.4 GHz/4254s, 100 units	17.579	12,100	10, 100 units	NSGA, SA, ICA	50
[125]	GA	ED	Pentium IV 1.6GHz/242.5s, 100 units	0.808	15,000	10–100 units	LR, GA	50
[24]	MGA	ED	Core i7 2.6GHz/2.06s	0.016	13,000	IEEE 37	GA, PSOcf, PSOw	100
[28]	GA	ED	–/–	–	35,000	10 units	FLA, GA	50
[57]	GA	DSM	–/–	–	12,600	–	RDO, RS, SA	210
[127]	GA	ESSM	i7-3630QM 2.4 GHz/-	–	2400	–	–	200
[129]	IVNS	ED, DSM	–/–	–	70,000	33, 180 bus	CBBO, PSO, VNS	–
[56]	AIS	UC	Core i3 2.67 GHz/100s	5	1200	12 units	LR, Fuzzy, PSO	60
[94]	EVDEPSO	UC	Core i7 2.6GHz/53.56s	0.188	2850	25 bus	VNS, PSO, IDE, FFA	10
[106]	MICA	DSM	–/–	–	432,000	–	C-PLEX	100
[126]	GA	DSM	Core i7 1.7GHz/-	–	328,000	–	Analytical approaches	400
[102]	BFA	ED	-/6s	1.5	40	MG	GA, ABC	10

[a] Values refer to the same tested system that is mentioned in the “Complexity” column.

authors in Refs. [157,158] apply a biased random-key genetic algorithm (BRKGA) and NSGA-II, in a multi-stage, or a multi-objective manner, in order to address the network reconfiguration problem (NRP). The maximization of priority loads restoration during blackout with multiple line faults is addressed through a self-healing scheme [159], where reconfiguration is carried out using a GA. In [130] NRP, along with selection of optimal number and size of DGs is considered. The parallelization of GAs has attracted attention lately; a multi-processor GA with fuzzy-adaptive rules for efficient processor data handling [30] and a GPU-based version utilizing minimum spanning trees to sort candidate topologies [29], are applied to the DG allocation problem and achieve significant speedup. The authors of [160] propose GA for optimal DG placement and sizing, while in Ref. [161] NRP is also taken into consideration. The crucial task of contingency planning (CP) in distribution networks was studied using GAs [162], while maintaining load balance (LB). A multi-objective GA is employed for RPL along with VPI in distribution networks, using TOPSIS to pinpoint the compromise solution [163]. Lastly, the joint problem of DG and storage allocation is

Table 4
Summary of papers on planning optimization.

#	Method	Objectives/ Tasks	Complexity (CPU/time, comments)	CPU time/iteration (s)	OF evaluations[a]	Systems tested on	Methods compared to	Population size
[151]	NAA	DSM	–/–	–	120,000	IEEE 15	-	48
[137]	BPSO	LB	–/–	–	1000	16 buses	-	50
[132]	PSO	RPL, VPI	-/16.2s	0.184	4400	IEEE 33	GA	50
[135]	PSO	DSM, LB	–/–	–	8	–	BA, SMO	50
[140]	MPSO	RPL	i7 2.4GHz/-	–	250	IEEE 33, IEEE 69	PSO	50
[36]	KHA	RPL	i3 3.3GHz/-	–	960	IEEE 33, IEEE 69	GA PSO, etc.	10
[146]	FA/CS	RPL, VPI	i5/11s, IEEE 30	1.1	500	IEEE 14, IEEE 30	ABC, GSA, etc.	50
[147]	CS	RPL	–/–	–	1200	IEEE 69	GA, PSO	20
[148]	ALO	RPL	–/–	–	15,000	69 buses	GA, CSA, etc.	30
[153]	DGSO	RPL, VPI	-/44s, 69 buses	74.8	30	IEEE 30, 69 buses	GA, PSO, etc.	51
[154]	ICSO	RPL, VPI	i3 3.19 GHz/-	–	2	IEEE 37	–	30
[165]	GA	DSM, GC	–/–	–	20	Smart grid	–	100
[159]	GA	RPL, LB, VPI	-/14s	7	100	33 buses	–	50
[26]	GOMEA	RPL	–/–	–	100,000	31 buses	GA	1024
[158]	NSGA-II	RPL, VPI, RESP	–/–	–	144	16 nodes	GA	16
[168]	LAHC	CP	–/–	–	5000	570 feeders	ILS HC	–
[50]	AIS	RPL, VPI, LB	2.8GHz/32.3s, IEEE 69	0.646	2500	IEEE 33, 69	GA	50
[152]	SEUMRE	DSM	-/315.64s	14.819	426	IEEE 33	PSO, GA	20
[49]	AIS	RPL	i7 3.1GHz/0.365s, IEEE 33	0.183	100	IEEE 33, 84, 136	ACO, AIS	50
[166]	AIS	RPL	Q8200 2.33GHz/16.9s	1.69	80	IEEE 33	Heuristics	8
[167]	AIS	RPL	C-60/-	–	96	IEEE 33, 69	Heuristics	8
[143]	COA	RPL, VPI	-/3047s, IEEE 123	6.094	12,500	IEEE 123, 137 buses	PSO, GA etc.	25
[150]	ICA	LB, VPI	–/–	–	40,000	IEEE 14, 39	ABC, EP, etc.	800

[a] values refer to the same tested system that is mentioned in the "Complexity" column.

considered through the prism of DSM of industrial [164] or residential [165] loads and is solved by a GA.

5.2.3. *Artificial immune systems*

Power loss reduction has been addressed with the use of AIS [50], through optimal location and sizing of distribution static compensators (DSTATCOM). In Refs. [49,166], AIS algorithms are applied to the problem of radial distribution systems reconfiguration with respect to operational constraints. The same problem is solved in [167], while also taking into account generation and load uncertainties.

5.2.4. *Non-population based metaheuristics*

A number of stochastic local search metaheuristics for integrated reconfiguration, reinforcement and extension plans of large-scale networks, is evaluated in [168].

6. Discussion and conclusions

To form a basis for discussion, in Tables 2–4 we present a quick overview of the reviewed papers on OPF, scheduling and planning, respectively, including only the papers that can be compared in terms of quantitative results and/or computational complexity. The tables contain information such as the adopted method, the objective, hyper-parameter settings, indicators of computational complexity and the methods used for comparison. Furthermore, Tables 5–7 present results for the fuel cost, emissions, power losses and voltage control objectives, wherever these are reported on common benchmarks such as IEEE-30 [35] or 10–100 generator [115] grids. To be more specific, Table 5 is concerned with OPF results, while Tables 6 and 7 show unit commitment and grid reconfiguration results, which pertain to scheduling and planning optimization, respectively. It should be pointed out that some works report results from a single run, while in other works, multiple simulation runs are performed. To establish a fair basis of comparison, Tables 5–7 depict the best result reported in each work, as far as the objective function is concerned. Finally, function evaluations are shown in Tables 5 and 6, which, as will be discussed later, can be used to assess the methods' computational complexity.

It is obvious that the main metaheuristic method categories have been applied invariably to all the major optimization tasks pertaining to the smart grid. Nevertheless, it is impossible to single out one method, or even one class of methods, that performs better across all tasks, a remark well in accordance with the "no free lunch" theorem [113]. Keeping this in mind, this section provides a discussion on cross-comparisons between metaheuristic approaches and points of superiority versus conventional mathematical optimization methods, within the following lines: (a) Problem handling (i.e. how the methods cope with discrete variables, uncertainty, constraints, etc.), (b) computational complexity with regard to accuracy and (c) multi-objective optimization performance. A unified approach is being followed to draw conclusions about the three different power grid optimization problems, discussing common elements that connect them and facilitating the identification of directions for future research in the section to follow.

6.1. *Problem handling*

The aforementioned power grid problems are naturally, in their exact formulation, non-convex, non-differentiable and sometimes non-continuous. Some of these shortcomings can be compensated by applying assumptions on the differentiability of OFs [56] and the continuity of discrete design variables [57,169]. The non-convexity property is usually alleviated by employing convex relaxation techniques such as semi-definite programming [152]. While these assumptions can assist any class of search methods, in practice traditional optimization methods require them in order to converge to an acceptable solution in reasonable time [12]. Unfortunately, this may lead to subpar results, since rounding discrete variables leads to large errors [169], while relaxation techniques may fail to produce a globally optimal solution. Furthermore, they have trouble incorporating discrete variables, due to incompatibility with the resulting high-order semi-definite programming constraints [170].

Since most metaheuristic methods are non-gradient-based, they can readily handle the non-differentiability of generator cost curves which contain sine components [54,88], or are piecewise quadratic [77,151]. Moreover, there exist metaheuristic methods, such as GAs, that inherently encode discrete variables in chromosomes [78,156], while population-based methods like PSO and ACO are traditionally oriented towards continuous variables. A number of authors choose to employ both classes of methods for the solution of the unit commitment task,

Table 5
Results on IEEE-30 for single-objective and multi-objective OPF.

Single-objective OPF						
#	Method	Fuel cost ($/h)	Emissions (ton/h)	Voltage metric	Losses (MW)	Function Evaluations
[83]	RTS	605.39[d]	0.1941	–	–	–
[25]	ESDE	799.03	0.2047	0.1241[f]	2.84	10,000
[35]	PSO	800.41 647.69[d]	–	0.1246[f]	–	5000
[58]	PSO–SSO	798.98	0.205	0.124[f]	2.86	4500
[77]	GA	617.11[d] 801.05	–	–	–	30,000
[59]	PSO	–	–	–	4.38	2000
[65]	PPSOGSA	800.52	–	0.0898[h]	3.10	5000
[80]	DE	–	–	0.0888[a,h]	4.41[a]	12,000
[79]	MODEA	799.08	–	0.0939[h]	2.853	10,000
[71]	WOA	–	–	–	4.59	900
[76]	IGA	800.80	–	–	–	–
[60]	CA-PSO	–	–	0.1225[h]	5.09	600
[33]	MODE	607.19[d]	0.1942	–	–	–
[61]	TS-PSO	585.17[d,e]	–	–	–	600
[54]	TS	802.29[b]	–	–	–	–
[73]	HMICA-SQP	863.72[c]	–	–	–	400
[78]	EGA-DQLF	799.56	–	0.1040[f,a]	3.20	–
[47]	ACO	803.12	–	–	–	–
[72]	NGBWCA	–	–	0.0458[h]	4.48	–

Multi-objective OPF					
#	Method	Fuel cost ($/h)	Emissions (ton/h)	Voltage metric	Losses (MW)
[83]	RTS	623.11[d]	0.1970	–	–
[25]	ESDE	799.60[a] 827.15[b]	–	0.1246[f,a]	5.22[b]
[35]	PSO	806.38	–	0.0891[h]	–
[65]	PPSOGSA	829.59	–	0.1103[h]	6.11
[33]	MODE	615.50[d]	0.2012	–	–
[79]	MODEA	820.88[b] 799.69[a]	–	0.1249[f,b]	5.59[a]
[78]	EGA-DQLF	822.87[a] 802.06[b]	–	0.1056 [g,b]	5.61[a]
[58]	PSO–SSO	834.80[a] 830.35[b] 865.18[c]	0.243[a] 0.224[c]	0.1246[f,b]	4.09[c]

[a] Incorporates stochastic RES generation.
[b] Solutions violate the slack bus lower q-limit.
[c] Includes valve point loading effects.
[d] Piecewise generator cost curve.
[e] Transient stability constraints.
[f] Voltage stability index (L-index).
[g] Sum of squared voltage stability indices.
[h] Total voltage deviation.

Table 6
Results for single-objective day-ahead unit commitment.

#	Method	Fuel cost ($)						Function Evaluations
		10	20	40	60	80	100	
[52]	SA	565,828	1,126,521	2,250,063	–	4,498,076	5,617,876	–
[115]	EC	564,551	1,125,494	2,249,093	3,371,611	4,498,479	5,623,885	25,000/50,000/100,000/150,000/200,000/250,000
[120]	EC	563,938 563,938	1,123,297 1,123,297	2,243,039 2,242,982	3,363,059 3,362,507	4,485,875 4,484,088	5,605,795 5,603,355	1440/7200/7200/7200/7200/1440
[100]	PSO	563,977	1,123,297	2,242,957	3,361,980	4,482,085	5,602,486	9000 (40-unit)
[107]	SFLA	564,769	1,123,261	2,246,005	3,368,257	4,503,928	5,624,526	2000 (10-unit)
[125]	GA	566,404	1,127,244	2,254,123	3,378,108	4,498,943	5,630,838	12,300 (20-unit)
[28]	GA	562,979	–	–	–	–	–	20,000 (40-unit)
[121]	EA	563,938	1,123,607	2,245,557	3,366,676	4,488,470	5,609,550	3600 (all systems)
[95]	PSO	563,938	1,123,297	2,242,953	3,361,738	4,482,417	5,601,457	400,000 (100-unit)
[124]	GA	563,938	–	–	–	–	5,605,918	10,000 (all systems)
[110]	GWO	563,936	1,123,892	2,239,051	3,355,735	4,471,858	5,591,197	–
[109]	FFA	–	–	–	–	–	5,601,298	60,000 (100-unit)
[98]	PSO	565,149		2,255,384	–	–	–	–

Table 7
Results of grid reconfiguration optimization.

#	Method	IEEE-33		IEEE-69	
		Loss Reduction (kW)	Minimum voltage (p.u.)	Loss Reduction (kW)	Minimum voltage (p.u.)
[140][a]	MPSO	56.70	0.940	100.30	0.942
[138][a]	MCPSO	63.75	0.942	123.62	0.949
[132][a]	PSO	76.30	0.893	–	–
	GA	67.40	0.893		
[141][a]	SPSO	69.53	0.942	126.38	0.949
	BPSO	66.81	0.936	125.84	0.923
[155][b]	DE	116.77[c] 174.19[d]	–	152.41[c] 203.72[d]	–
[36][b]	KHA	123.82[d]	0.968	150.12[d]	0.979
[145][b]	EMA	116.74[d]	0.963	150.10[d]	0.979
[130][b]	GA	148.49[c]	0.972	–	–
[163][b]	GA	123.81[d]	0.968[d]	151.12[d]	0.972
[166][a]	AIS	139.55	0.93	–	–
[167][a]	AIS	127.2	0.95	77.32	0.9522
[160][a]	GA	63.13	0.938	125.36	0.943

[a] reconfiguration.
[b] reconfiguration & 2 DGs placement and sizing.
[c] DG type I: Active generation model.
[d] DG type II: Active and reactive generation model.

dedicating the discrete-coded method to handling the binary generator status variables and the real-coded method to handling the continuous generator output variables [98,109].

Unfortunately, the OPF problem often cannot be decomposed in this manner. This necessitates the application of a continuous algorithm, employing rounding operations to enforce discreteness wherever needed. A number of authors claim that this practice does not sacrifice solution quality in the case of transformer tap variables [62], since the discrete interval is so small that it can be ignored. However, VPI performance seems to suffer when treating reactive shunt compensator variables as continuous valued [169]. Considering the relevant results of PSO-based methods of [35,60], versus their DE-based counterparts of [25,80], it is apparent that the latter achieve significantly better VPI performance, as shown in Table 5. This is further reflected on the results of RPL minimization, which is also dependent on effective reactive power control. Indeed, GA [78] as well as DE-based [25] methods seem to achieve superior performance through direct handling of integer values of reactive control devices, when compared to their swarm-based counterparts.

Smart grid optimization problems often involve variables exhibiting a considerable amount of uncertainty, e.g. the output power of RES, or the load demand [171]. A probabilistic approach is a common way to deal with uncertainty, aiming to estimate the statistical parameters of the relevant variables [86,130]. Stochastic scenario-based optimization methods can then be formulated, where the objective function is optimized for a set of possible scenarios [93,134,152,156]. Fuzzy set theory can also be applied to represent uncertainties, especially when there is insufficient information for the probabilistic parameters of the uncertain variables [112]. Even though such techniques result to more complex objective functions, metaheuristic search methods are well equipped to handle them efficiently.

Finally, it must be noted that the vast majority of optimization methodologies can inherently handle only unconstrained problems. It is a fact that the OPF, scheduling and planning problems include hard constraints based on the system's operational characteristics, such as voltage and current constraints [35,50], ramp-up/down limits and min/max operating times [91] and power constraints of DG units [30]. To overcome this problem, several techniques have been devised, such as the penalty functions method (PFM), the feasible solutions method (FSM), specialized operators, repair algorithms, etc [88,172].

6.2. Computational complexity & accuracy

When discussing the performance of an optimization algorithm, the balance between computational complexity and accuracy for the task at hand must be properly assessed. In the power grid case, it used to be that the OPF problem was primarily concerned with achieving such a balance, due to its short time horizon. However, with the increased penetration of RES, the scheduling problem horizon is also shifting from the typical day-ahead formulation to an hours-ahead one – therefore, its computational complexity must be considered too. Lastly, the planning problem usually employs a longer optimization horizon and therefore its execution time may be of less practical importance. Accuracy of the results, on the other hand, determined by the search method's ability to efficiently explore the search domain and to converge to satisfactory solutions, remains important for all three power grid problems. In this context, metaheuristic methods have a significant advantage over standard mathematical optimization approaches as they are better equipped to handle the non-convexity present in most power grid problem formulations. Gradient-based techniques on other hand, usually get easily trapped in local minima, thus compromising accuracy [10]. This point is especially exacerbated in the case of the CHP economic dispatch problem, where accurate modelling calls for the incorporation of valve-point loading effects [88]. This is accomplished through the addition of a sinusoidal term to the cost function of the CHP units, which generates a high number of local minima [75]. Lastly, population-based metaheuristics, though being more computationally intensive, are suitable for parallelization [13], thus fully exploiting the advantages of multi-core processors, or computing clusters [32].

A common criticism against metaheuristic methods involves the lack of rigorous mathematical analysis and more specifically, convergence analysis. While this remains true for the majority of the methods, there exist theoretical studies proving convergence for significant metaheuristics like PSO [173] and more research is underway [174]. Furthermore, the plethora of successful applications even on NP-hard problems, as well as the large number of reported results on well-known power grid benchmark studies (Tables 2–4), provide some evidence on the superiority of metaheuristic search methods over traditional mathematical optimization approaches from a practical point of view.

As far as cross-comparison between metaheuristic methods is concerned, it must be stressed that an attempt to objectively rank different metaheuristic methods in terms of effectiveness on the smart grid optimization problems is a rather difficult task. Firstly, method accuracy is dependent on problem formulation, a multitude of which exist. Secondly, the computational burden cannot be directly inferred by the method runtime; even though this is the most reported metric in the literature, it can vary in practice even when the method is run multiple times on the same CPU. Regarding accuracy, objective conclusions can only be drawn when cross-comparing results on the same testbeds and cases. Similarly, a more objective metric regarding computational complexity can be set as the total number of function evaluations:

$$N_{eval} = n_{iter} \times n_{pop} \tag{1}$$

where n_{iter} is the number of algorithm iterations until convergence and n_{pop} is the population, or swarm size. This metric has been computed for all the works where relevant information was available and results are reported in Tables 5 and 6 Therefore, the results of each method can be compared on this basis and conclusions can be drawn regarding suitability towards a specific application.

As shown in Table 5, evolutionary computation methods (DE/GA) seem to establish improved solutions for all single-objective OPF formulations on an average basis, but their main downside is the high number of function evaluations required for convergence. Indeed, EC methods that surpass swarm-based ones on the respective objectives, do so at a burdensome computational price. For example, when comparing

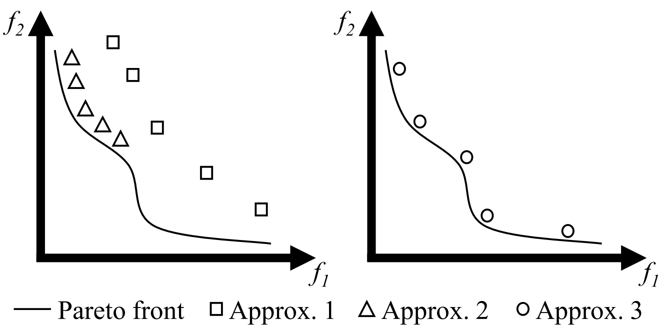

Fig. 2. Examples of approximations of the Pareto front of a two-objective function.

PSO-based [35] and GA-based [77] methods, a 4.6% decrease in the fuel cost objective came at a 500% increase in function evaluations. Ultimately, the practitioner must decide if additional accuracy is warranted, since it may compromise the feasibility of a real-time OPF implementation. These observations are confirmed for larger OPF problems too: Test systems such as the IEEE-57 and IEEE-118 translate to significantly higher function evaluations for EP methods [77,80], compared to swarm-based methods. The latter appear generally more insensitive to problem dimensionality [60,73].

The above observations do not seem to apply for the single-objective scheduling and planning problems. Swarm-based techniques achieve, on average, superior accuracy throughout the different scheduling test systems [110], as shown in Table 6. Also, we can confirm the presence of EC algorithms that require less OF evaluations than PSO both on medium (40 units) and large scale (100 units) systems. Regarding the planning problem, we can only comment on the quantitative results, as OF evaluations are not available. As shown on Table 7, PSO variants achieve larger losses reduction compared to GA, when reconfiguration is examined. Nevertheless, when DG sizing and placement are examined, EC methods do exhibit superior performance compared to swarm-based ones [155]. However, the number of instances is so small that it prohibits universal conclusions.

A general observation to be noted is that the population parameter of most swarm-based techniques (notwithstanding a few special exceptions [110,120]) lies in the relatively small range of {20, 50}, regardless of test system size, problem type, or problem dimensionality. Generally, this is not a novel observation for SI-based methods. Sensitivity analyses for various non-power grid related engineering problems have arrived at the same conclusion [175], noting that too small a population would fail to explore all of the search domain, while too large would require more computational resources, without effectively aiding towards a higher solution exploitation. Moreover, although swarm-based methods seem to dominate applications for the power grid problems, they demonstrate some variability between the converged solutions [66,67]. DE-based methods seem to perform better in this respect, as illustrated in [79], where the proposed method repeatedly converges on the same compromise solution.

Another feature adding to the complexity of metaheuristic methods is the large number of hyperparameters. While a suboptimal hyperparameter tuning will seldom incur failure of convergence, one must specifically tune their metaheuristic method in order to achieve the best results possible for the problem at hand. Research has progressed in order to overcome this disadvantage as metaheuristic algorithms such as GWA [110] and TLBO [176,177] aim to use fewer number of parameters. Another interesting approach involves using meta-optimization algorithms based on EC for tuning hyperparameters [178].

6.3. Multi-objective optimization performance

Optimization tasks encountered within planning, scheduling and OPF can be formulated as MOO problems, since they comprise multiple and often conflicting, objectives [78]. An effective MOO method must approximate the Pareto front as closely as possible. Conventional mathematical optimization algorithms may fail in that regard, even though they are simple to implement. Firstly, they produce a single solution per iteration; therefore, they need to employ approaches like the weighted sum [37], or the ε-constraint [79] techniques, which require multiple runs in order to generate a Pareto front approximation. In the case of weighted sum, the approximation may fail to be well-converged or well-diversified when the underlying front is non-convex or non-continuous. The importance of these two characteristics is visually depicted in Fig. 2, where an underlying Pareto front and its approximations are shown. Approximation 1 is well-diversified but not well-converged, approximation 2 is well-converged but not well-diversified and approximation 3 is both well-converged and well-diversified. Another possible shortcoming of conventional mathematical optimization algorithms is that the approximation they provide may be unacceptable, even when the underlying Pareto front is convex. An example is shown in [33], where a sequential quadratic programming algorithm is coupled with the weighted sum method.

Metaheuristic MOO methods can deal with challenging Pareto fronts and, especially population-based metaheuristics can potentially generate an approximation of the Pareto front with a single evaluation [11,158]. The quality of the Pareto front approximation can be assessed on the basis of solution set diversity and distance from the ideal solution. A number of metrics exist which measure the diversity, such as hypervolume or inter-generational distance [158]. In the OPF literature, a few authors evaluate the proposed MOO methods on this basis; most choose to cross-compare the reported results using only a compromise solution, as discussed in the next paragraph. In contrast, the usage of the aforementioned metrics in the scheduling and planning literature is widespread, while compromise solutions are rarely reported.

Regardless of the means used for evaluating the results of a MOO method, once the non-dominated solution set is obtained, a final compromise solution must be implemented. This is a selection made by the decision maker (DM), who can be either a physical entity (such as the grid operator), or an automated process; the latter is preferred in the case of the OPF problem, due to its short time horizon. The most straightforward approach and the most common one in the reviewed OPF literature, is to select the knee-point solution of the set (that is, the solution with the minimum Euclidean distance from the ideal solution) [64]. More sophisticated approaches (prevalent in all three power grid problems) use fuzzy DM techniques [25,78,134,179]. Heuristic DM techniques include the ranking of solutions based on a secondary "objective" that is not present in the MOO problem; for example the minimization of RPL [64], or the TOPSIS method [46,163].

In summary, the literature review provides evidence that there is a growing interest towards robust MOO algorithms in the face of different system states [58], generation scenarios [80], or generation cost fluctuations [46]. Other studies [25,73,121] perform sensitivity analysis on the hyper-parameters of the proposed MOO methods, confirming their robustness to a suboptimal tuning.

7. Recommendations and suggestions for future research

As far as the practices of metaheuristic search application for smart grid optimization are concerned, the following recommendations are derived:

- There is a need for a consistent benchmarking framework regarding the application of optimization tasks in smart grid, so that different metaheuristic approaches can be compared objectively. As far as the planning tasks are concerned, with the exception of network reconfiguration, there are no common benchmark problems to test the proposed optimization approaches. But even for OPF and scheduling, where benchmarks such as the IEEE-30 and 10–100 generator test

grids exist, a direct comparison between different methods is not an easy task, as it has become apparent from the previous discussion. The reason is that each study usually applies different optimization objectives and reports different metrics. Thus, a compact set of key performance indicators should be established for each optimization task, in order to assess the methods' accuracy and complexity. With respect to the latter, we propose that the number of function evaluations until convergence should be reported along with the usual CPU run time, so that computational complexity can be objectively inferred. Regarding MOO, the use of standard metrics such as hypervolume and inter-generational distance [124] is encouraged for evaluating the resulting Pareto front approximations in OPF problems.
- The need of hyperparameter tuning for optimal performance has been also identified as an important drawback of existing - and quite probably of upcoming - metaheuristic optimization methods. A variety of different optimization tasks occurs within the smart grid and the use of meta-optimization algorithms could help practitioners to adjust the hyperparameters of metaheuristics to the task at hand. Nevertheless, researchers in the field of metaheuristics are encouraged to report hyperparameter sensitivity analyses for their proposed methods.
- Research on load and renewable generation prediction using machine learning models, including neural networks and other similar approaches that can cope with the complexity and nonlinearity of the problem, has boomed in the last decades [180,181]. The vast majority of the reviewed literature though, does not incorporate such models within the formulation of the optimization problem; most of the papers treat future load and renewable generation as known, or at best use estimations for their statistical parameters. Machine learning models could provide far more accurate estimations for these quantities, albeit at the cost of increasing the computational complexity, due to the nonlinearity of such approaches. Metaheuristic search methods though, are very well equipped to handle efficiently the computational burden imposed by employing data driven learning-based models and a few implementations in the ED [91,102,104] and UC problems [124] have only appeared recently. Intensifying research on this subject and expanding the application to different smart grid optimization tasks is a fruitful research direction.

Regarding the development of metaheuristic search techniques, the authors believe that research should be more focused on improving the search mechanisms with regard to the challenges of the smart grid optimization tasks. To this end, the following directions are suggested:

- Most metaheuristic search methods are inherently capable of parallelization, which can lead to significant performance gains [32]. Intensification of research on more efficient ways of parallelization [30], including distributed and cellular algorithms for population-based metaheuristics and multi-start algorithms for non-population based ones [182], could further boost the performance, allowing applicability to real-time OPF.
- Cooperative algorithms have been developed that partition the solution candidate pool into clusters that each seek to optimize different parts of the solution vector through cooperation [183]. Though such schemes have already proven to be very effective for high-dimensional problems, the development of similar methods for modern smart grid optimization, which employs a much higher number of design variables than before, is up to now very scarce [138].
- Hybrid metaheuristic algorithms form an emerging trend in smart grid optimization. The combination of diverse metaheuristics can lead to new exciting approaches since hybridization can be used to combine the advantages of different metaheuristics in exploring and exploiting the search space. Taking [58, 73, 142] as starting points, more hybrid approaches should be investigated.

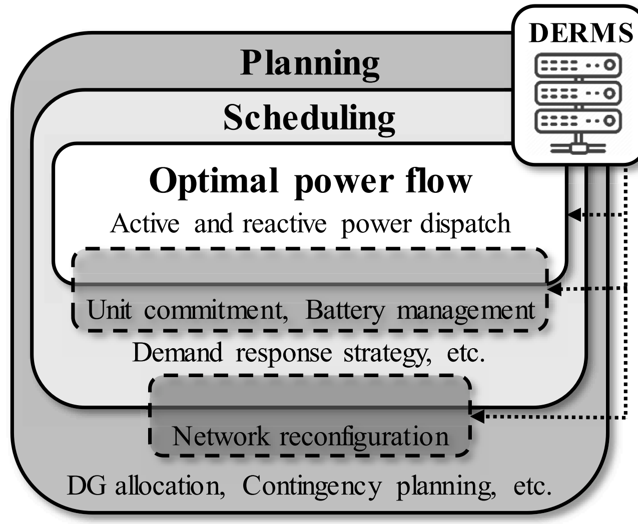

Fig. 3. The future paradigm in smart grid optimization: The emerging DERMS technology enables some tasks to transcend their usual time horizon boundaries and be incorporated in a common time frame.

Finally, new smart grid challenges are emerging that could be addressed using metaheuristic methods:

- RES inverter-based reactive power control has recently been made possible by the actualization of DERMS. While this has attracted significant research attention for real-time grid voltage control [184], very few works were implemented in OPF [65]. Its inclusion entails challenges on an optimization level, since the bound constraints of the problem are transformed to nonlinear inequalities (an inverters' reactive power capacity is bounded by the injected active power generation, which is a design variable).
- The development of decentralized units based on renewables has given rise to energy markets. The clearing of the all-European electricity market is already an active field [185] and the EUPHEMIA algorithm [186] deals with the unification of power exchanges through the solution of a rather complicated multi-zonal market coupling and the harmonized allocation of potentially large numbers of energy orders. However, the procurement of ancillary services still presents serious difficulties [187]. Thus, it is essential for smart grid scheduling optimization to integrate market price schemes [188]. The non-convexity, nonlinearity and use of mixed-type variables [185] make the use of metaheuristics a promising approach in this direction, but only limited research has taken place during the last three years, featuring implementations to the ED [91] and DSM [106, 126] tasks. Furthermore, the integration of energy market clearing intensifies even more the need for predictive models to obtain day-ahead energy price forecasts [127].
- Recent developments on DERMS, together with the increasing practical application of microgrids [2], have transcended the standard horizon boundaries of the classic planning, scheduling and optimal power flow problems, allowing for some of their respective optimization tasks to converge, such as in Refs. [164,189]. A new paradigm emerges, as shown in Fig. 3. DERMS, together with the new communication infrastructure, has enabled the automatic evaluation of several smart grid tasks, such as active & reactive power dispatch (OPF), unit commitment (scheduling) and network reconfiguration (planning), allowing them to be carried out concurrently. This new paradigm accommodates for the efficient incorporation of RES generation and microgrid operation. It is the authors' intuition that the

future of smart grid optimization involves tightly coupled tasks under a holistic optimization framework, entailing a number of serious challenges that can be addressed successfully by metaheuristic optimization methods.

Declaration of competing 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.

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