Metaheuristics for Transmission Network Expansion Planning

Chapter 2. Metaheuristics for Transmission Network Expansion Planning

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Abstract – This chapter presents the characteristics of the metaheuristic algorithms used to solve the Transmission Network Expansion Planning (TNEP) problem. The algorithms used to handle single or multiple objectives are discussed on the basis of selected literature contributions. Besides the main objective given by the costs of the transmission system infrastructure, various other objectives are taken into account, representing generation, demand, reliability and environmental aspects. In the single-objective case, many metaheuristics have been proposed, in general without making strong comparisons with other solution methods, and without providing superior results with respect to classical mathematical programming. In the multi-objective case, there is a better convenience of using metaheuristics able to handle conflicting objectives, in particular with a Pareto front-based approach. In all cases, improvements are still expected in the definition of benchmark functions, benchmark networks and robust comparison criteria.

2.1. Introduction

The typical partitioning of the solution methods for the Transmission Network Expansion Planning (TNEP) problem considers classical mathematical programming, application of heuristic rules, and metaheuristic models (Kishore & Singal 2014; Lumbreras & Ramos 2016). Metaheuristic algorithms are a viable option for the solution of optimisation problems, and are of interest because of their capability to solve non-convex, non-linear, integer-mixed optimisation problems, such as the TNEP problem. In particular, these methods are useful to address discrete optimisation, in which the integer part of the problem cannot be eliminated, as it happens in the TNEP in which the transmission lines to add cannot be fractioned (Gallego et al. 1997), and for a large system this leads to combinatorial explosion

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of the number of variables. With respect to the heuristic rules, which are simple and enable the inclusion of detailed modelling, but generally are driven by sensitivity and experience and are not mathematically rigorous (Qu et al. 2010), the metaheuristic algorithms are guided by solution strategies that should guarantee their convergence to the global optimum of the problem. However, it has to be pointed out that a formal proof of convergence to the global optimum is available only for some metaheuristics. Moreover, the available proofs generally indicate asymptotic convergence (i.e., after an infinite number of iterations). This is mathematically relevant, however, in engineering terms, metaheuristics do not guarantee the convergence to the global optimum, and provide no indications on how far the solutions are from the global optimum.

This chapter addresses the application of metaheuristics to the TNEP problem, on the basis of selected literature contributions (mostly journal articles). Advantages of using metaheuristics are the simplicity of implementation and the availability of a set of good solutions – not only a single solution (Hinojosa et al. 2013). The latter aspect may be of interest in today's systems, with growing uncertainties and higher complexity introduced by distributed energy resources, energy markets and policies (Gacitua et al. 2018). Furthermore, the metaheuristics use only the results of power system solvers, with no need of converting the power system model in the optimisation solver (Hemmati et al. 2013). On the other hand, the metaheuristic solver has to be customised to include the problem constraints.

In the last years, there has been a proliferation of metaheuristic algorithms applied to many engineering problems. In many cases these algorithms have been applied without clearly demonstrating their superiority with respect to other solvers, because of the use of simple and weak metrics to compare the solutions, such as the best solution found, the mean solution, and so forth. In this way, part of the research on metaheuristics has been switched to the mere testing of new algorithms, shifting the attention on the real innovations and progresses occurring in the metaheuristics field (Sörensen 2015).

According to the survey results indicated in Chicco & Mazza (2019), power system planning topics, and the TNEP problem in particular, have been less involved by the massive testing of metaheuristic solvers and variants than other typical problems in the power system area (such as economic dispatch or optimal power flow). However, the number and variety of algorithms implemented to solve the *single-objective* TNEP is still quite high, and weak comparison criteria have been adopted in many cases. Conversely, for the *multi-objective* TNEP the number of metaheuristics applied has been much more limited. This fact is interesting, considering that many efficient non-metaheuristic methods can solve the single-objective TNEP, while for the multi-objective TNEP the metaheuristics have proven to be appropriate and fully competitive in many applications.

In the next sections of this chapter, the basic concepts concerning the decision variables and metaheuristic principles are first recalled. Then, the single-objective and multi-objective TNEP are addressed separately, highlighting specific aspects of the solvers used. Finally, the last section contains the conclusions.

2.2. Decision variables and metaheuristic principles

2.2.1. Decision variables

The decision variables that appear in all the contributions addressed are the circuits added between two nodes in each corridor (also indicated as right-of-way). In addition, other decision variables can be considered in single-objective or multi-objective TNEP problems, also depending on the inclusion of generation sources or demand-based strategies in the problem formulation.

In the single-objective TNEP, two main aspects are considered, i.e., the cost of the system and reliability-related aspects. In the first case, the decision variables may be:

1. The outputs of the generators in the different time periods (Sadegheih & Drake 2008; Georgilakis 2010; Hinojosa et al. 2013; Kamyab et al. 2014, 2016; Sun et al. 2017).
2. The proposed installed capacity and the predefined capacity (Gupta et al. 2014).
3. The proposed installed capacities for different generation companies, whose profit is maximised into a low level problem (Hemmati et al. 2016).
4. The installed capacities of the new generation together with the cost of the fuel infrastructure (Verma et al. 2019).

The reliability of the system is taken into account as:

a) Loss of load/load shedding under normal condition (Da Silva et al. 2000, Gallego et al. 1997, Gallego et al. 2017, Gil & Leite da Silva 2001, Hinojosa et al. 2013, Leite da Silva et al. 2010, Miranda de Mendonça et al. 2016, Rastgou & Moshtag 2014, Rastgou & Moshtag 2016, Torres & Castro 2015). The loss of load under normal condition is null for feasible solutions, so it is a constraint integrated into a penalised objective function.
b) Interruption costs seen from the point of view of generators, customers and transmission owner (Gupta et al. 2014).
c) Load management imposed by the central dispatching centre (Verma et al. 2019).

Other aspects addressed are the costs associated to CO_2 emissions (Sun et al. 2017) and the increase of the wind generation share (Rathore & Roy 2014, 2016; Hemmati et al. 2016; Moradi et al. 2016).

In the extended multi-objective approach presented in Jadidoleslam et al. (2017), which combines TNEP with the planning of wind capacity, the added capacity of wind plants is taken as a further decision variable, and new circuits between existing nodes not previously connected are also allowed. In the multi-objective approach presented in Hu et al. (2016), the set of decision variables includes also the candidate gas pipelines and gas compressors.

2.2.2. Metaheuristic principles applied to the TNEP problem

The term *heuristic* is generally used to identify a tool that helps the user discovering something. In particular, heuristic methods are useful if they are able to provide solutions when the solution space is unknown, or too large, or highly irregular. The term metaheuristic is also typically used, by adding the prefix *meta* that represents the presence of a higher-level strategy that drives the search. Many metaheuristics are based on translating the representation of natural phenomena or physical processes into computational tools.

In general, the metaheuristics can be partitioned into *single solution update* methods (in which a succession of solutions is calculated, each time updating the solution only if the new one satisfies a predefined *criterion*) and *population-based* methods (in which many entities are simultaneously sent in parallel to solve the same problem). The metaheuristics may be characterised by considering a set of underlying principles (i.e., acceptance, decay, elitism, immunity, parallelism, selection, self-adaptation, and topology) that form a common basis for the various methods, or embed the structural differences among the methods (Chicco & Mazza 2011). In many cases different metaheuristics have been constructed without verifying whether they have new features or underlying principles to propose (Sörensen 2015). In other cases, metaheuristics are simply tested on TNEP trying to find a solution that reaches or improves previous results, then claiming that the solution method is superior to the other ones. This claim contains a major drawback, that is, the confusion among a good solution found with a method and the overall performance of the method. As discussed in Chicco & Mazza (2019), "if the solutions found on a specific problem by using one solver are better than with another solver, this does not mean that the solver is better". In the next part of this chapter, these ideas are applied to address the solutions of the TNEP problem.

2.2.3. Scheme of the population-based metaheuristics

Population-based metaheuristics are used in the large majority of the cases to solve the TNEP problem. The flow chart presented in Figure 2.1 shows a relatively general scheme for the solution of a population-based problem. The data input is assumed to be appropriate for the problem to be solved. On the basis of this scheme, the details of the TNEP solution approaches are discussed with reference to the various blocks. The variable *iter* is the iteration number. Without loss of generality, in the scheme of Figure 2.1 the creation of the new population has been inserted after the stop criterion, while in some references the stop criterion is checked after the new population has been created. The decision making to determine the final solution is needed for the multi-objective approaches that generate multiple compromise solutions, to provide an indication on the most appropriate solution.

In the next sections, the use of metaheuristics to solve single-objective and multi-objective TNEP problems is addressed separately. On the basis of the scheme presented in Figure 2.1, it is illustrated how to take into account the specific aspects of the TNEP in the various steps of the solution procedure.

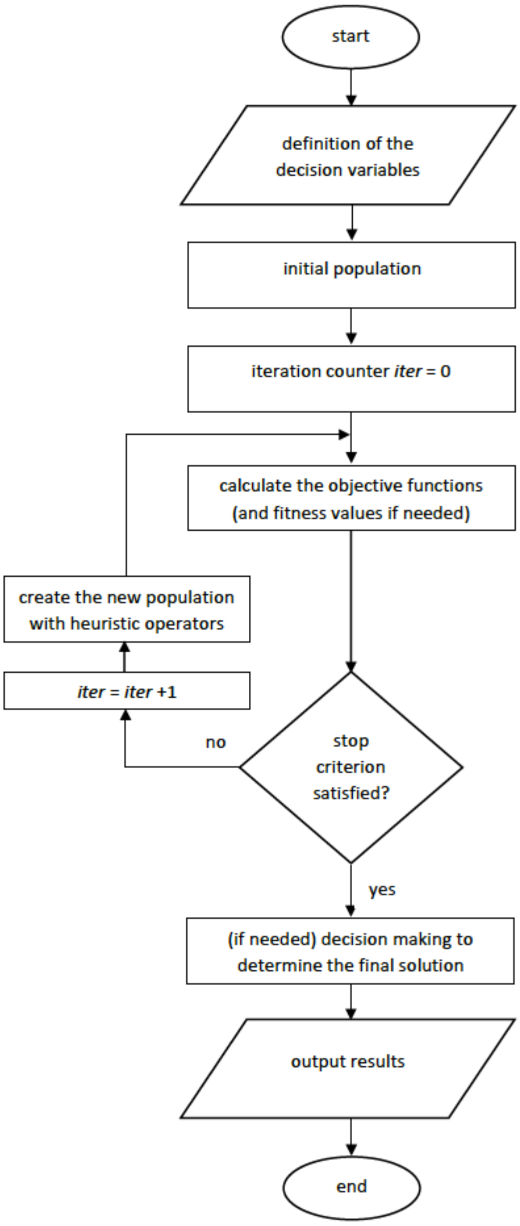


Figure 2.1. Scheme of a population-based metaheuristic.

2.3. Metaheuristics for the single-objective TNEP

2.3.1. Metaheuristics list

Numerous metaheuristics have been applied to the TNEP. A non-exhaustive list of metaheuristics used in the contributions addressed in this chapter (in their standard forms, or in customised variants) includes:

AC:	Ant Colony (Leite da Silva et al. 2010)
BI:	Bio-Inspired with PSO (Miranda de Mendonça et al. 2016)
COA:	Chaos Optimal Algorithm (Qu et al. 2010)
DE:	Differential Evolution (Georgilakis 2010; Torres & Castro 2015; Verma et al. 2019)
EP:	Evolutionary Programming (Leite da Silva et al. 2016)
FF:	Firefly (Rastgou & Moshtagh 2016)
GA:	Genetic Algorithm (Da Silva et al. 2000; Gil & da Silva 2001; Sadegheih & Drake 2008; Mahdavi et al. 2009; Gupta et al. 2014; Gallego et al. 2017; Poubel et al. 2017; Rad & Moravej 2017; Sun et al. 2017)
GABC:	Gbest-guided Artificial Bee Colony (Rathore & Roy 2016)
HAS:	Harmony Search Algorithm (Rastgou & Moshtagh 2014)
ICA:	Imperialist Competitive Algorithm (Moradi et al. 2016)
MGBMO:	Modified Gases Brownian Motion Optimisation (Rathore & Roy 2014)
PSO:	Particle Swarm Optimisation (Shayeghi et al. 2010; Hooshmand et al. 2012; Kamyab et al. 2014; Mortaz et al. 2015; Hemmati et al. 2016; Shayeghi et al. 2010b)
SA:	Simulated Annealing (Gallego et al. 1997)
SR:	Simulated Rebounding (Hinojosa et al. 2013)
TS:	Tabu Search (Sadegheih & Drake 2008)

2.3.2. Initial population

In the single solution update methods (e.g., the SA method in Gallego et al. 1997), a single initial solution is provided. In the population-based methods, the most used way is to create the initial population at random. There are various exceptions, motivated in different ways. Techniques to obtain higher solution diversification are used in Hinojosa et al. (2013), in Kamyab et al. (2014) for the definition of the initial swarm, Rastgou & Moshtagh (2016) in the initial feasibility process, and Gallego et al. (2017) with the implementation of an efficient constructive heuristic algorithm (ECHA). In Da Silva et al. (2000), the initial population is found by constructing a number of head individuals by using a linear programming (LP) approach with continuous decision variables and selecting the initial population from them (Da Silva et al. 2000). Similar concepts are applied in Gil & da Silva (2001), in which the initial population is found from head individuals determined by the solution with continuous variables. Other approaches use the tree search algorithm (Poubel et al. 2017) and clustering (Rad & Moravej 2017). In the AC implementation in Leite da Silva et al. (2010) different sequences are formed starting from the last year. In Leite da Silva et al. (2016) an intelligent initialisation procedure (InI) is formulated, and an interesting discussion is provided to indicate that the InI procedure could make the execution faster, however the success rate and the quality of the solutions are higher with the random initialisation. In Qu et al. (2010) the initial values for the COA are generated in the range [0,1].

2.3.3. Objective functions and customisation for TNEP

The general objective of the methods addressed in this section is the cost of the transmission infrastructure. However, in the single-objective formulations, other terms appear, typically expressed as costs as well, referring to various aspects (the abbreviations are the ones used in Table 2.1):

CS: congestion surplus
DM: demand management
E: CO_2 emissions
EV: electric vehicles
F: fuel infrastructure
G: generation
LL: loss of load
LS: load shedding

In addition, there are many specific aspects considered in the construction of the solution methods, some of which are briefly recalled here. Two peculiar aspects of the TNEP problem that should be taken into account are the *incoherence* of the system after the addition of a transmission circuit and the *economies-of-scale*. These two aspects have an effect on the expected loss of load after the investment. In fact, the incoherence leads to an increase of the power transmitted on at least one circuit after the installation of a new circuit with respect to the power flow pre-investments. On the other hand, the economy of scale can lead to a larger reduction of loss of loads than the one obtainable by applying more small investments having the same capital cost. These two aspects have been detailed in Gil & da Silva (2001), where the authors introduced the *loss of load limit curve*. The idea is to avoid the use of high penalty factors at the beginning of the optimisation procedure (which certainly leads to suboptimal solutions), by using *low* penalty factors to produce solutions that are infeasible (they are affected by loss of load). Starting from those solutions, it is possible to build the loss of load limit curve that contains an approximate cost of the optimal solutions. Then, by starting from the infeasible solution presenting the lowest amount of loss of load and modifying the penalty factor, the GA can determine the optimal solution.

An improvement in the analysis of TNEP problems is the incorporation of multiple contingencies in the GA for evaluating the loss of load. The evaluation of the condition with multiple contingencies requires an efficient calculation tool, for avoiding excessive computation time. In Gupta et al. (2014) the calculation of *generalised line outage distribution factor* (GLODF) is used. The corresponding GLODF matrix allows reducing the memory used to store information, and contributes to drive the optimisation process towards solutions with higher reliability.

The chronological aspects in TNEP are taken into account by considering multi-periods problem formulation. In Leite da Silva et al. (2010) this aspect has been considered by using a heuristic method (in this case AC) for choosing the best investment according to the conditions of the last year of the planning horizon. Then, the investments for the previous years are coordinated with the ones related to the last year, by finally evaluating also the interruption costs associated to the different time sequences.

The calculation of the operational cost associated to a single investment proposal can be inaccurate, and thus an hourly demand should be considered. However, the calculation of the hourly OPF can be computationally too expensive. For that reason, the cost value has been evaluated in Mortaz et al. (2015) through the use of multivariate interpolation, which allows calculating the variation of the operation costs (incorporated into the objective function) by varying parameters such as the fuel cost and demand. The method is included in the optimisation process (based on PSO) as a tool for evaluating the objective function considered as feasible with a predefined range of values of the parameters taken into account. The values of the parameters are taken uniformly distributed, and in case of particles characterised by different values the multi-variate interpolation is applied.

A further practical aspect is related to the *budget constraint*. In fact, even though the minimisation of the costs is the most common objective function in TNEP problems, the result of the minimisation can be higher than the available budget. This particular aspect can be addressed by inserting the budget constraint in the optimisation problem, as in Shayeghi et al. (2010b), where the authors maximise the *adequacy* of the system by using the PSO as the solution algorithm.

2.3.4. Stop criterion

The iterative process used in the metaheuristics cannot guarantee that the global optimum has been reached. Thereby, the iterations tend to continue by generating new solutions. A suitable *stop criterion* (or *termination* criterion) is then needed. Many papers use as stop criterion the maximum number of iterations. However, this criterion is generally not appropriate, because two situations may happen (Chicco & Mazza 2013):

1) *Early stopping*: the process could stop when significant improvements are still occurring; or

2) *Unnecessarily late stopping:* the process could stop when the solution had practically no variation in many of the last iterations.

A better stop criterion is to terminate the iterations when no change in the objective function occurs after a given number of successive iterations. This *adaptive* stop criterion (also indicated as stagnation) is the most appropriate for a metaheuristic. The maximum number of iterations may be left together with the adaptive stop criterion as a last-resource option.

Notwithstanding the clear convenience of the adaptive stop criterion, most of the contributions considered adopt only the maximum number of iterations. The adaptive stop criterion is exploited in Georgilakis (2010) to switch from one method to another, Gil & da Silva (2001), Gupta et al. (2014), Hooshmand et al. (2012), Leite da Silva et al. (2010; 2016), Mahdavi et al. (2009), and Poubel et al. (2017). In addition, specific stop criteria are used depending on the algorithm executed. For example, in Gallego et al. (1997) the SA stops when the minimum "temperature" parameter is reached, in Hinojosa et al. (2013) the SR stops when no new solution can be reached, in Moradi et al. (2016) the ICA stops when only one empire remains, in Qu et al. (2010) the iterations stop when the optimal solution appears for a predefined number of times (this is viable for relatively small systems), and in Sadegheih & Drake (2008) the TS stops when no changes occur.

2.3.5. Test systems for case study applications

The TNEP problem has been solved by using multiple test and real system models. The second column of Table 2.1 shows the various networks used in the literature references considered, synthesised with the following identifiers:

AR: Azerbaijan regional (Mahdavi et al. 2009)
B6: 6-node test (Leite da Silva et al. 2010)
BS: Brazilian Southern (Romero & Monticelli 1994; 1994b)
BST: Brazilian Sub-transmission (Leite da Silva et al. 2010)
BNE: Brazilian Northeastern (Romero et al. 2002)
BNNE: Brazilian North-Northeastern (Romero et al. 1995)
BSE: Brazilian Southeastern (Da Silva et al. 2000)
CCI: Chilean Central Interconnected (Hinojosa et al. 2013)
C10: Chinese 10-bus (Wang & McDonald, 1994)
C18: Chinese 18-bus (Sadegheih & Drake 2008)
CO: Colombian (Escobar et al. 2004)
EC: Ecuadorian (Hinojosa et al. 2013)
G6: Garver 6-bus (Garver 1970)
IE5: IEEE 5-bus (Gupta et al. 2012)
IE24: IEEE 24-bus (Rider et al. 2007)
IE25: IEEE 25-bus (Ekwue & Cory 1984)
IE30: IEEE 30-bus (Christie 1993)
IE118: IEEE 118-bus (Illinois Institute of Technology)
IR: Iran 400 kV (Rastgou & Moshtagh 2016)

N6: 6-bus (Roh et al. 2009)
ZR: Zanjan Regional (Rad & Moravej 2017)

The G6 network is a classical benchmark, as well as the IEEE networks, in which sometimes a few modifications have been introduced to take into account current developments, e.g., with renewable generation. Historically, some South-American networks have been used for comparisons. A few other test and local real networks have been introduced more recently.

Table 2.1. Test and real networks used in the selected literature references.

reference	*networks*	*objectives*	*initial population*	*comparison metric*
Da Silva 2000	BS, BSE, CO	LL	random (head)	no improvement
Gallego 1997	G6, BS, BNNE	LL	single initial	best
Gallego 2017	BS, BNNE, CO	LS	ECHA	best
Georgilakis 2010	IE30	G	random	best
Gil 2001	BS, BNNE	LL	random (head)	best
Gupta 2014	IE5, IE24, IE118	G, LL	random	best
Hemmati 2016	N6, EC, CCI	G	random	reserve margin
Hinojosa 2013	G6, EC, CH	G, LL	different	rate of success
Hooshmand 2012	G6, IE24	CS	random	best
Kamyab 2014	G6, IE24	G	random	swarm diversity
Leite da Silva 2010	B6, BST		different	various indices
Leite da Silva 2016	IE24, BS	G	random & InI	various indices
Mahdavi 2009	AZ		random	(none)
Miranda de Mendonça 2016	IE24, BS, CO	LL	random	best
Moradi 2016	IE24, IE118	G	random	best
Mortaz 2015	G6, IE24	G	random	best
Poubel 2017	G6, BS		tree search	best
Qu 2010	G6, BS		values in [0,1]	(none)
Rad 2017	ZA		clustering	(none)
Rastgou 2014	IE24, IE118	LL	random	LMP
Rastgou 2016	IE24, IE118, IR	LL	feasibility	best
Rathore 2014	G6, IE24, IE25	G	random	best
Rathore 2016	IE24, CO, BS	G, EV	random	best
Sadegheih 2008	C10, C18	G	random	best
Shayeghi 2010	G6, AR		random	fitness
Shayeghi 2010b	G6, AR		random	fitness
Sun 2017	G6, AR	G, E	random	costs
Torres 2015	G6, IE24, BNE	LL	random	best et al.
Verma 2019	G6, IE24	F, DM	random	Fr-test, box plots

2.3.6. Comparisons among the solution algorithms

Most of the contributions considered contain comparisons among the metaheuristic and other methods used for TNEP. The comparisons have been carried out by using different indicators.

For the single objective TNEP, the simplest metric, e.g., the best value obtained, is used in many cases. The comparisons carried out with this metric are rather weak, because the best solution could be obtained by chance during the solution process, without meaning that the metaheuristic used is better than others (Chicco & Mazza 2019). In Torres & Castro (2015) the set of indicators is extended from the best to the average and worst solutions, still with a lack of robustness in the comparison. Other criteria are the rate of success (Hinojosa et al. 2013) or the percentage of best solutions achieved (Torres & Castro 2015). Only a few papers contain indications on other quality metrics that can represent more detailed and sound comparisons. The set of indicators used in Leite da Silva et al. (2010; 2016), including quality index, mean quality index, average index for the top ten plans, success rate, and mean time of success runs, is a positive attempt to find more elaborated performance indicators. The Friedman test (Fr-test) and the box plots shown in Verma et al. (2019) are another useful effort in the direction of providing comparisons with better statistical significance and the possibility of ranking the solution algorithms. To get further insights, the concept of first-order stochastic dominance introduced in Chicco & Mazza (2019) can be exploited to construct indicators denoted as *OPISD* (Optimisation Performance Indicator based on Stochastic Dominance). These indicators make it possible to rank the solutions obtained with heuristic methods, both when the global optimum is known (in this case, the effectiveness of the metaheuristic may be tested), and when the global optimum is unknown (making a relative comparison among the cumulative distribution of the solutions). Further contributions adopt qualitative comparisons based on specific outputs such as the swarm diversity (Kamyab et al. 2014), locational marginal price (Rastgou & Moshtagh 2014), load, generation and reserve margin (Hemmati et al. 2016), and various costs (Sun et al. 2017).

2.3.7. Hybridisation of metaheuristic solvers and other solutions

Various hybridisations have been presented by coupling metaheuristics between them, or by coupling a metaheuristic with another algorithm. One of the most successful hybridisations is the evolutionary PSO (EPSO), which combines the positive characteristics of evolutionary programming and PSO, to obtain an evolutionary model with self-adaptation in which the particle movement operator from PSO is introduced to produce diversity (Miranda & Fonseca 2002). The EPSO has been applied to TNEP in its discrete form (DEPSO) in Costeira da Rocha (2012; 2013). In Chung et al. (2003) a multi-objective problem with three objectives (investment cost, reliability and environmental impact) has been transformed into a single-objective problem by summing up the objectives. Then, a GA has been applied to generate the solutions, together with a fuzzy decision analysis to select the best solution. A more recent hybrid approach presented in Shivaie & Ameli (2016) combines Melody search and the Powell heuristic, also using information-gap decision theory to handle the planning risks of planning depending on severe uncertainty. The general concepts indicated about the initial population, the stop criterion and the comparisons with other methods are still valid for these hybrid versions.

2.4. Metaheuristics for the multi-objective TNEP

2.4.1. Relevance of metaheuristics and objective functions for multi-objective TNEP

For the single-objective TNEP, the metaheuristic approach is not the prevailing one, as many other classical mathematical optimisation algorithms and heuristic rules are used. Conversely, in the multi-objective TNEP the situation is practically reverted, and the metaheuristics become the leading solution techniques because of their versatility in handling different conflicting objectives.

In general, the solvers used in multi-objective problems are partitioned into those based on weighted sums (which convert the multi-objective problem into a single-objective one, applicable to convex domains), goal programming approaches, and Pareto front-based approaches. In the case of TNEP, the weighted sums approach cannot be used because of the non-convexity of the domain. The goal programming approach, applied in Xu et al. (2006), needs to know a priori information on the preferences of the decision maker (Maghouli et al. 2009). The Pareto-based approach has been widely adopted in the current literature.

Selected papers are considered to illustrate the main aspects of the objective functions used to solve the multi-objective TNEP problem and the solution approaches (Table 2.2). The metaheuristics used are the multi-objective versions of population-based methods. The objective functions considered are:

CC: congestion costs
CEC: carbon emission costs
CENS: cost of energy not supplied
CL: curtailed load
ENS: energy not supplied
NIC: network investment costs
PC: production costs
NSWLS: number of scenarios without load shedding
WPPC: wind power plant capacity

A detailed view of the formulations of these objective functions is outside the scope of this chapter. In some cases, conventional optimisation methods are used to compute the values of the objective functions that are used to create the Pareto fronts. Examples are the quadratic optimisation problems solved in Maghouli et al. (2009) to compute the congestion cost of each alternative and the amount of load shedding, the two linear programming problems solved in Jadidoleslam et al. (2017) for market clearing and to calculate the *ENS* in a bi-level programming model, and other methods indicated in Section 2.4.5.

A further aspect refers to the possible incorporation of uncertainty in the model. The earlier contributions (Wang et al. 2008; Maghouli et al. 2009) did not address uncertainty. The more recent contributions take into account uncertainty in different ways, with reference to wind power (Hu et al. 2016), wind and load (Moeini et al. 2012a; Jadidoleslam et al. 2017), hydro generation (Sousa & Asada 2015), and the probabilistic reliability criterion used in Hiroki & Mori (2014).

Table 2.2. Characteristics of the multi-objective problems for TNEP

reference	number of objectives	min {NIC}	min {ENS}	min {CENS}	min {PC+CEC}	max {WPPC}	min {CC}	min {CL}	max { NSWLS }	metaheuristic
Wang et al. 2008	3	■		■			■			improved SPEA
Maghouli et al. 2009	3	■					■	■		NSGA-II
Moeini et al. 2012a	3	■		■			■			NSGA-II
Hiroki & Mori 2014	2	■	■							CNSGA-II
Sousa & Asada 2015	2	■							■	SPEA2
Hu et al. 2016	2	■			■					NSGA-II
Jadidoleslam et al. 2017	3	■	■			■				MOSFLA

In the next part of this section, the conceptual framework to analyse conflicting objectives through the creation of Pareto fronts is first recalled. On the basis of the general scheme presented in Figure 2.1, it is illustrated how to take into account the specific aspects of the TNEP in the various steps of the solution procedure.

2.4.2. Conflicting objectives and Pareto front construction

Multi-objective problems are defined by considering different objectives simultaneously. In order to set up a multi-objective problem, the objectives considered have to be in *conflict* with each other. Namely, when an objective is improved, at least another objective has to become worse. In this way, the multi-objective optimisation provides as results not only the best values for the individual objectives, but also a number of *compromise solutions* seen as feasible decision-making alternatives. In order to represent the compromise solutions, the concept of *dominance* is applied. A solution is *non-dominated* when no other solution does exist with better values for all the individual objective functions. The compromise solutions are then found as the non-dominated solutions of the multi-objective problem. These non-dominated solutions form the *Pareto front.* The resulting concept of Pareto dominance depends on the nature of the objective function, that is, on whether the objective function has to be maximised or minimised. Figure 2.2 shows in the two-objective case how a given solution point dominates other points for different combinations of objective functions to be minimised (f_1 and f_2) or maximised (g_1 and g_2). In each plot, the filled area corresponds to the points dominated by the point A indicated in the figure, and the filled circled points are the ones located on the Pareto front.

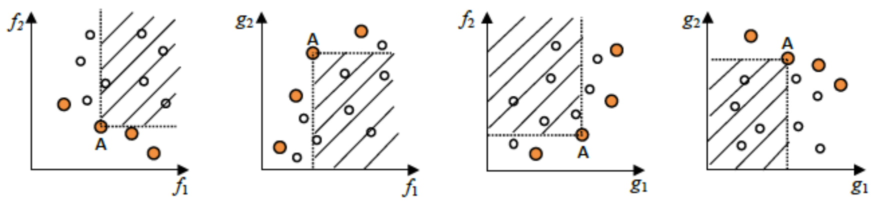


Figure 2.2. Concept of Pareto dominance. The functions f_1 and f_2 are minimised. The functions g_1 and g_2 are maximised.

The construction of the Pareto front is also a way to establish whether two or more objectives are conflicting with each other. In fact, for non-conflicting objectives the Pareto front degenerates into a single point.

In practical applications, it could be infeasible to calculate the entire Pareto front. In these cases, the *best-known* Pareto front is determined as the computable set of non-dominated solutions.

In the classical construction of the Pareto front, all the compromise solutions have the same importance, so that a solution ranking mechanism has to be implemented to identify the most appropriate solution from the Pareto front (Section 2.4.7).

An alternative approach is to use fuzzy-based dominance degrees (Benedict & Vasudevan 2005), in which the rank of each solution is directly identified in each Pareto front (Jadidoleslam et al. 2017). In this case, for $k = 1,\ldots, K$ objectives, the solution point $\mathbf{c}_1 = \{c_{k,1}\}$ is dominated by the solution point $\mathbf{c}_2 = \{c_{k,2}\}$ at the degree of dominance $\kappa(\mathbf{c}_1, \mathbf{c}_2)$ given by

$$\kappa(\mathbf{c}_1, \mathbf{c}_2) = \frac{\prod_{k=1}^{K} \min\{c_{k,1}, c_{k,2}\}}{\prod_{k=1}^{K} c_{k,2}} \tag{1}$$

The degree of dominance ranges from 0 to 1. If $\kappa(\mathbf{c}_1, \mathbf{c}_2) = 1$, the solution point $\mathbf{c}_1$ is absolutely dominated by $\mathbf{c}_2$. If $\kappa(\mathbf{c}_1, \mathbf{c}_2) < 1$ and $\kappa(\mathbf{c}_2, \mathbf{c}_1) < 1$, the two solution points are not dominated with each other.

In this framework, the rank index of each solution $\mathbf{c}_i$ belonging to the Pareto front $\mathcal{P}$ (in which the best solutions are the ones with the lowest values) is expressed as:

$$r(\mathbf{c}_i) = \text{mean}_{\mathbf{c}_j \in \mathcal{P}}\{\kappa(\mathbf{c}_i, \mathbf{c}_j)\} \tag{2}$$

2.4.3. Concepts referring to the Pareto front for multi-objective metaheuristics

The main concepts used in the solution methods are the ones borrowed from the general multi-objective solvers, that is:

- *Pareto front ranking* (or *non-dominated sorting*): the non-dominated solution points form the top ranked Pareto front (rank $r = 1$); then, by removing these points, the resulting set of non-dominated solution points form the front with rank $r = 2$. This procedure continues for the successive ranking (Figure 2.3).
- *Crowding distance*: the crowding distance represents the *average distance* between the ith solution and the closest solutions belonging to the same Pareto front, and estimates the *density* of the solutions located around that solution. The calculation of the crowding distance is performed by considering all the normalised objectives, and the crowding distance may also represent an indication on the perimeter of the cuboid (represented in two-dimension solution space with the rectangle shown in Figure 2.3). A larger crowding distance means that the ith solution is representative of that part of the solution space, and no other can substitute it. So, it is a good candidate to maintain the *diversity* of the solution set. On the other hand, a smaller crowding distance means that several solutions can be representative of that part of the solution space; hence, maintaining all of them during the optimisation process could reduce the diversity of the solution set.

Another indicator used in Wang et al. (2008) to express the location uniformity is the spacing index S taken from the unpublished M.S. thesis of Schott (1995), formulated for $k = 1, \ldots, K$ objectives as:

$$S = \sqrt{\frac{1}{K-1}\sum_{k=1}^{K}\left(\bar{d} - d_k\right)} \tag{3}$$

in which, denoting as $\mathbf{1}_J$ a column vector containing J values equal to unity, being J the number of points in the Pareto front $\mathcal{P}$:

$$\bar{d} = \frac{1}{K-1}\sum_{k=1}^{K} d_k \tag{4}$$

$$d_k = \min_{\mathbf{c}_i \in \mathcal{P}}\left\{\mathbf{1}_J^{\mathrm{T}}\left|\mathbf{c}_k - \mathbf{c}_i\right|\right\} \tag{5}$$

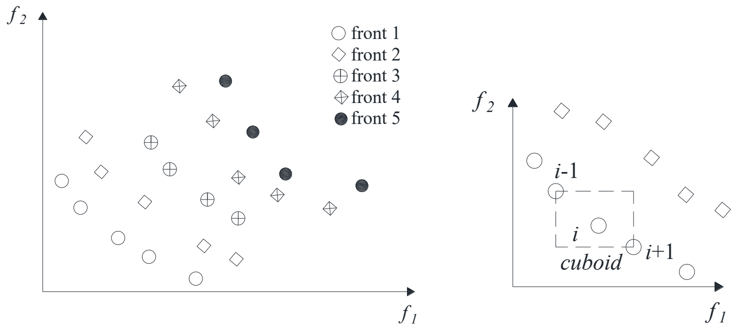


Figure 2.3. Pareto front ranking and notion of crowding distance.

2.4.4. Initial population

Given the network constraints, a random choice of the initial population would be rather ineffective. For this reason, specific knowledge on the TNEP problem is exploited in the selection of the initial population, in different ways.

In Wang et al. (2008), knowledge from TNEP is added to the SPEA algorithm. A random initialisation is used to generate a number of candidate networks, many of which could have isolated nodes. Then, an "isolated node absorbing initialisation" is carried out. In this procedure, a main network is created, and the possible isolated nodes (or groups of nodes) are then connected to the main network through the random addition of new lines. The procedure continues until there is no isolated node. In addition, the so-called "borderline search" strategy is added to avoid branch overload. For any candidate network in which there is an overload, the reduction of overloading that can be obtained by adding one line to a corridor, and the line that leads to the highest overloading reduction is added to the candidate network. In this way, the initial population satisfies the constraints. In Sousa & Asada (2015) the initial population is composed of feasible network topologies. A modified Constructive Heuristic Algorithm is applied to each unfeasible topology by solving a linear programming problem with the use of a DC power flow model. If the resulting configuration is feasible, it is accepted and applied to each scenario; otherwise, a tournament-based method based on a sensitivity index is used to select a line to add, and the linear programming is solved again, continuing the process until a feasible configuration is found.

In Maghouli et al. (2009) the initial solutions are selected at random among the feasible solutions. The initial population is indicated in Moeini et al. (2012a) and Jadidoleslam et al. (2017) to be composed of alternative solutions, without further details. Also in Hiroki & Mori (2014) and Hu et al. (2016) the initial population is randomly initialised. It can be considered that these solutions have to be feasible, i.e., the problem constraints are satisfied.

2.4.5. Solution methods and customisation on the TNEP

The specific knowledge on the TNEP is applied during the generation of the solutions. In particular, the TNEP constraints are applied to the solutions to avoid the creation of unfeasible networks. For all the contributions addresses, the equality constraints are given by the DC power flow equations and the power balance at each node. In Maghouli et al. (2009) the DC power flow is calculated in normal and contingency cases. In Hu et al. (2016) the operation and security constraints are calculated for the electricity and natural gas networks, and for the candidate transmission lines to be added. Furthermore, there are operation constraints of existing and candidate gas pipelines and gas compressors, and an energy conversion equality constraint that links the electricity and natural gas systems.

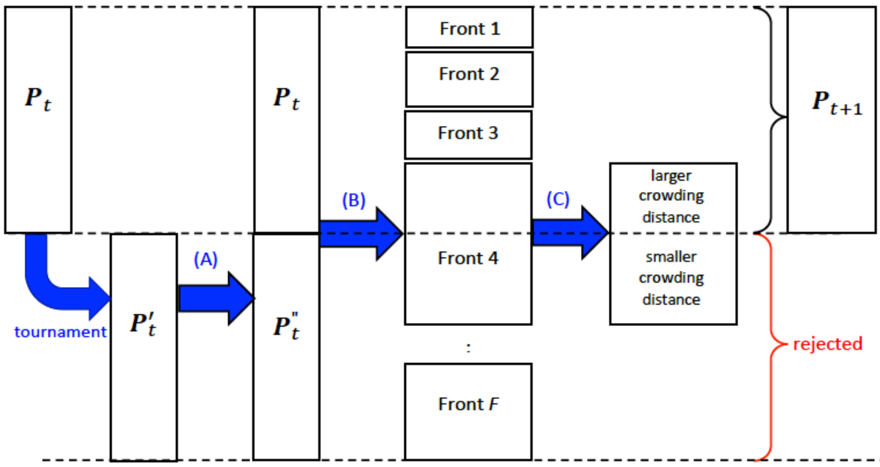
The inequality constraints included generally refer to the maximum number of new lines added to a corridor (or the maximum number of transmission lines in each corridor), the power flow limits at each line, and the limits on active power generation outputs. Further specific limits depending on the problem addressed are set on load values (Wang et al. 2008), load curtailment (Maghouli et al. 2009), positive profit, maximum risk for wind power installation, and maximum wind capacity per site (Jadidoleslam et al. 2017), and rescheduling of generators (Hiroki & Mori 2014). An explicit network connectivity constraint is indicated in Hiroki & Mori (2014), while in the other contributions network connectivity is assured with the customised procedures aimed at obtaining feasible solutions.

The metaheuristic algorithms problems (indicated in Table 2.1) adopted to solve the TNEP are taken from the literature:

- Non-dominated Sorting Genetic Algorithm (NSGA-II, Deb et al. 2002) most used as a metaheuristic solver, or as a comparison benchmark for other metaheuristics. An example of formation of the population in NSGA-II is shown in Figure 2.4. Different fronts are constructed by using non-dominated sorting, of which the first one is the Pareto front. The solutions to form the new population are then picked up from the successive fronts. If the number of solutions in the last front exceeds the size of the population used, the solutions with the smaller values of crowding distance are eliminated.

- Controlled Non-dominated Sorting Genetic Algorithm (CNSGA-II, Deb & Goel 2001), in which the diversity of the set of solutions is claimed to be improved with respect to NSGA-II by using the reproduction of the solution candidates in the successive iterations.
- Improved version of the Strength Pareto Evolutionary Algorithm (SPEA, Zitzler & Thiele 1999), where the improvement indicated in Wang et al. (2008) consists of the population initialisation and borderline search mentioned before.
- Strength Pareto Evolutionary Algorithm 2 (SPEA2, Zitzler et al. 2001).
- Multi-objective Shuffled Frog Leaping Algorithm (MOSFLA, Benedict & Vasudevan 2005).

Specific knowledge on the TNEP is applied in the generation of the solutions with calculation of the objective functions. If the problem formulation does not incorporate *N*-1 security aspects, as in Wang et al. (2008), the *N*-1 security of the Pareto front points is checked after the formation of the Pareto front and is used as a mechanism to reduce the number of points. For each alternative solution, in Moeini et al. (2012a) the congestion cost is determined through a probabilistic optimal power flow based on the Point Estimation Method (PEM), and the annualised value of the expected energy not supplied considering the uncertainties in wind power generation and load is obtained from probabilistic linear programming again using PEM. An improved PEM that takes into account the correlations among different wind farms is used in Hu et al. (2016) to solve an optimal power flow and determine the expected production costs and the load curtailments.



(A) Crossover and mutation on the population P'_t

(B) Non-dominated sorting of the combined front $P_t \cup P''_t$

(C) Crowding distance sorting on the ordered Pareto front that leads to exceed the population size (e.g., Front 4 in this case)

Figure 2.4. Example of formation of the population at iteration *t* in NSGA-II.

2.4.6. Stop criterion

The references addressed adopt the maximum number of iterations as the stop (or termination) criterion. The only (positive) exception is indicated explicitly is Maghouli et al. (2009), where the iterative process is terminated when no other non-dominated solution is found in a predefined number of successive iterations. This corresponds to the adaptive stop criterion indicated in Section 2.3.4 as the most appropriate one. In Moeini et al. (2012a) there is a generic indication about the possible consideration of the number of individuals in the first Pareto front, in addition to the maximum number of iterations.

2.4.7. Final decision from solution ranking

Finally, the compromise solutions can be *ranked* to assist the decision-maker in determining the most likely solution from the Pareto front. Some ranking methods such as the Analytic Hierarchy Process (AHP) require translating the personal judgement of the decision-maker into numerical values (from 1 to 9, according with the Saaty scale, Saaty 1977) to be used in the computation (the comparisons among the different Pareto front outcomes can be carried out in an automatic way as in Mazza et al. 2014). Other tools generally adopted to rank the Pareto front points are the Technique of Order Preference by Similarity to Ideal Solution (TOPSIS, Hwang & Yoon 1981), and fuzzy-based tools (Deb 2001; Benedict & Vasudevan 2005). In the selected contributions addressed, fuzzy-based decision-making is the most applied. In Moeini et al. (2012a) and Jadidoleslam et al. (2017), for each objective function $k = 1, \ldots, K$, a fuzzy membership is defined (if all the objective functions have to be minimised) as

$$\mu_{c_{k,i}} = \begin{cases} 0 & c_{k,i} > c_k^{\max} \\ \frac{c_k^{\max} - c_{k,i}}{c_k^{\max} - c_k^{\min}} & c_k^{\min} \leq c_{k,i} \leq c_k^{\max} \\ 1 & c_{k,i} < c_k^{\min} \end{cases} \tag{6}$$

Then, the decision maker establishes the target levels $\hat{\mu}_k$ for each objective, and the best solution i^* is found by solving the optimisation problem:

$$i^* = \operatorname{argmin}_{\mathbf{c}_j \in \mathcal{P}} \sum_{k=1}^{K} \left| \hat{\mu}_k - \mu_{c_{k,i}} \right|^{\nu} \tag{7}$$

where the exponent is an integer number $\nu > 0$. From Deb (2001), the use of larger values of ν reduces the sensitivity of the final solution to the target values.

Another TNEP-related criterion is the comparison among non-dominated solutions by using the incremental Cost Benefit (*ICB*) ratio (Maghouli et al. 2009), given by the ratio between the reduction in the congestion cost with respect to the base case and the investment corresponding to the solution under analysis (as the base case has no investment).

Furthermore, the Ranking index *RI* is used in Wang et al. (2008) for the Pareto front solutions (for all variables to be minimised). All the variables are normalised by considering the corresponding maximum and minimum values of each objective $k = 1, \ldots K$, to make them comparable. For a given point $\mathbf{c}_i = \{c_{k,i}\}$ located on the Pareto front, its normalised version is:

$$c'_{k,i} = \frac{c_{k,i} - c_k^{\min}}{c_k^{\max} - c_k^{\min}} \tag{8}$$

The ranking index *RI* is calculated as the Euclidean distance between the normalised variables:

$$RI_i = \sqrt{\sum_{k=1}^{K} c'_{k,i}} \tag{9}$$

The solution with the lowest ranking index *RI* is taken as the best one.

2.4.8. Test systems for case study applications

The various contributions have used different test and real networks for their case study applications. An 18-bus test system and a 77-bus system have been tested in Wang et al. (2008). The Garver test system (Garver 1970) has been used in Sousa & Asada (2015). The IEEE 24-bus reliability test system (Reliability Test System Task Force 1999) is the most used one, either in its classical version (Maghouli et al. 2009; Hiroki & Mori 2014; Sousa & Asada 2015), or in a modified version with wind power (Moeini et al. 2012b; Jadidoleslam et al. 2017), or integrated with a 15-bus natural gas system (Hu et al. 2016). Further local systems have been used from Southern Brazil (Sousa & Asada 2015), Iran (Maghouli et al. 2009; Moeini et al. 2012b), and China (Hu et al. 2016).

2.4.9. Comparisons among the solution algorithms

The comparisons among the proposed approaches and other algorithms used in the literature are generally limited. In Moeini et al. (2012b) and Hu et al. (2016) there is no comparison with other algorithms, and all the comparisons refer to "internal" cases developed inside the paper. The approach presented in Maghouli et al. (2009), based on NSGA-II, is compared with the expansion plan proposed by the Iranian Grid Management Company. In Wang et al. (2008) the comparison is carried out between the original SPEA and the improved SPEA proposed in the paper, concluding that the proposed algorithm finds more solutions than the original SPEA at the same iteration times, and also provides better location uniformity. In the other three contributions (Hiroki & Mori 2014, Sousa & Asada 2015; Jadidoleslam et al. 2017), the proposed method is compared with NSGA-II. In summary, the CNSGA-II method used in Hiroki & Mori (2014) maintains better solution diversity in part of the Pareto front with respect to NSGA-II. In Sousa & Asada (2015), SPEA2 and NSGA-II exhibit similar solution quality. In Jadidoleslam et al. (2017), the results obtained with MOSFLA are indicated to be better than the ones obtained with NSGA-II in Moeini et al. (2012b).

For multi-objective solvers, classical methods to rank the Pareto front solutions such as AHP and TOPSIS have not been used in the journal contributions addressed. The most exploited approach is based on fuzzy memberships. However, the comparisons among the Pareto fronts obtained have not been a subject of particular attention yet. These comparisons may be done by using quality indicators. An overview of the indicators proposed in the literature is presented in Zitzler et al. (2003). The distance between points located in the Pareto front under analysis and the closest points of the optimal or pseudo-optimal Pareto front can be considered, calculating for instance the quality indicator as the average of these distances. In other cases, the quality indicator is assessed with a chi-square-like deviation measure, in order to exploit the Pareto front diversity (Srinivas & Deb 1994, Zitzler et al. 2003). An appropriate quality indicator is the *hyper-volume* determined from the Pareto front (Zitzler et al. 2008, Brockhoff et al. 2013), used both for performance assessment and for guiding the search in various hyper-volume-based metaheuristics (Augera et al. 2012). General formulations for an efficient calculation of the hyper-volume from Pareto fronts in multiple dimensions are still not available. However, the Pareto fronts indicated in the above sections for the TNEP problem are defined in two and three dimensions. Hypervolume calculations for these cases are available, as illustrated in Guerreiro & Fonseca (2018).

2.5. Conclusions

Some main conclusions may be drawn from the contents of this chapter:

- The most successful applications of metaheuristics to the TNEP problem are the ones that solve multi-objective problems. The classical metaheuristic algorithms for multi-objective programming have to be revisited to incorporate the specific knowledge on the technical aspects that concern the network topology.
- The current literature considers single aspects of the TNEP, however an overall approach that incorporates several aspects is still lacking. Modern formulations of the TNEP problems have to be developed to take into account the evolving aspects of the energy systems, markets and sustainable development. The recent contributions have started mixing up various TNEP objectives, and this

line is expected to continue and to be reinforced, even though the complexity of the problem formulation and solution could increase.

- There is a need for establishing benchmark functions and benchmark networks. The network structures have to incorporate the main elements that appear in today's systems and take place in the TNEP formulations.
- From the current literature results, there is an apparent need to exploit more robust performance indicators for comparing the solutions obtained from metaheuristics with single objective or multiple objectives, to avoid an uncontrolled proliferation of solution algorithms that do not carry methodological insights.

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