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A review of meta-heuristic algorithms for reactive power planning problem

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Abstract Reactive power planning (RPP) is generally defined as an optimal allocation of additional reactive power sources that should be installed in the network for a predefined horizon of planning at minimum cost while satisfying equality and inequality constraints. The optimal placements of new VAR sources can be selected according to certain indices related to the objectives to be studied. In this paper, various solution methods for solving the RPP problem are extensively reviewed which are generally categorized into analytical approaches, arithmetic programming approaches, and meta-heuristic optimization techniques. The research focuses on the disparate applications of meta-heuristic algorithms for solving the RPP problem. They are subcategorized into evolution based, and swarm intelligence. Also, a study is performed via the multi-objective formulations of reactive power planning and operations to clarify their merits and demerits.

1. Introduction

Nowadays, reactive power planning (RPP) problem has become one of the most challenging problems in power systems. It has been an important stage of transmission expansion planning (TEP) problem in recent years [1–3]. In addition, reactive power control/dispatch is an important function in the planning process for the future of power systems. It aims to utilize all the reactive power sources efficiently, which are suitably located and sized in the planning process [4–10].

Generally, the various RPP solutions are divided into three groups which are analytical approaches [11–13], arithmetic programming approaches [3,4,11,12–15,16(Ch. 2),17(Ch. 3),18–23], and meta-heuristic optimization techniques. Various Meta-heuristic Optimization Algorithms (MOA) have been applied to the RPP problem such as Genetic Algorithms (GA) [5,24–33], Differential Evolution (DE) [6,17,24,34–42],

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Harmony Search (HS) [43–45], Seeker Optimization Algorithm (SOA) [46–48], Evolutionary Programming (EP) [49–54], Ant Colony Optimization (ACO) [7,55], Immune Algorithm (IA) [8], Particle Swarm Optimization (PSO) [2,9,16,56–58], Artificial Bee Colony (ABC) [59], Gravitational Search Algorithm (GSA) [60,61], Firefly Algorithm (FA) [62], Teaching Learning Algorithm (TLA) [63], Chemical Reaction Optimization (CRO) [64], Water Cycle Algorithm (WCA) [65], and Differential Search Algorithm (DSA) [66]. Hybrid techniques have been suggested in some researches that make use of advantages of different algorithms simultaneously to improve the quality of solution [5,10,16(Ch. 5),53,55,67–75].

Also, multi-objective formulation of optimization problems for reactive power planning and operation has been treated using the mathematical sum approach [1,11,24,25,28,35–38,50,51,53,56,68], weighting functions [27,29,40,43,44,47,69], ε-constraint approach [6,18,20,43,76,77], fuzzy goal programming techniques [28,58], and Pareto concept [4,8,16(Ch. 4),17,26,31–34,57].

Various conventional methods have been presented to solve the RPP problem and assured their incompetence in handling multi-objective nonlinear problems and they may converge to a local optimum. MOAs that mimic the nature opened a new era in computation. For the past decades, numerous research applications of MOAs have been concentrated for solving the RPP problem. In this particular area, the research is still young which broadens the scope and viability of MOAs exploring new modifications and developments in solving the RPP problem. This paper presents a broad overview of solution methods for solving the RPP problem which are analytical approaches, arithmetic programming approaches, and meta-heuristic optimization techniques. Also, the different applications of meta-heuristic algorithms for solving the RPP problem are extensively reviewed and thoroughly discussed. Furthermore, the multi-objective formulations of reactive power planning and operations are studied to clarify their merits and demerits. This paper is organized as follows. The formulation of the RPP problem is presented in Section 2. Section 3 discusses the different methods applied to solve the RPP problem. The multi-objective formulations of the RPP problem are discussed in Section 4. The concluding remarks are highlighted in Section 5.

2. General formulation of the RPP problem

The purpose of the RPP problem is to determine "where" and "how many" new VAR compensators must be added to a network for a predefined horizon of planning at minimum cost while satisfying an adequate voltage profile during normal conditions and contingencies. Fig. 1 illustrates the flowchart of the RPP problem.

After defining the system data, the generation/load patterns are developed for a predefined horizon of planning. Then, the optimal locations of new reactive power sources are identified. They may be selected according to certain indices or all load buses may be considered as candidate buses [14,15].

After that, the control variables (RPP variables) are optimized to achieve certain objective functions subject to set of equality and inequality constraints. Control variables include generator bus terminal voltages, reactive power generation of existing and new VAR sources and transformer tap ratio.

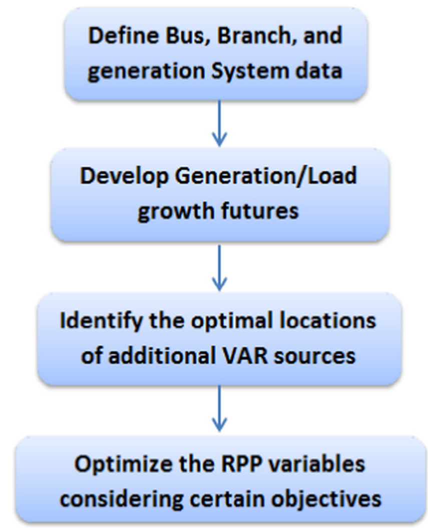

Figure 1 Flowchart of the RPP problem.

The generator bus voltages are continuous in nature, while both reactive power generation of existing and new VAR sources and transformer tap ratio are discrete. The dependent variables include load bus voltage magnitude, active power generation at slack bus, the power flows through the transmission lines, and reactive power outputs of the generators.

There are various objective functions that have been utilized in the RPP problem such as minimization of VAR investment cost and system operational cost of real power losses, improvement of voltage profile, and enhancement of voltage stability. However, the modeling of each objective has different shapes. Conventionally, the classical objective of the RPP problem is to achieve the minimum investment cost of additional reactive power supplies and minimize the system operational cost of power losses [1,11,24,25,28,35–38,50,51,53,56,68] as follows:

$$\text{Min } F = \text{Min}(I_C + O_C) \tag{1}$$

where I_C is the investment cost of new reactive power supplies and O_C is the operational cost of power losses. The investment costs of VAR sources can be generally modeled with two components, a fixed installation cost at bus i (e_i) and a variable purchase cost of capacitive or inductive source at bus i ($C_{ci}|Q_{ci}|$), [16,24–26,28,31,34,35,37,38,50,51,53,56,68] as follows:

$$I_C = \sum_{i=1}^{N_c} (e_i + C_{c_i}|Q_{c_i}|) \tag{2}$$

where N_c is the reactive compensator buses. This model requires considering the reactive power devices to be already installed before the optimization for its size. On the other hand, another general model of I_C has been used as [1–3,27,43]:

$$I_C = \sum_{i=1}^{N_b} (e_i + C_{c_i}|Q_{c_i}|)\beta_C \tag{3}$$

where N_b is the total number of busses, and β_C is the binary decision variables for installing capacitive source. Although the complexity of using binary variables to indicate whether the VAR source will be installed, this model will give a chance to consider all load buses to be candidates to install new reactive power sources. Traditionally, the annual cost of energy losses has been used as a direct measure to the operational costs (O_C) [1,16,24,25,28,31,34–38,51,53,56,68] as follows:

$$O_C = h\sum_{i=1}^{N_L} d_L P_{loss}^L \tag{4}$$

where h is the per unit energy cost, d_L is the duration of load level (h), N_L is the number of load level duration, and P_{loss}^L s the real power loss during the period of load level L. On the other side, the minimization of network transmission power losses (P_{loss}) has been sometimes used directly instead of converting it to operational costs in the reactive power operation [4,29,32,39–41,46,47] and planning [20,43,44,52]. Also, the power system has to satisfy equality and inequality constraints corresponding to the load flow model and operational variables as follows:

$$Q_{g_i} - Q_{L_i} + Q_{C_i}^n + Q_{C_i} - V_i\sum_{j=1}^{N_b} V_j(G_i \sin\theta_{ij} - B_{ij}\cos\theta_{ij}) = 0,$$
$$i = 1,2,\ldots N_b \tag{5}$$

$$P_{g_i} - P_{L_i} - V_i\sum_{j=1}^{N_b} V_j(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) = 0,$$
$$i = 1,2,\ldots\ldots.N_b \tag{6}$$

$$Q_{g\ i}^{\min} \leqslant Q_{g\ i} \leqslant Q_{g\ i}^{\max}, \quad i = 1,2,\ldots\ldots N_{pv} \tag{7}$$

$$V_i^{\min} \leqslant V_i \leqslant V_i^{\max}, \quad i = 1,2,\ldots\ldots N_b \tag{8}$$

$$T_k^{\min} \leqslant T_k \leqslant T_k^{\max}, \quad k = 1,2,\ldots\ldots N_t \tag{9}$$

$$\left|S_L^{flow}\right| \leqslant S_L^{\max}, \quad L = 1,2,\ldots\ldots N_L \tag{10}$$

$$0 \leqslant Q_{C\ e} \leqslant Q_{C\ e}^{\max}, \quad e = 1,2,\ldots\ldots N_C \tag{11}$$

$$0 \leqslant Q_{C\ j}^n \leqslant Q_{C\ j}^{\max(n)} \cdot \beta_{C\ j}, \quad j \in \text{candidate buses} \tag{12}$$

$$P_s^{\min} \leqslant P_s \leqslant P_s^{\max} \tag{13}$$

where V_i and V_j are voltages at buses i and j, respectively; θ_{ij} is phase angle between buses i and j; G_{ij} and B_{ij} are mutual conductance and susceptance between buses i and j, respectively; ($P_{gi} - P_{Li}$) and ($Q_{gi} - Q_{Li}$) are the net real power injection at bus i, and the net reactive power injection at bus i, respectively; Q_{Ci} is the capacitive or inductive power of existing VAR source installed at bus i. Q_{Ci}^n refers to the capacitive or inductive power of new VAR source installed at bus i. Q_{gi} is the reactive power output of a generator i, and N_{pv} refers to the total number of voltage-controlled buses. V_i is the voltage magnitude of bus i. T_k is the tapping change of a transformer k, and N_t refers to the total number of on-load tap changing transformers. S^{flow} refers to the apparent power flow, $S^{\max}$ is the maximum MVA rating of the transmission lines and transformers, and N_L refers to all transmission lines in the system. Q_{Ce} is the reactive power output of existing VAR source at bus e, $Q_C^{\max}$ s its maximum capacity, and N_C refers to the total number of existing VAR sources. n refers to the new installed VAR sources, and β_C is always equal 1 for the investment cost of VAR sources modeled in Eq. (3). P_s is the active power generation at the slack bus.

3. Solution methods for the RPP problem

RPP is a nonlinear multi-objective constrained combinatorial optimization problem for large power systems with a lot of uncertainties. Generally, the RPP problem has been solved by analytical approaches, arithmetic programming approaches, and meta-heuristic optimization techniques. Fig. 2 depicts the family and subcategories of the solution algorithms for the RPP problem. As shown, the several applications of meta-heuristic algorithms are subcategorized into evolution based, and swarm intelligence [78]. Added to that, hybridization between different algorithms is taken into consideration to improve the solution quality.

3.1. Analytical approaches

Analytical approaches are very important to understand the different effects and benefits of the location and size of reactive power sources [11–13]. The issues of RPP have been analyzed with reactive power pricing in [11] where a trade-off between the transmission loss and installation cost of new capacitors has been executed incorporating detailed hourly loading conditions. In [12], three economic benefits with assumption of a constant VAR injection and a fixed location have been analyzed. These benefits include reducing losses, shifting reactive power flow to real power flow, and increasing the transfer capability. The economic benefits have been updated by executing a set of optimal power flow (OPF) runs. Also, the reactive market-based of economic dispatch has been addressed in [13]. However, the benefits to the utilities from the allocation, installation, and operation of VAR compensators have not been discussed. Analytical approaches lend a lot of information and clear vision about the economic and technical benefits under different scenarios. They are quite helpful to design future framework of reactive power management and pricing for different players in the deregulated environment. On the other hand, they are time-consuming and may not be suitable for medium and large-scale power systems. Analytical approaches are as accurate as the model developed. They are based on its corresponding OPF which has been usually solved using nonlinear algorithms such as Modular Incore Nonlinear Optimization System (MINOS) [11–13] using General Algebraic Modeling Systems (GAMS) procedures [79].

3.2. Arithmetic programming approaches

Arithmetic programming approaches are also called Conventional Optimization Algorithms (COAs). A variety of conventional methods have been widely used to solve the reactive power operation and planning for years [14–16(Ch. 2),17(Ch. 3)]. COAs have been developed and implemented to solve the RPP problem. Table 1 shows a comparison between various COAs that have been applied to the RPP problem.

3.3. Meta-heuristic optimization algorithms

Meta-heuristic Optimization Algorithms (MOAs) are extensively used in solving multi-objective optimization problems

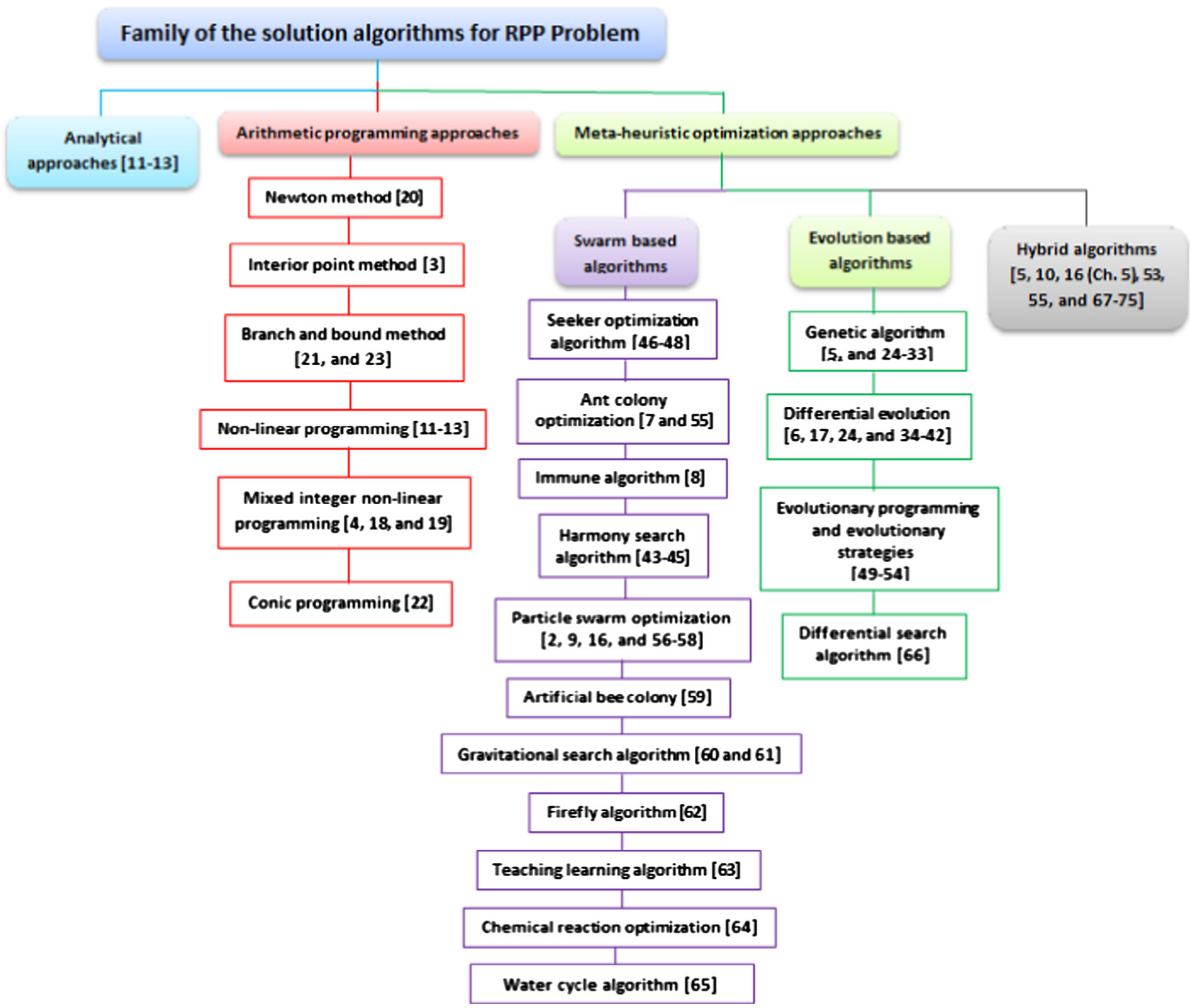

Figure 2 Family and subcategories of the solution algorithms for the RPP problem.

since they can find multiple optimal solutions in a single run. Different MOAs are applied efficiently to solve the RPP problem. Table 2 shows a comparison between various MOAs that have been applied to the RPP problem.

Since, the settings of their key parameters have a large impact on their performance, the adaptive MOAs have been developed recently and applied to the RPP problem. Some of the adaptive MOAs reported are as follows: the IHS algorithm [44], Chaotic DE algorithm [17], JADE-vPS algorithm [6], adaptive model of IA [8], EPSO [10,71], improved model of DE algorithm [42,80], SARGA [30], FAPSO algorithm [67], and MNSGA-II [31–33,76]. Although the adaptive models of MOAs reduce the complexity of parameter selection, the selected adaptation strategy influences on their performance and they have a high computational burden that needs more calculations to adapt the parameters.

4. Multi-objectives treatment of the RPP problem

In recent years, the RPP problem has been formulated as multi-objective optimization problem. Several methods have been presented to handle the multi-objective formulation of the reactive power planning and operation problems.

4.1. The mathematical sum approach

Multi-objective RPP problem has been treated using the mathematical sum approach as in Eq. (1) to minimize both the investment and operational costs [1,11,24,25,28,35–38,51,53,56,68]. Although this model is very simple, it doesn't prefer any objective over the others. Also, it is restricted where the multi-objectives should be with the same nature as in Eq. (1); both objectives are in the same kind (costs in dollar), else it will be meaningless.

4.2. The weighted sum approach

Multi-objective RPP problem has been treated also using weighted objective functions [27,29,40,43,44,47,69]. Weighted sum of different objectives can be generally modeled as follows:

$$\text{Min } F = \text{Min} \sum_{i=1}^{N_F} \omega_i F_i \quad \text{where} \quad \sum_{i=1}^{N_F} \omega_i = 1 \tag{14}$$

where ω_i and F_i are the weighting factor and the objective function for each goal i, respectively and N_F is the total

Table 1 Comparison among COAs implemented to solve the RPP problem.

Category	Ref.	Remarks	Merits	Demerits
NonLinear Programming (NLP) method Modular Incore Nonlinear Optimization System (MINOS) solver*	[11–13]	• MINOS employs a project Lagrangian algorithm with a linear approximation to the nonlinear constraints. It then uses the reduced-gradient algorithm for solving a linearly constrained sub-problem with a sequence of iterations	• Fast computation performance. It solves quickly a large number of single optimizations which corresponds to different loading and contingency conditions	• It is based on simplifications of sequential linearization • It is highly dependent on choosing the starting point • It finds locally optimal solutions
Mixed Integer NonLinear Programming (MINLP) solver (KNITRO 8 solver)	[19]	• The load uncertainty and different contingencies have been considered in multi-scenarios extracted using a scenario tree reduction methodology. KNITRO implements the interior method where, the nonlinear programming problem is replaced by a series of barrier sub-problems	• Fast computational performance. • Very suitable to handle with both continuous and discrete variables • No need for calculating 1st or 2nd derivatives of the nonlinear objectives or constraints	• It could be trapped in a local optimum and there is no guarantee to find the global optimum even if you run the algorithms for infinite long because the diversity of the solutions is limited • The multi-objective functions have been treated mathematically sum for each scenario in [19]
Interior Point (IP) method	[3]	• RPP problem has been formulated as a stage of TEP problem • The candidate buses to install VAR sources have been selected based on *L*-index as a voltage stability index	• Iterative approach for computing steps	• Neglecting the effect of transformer tap changing on the RPP problem in [3]
DIscrete and Continuous OPTimizer (DICOPT) solver*	[4,18]	• DICOPT solves a series of NLP and Mixed Integer Programming (MIP) sub-problems. It is based on outer approximation of the objective function, equality relaxation, and augmented penalty of the inequality constraints and the objective function.	• Suitable for solving the RPP problem as a MINLP problem that involves integer variables and continuous variables • Fast computation performance	• It does not necessarily obtain the global optimum • It is based on linear approximations of nonlinear functions at each iterations and accumulating them due to outer-approximations
Penalty Successive Conic Programming (PSCP) method	[22]	• PSCP method is generally a linear program with an additional nonlinear conic constraints corresponding to multiple state constraints as a penalty function • The PSCP algorithm has been solved by polynomial time primal–dual IP methods to find a common value of the decision variables in each state in a successive manner	• Very fast computational method • This method handled with outage scenarios and different load levels under voltage profile and stability constraints	• The solution of each conic program employs a linearization of the power flow equations at the current operating point • High computational burden due to multiple states VAR planning includes outage scenarios and different load levels
Dual Projected Pseudo Quasi-Newton (DPPQN) method	[20]	• This method considered only power losses as a single objective RPP problem • The investment cost for reactive power sources has been handled as budget constraint	• Fast computational technique • Efficient for solving RPP problems	• It becomes too slow if number of variables is large • It ignored the effect of generator voltages and tap changing transformers considering only the VAR patterns as control variables • Complex and high computational burden due to many levels and load cases
Branch and Bound (B&B) method	[21,23]	• This method employed a sequence of MIP method where, sensitivities of voltage stability margin and voltage magnitude have been used in this RPP formulation • In B&B, the search continues by creating two new sub-problems, each one is then solved by the same procedure, resulting in a search-tree of sub-problems	• No need for restarting the tree search and only a single tree is required • It is fast • It provides good solutions for large-scale power systems	• The formulation has been approximated to be linear using voltage stability margin sensitivities and voltage magnitude sensitivities • It finds locally optimal solutions

* MINOS solver [11–13], and DICOPT solver [4,18] have been formulated in GAMS software [79].

Table 2 Comparison among MOAs implemented to solve the RPP problem.

Category	Ref.	Remarks	Capabilities	Demerits
Genetic Algorithm (GA)	[27–29,50]	• The chromosomes are coded as binary bit strings This model is called Simple GA (SGA) • In [29], SGA has been applied to solve the reactive power dispatch based on the Fuzzy Goal Programming (FGP) to minimize the weighted sum of membership goals	• It involves a high degree of randomness • Good diversity of the solutions to avoid being trapped in a local optimum • Easy to use	• Slow convergence rate • No guarantee that GA will find a global optimum • Some difficulties in chromosome encoding • It is highly dependent on crossover and mutation rates
	[28]	• The RPP problem has been formulated in a stochastic model which represented the uncertainties of generator outputs and load demands with specified probability distributions • SGA based on Monte Carlo simulation has been used as a solution tool to minimize both the costs of energy loss and investments of new VAR sources	• The violation probability shouldn't exceed a chosen confidence level • Different planning schemes have been presented by altering the confidence levels of the objective and constraints	• The voltage constraints may be violated in some exceptional cases • The most appropriate choice hasn't been determined • The effect of tapping change of transformers hasn't been considered in the model
	[24,25]	• The chromosomes have been coded as a finite-length string of real numbers This model is called real coded GA (RGA) • Blend crossover (BLX-α) and normally distributed mutation operators have been applied directly to real values	• It can find the global optima as the number of iterations approaches infinite • Easy to be modified and joined with other approaches	• Since BLX-α is based on the interval process for real variables, the new off-springs depend on the location of both parents and so they will be close to the parents if both parents are close to each other, and vice versa [5]
	[30]	• A self-adaptive model of real coded genetic algorithm (SARGA) has been presented to solve the optimal reactive power dispatch (ORPD) problem The simulated binary crossover (SBX) operator has been used to create offsprings relative to the difference in parent solutions	• In this type of crossover, close-parent solutions are monotonically more likely chosen as offspring than solutions distant from parents	• It is highly dependent on crossover and mutation rates and effect on stability and convergence • It finds sub-optimal solutions
	[5]	• Representation of both binary and real variables has been deemed This improved GA carried out the uniform mutation operator to the mixed variables with some modifications, the blend crossover operator (BLX-α), and simple crossover for real and integer parts, respectively	• Design for binary and real search spaces	
	[26]	• Non-Dominated Sorting Genetic Algorithm II (NSGA-II) has been utilized to solve the multi-objective RPP to minimize the investment costs of shunt compensation and the average load bus voltage deviation as well NSGA-II ranks the individuals based on the concept of Pareto non-dominance	• Updating Pareto set using a Crowding Distance (CD) operator • More diversity of non-dominated solutions	• Lateral diversity is lost • More computational complexity
	[31–33,66 (Ch. 8)]	• A Modified NSGA-II (MNSGA-II) has been applied to the RPP problem In [31,33], Pareto-front has been created by converting the multi-objectives into single one using conventional weighted sum method and varying the weighting	• Dynamic modification of Pareto set using Dynamic Crowding Distance (DCD) • High uniformity and maintains good diversity since the lowest DCD individual has been removed every time and DCD has been recalculated for the remaining individuals	• High computational complexity • In [33], the best compromise solution hasn't been included and the obtained Pareto front has been considered to give more choices to the decision

		factors randomly. In [31,66 (Ch. 8)], the best compromise solution among Pareto-optimal solutions has been determined based on TOPSIS method • In [32], MNSGA-II has been employed to the ORPD to minimize the real power losses and maximize the voltage stability using the L-index. In this paper, multiple runs of single objective optimization with weighted sum of objectives have been used to obtain Pareto-set		maker. Otherwise, the effect of the existing reactive power sources has been ignored in this reactive power dispatch model
Differential Evolution (DE)	[34–37,25,38]	• DE algorithm has been used to solve the RPP problem to minimize both the VAR and energy loss costs • In [34,35], the discrete variables have been treated as continuous and then rounding it to the nearest integer • In [36], the RPP problem has been formulated as a contingency constrained optimal RPP problem. The single line contingency analysis firstly has been used to identify the severe state and its voltage violated buses. Then, these voltage violations have been added as an additional constraint to the base RPP problem • In [37,38], Fast Voltage Stability Index (FVSI) has been used to identify the weak buses for the RPP problem which has been solved using DE algorithm	• It can find near optimal solution regardless the initial parameter values • Efficient method where it cannot be easily trapped in local minima • Suitable convergence speed • Robust • It uses few number of control parameters • Simple in coding and easy to use • Easily handling integer and discrete optimization • Very suitable to solve multi-dimensional function optimization as the RPP problem	• Efficiency is very sensitive to the setting the control parameters. It is dependent on three main parameters which are population size (Np), mutation rate (F), and crossover rate (CR) • Parameter tuning mostly by trial-and-error • Crossover has the potential to destroy the directional information provided by the difference vectors for the sake of increasing diversity • The convergence is unstable with a small population size • It may drop in local best
	[39,40]	• A multi-objective reactive power and voltage control problem has been solved by DE approach. In [39], the candidate buses for VAR injection have been selected based on L-index to minimize real losses, voltage deviation and voltage stability index (L-index) • In [40], the power losses and the voltage deviation have been minimized		
	[41]	• DE algorithm has been implemented to achieve losses minimization, voltage profile improvement, and voltage stability enhancement		• Handling the RPP problem as a single objective optimization problem
	[52]	• DE algorithm has been tested to solve the RPP problem, including the placement and sizing of TCSC devices. The main factor to determine the optimal location of the TCSCs has been the loss reduction while, voltage stability enhancement, and voltage deviation reduction have been added as penalty terms	• Severe line outages have been taken into consideration to improve voltage stability	• It considered real power of generators as decision variables which have more effects on losses • More complex by solving both P and Q optimization problems in a single step

(*continued on next page*)

Table 2 (*continued*)

Category	Ref.	Remarks	Capabilities	Demerits
	[17]	• A Self Adaptive DE (Chaotic DE) algorithm has been implemented to the RPP problem. It changes the mutation and crossover parameters to be updated each generation	• Self adaptation of mutation and crossover rates to improve efficiency	• Efficiency is still sensitive to population size • More computational burden
	[42]	• An improved model of DE has been presented to minimize both the energy loss and the installation costs while, the critical lines and buses to install FACTS controllers have been determined based on FVSI	• The mutation factor has been changed dynamically instead of being constant as in the classic DE model	
	[6]	• A new adaptive DE algorithm called (JADE-vPS) has been applied to minimize the total fuel cost with satisfying a minimum voltage stability margin for the optimal power flow. In this paper, an adaptive penalty function has been introduced where the penalty coefficients has been altered automatically from data gathered from the search process	• Not only mutation factor and crossover rate have been already self-adapted, but also population size has been automatically adapted in a very similar manner to the other two parameters.	• High computational burden and complexity
Immune Algorithm (IA)	[8]	• IA has been implemented in adaptive model to solve the reactive power flow in order to minimize power losses, voltage deviation, and enhance static voltage stability. Crossover rates, mutation rates and clone rates have been used all adaptive to change automatically at each generation related to the global affinity function	• Adaptive parameters avoid premature convergence and falling into a local optimal solution trap • Good efficiency and convergence	• More computational burden and complexity
Seeker Optimization Algorithm (SOA)	[46,48]	• In [46], SOA has been executed to the ORPD problem to minimize the real losses as a single objective function. In [48], SOA has been implemented to minimize the power losses, voltage deviation and increasing voltage stability using L-index. This ORPD has been handled as minimizing different single objective functions	• Easy to understand • Suitable performance in balancing global search ability and convergence speed • Although SOA handled only continuous variables, Refs. [46,47] tackled this problem by searching in a continuous space, and then curtailing the corresponding dimensions of the seekers' real-values into the integers	• SOA may be stuck at a local optimum for multi-modal functions • SOA is heavily dependent on its structures and parameters
	[47]	• A multi-objective reactive power control has been addressed using SOA. In this paper, the multi-objective functions were to minimize the transmission loss and voltage deviations while the voltage stability margin would be maximized by minimizing the eigenvalue of the non-singular power flow Jacobian matrix		• The different objectives have been normalized to be treated as a single objective with weighting factors • Such complexities to determine the weighting factors
Harmony search algorithm	[43]	• HS method has been used to determine the locations and the outputs of Static VAR Compensators (SVCs) to minimize the total investment costs, average voltage deviation and total system loss	• Simple in concept • Easy to be implemented • Suitable convergence speed	• It is dependent on three parameters which are harmony memory considering rate, pitch adjustment rate, and bandwidth vector

	[45]	• HS algorithm has been to minimize transmission loss, L-voltage stability index, and voltage deviation		• Each objective function has been handled separately as a single objective optimization
	[44]	• An Improved Harmony Search (IHS) algorithm has been carried out to reduce losses, installation cost, and achieve better voltage improvement by assigning the SVC placement and sizing	• Dynamically Altering PAR and b_w to eliminate the drawbacks of keeping constants in the HS model	• More computational burden and complexity
Evolutionary programming (EP) and evolutionary strategies (ES)	[50,51]	• EP and ES work on the basis of organic evolution models. In [50], the RPP problem has been decomposed into P and Q optimization modules and each one is solved iteratively using EP and evolutionary strategy • In [51], the RPP problem has been solved using EP method considering the highest load buses to place the new VAR sources	• Simple and direct method to represent system variables • More randomness • Good diversity • ES converges faster compared to EP • EP is less likely to fall into a local minimum	• ES has a higher probability to fall into a local minimum • No guarantee for finding optimal solutions in a finite amount of time • Parameter tuning is needed • Such a complexity in the system of mutations
	[54]	• EP technique has been applied to solve two separate RPP procedures which addressed the optimal reactive power dispatch and the optimal transformer tap changer setting		• A single objective optimization has been implemented for minimizing only transmission losses
	[66(Ch. 6),67]	• A Covariance Matrix Adapted Evolution Strategy (CMAES) has been employed to solve the RPP problem. In [67], the RPP problem handled the voltage stability index (*L*-index) as an additional constraint with specified threshold • In [66 (Ch. 6)] , CMAES has been applied to solve RPP problem in hybrid (pool and bilateral coordinated) electricity market. In this chapter, different objectives have been considered which were the total production cost of real and reactive power and the allocation cost of additional reactive power sources (SVC)	• Self-adaptation of the covariance matrix (CM) and the global step size during each generation to increase efficiency • Due to its consistency, CMAES has been usually used to generate reference Pareto-front to compare the performance of other MOAs [31–33,66 (Ch. 8)]	• Slower convergence performance • The adaptation process in CMAES is very complex and the computational burden of sophisticatedly strategy parameters is very high
Ant Colony Optimization (ACO) algorithm	[55]	• ACO algorithm has been hybrid with immune algorithm to solve the problem of reactive power optimization to reduce only the transmission loss	• Stochastic kind • Inherent parallelism • Adaptation capability • Using positive feedback	• Using trial and errors to parameters initializations • Its mathematical execution and analysis is difficult • slower convergence speed
	[7]	• The ORPD has been solved using ACO method to minimize the losses as a single objective function. Sensitivity parameters have been used to express objectives and dependent variables in terms of control variables and based on a modified model of fast decoupled load flow	• Convergence is guaranteed	• Linear approximation using sensitivities • Each objective function has been handled separately as a single objective optimization problem
Particle Swarm Optimization (PSO) algorithm	[58]		• Simple in concept • Easy to be implemented • Suitable convergence speed	• Slow convergence rate • Trapping into local optima

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Table 2 (*continued*)

Category	Ref.	Remarks	Capabilities	Demerits
		• PSO algorithm has been applied to find the optimal placement of FACTS devices based on the contingency severity index (CSI) values which consider single and multiple contingency	• Efficient • Having few parameters to be adjusted • Less dependent on initial points	• It is dependent on the inertia weight and learning constants. • Using trial and errors to parameters initializations • The effect of tap settings hasn't been considered for more simplicity in handling the RPP problem as a stage of the TEP problem
	[2]	• PSO method has been applied to the RPP problem as a second stage to minimize of the VAR investment costs. This model considered load uncertainties and the uncertainties of wind turbine output obtained by a probability distribution function (PDF) using MCS while the reliability has been taken into consideration		
	[56]	• PSO algorithm has been used for solving the RPP problem to minimize the operation cost and investment cost of reactive power sources	• Handling the integer variables has been done by rounding it to the nearest discrete after relating it as floating variable	• The state variables have been added to the objective as penalties, such complexity is existed to determine the penalty factors
	[57]	• The RPP problem has been solved using PSO technique incorporated with Pareto dominance to minimize real power losses and installation costs	• A well-distributed Pareto front by adding an external archive to decide whether a solution can be stored or not, based on Pareto dominance	• More computational burden and complexity to update the best positions based on the global best stored in the archive using crowding and roulette wheel selection
	[16 (Ch. 4)]	• A Vector Evaluated PSO (VEPSO) method has been implemented on the multi-objective RPP problem	• Good efficiency • A fuzzy based mechanism is employed to extract the best compromise solution over the trade-off front	• More computational burden and complexity to determine Pareto front that VEPSO generates two swarms where each one is based on an objective, and to extract the best compromise solution
	[9]	• A modified PSO method has been applied for scheduling of reactive power control variables to maximize the reactive power reserves. In this paper, the ε-constraint approach has been used to assure desired static voltage stability margin based on a proximity indicator	• Better efficiency where, a fly-back mechanism has been applied to enable any violated particle to fly back to its previous position	• More computational burden to execute the fly-back mechanism
Artificial Bee Colony (ABC) algorithm	[59]	• ABC was inspired by the foraging behavior of honey bee swarm. It has been executed for handling the ORPD problem in deregulated power systems after assuming an already established real power market	• It is as simple as PSO and DE with few control parameters such as colony size and maximum cycle number • It is robust against initialization • It has the ability to explore local solutions	• ABC has poor exploitation characteristics • Its convergence speed is also an issue in some cases • It may get stuck in local optimum
Gravitational Search Algorithm (GSA)	[60,61]	• GSA was based on Newton's law of gravity and motion. In [60], it has been applied to the RPP using FACTS to minimize the losses and bus voltage deviations. In [61], opposition-based GSA for population initialization has been presented to solve the ORPD problem	• It is simple and easy to implement • It has a high randomness of the individual moves. Thus, it provides the global exploration in the search space	• The local search ability of GSA is weak • In [60], it isn't robust against initialization. This feature is improved in [61] • In [60,61], the considered problem was formulated as a single objective optimization problem
Firefly Algorithm (FA)	[62]	• FA was based on swarm behavior and has many similarities with PSO algorithm. It has been applied to minimize the real power loss or the voltage deviations	• FA is simple and easy to implement • It is good at exploration • It includes the self-improving process with the current space and it improves its own space from the previous stages	• FA often traps into local optima • The minimization of power losses or voltage profile improvement is handled as a single goal optimization • Its parameters were set fixed and they do not change with the time
Teaching	[63]			TLA often converges to local optima

Learning Algorithm (TLA)		• TLA was based on the simulation of a classical learning process which composed of two phases: (i) learning through teacher and (ii) learning through interacting with the other learners. It has been applied to handle the ORPD problem considering only the power loss	It has balanced global search ability and convergence rate. It has a good capability for global and local searching	The exploration features need more support Power loss was the only considered objective
Chemical Reaction Optimization (CRO)	[64]	• CRO was based on the various chemical reactions occur among the molecules. It has been applied to the RPP using FACTS to minimize the transmission loss, improve the voltage profile and voltage stability	• CRO is easy to implement • However, CRO behaves like a random search to traverse the whole solution space, which could confine the algorithm's search ability • It is robust against initial seeds	• The local search needs more modifications since it may stick in local optima • However, it has good robustness indices for solving the considered RPP in [64], it is highly sensitive to the initial kinetic energy and the concerned loss rate
Water Cycle Algorithm (WCA)	[65]	• WCA is inspired from nature and based on the observation of water cycle and how rivers and streams flow downhill toward the sea in the real world. It has been applied to minimize the weighted sum of the losses and the voltage deviations	• It is simple and easy to use • It has few control parameters • It has a good exploration features	• Its local search ability of is weak • It is often traps into local optima • Its robustness and consistence need more uphold
Differential Search Algorithm (DSA)	[66]	• DSA was inspired by migration of super-organisms utilizing the concept of Brownian like motion. It has been applied to solve the non-feasibility problem solution of the fuel cost minimization problem (for a given operating point) by optimizing the RPP problem • The candidate placements of VAR sources have been selected based on FVSI	• It has a good exploration feature in the search space to locate the region of global optimum • Therefore, its convergence rate is fast but it is also a problem in some cases	• The minimization of fuel cost or load voltage deviations is handled as mono-objective optimization in two separate levels • Transformer tap settings and VAR sources are treated as continuous variables • Its exploitation of the optimal solution requires more support • DSA is still novel and further researches are necessary to be developed and improved
Hybrid techniques	[16 (Ch. 5),68]	• A hybrid PSO-DE algorithm has been implemented for solving the reactive power control problem in electricity market • PSO-DE algorithm carried out a differential operator from DE in the update of particle velocity of PSO	• A selection strategy has been added that a particle is moved to a new location only if the new location yields a better fitness value	• Slow convergence rate • More computational burden and complexity • Both algorithms are very sensitive to the setting of the control parameters • Using trial and errors to parameters initializations
		• A hybrid PSO-GA algorithm has been implemented to minimize the cost of reactive power generation, reactive power compensators and active power losses. BLX-α, and uniform mutation operators from GA algorithm are applied on the PSO particles	• Crossover and mutation are done if there is no change in the global position for a number of iterations to avoid premature convergence	
	[69]	• Another model of hybrid PSO-GA has been performed to search for the optimal placement of SVC. PSO algorithm is implemented firstly until	• Simple hybrid model and easy to implement • Good diversity	• Slower convergence performance • More control parameters which needed to be tuned • Using trial and errors to parameters initializations

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Table 2 (*continued*)

Category	Ref.	Remarks	Capabilities	Demerits
		its stopping iteration number is reached. Then, GA updates the population considering the last PSO population as its initial population		
	[55]	• IA has been combined with ACO algorithm composing a hybrid Artificial Immune Ant Colony Algorithm (AIACA) to minimize objective only the real power losses	• It makes use of the positive feedback principle of ACO method and the rapidity of IA to avoid trapping into a local optimal solution	• Handling the reduction of the transmission loss as a single objective optimization problem • Slow convergence rate
Hybrid techniques	[53]	• A Hybrid Evolutionary Programming method (HEP) has been executed to solve the RPP which combines EP technique as a base stage search toward the optimal region, and a direct search technique to reduce the size of search region to locally search for the global optimum. The fittest individuals in the combined population haven't been chosen in the next generation but they have greater chances than others	• The direct search technique tackles difficulties in a fine-tuning of local search in EP method by direct searching toward the optimal region • Reducing the size of search region • Finer convergence and improving the solution quality	• The direct search technique is very dependent on the initial starting point • Slower convergence speed • Parameter tuning is needed • Such a complexity in the system of mutations
	[70]	• A hybrid method combines the direct search, and PSO technique has been implemented to solve the ORPD, and compared with HEP method		• Handling a single objective optimization problem which is the real losses
	[10,71]	• Evolutionary Particle Swarm Algorithm (EPSO) method has been applied to the reactive power control and planning. EPSO formulation is based on the particle movement like the classical PSO where, the weights are mutated using EP mutation factor	• More diversity of solutions • Considering different contingencies and load levels in [71]	• Such a complexity due to EP mutations • Parameter tuning is needed
	[73]	• A hybrid between fuzzy reasoning approach and PSO method has been introduced. Fuzzy membership of loss sensitivity at each bus has been evaluated to determine candidate buses to install shunt capacitors. PSO has been used immediately to minimize the investment costs and transmission losses as well	• Simple model as it provides two different levels where, fuzzy memberships are used for capacitor placements and the control variables are handled by PSO technique	• It is still dependent on the inertia weight and learning constants • It may trapped into local optima • Using trial and errors to parameters initializations
	[67]	• A Fuzzy Adaptive PSO (FAPSO) method has been presented for solving the problem of reactive power and voltage control. A fuzzy optimization approach based on pseudo-goal function has been used to convert the different objectives, which were the active power loss, voltage deviation and the voltage stability index, into a single-objective optimization problem. Then, this single-objective optimization problem has been solved using the FAPSO approach	• In FAPSO approach, the inertia weight and the learning coefficients have been dynamically varied by fuzzy rules based on the fitness values of particles during optimization process	• More complexity of representing fuzzy memberships • More computational burden to adapt PSO parameters • Slow convergence rate
	[72,74]		• Fast computational performance • Handling easily conflicting objectives	

	• A hybrid between the fuzzy modeling technique and the Linear Programming (LP) method has been introduced for solving the problem of reactive power management [72]. In [74], this procedure has been applied for preparing different preventive control actions to overcome any emergency condition and to restore the system to the normal state		• Linear approximation using sensitivity parameters based on a modified model of fast decoupled load flow
[75]	• A hybridization of PSO and GSA has been introduced to solve the ORPD problem to minimize the losses and the voltage deviations. Both objectives are treated using the weight factors	• This hybrid PSOGSA has better convergence rate compared to PSO and GSA • It has a high global exploration	• The local search ability is still weak • It is sensitive to initialization • It needs more comparisons with other techniques

number of objective functions. A normalization process has been incorporated to the weighted sum approach in [44,47]. In [44], each objective function (real power losses, voltage deviation, and VAR investment cost) has been normalized in a comparative manner with its base case value. Also, the normalization process can be done as a fuzzification process [47] to map all objectives within the range of $[0, 1]$. Then it is generally modeled as weighted sum defined in Eq. (14). The normalization process enables comparing the different objectives in a fairly manner. The optimal solution is greatly affected by the selection of the weights. Another problem associated with this approach is that it may find solutions that are close to one or more operating constraint violations [26].

4.3. The ε-constraint approach

The ε-constraint approach has been used in tackling multi-objective problems of reactive power planning and control [6,18,20,43,76,77]. This method optimizes the main objective (F_m) as a single objective optimization problem while, it considers other objectives as constraints restricted by some chosen threshold levels.

$$\begin{aligned} &\text{Min } F_m \quad \text{while} \quad F_i \leqslant \varepsilon_i \\ &i = 1, 2, 3, \ldots\ldots N_F, \quad i \neq m \end{aligned} \tag{15}$$

where ε_i is a threshold level specified by the user for each objective (F_i). Choosing ε_i is easier than choosing adequate values for weight factors (ω), but the optimal solution still depends on its value. In [20], the capacitors has been installed to minimize the real losses (main objective) while its investment cost has been handled with budget limit (ε-constraint). Also, the loading parameter (λ) has been a constrained to guarantee a minimum voltage stability margin in [6,18]. In [9], Schur's inequality has been used to assure required static voltage stability margin. The eigenvalue analysis has been used as a stability margin proximity indicator where a threshold value of proximity indicator must be specified for secure operation. Also, the objective of enhancing the voltage stability has been achieved by restricting the static voltage stability index (L-index) by a maximum level [76,77].

4.4. The fuzzy goal programming approach

Fuzzy Goal Programming (FGP) has been presented in [29,67] for solving the problem of reactive power and voltage control. The active power loss, voltage deviation and the voltage stability index (L-index) have been converted into a single-objective optimization problem. In [29], GA has been employed as a solution tool to the FGP formulation to minimize the weighted sum of membership goals. Fuzzy adaptive particle swarm optimization (FAPSO) approach has been implemented based on the maximum–minimum value of all membership functions of the objectives and constraints [67]. The main advantage of the FGP formulation is treating the multi-objective as a single objective optimization problem effectively without selecting weights or thresholds as in the weighted sum or ε-constraint methods, respectively.

4.5. The Pareto optimality approach

Multi-objective RPP problem has been achieved using the concept of Pareto-optimality [4,8,16(Ch. 4),17,26,31–34,57]. The solution is said to be Pareto-optimal if there is no a better solution in terms of all objectives.

4.5.1. Methods of creating Pareto front

Meta-heuristic algorithms typically generate sets of solutions, allowing computation of the Pareto set based on the non-dominance concept [8,26,57]. Also, Pareto-front has been created using various runs of single objective optimization with varied weight factors of different objectives [31–34,76(Chs. 7 and 8)]. The ε-constraint method has also been implemented with Pareto optimal front where the specified bounds of objective constraints are changed to get the Pareto front [4]. However, this method is time-consuming and tends to find weak non-dominated solutions in Pareto front since it depends on the objective bounds specified by the user. Moreover, Vector Evaluated PSO (VEPSO) method has been used to solve the multi-objective RPP problem to minimize the operational and installation costs and the voltage stability index (L-index). VEPSO determines Pareto front by generating two swarms, one swarm for each objective [16(Ch. 4)]. The strength of Pareto Evolutionary Algorithm (SPEA) has been used for solving the multi-objective RPP problem to minimize the real power loss and the bus voltage deviations [17]. It firstly stores the non-dominated solutions in an external Pareto set to give scalar fitness values (strength) to individuals. Then, it uses clustering approach to reduce the Pareto set when the number of the non-dominated solutions exceeds the pre-specified value. The fitness (strength) of any individual is calculated based on only the solutions stored in the external Pareto set. The selection operator is applied to the population individuals and all solutions in the external Pareto set.

4.5.2. The best compromise solution over Pareto solutions

Determination of a single optimal solution that simultaneously optimizes all multi-objective functions is difficult. However, the decision makers can perform a trade-off analysis and select among the set of the non-dominated solutions [33,34,57]. The fuzzy decision-making tool has been presented to determine the best compromise solution for the RPP problem [4,16(Ch. 4),17]. Each objective F_i is fuzzified with a membership function μ_i as in Eq. (16) and Fig. 3 shows its related fuzzy modeling. Then, the best solution is selected, which achieves the maximum membership μ^k which is defined in Eq. (17) or the maximum normalizing membership μ^k which is defined in Eq. (18) [4]:

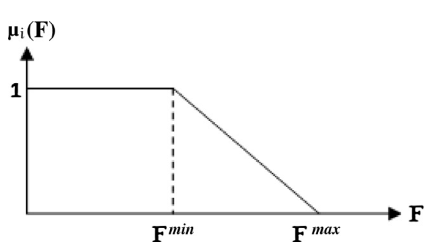

Figure 3 Fuzzy membership model for objective functions.

$$F_i = \mu_i(F_i) = \begin{cases} 1 & F_i < F_i^{\min} \\ \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} \leqslant F_i \leqslant F_i^{\max} \\ 0 & F_i > F_i^{\max} \end{cases} \tag{16}$$

$$\mu^k = \frac{\sum_{i=1}^{M} \mu_i(F_i^k)}{\sum_{k=1}^{N}\sum_{i=1}^{M} \mu(F_i^k)} \tag{17}$$

$$\mu^k = \frac{\sum_{i=1}^{M} \omega_i \mu_i(F_i^k)}{\sum_{k=1}^{N}\sum_{i=1}^{M} \omega_i \mu(F_i^k)} \tag{18}$$

where k refers to each non-dominated solution, M is the number of objectives, n is the total number of the non-dominated solutions, and ω_i refers to weight value of the ith objective function. This method suffers from the problem of how to select the weight values ω_i. In [4], the weight values ω_i has been selected based on the importance of economic and technical aspects. Moreover, the best compromise solution could be obtained using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method [31,32,76(Chs. 7 and 8)] as a multiple criteria decision making approach. In this technique, the relative performance of each non-dominated solution with respect to each criterion is identified and the geometric distance between each solution and the ideal solution in each criterion is calculated. Finally, the best compromise solution can be determined according to the maximum relative closeness to the ideal solution. In [32], TOPSIS approach has been used to rank the obtained MNSGA-II solutions for the reactive power dispatch to minimize two objectives, real power losses and L-index. The best compromise solution has been determined by a single decision maker. In [31], TOPSIS approach has been also used to find the best compromise for the RPP problem to minimize the combined operating and VAR allocation cost improves the voltage profile and enhances the voltage stability. In spite of its simplicity, TOPSIS approach does not take the relationships of different criteria into consideration. On the other hand, Pareto concept has been incorporated to the immune algorithm in [8] to define the partial affinity of an antibody (solution) to each antigen (objective). Then, the best compromise solution was based on the global affinity (sum of partial affinities).

5. Conclusion

Meta-heuristic optimization algorithms are going to be a new revolution in computer science. They opened a new era in the next generation of computation and optimization. In this paper, the solution algorithms of one of the widely significant optimization problems in electric power systems which is the RPP problem are extensively reviewed and thoroughly discussed. They are categorized into analytical approaches, arithmetic programming approaches, and meta-heuristic optimization techniques.

Analytical approaches present detailed information about the installations of reactive power compensators and its economic and technical benefits under different scenarios. They are quite helpful to design future framework of reactive power management and pricing for different players in the deregulated environment. However, they are time-consuming and may not also be suitable for medium and large-scale power systems. They are as accurate as the corresponding OPF model.

Arithmetic programming approaches have been widely used to solve the reactive power operation and planning for years. They are usually based on some simplifications such as sequential linearization and using the first and second differentiations of objective function and constraints. They may converge to a local optimum. They are very weak in handling multi-objective nonlinear problems. On the other side, they have fast computation performance and thus they provide the capability to solve a large number of single optimizations associated with different loading and contingency conditions.

An overview of a range of MOAs drawn from an evolutionary based or swarm intelligence is presented including GA, DE, HS, SOA, EP, ACO, IA, PSO, ABC, GSA, FA, TLA, CRO, WCA, and DSA. Each algorithm is distinguished with different features. Generally speaking, they perform with heuristic population-based search strategies that involve stochastic variation and selection. They are very suitable in solving multi-objective RPP problem. They are robust, effective, consistent, and can find multiple optimal solutions in a single simulation run.

Particularly, the scope of this area is really vast and there are great opportunities in applying novel approaches/algorithms to solve the RPP problem. Moreover, hybridization of different techniques is another research area to make use of different advantages to improve the quality of solution of the RPP problem. Otherwise, the adaptive strategies of MOAs to the strategic parameters are required to reduce the complexities of its selection.

Also, the multi-objective reactive power planning and operation are discussed to clarify their merits and demerits. Meta-heuristic algorithms typically generate Pareto set based on the non-dominance concept. Also, Pareto-front can be created using the conventional weighted sum or the ε-constraint method.

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