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Review

Multi-Objective Planning Techniques in Distribution Networks: A Composite Review

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Abstract: Distribution networks (DNWs) are facing numerous challenges, notably growing load demands, environmental concerns, operational constraints and expansion limitations with the current infrastructure. These challenges serve as a motivation factor for various distribution network planning (DP) strategies, such as timely addressing load growth aiming at prominent objectives such as reliability, power quality, economic viability, system stability and deferring costly reinforcements. The continuous transformation of passive to active distribution networks (ADN) needs to consider choices, primarily distributed generation (DG), network topology change, installation of new protection devices and key enablers as planning options in addition to traditional grid reinforcements. Since modern DP (MDP) in deregulated market environments includes multiple stakeholders, primarily owners, regulators, operators and consumers, one solution fit for all planning scenarios may not satisfy all these stakeholders. Hence, this paper presents a review of several planning techniques (PTs) based on mult-objective optimizations (MOOs) in DNWs, aiming at better trade-off solutions among conflicting objectives and satisfying multiple stakeholders. The PTs in the paper spread across four distinct planning classifications including DG units as an alternative to costly reinforcements, capacitors and power electronic devices for ensuring power quality aspects, grid reinforcements, expansions, and upgrades as a separate category and network topology alteration and reconfiguration as a viable planning option. Several research works associated with multi-objective planning techniques (MOPT) have been reviewed with relevant models, methods and achieved objectives, abiding with system constraints. The paper also provides a composite review of current research accounts and interdependence of associated components in the respective classifications. The potential future planning areas, aiming at the multi-objective-based frameworks, are also presented in this paper.

Keywords: active distribution network (ADN); distributed generation (DG); distributed energy resources (DERs); distribution network planning (DP); multi-objective optimization (MOO); multi-criteria decision analysis (MCDA); distributed generation placement (DGP); volt-ampere reactive power (VAR) compensation and power quality (VPQ); component reinforcement and up gradation (CRU); network (distribution) topology change and reconfiguration (NTR); planning techniques (PT); multiple objective planning (MOP); multi-objective planning techniques (MOPTs); future distribution networks (FDNs)

1. Introduction

Electrical power grids (as hierarchical networks) are traditionally responsible for the unidirectional flow of power from centralized generation sources via transmission networks (TNWs) to distribution networks (DNWs) for ultimate electricity consumption. Increasing load demands, fewer expansion options, increasingly competitive electricity market scenarios and environmental concerns result in stressed operating conditions for both TNWs and DNWs. In comparison, DNWs gets a higher share of stressed conditions due to their design, planning and operation limitations [1]. Traditionally DNWs were purposely planned to operate in a radial configuration to maintain one-way power flow. Such a setup was preferred largely due to simple protection equipment, reduced short circuit currents (SCCs) of the networks, easy control requirements, a safe and economical operation for the end consumer. However, the rapid growth of DNWs and associated loads over large geographical areas results in technical issues like voltage instability, increased system losses, low network reliability, compromised power quality and capacity enhancement concerns, respectively [2,3].

The factors above are motivating system planners to find alternative methods rather than traditional ones, to meet the increased demand and concerned issues promptly. The possible solution strategy calls for planning modifications on short/medium/long-term basis in the potential areas of generation capacity enhancement, improving power quality, load management, emissions control and ensuring overall system reliability.

1.1. Traditional Versus Modern Distribution Planning

Traditional distribution planning (TDP) methods had the narrow aim of finding economically feasible solutions based on single objective optimization techniques. The respective methods usually focus on grid reinforcements with optimal location and capacity of future substations (SSs), feeders (Fr), and conductors (branches) to address future load demands (across the planning horizon). These evaluations usually favor one decision maker (distribution companies) regarding decision support [4]. Major planning restrictions are also faced within TDP when high distributed generation (DG) penetration exists. The DNW design complications may result in further deterioration of the aforesaid technical issues rather than solving them. The conventional "fit-and-forget" approach has resulted in unfeasible costly reinforcements, to address various technical issues and retain DNW within operation limits.

Modern distribution planning (MDP) methods are somewhat both better and complex than their traditional counterparts in various aspects. The most important feature aims at planning with "active network management" (ANM) for increased DG penetration abiding with system operational limits rather than the "fit-and-forget" approach. The concept of ANM introduces new planning concepts in modern planning paradigms, predominately renewable energy sources (RES) integration, distributed storage technologies (STs) and electrical vehicles (EVs); supported by communication, intelligent metering, active demand side management (DSM) and advance distributed automation (ADA) [5]. Another significant feature of MDP methods is that they can exploit various multi-objective planning techniques (MOPTs) to sort out viable trade-off (compromised) solutions among conflicting objectives that satisfy multiple (diverse) stakeholders [6,7].

1.2. Potential Planning Techniques in Modern Distribution Planning

The distribution network planning (DP) problems are becoming more complicated with the active participation of several stakeholders in the competitive energy market. The achievement of acceptable solutions ensuring economic viability, acceptable power quality, utmost reliability and improved operational aspects (better voltage stability and reduced power losses) among major market participants is one of the key motives of modern planning studies. Since the MDP problem essentially needs multi-objective optimization (MOO) methods to find a feasible solution in the setup above, therefore it can be established that MDP is a multi-objective planning (MOP) problem [7–10]. Numerous distribution planning techniques proposed in the literature since the last decade address the complex nature of DP problems from MDP perspectives. Major research accounts are nowadays more focused on DG planning options, conventional solution techniques and modified grid reinforcement strategies [6–17].

Wang et al. [6] provided a review of multi-criteria decision making (MCDM) for decision aids in MOP problems till 2009. A critical review of "state-of-the-art survey" was presented by

Rodriguez et al. [7] regarding MO-based DG/DER planning methods till 2009. Georgilakis and Hatziargyriou [8,10] presented two notable planning surveys for optimal DG placement and grid reinforcements, respectively. The multi-objective planning (MOP) problem had partially addressed in both works. Kalambe in [9] offered a bibliographic survey regarding single objective techniques focusing on loss minimization for DG, capacitor placement, and network reconfiguration (NTR) respectively. DG as an attractive planning alternative for utilities regarding loss minimization, voltage stability and deferring costly grid reinforcements has advocated in [10–12].

The integration of RES-based DGs (REG) to achieved clean energy and emission reduction are among the notable motives for researchers. However planning with only high penetration of REG is not very productive due to the limitations in traditional operational (inadequate reactive power support at unity power factor, power quality) and protection capabilities of current DNWs [13]. Hence, volt-amphere reactive (VAR) power compensation and power quality issues have been addressed with planned allocation of capacitors [14] and advanced power electronic devices [15]. The protection issue has addressed with planned allocation of protection and automation devices; to ensure reliability and system stability under both normal and emergency scenarios [16]. Also, a few new MDP strategies are employed to address load management issues by employing coordinated planning of multiple components (DG units, capacitors, protection devices) with NR (and/or topology alteration) [17–19].

A review of the literature shows that most of the planning techniques address single objectives optimization on a large scale. However, little attention is paid to various planning techniques (PTs) in multi-objective framework [20], which can be interdependent, integrated and coordinated with traditional planning options from a MDP viewpoint. Hence the potential planning techniques in this paper are distinctly classified into four categories. The first category covers planning components, primarily DG units (of various types and concepts), STs and EVs. The second category comprises capacitors (types) and power electronic devices, to ensure VAR compensation and power quality. The third category contains protection, automation devices, and traditional grid reinforcements to guarantee reliability and system stability under new or expansion planning scenarios [8,18,19]. Finally, network topology optimization with alteration and/or NTR (to retain the radial nature of distribution systems) has been considered as a planning option.

1.3. Paper Contribution

The paper presents a composite review of prominent planning techniques applied to distribution systems. Most notably, the review indicates the interdependence and coordination of planning components in MDP. The core focus of this paper will remain on four MOPTs, associated methods, achieved objectives and associated taxonomy (consisting of 80 papers published in the last decade as a whole, since 2005 in particular and more specifically after 2010) on a relatively large number of works. The PT categorizations have designated in this paper by DG placement (DGP) [21–52]. Followed by VAR compensation and power quality (VPQ) [53–70]. Moreover, component (protection and automation devices) placement, modern grid reinforcement and upgrades (CRU) [71–89]. Finally a change of topology and/or NTR has discussed as a planning option in [90–100]. The details in each category are discussed in later sections. Besides distinct classifications, the interdependence of individual planning components in each PT will also be presented. This work compliments the existing works by:

(1) Offering a composite review for researchers, planning engineers and distribution companies, regarding multiple planning techniques aiming at MDP under MO framework.
(2) Presenting planning components' interdependence, interaction, coordination (in each PT) and addressing the contributions of each PT from the perspective of MOO in DNWs.
(3) Discussing objective attainment, methods, test systems, challenges/requirements and future research directions.

It is a well-established fact that real world planning problems are multi-objective (MO) in nature. Also, more investigation is needed to carry out realistic (MO) planning by upgrading conventional to smart DNWs or redesigning them from the beginning. Hence, the core aim of this paper is to provide a background for future distribution network (FDN) planning on the basis of the limitations perceived in available works and from the perspectives of MO achievement.

The paper is organized as follows: Section 2 covers classification details of planning techniques, objectives, MO formulations and major considerations for MOP models. A composite review of studied works has presented regarding decision variables, constraints, objectives, test systems, methods and considered models within PT taxonomies in Section 3. Section 4 outlines MO method classification. The contribution of the reviewed work has presented in Section 5. Future research directions have been suggested in Section 6. The paper concludes in Section 7.

2. Classifications of Planning Techniques and Key Enablers

The primary objective from the perspective of planning, operation, and upgrading of any DNW is to meet the demands of end consumers in a better, safe, economical, reliable and timely manner (planning horizon). The general DP problem is considered a mixed integer nonlinear programming problem (MINLP) [8,10]. The TDP problem focuses on minimization of economic cost objectives for traditional reinforcements subject to a set of constraints. The MDP problem focuses on planning techniques (PT) from various aspects, multiple objectives, decision variables, load models while abiding with system constraints. Based on our literature survey, four PTs are presented in Sections 2.1–2.4.

2.1. Distributed Generation Placement (DGP)

The DG is defined as "a small-scale electrical power generation source connected directly to the DNW or on the consumer side of the meter". The DG type by connection and voltage level includes DGs on the DNW side with a medium voltage (MV) or low voltage (LV), whereas usually LV is on the consumer side. The DG units connected directly to DNW (close to load centers) are considered as an attractive planning alternative for utilities worldwide. However, high DG penetration has changed the nature of DNW from passive to an active one with bidirectional power flows. The prominent benefits attributed to DGP-based planning include voltage support, loss minimization, an alternative to costly reinforcements, and reduction of GHG (with REGs). Broader DG concepts by types are covered in [11–13] as follows:

- Conventional (synchronous) DG units, for example, microturbines and diesel generators.
- Non-conventional, for example, fuel cells (FCs), EVs, plug-in EV (PEV).
- Wind (asynchronous) and photovoltaic (PV/electronic converter)-based REG units.
- Distributed energy resources (DERs) concepts (including DG, ST, and RL).
- Various types of storage technologies (ST) and concepts like DSS.

2.2. Volt-Ampere Reactive Power Compensation and Power Quality (VPQ)

Capacitor (Cap) placement is one of the oldest techniques, still in use today (as shunt capacitor banks). They primarily provide VAR compensation within DNWs (located at SS or distributed in the field) to reduce reactive power losses, power factor correction and voltage stability. Moreover, improvement in power electronics, particularly FACTS devices and power filters, make room for modifications in planning approach, which is meeting load demands ensuring both VAR compensation and power quality during the planning process. The broad VPQ category, comprising of planning components, are arranged as per following types [14,15]:

- Capacitor types: Fixed, switched and combined fixed/switched (VRCs).
- Power electronic devices types: FACTS (SVC and STATCOM) and power filters (passive, active or hybrid).

2.3. Component Reinforcements/Allocations and Upgradations (CRU)

The main motive of this technique is to find a most economical solution for future substations, feeders, and upgraded devices to meet future requirements ensuring the quality of service promptly. It can be divided into two sub-classes as follows [10,16].

2.3.1. Grid Reinforcement Component (GRC)

This sub-class mainly deals with the traditional planning aspects for network expansions and component replacement for a static or dynamic period [4,10]. Main GRCs include: (1) branches or cables or conductors (Br); (2) feeders (Fr); (3) transformers (TF); (4) substations (SS).

2.3.2. Grid Upgrades with Devices/Components (GUC)

This sub-class deals with the grid upgrading with devices or components [14,15], vital for necessary upgrades, such as: (1) automatic-reclosers (RA) for automation/protection; (2) normally open (NO)/tie-switches (TSW) and normally closed (NC)/sectionalizing switches (SSW) placement in DNW for load management; (3) devices placement like voltage regulators (VR) or automatic voltage regulators (AVRs) and online tap changers (OLTCs).

2.4. Distribution Network Topology Alteration and Reconfiguration (NTR)

This technique refers to the operational planning with variation in the DNW topology [17–19]. Topology changes are realized by changing the open/close status of (SSW/NC and TSW/NO) switches to ensure primarily radial configuration, load management and system protection (with unidirectional power flow) in current DNWs. The topology can be changed to loops by simply closing TSW between two radial feeders with an advanced or upgraded protection scheme. However, the key motive is to find the best switching combination that ensures system loss reduction, cost minimization, ensuring the quality of service and reliability. Other benefits attributed to NTR include load balancing and planning maintenance outages.

2.5. Classification of Objectives

Any planning process aims towards achieving maximization (↑↑) and minimization (↓↓) of certain objectives respectively. The objectives associated with the planning have broadly classified into four major types, which have presented in the Sections 2.5.1–2.5.4, respectively.

2.5.1. Technical Objectives

(1) *Network power losses (NPLs)*: The minimization (↓↓) of system losses in the literature have been addressed as energy losses in distribution lines (EL), real/resistive (P-loss), reactive/inductive (Q-loss), P-loss index (ILP), Q-loss index (ILQ) and reactive power deviation (QPD).
(2) *Voltage stability (VS)*: The voltage objective from the maximization (↑↑) aspect in the literature has been evaluated regarding magnitude of profile (VMP), profile index (VPI), stability level (VSL), stability index (VSI), stability margin or load-ability limit (VSM) and high-level limit (MaVL). Also, voltage criteria regarding minimization (↓↓) have been addressed as sag level (VSgL), deviation/drop (VD) and total variation (TVV). Furthermore, an error at power buses (VEPB), unbalance profile (VUBP), deviation index (IVD), minimum limit (MiVL) and level at DG (VLDG) have been minimized.
(3) *Power quality (PQ)*: Objectives have achieved with minimization (↓↓) of total harmonic distortions (THD); voltage THD (VTHD) (↓↓), P-loss under THD (PLHD) and reactive current component (QIC).
(4) *Capacity enhancement*: Maximization (↑↑) with DG is designated with penetration (CEDGP) and penetration level (DGPL) respectively.
(5) *Load balancing (LB)*: Must be achieve with a minimum number of switching actions for NTR (↑↑).

(6) *Reinforcement components*: The performance is normally evaluated as the possibility of overload (OL) at SS, Fr, loads nodes (LN) (OLSSFrLN) (↓↓), feeder current flow (FCF), reserve capacity of conductor (RCC) and RCC index (RCCI). Other performance indicators are capacity security margin of TFs and feeders (CSM) (↑↑), network capacity release (NCR), current carrying capacity of branch (CCC) (↑↑), CCC index (CCI) (↑↑), line loading Index (LLI) (↑↑) and line flow limit index (IC).
(7) *Protection*: Primarily evaluated with performance based indices. Notably, short circuit level (SCL) (↓↓), short circuit index (SCI) (↓↓), three-phase short circuit (3-ph-SC), single-phase-ground (1-ph-G), fault current level (FCLL) due to DG (FCLLDG) (↓↓).
(8) *Overall system stability*: Besides voltage, frequency and phase angle; is evaluated with critical clearing time (CCT) for transient stability (↓↓) and average network security index (ANSI) (↑↑).

2.5.2. Economic Objectives

(1) *Project planning costs*: They have been addressed in the literature; aiming at minimization of (↓↓) payback year (PBY), net present value (NPV) of components/systems, project installation (ItC), network upgrading (CNU) and annual (AC) costs. The objectives are also targeted at maximization of (↑↑) time deferral in new installations and economic index (EI), respectively.
(2) *System running (operation) costs*: These objectives comprise cost minimizations (↓↓) in investment (InvC), operation (OC), maintenance (MC), O&M (OMC), investment and operation (IOC) and capacity adequacy cost (CAC).
(3) *Stakeholder economics*: They concern objective maximization (↑↑) of profits, net savings (NS), the benefit to cost ratio and DG owner income (DGOI).
(4) *Technical costs*: These involve cost minimization (↓↓) of power (CPL) or energy (CEL) losses and overall power losses during operations (OCPL) (↓↓).
(5) *Cost of reliability*: This has been evaluated regarding overall cost minimization (↓↓) with the reliability indices, such as energy not supplied (CENS), system average interruption frequency index (CSAIDI), interruption (IntC) non-distributed energy (NDE) and customer service interruptions (CSI). Also, cost objective minimization (↓↓) concerning customer interruption (CIC) and DG unavailability (DGUI) have also considered in the literature.
(6) *Market economics*: Market-based objectives concern the minimization (↓↓) of economic risks in electricity market price (EMP) and cost of purchased energy (CPE) (↓↓).
(7) *Planning component costs*: The monetary functions, focusing on a wide range of planning components, have been evaluated as cost (or investment) minimization (↓↓) of: (1) equipment (EC); (2) switching (SWC); (3) NTR operations (NRC); (4) capacitor (CC); (5) DG installation (CDG); (6) DG investment (DGI); (7) voltage regulator (VR); (8) VRC (CVR/C); (9) DG and PPF (ICDGPPF); (10) switch purchase and maintenance (SPMC); (11) reinforcements (IRC); (12) energy loss reduction (ELC); (13) DG and capacitors (IC_{All}); (14) monetary risk (MnC) and (15) system upgrades (SUCs).
(8) *Other planning-related costs*: The addressed objectives in this subcategory deal with cost minimization (↓↓) of investment, EL and O&M cost (IELOM); system planning (SCP), overall fixed and variable cost (OFVC) and overall new and old devices (COD). Also, includes operation and investment (EOI); total operation cost (TOC); expected global cost (EGC) and overall complete system (OCS) (including installations, O&M, power losses, reliability excluding profits).

2.5.3. Techno-Economic Objectives

(1) System efficiency (↑↑).
(2) Optimizing spinning reserve (SR) (↓↓).
(3) Social benefits have addressed in the literature improving electricity service quality (↑↑), reducing the unit rate for consumers (↓↓) and consumer interruption level (CILL) (↓↓).

(4) Electrical service security and control (↑↑).
(5) System reliability maximization (↑↑) can be achieved with objective minimization (↓↓) of: (1) system average interruption frequency index (SAIFI); (2) system average interruption unavailability index (SAIUI); (3) system average interruption duration index (SAIDI); (4) energy not supplied (ENS); (5) ENS for average case (AENS); (6) expected ENS (EENS); and (7) overall contingency load loss index (CLLI).
(6) Techno-economic hazards minimization (↓↓) has considered as objectives addressing system failure, malfunctions and conditional value at risk (CVaR).
(7) Reliability of DG (DGR) (↑↑).

2.5.4. Environmental Objectives

(1) *Greenhouse gases* (GHGs): The minimization (↓↓) of GHG emissions (GHGE) are among the key objectives of modern planning. In literature, emissions have addressed with minimization (↓↓) of average (annual) GHG (ACE), grid (GHGG) and DG (GHGDG) respectively.
(2) *Penetration of REGs* (↑↑).
(3) *Energy diversity with REG* (↑↑).
(4) *Cost and quantity* of fossil fuel saving with less costly alternatives (↓↓).
(5) *REG-based objectives*: They principally deal with minimization (↓↓) of external cost of energy (ECE); power buying (PB) from SS (PBSS) and DG owner (PBDG); energy imported from the grid (EIG) and distributed storage system (DSS) energy losses (DEL). Also, energy export from DG (REG) to grid (EEDG2G) needs to be maximized (↑↑).
(6) *Health care costs* due to GHGs and particle emissions needs to be minimized (↓↓).

2.6. Classification of MOP Formulations

The classic TDP techniques were single objective, single stakeholder, and single dimensional approaches. In contrast, MDP considers diverse stakeholder participation in the presence of various planning techniques, active network management and ownership (distribution system operator, DG operator, consumer, etc.) has led to planning objectives that are conflicting in nature. For example; switching radial DNW topology to loop will increase DG penetration, improve voltage and increase reliability, however, system losses increases. Therefore MOO can be employed to bring a compromise solution among conflicting objectives, abiding system constraints to satisfy all stakeholders. Finding a single solution for MOP involves two steps, comprising of optimization and decision making (DM). Depending on the order, in which these steps have performed, MO formulations can be classified as two core approaches (classes), shown as follows [6,7,20].

2.6.1. MO + W or Priori Class

In this type of formulation, DM precedes optimization. The multiple objectives transform into the single objective function, and the individual weights are assigned to each objective by user-defined (decision maker) preferences before execution of optimization algorithms. This class is also known for a priori articulation of preferences. The optimization of the single objective function is more qualitative in nature (with preferred weights) and results in a single optimized solution. Also, a great deal of background knowledge is required to evaluate the required weights. Key methods like goal programming and MO performance index (IMO) can be included in this classification. The DM approaches utilized in these formulations are generally from the family of multi-criteria decision analysis (MCDA). Major MCDA-based DM techniques employed in MO formulations include weighted sum method (WSM), weighted product method (WPM), analytical hierarchal process (AHP), max-min and fuzzy DM (FDM) approaches. For simplicity, this type of problem is shown with term "MO + W" in the rest of the paper.

2.6.2. MO-P or Posteriori Class

In this class, optimization is preferred over DM to achieve realistic solutions. An optimization algorithm determines a set of potential solutions (Pareto frontier), also called Pareto optimal set solutions, and are usually non-dominated (or non-inferior) in nature. The decision maker then chooses a solution from the resulting Pareto set on the basis of respective preferences, also called posteriori articulation of preferences. It is important to note that MO solutions obtained with no articulation of preferences are related arbitrary to the class of Pareto optimal set. Such approach is more quantitative in nature, and evolutionary (meta-heuristic) algorithms have normally utilized as optimization processes. This type of problem formulation has shown with the term "MO-P".

2.7. *Classification of Models in MOP*

The associated classifications of key enablers aiming at MOP problem, have presented in Sections 2.7.1–2.7.6, respectively.

2.7.1. Key Decision Variables (DV) for PT

- *DGP*: (1) Location (L); (2) capacity (C); (3) L + C; (4) L + C + Type (T) (DG/DER or storage (ST) or others like EV); (5) L + C + Number (N) (single (S) or multiple (M)); (6) L + C + T + N.
- *VPQ*: (1) L; (2) C; (3) L + C; (4) L + C + T (capacitor, FACTS devices and power filters); (5) L + C + N; (6) L + C + T + N.
- *CRU/GRC*: (1) Feeder (Fr.) location (L); (2) Fr. location (L) and capacity(C) (L + C); (3) substation (SS) location (L) + SS capacity (C) + Fr. (L); (4) SS (C) + Fr. (L + C); (5) SS (C) + Fr. (L + C); (6) SS (L + C) + Fr. (L + C); (7) SS (L) + Fr. (C) + Load (Ld) allocation; (8) SS (L + C) + Fr. (C) + Ld allocation; (9) SS (C) + Fr. (C) + capacity of reinforcement planning components (SS, TF, Fr. and Br.) and up-gradation devices (DG, capacitor, device, switches) or simply component capacity (Cc); (10) SS (C) + Fr. (C) + Cc + Ld allocation; (11) SS (L + C) + Fr. (L + C) + Cc + Ld allocation;
- *CRU/GUC*: (1) L; (2) C; (3) L + C; (4) L + C + T (VR, SWs, RAs); (5) L + C + N; (6) L + C + T + N.
- *NTR*: (1) L; (2) N; (3) N + L; (4) Switching status (NO/NC); (5) Radial (retained) topology (RT); (6) N + L + (NO/NC); (7) N + L + (NO/NC) + RT; (8) Loop Topology (LT); (9) N + L + (NO/NC) + LT.

2.7.2. Multi-objective Planning Types by Planning Period/Horizon

The general classification of planning can be divided into: (1) short; (2) medium and (3) long term basis. Planning process on the basis of the application comprises of: (1) new; and (2) expansion type considering load growth over the planning period/horizon (PP). A broad classification of DP problems on PP basis includes: (1) static type (one-step/single stage); (2) dynamic type (multistage).

2.7.3. Multi-objective Planning Types by Planning Components Coordination

The optimization problem type can-be related to the planning components or combination of them (interdependence) as follows: (1) optimal DG placement (DGP); (2) optimal capacitor, FACTS devices and PF placement (VPQ); (3) optimal grid component reinforcement, allocation and upgradations (CRU); (4) network topology and/or reconfiguration (NTR); (5) A + B; (6) A + C; (7) A + D; (8) B + C; (9) B + D; (10) C + D; (11) A + B + C; (12) A + B + D; (13) A + C + D; (14) B + C + D and (15) A + B + C + D.

2.7.4. Major Constraints

The most important constraints considered on broader scale includes: (a) Bus voltage drop limit; (b) Power flow equality constraint; (c) Branch/Feeder capacity; (d) Transformer overloading limit; (e) Harmonics limit; (f) Radial operation constraint; (g) Short circuit current limit; (h) Power-factor limit for utilities; (i) Reliability limits; (j) Protection limits; (k) Types of load; (l) Load flow constraint; (m) DG capacity limit; (n) Unique parameter selection limit; (o) DISCO limitation; (p) Cost constraints; (q) Budget constraint; (r) Standard size of components; (s) Planning periods; (t) Weight factor;

(u) Number of components (DG, Cap, devices, switches); (v) Thermal limits; (w) Stability limit; (x) Vector constraint; (y) Real (P) and reactive (Q) power compensation limit; and (z) Future constraints (incorporating new, ANM and other related constraints).

2.7.5. Classification of Load Variables (Models and Profiles)

- *Load Models (LdM)*: The load (Ld) variables are usually modeled as:

  (1) Balanced three-phase loads represented by a single phase load:

    (a) Distributed type loads (across the branches).
    (b) Concentrated type loads (on the nodes/buses).

      i. Constant loads (CLd).
      ii. Variable load (VLd). (Time-varying or voltage dependent).
      iii. Fuzzy load (FLd).
      iv. Probabilistic load (PLd).

  (2) Balanced three-phase loads (BL).
  (3) Unbalanced three phase loads (UL).
  (4) Combined three and single phase loads (UBL).
  (5) Controllable (responsive or flexible) loads (CL).
  (6) Non-controllable/non-linear loads (NL).

- *Load Profiles (LdP)*: The general load profiles have modeled as:

  (1) Single load level (SLL).
  (2) Multiple load levels (MLL).
  (3) Fuzzy load level (FLL).
  (4) Probabilistic load level (PLL).
  (5) Time-varying load level (TVLL).
  (6) Critical load level (CLL).

2.7.6. Test Distribution System Types

The test distribution system by voltage level includes: (1) primary at MV level (6.6 KV–34.5 KV); (2) secondary at LV level (110 V–600 V); (3) combination of both (primary and secondary) DNWs. The test system on application basis may include: (1) real; (2) test DNW, as considered by researchers.

3. Composite Review of MOP Techniques with Taxonomy

In this section, a composite review of related research aiming at PT (individual, integrated and interdependent) is presented from the perspective of the MOP problem. Furthermore, from the readers' comfort viewpoint, the information about planning components (in each PT), decision variables, major constraints, considered objectives, the test DNWs, MO classification, algorithms or methods, planning periods, online year, load models, profiles and concerned information have arranged in tabular format throughout the Tables 1–4, respectively. Planning components associated to each PT in reviewed work are designated with symbols A, B, C, and D, respectively, also shown in an overarching diagram as in Figure 1. The color coding allocated to each PT in the arrangement order includes green (A) for DGP [21–52]; orange (B) for VPQ [53–70]; blue (C) for CRU [71–89] and purple (D) for NTR [90–100]. It is important to note that date of publication in each table represents the online date of the article. In each table, refer to Section 2.7.1 for decision variables (DVs). Major constraints have provided in Section 2.7.4. The objective classifications with abbreviations are provided in Section 2.5. The MO classifications are provided in Section 2.6; planning algorithms are discussed in Section 4 and finally load models in Section 2.7.5.

Table 1. MO Planning with DGP.

Ref.	PT	(DV) (L,C, N, T)	Major Constraint	Objective Function (OF)/Considered Objectives	Test DNW	MO Class/Algorithm/Planning Period (PP)/ Others	Year (Online)/LdM + LdP/Others/
[21]	A.	M/(DG) (L + C)	a), b), c), f),	Cost [Upgradation; purchased energy; losses; energy not supplied] (↓↓)	Real Italian DNW	(MO-P)/GA + ε constrained/Dynamic (20 years)/	May 2005/CLd + PLL/
[22]	A.	M/(DG) (L + C)	a), b), c), e), g), f),	[Cost of energy losses; Voltage deviation; VTHD] (↓↓)	18 Bus Test DNW	(MO-P)/GA + ε constrained/Dynamic (10 years)	Jul. 2005/CLd + PLL/
[23]	A.	M/(DG) (L + C + T)	a), b), c), f), l), q),	[Power losses (↓↓); Voltage Profile (↑↑)]	IEEE 34 Bus DNW	(MO-P)/MCS + GA/Static (1 year)	Mar. 2007/VLd + TVLL/
[24]	A.	M/(DG) (L + C)	a), b), c), f), h), m)	[IELOM, OLSSFrLN, EMP] (↓↓)	9 Bus DNW	(MO-P)/NSGA-II + max-min/Dynamic (30 years)	Mar. 2008/FLd + FLL/
[25]	A.	S/(DG) (L)	a), b), c), f), v)	Single OF (SOF) with weights: [P-loss; Q-loss; VD; CRC; 3-ph-SC; 1-ph-G]	IEEE 34 Bus DNW	(MO+W)/ES/Static (1 yr.)/Wt. (1–6): [0.33; 0.10; 0.15; 0.07; 0.07; 0.15]	Apr. 2008/CLd + TVLL/
[26]	A.	M/(DG) (L + C)	a), b), c), f), m), u), s), k)	[P-loss (↓↓); Voltage Deviation (↓↓)]	IEEE 34 Bus DNW	(MO + W)/Fuzzy goal programming (FGP) + GA/Dynamic (5 years)	Apr. 2008/VLd + MLL
[27]	A.	M/(DG) (L)	a), b), c), f), v)	[EEDG2G (↑↑); P-loss (↓↓); SCL (↓↓)]	IEEE 34 Bus DNW	(MO-P)/NSGA/Static (1 year)	Sep. 2008/CLd + TVLL
[28]	A.	S/(DG) (L + C)	a), b), c), f),	Multi-objective performance index (IMO): [P-loss; Q-loss; CCI; VP]	16 Bus.; 37 Bus Test DNW.	(MO + W)/ES [GA vs. ES]/Static/Wt.(1–4) [0.40; 0.20; 0.25; 0.15]	Feb. 2009/VLd + MLL/
[29]	A. D.	M/(DG) (L + C + T)	a), b), c), f), g),	Single OF (SOF) with weights: FMOI = [VDI; PLI; QLI; LLI; SCI]	IEEE 33; IEEE 69; 25 Bus Test DNW;	(MO + W)/Fuzzy GA + WSM/Static/Wt.(1–5) [0.25; 0.40; 0.15; 0.10; 0.10]/	Jul. 2010/CLd + SLL/
[30]	A.	M/(DG) (L + C + T)	a), b), c), f), l), m), p), q), r),	SOF for total cost of DG: [IC; MC; OC; CAC, NLC]	IEEE 37 Bus DNW	(MO + W)/GA + MCS, AHP/Chance constrained programming (CCP) model/Dynamic (3 years)/Wt.(1–5) [0.34; 0.34; 0.11; 0.11; 0.10]/PEV	Oct. 2011/PLd + PLL/
[31]	A.	M/(DG) (L + C)	a), b), c), f), l), m), n), v)	[P-loss (↓↓); VP(↑↑); VSI(↑↑)]	IEEE 33; IEEE 69 Bus DNW;	(MO + W)/Hybrid GA + PSO [GA: DG (L); PSO: DG (C)]/Static	Jan. 2012/CLd + SLL
[32]	A.	M/(DG) (L + C + T)	a), b), c), f), g),	GMOI(↓↓): [VDI (↓↓); PLI (↓↓); QLI (↓↓); LLI (↓↓); SCI (↓↓)]	IEEE 33Bus DNW; 25Bus Test DNW;	(MO + W)/GA + Goal programing (Goal P)/Static/	Feb. 2012/CLd + SLL/
[33]	A.	M/(DG) (L + C + T)	a), b), c), f), m),	Minimize OF: [EL ; VD] (↓↓)	24 Bus rural DNW	(MO + W)/Two-stage (heuristic iterative method + ES)/Dynamic (3 years)	Sep. 2012/VLd + TVLL
[34]	A	M/(DG) (L + C + T)	a), b), c), k), l), m),v), y),	[OCS (↓↓); DGR (↑↑)] MS * = Maintenance schedule	IEEE 37 bus DNW	(MO-P)/GA + MCOM (Multi-criteria optimization model)/Dynamic (20 years)	Jan. 2013/PLd + PLL/
[35]	A.	M/(DG) (L + C)	a), b), c), f), h), i),	[P-loss (↓↓); VP (↑↑)]	IEEE 33; IEEE 69 Bus DNW;	(MO-P)/IMOHS framework/Static	Mar. 2013/VLd + TVLL/
[36]	A.	M/(DG) (L + C + T)	a), b), c), m), u)	[P-loss (br. & TF); VD; CCT] (↓↓)	IEEE 33Bus DNW	(MO-P)/Hybrid PSO-SFL, FDM/Static/DIgSILENT®/Wt. 0.4–0.9	Jun. 2013/[CLd , VLd (voltage)] + MLL/
[37]	A	M/(DG) (L + C)	a), b), c), f), h), v),w),y)	[P-loss (↓↓); VSI (↑↑); TVV (↓↓)]	IEEE 33; IEEE 69 Bus DNW;	(MO-P)/PFDE/Static	Nov. 2013/CLd + SLL/

Table 1. *Cont.*

Ref.	PT	(DV) (L,C, N, T)	Major Constraint	Objective Function (OF)/Considered Objectives	Test DNW	MO Class/Algorithm/Planning Period (PP)/ Others	Year (Online)/LdM + LdP/Others/
[38]	A	M/(DG) (L + C + T *)	a),b),c),f),h),l), m),p),s),u),z *)	[SCP; GHGE] (↓↓); z * = Plug-in EV (PEV) and REGs	Test 38 bus DNW	(MO-P)/MCS + NSGA II (MINLP)/Dynamic (20 years (Yr.))	Jan. 2014/PLd + PLL/
[39]	A	M/(DG) (L + C + T)	a), b), c), d), f), m), v),	[MnC; GHGE] (↓↓);	9 bus Test DNW	(MO-P)/(Augmented ε-constrained + FCM/MCS) + MINLP framework/Dynamic (10 years)	Jan. 2014/PLd + PLL/
[40]	A	M/(DG + DR + SR) (L + T)	a), b), c), l), m), r), z1), z2),	[TOC; GHGE] (↓↓); z1 = DRP * constraint z2 = spinning reserve (SR) constraint.	69 Bus DNW	(MO-P)/(AεCM)/Dynamic (24 h (Hr.)) for Short-term planning (STP)/ DRP *: Demand response provider	Mar. 2014/PLd + PLL/
[41]	A.	M/(DG *) (L + C + T *)	a), b), c), f), p), q), u)	[ENS (with CVaR); EGC] (↓↓), * DG types: PV, wind, ST, EV	IEEE 13 Bus DNW	(MO-P)/Fast NSGA II, MCS-OPF framework/Static/	Jun. 2014/PLd + TVLL/
[42]	A.	M/(DG) (L + C)	a), b), c), f), m), v)	MOF = min(OF1 + PC1 OF2 + PC2 OF3) [P-loss (↓↓); VD(↓↓); VSI (↑↑)]	IEEE 33; IEEE 69; 118 Bus DNW;	(MO-P)/QOTLBO/Static/PC1 = 0.35; PC2 = 0.65	Jul. 2014/CLd + SLL/
[43]	A.	M/(DG) (L + C)	a), b), c), d), o), p), q)	OF1 = DG owner cost: [DGOI(↑↑); DGI(↓↓); MC(↓↓); OC(↓↓)] OF2 = DISCO owner cost: [PBSS (↓↓); PBDG (↓↓); CIC (ENS) (↓↓)]	IEEE 33Bus DNW;	(MO-P)/MOPSO + FDM /Dynamic (20 years)/Goal1: Cost of DISCO (↓↓); Goal2: DG owner benefit (↑↑);	Aug. 2014/VLd + TVLL
[44]	A	M/(DG) (L + C + T)	a), b), c), k), l), m)	[MnC; GHGE] (↓↓);	IEEE 33Bus DNW;	(MO-P)/IMOPSO-PS/Static (1 year)	Aug. 2014/CL + CLL
[45]	A	M/(DG) (L + C + T)	a), b), c), m), p)	Single OF with weights: [VD; FCF; NPL; ECE; DEL] DSS *: Distributed storage system.	IEEE 34 bus DNW	(MO + W)/MISOCP + AHP/Dynamic (5 years)/Wt. (1–5): [0.0562; 0.0396; 0.2535; 0.6421; 0.0086]/	Sep. 2014/VLd + TVLL/
[46]	A.	S/M (DG) (L + C)	a), b), c), d), f), l), m), v)	IMO: [P-loss; Q-loss; VP; RCCI;]	IEEE 69; IEEE 123 Bus DNW	(MO + W)/S-BB-BC algorithm/Static/Wt. (1–4): [0.40; 0.20; 0.15; 0.25]	Nov. 2014/CLd + SLL for 69 bus; UB + TVLL for 123;
[47]	A	M/(DG) (L + C)	a), b), c), f), v)	Single OF with weights: [ILP; ILQ; VSI; IC; IVD]	Test 38 bus; IEEE 69 bus DNW	(MO + W)/CABC/Static/Wt. (1–5): [0.35; 0.15; 0.10; 0.25; 0.15]	Nov. 2014 /VLd + MLL/
[48]	A.	M/(DG) (L + C)	a), b), c), m), r), z *)	Single objective function: [PBY (↓↓); P-loss (↓↓); VSL (↑↑)] z * = RES penetration constraint	28 Bus rural DNW	(MO + W)/MOPSO + FDM/Static (1 year)/Focus on DSM.	Jan. 2015/VLd + TVLL/
[49]	A.	S/M (DG) (L + C)	a), b), c), f), m)	[P-loss; CDG] (↓↓)	15 Bus DNW	(MO-P)/SQP + WSM, FDM/Dynamic (20 years)/	Apr. 2015/CLd + SLL
[50]	A	M/(DG) (L + C)	a), b), c), f), m), v)	[P-loss (↓↓); VD (↓↓); VSM (↑↑)]	IEEE 33; Real 292; Real 588 bus DNW;	(MO-P)/Improved-NSGA-II (INSGA-II) + FDM/Static (1 year)	Apr. 2015/VLd + MLL
[51]	A.	S/M (DG) (L + C)	a), b), c), m), u)	[NPL; VD; CDG] (↓↓)	IEEE 33Bus Radial DNW	(MO-P)/(MOShBAT)/Static/	Jan. 2016/VLd (Voltage) + MLL
[52]	A. B.	M/(DG + Cap) (L + C + T)	a), b), c), d), f), m), u), y)	[EI (↑↑); VSI (↑↑); ANSI (↑↑); ACE (↓↓)]	28 bus rural DNW	(MO-P)/MOPSO + FDM/Dynamic (5 years)	Apr. 2016/VLd + MLL/

Notes: PT: in Sections 2.1–2.4; DV: Decision Variables (Location, capacity, numbers and types); Constraints in Section 2.7.4; Objectives in Section 2.5; MO Class in Section 2.6; LdM, LdP in Section 2.7.5. Also, "*" indicates any additional information about a particular decision variable, constraint and objective, respectively.

Table 2. MO Planning with VPQ.

Ref.	PT	(DV) (L, C, N, T)	Major Constraint	Objective Function/Considered Objectives	Test DNW	MO Class/Algorithm/Planning Period (PP)/Others	Year (Online)/LdM + LdP/Others/
[53]	B.	M/(Cap) (L + C)	a), b), c), f),	[P-loss; CC] (↓↓)	Portuguese 94 bus DNW	(MO-P)/Tabu Search (TS)/Static	May 2005/VLd + MLL/
[54]	B.	M/(Cap) (L + C + T)	a), b, f),	[NS (↑↑) (with EL (↓↓)); VD (↓↓)]	IEEE 69 Bus DNW	MO + W/Fuzzy-GA (MO) approach/Static/wt(1–2): [0.5;0.5]	Aug. 2007/CLd + MLL
[55]	B.	M/(Cap) (L + C + T)	a), b), c), d), f), p),	[CCI (↓↓); P-loss (↓↓); VD (↓↓); CSM (↑↑)]	IEEE 69 Bus DNW/Two stage approach	(MO-P)/1). IA; 2). Compromise programming (TSIAECP)/Static	Mar. 2008/CLd + MLL
[56]	B.	M/(Cap) (L + C + T)	a), b), c), f), m),	[EL; VD] (↓↓)	12 Bus DNW Radial	(MO-P)/Hybrid SA-PSO, (IBVT) approach/Static (1 year)	Jan. 2009/CLd + MLL
[57]	B. C.	[M/(Cap) + S/(AVR)] (L + T)	a), b), c), f), p), u), x),	[EL; VD; OCS] (↓↓)	IEEE 69 Bus DNW Radial	(MO-P)/(SPEA2) improved with fuzzy logic/Static (1 year)	Aug. 2010/CLd + MLL
[58]	B.	M/(Cap) (L+C)	a), b), c), f), y),	[P-loss; CC] (↓↓)	Portuguese 94 bus DNW	(MO-P)/Elitist NSGA-II (ENSGA-II)/Static/	Jun. 2012/CLd + MLL/
[59]	B. C.	[M/(Cap) + M/(VR)] (L+ C + T)	a), b), c), f), m),	[(CVR/C + OCPL); VD] (↓↓)	IEEE 69; Test 136 bus DNW	(MO-P)/MILP model / Static (1 year)	Jan. 2013/CLd + MLL
[60]	B.	M/(Cap) (L + C + T)	a), b), f), m),	[AC (↓↓); P-loss (↓↓); VD (↓↓)]	IEEE 9; IEEE 34 Bus DNW	(MO-P)/SAMHBMO/Static (1 year)	May 2013/PLd + PLL/
[61]	B.	M/(Cap) (L + C + T)	a), b), c), f), h), l), m), y),	[P-loss (↓↓); VSI (↑↑); NS (↑↑);]	IEEE 34; Test 118 bus DNW	(MO + W)/APSO/Static (1 year)	May 2013/CLd + SLL: 34 bus CLd + MLL: 118 bus
[62]	B.	M/(Cap) (L + C + T)	a), b), c), f), h), l), m), y),	[P-loss (↓↓); VSI (↑↑); NS (↑↑);]	IEEE 34; Portuguese 94 bus DNW	(MO + W)/ABC/Static (1 year)/	Jul. 2013/CLd + SLL
[63]	B.	M/(Cap) (L + C + T)	a), b), c), f), m),	[AC (↓↓); P-loss (↓↓); VD (↓↓)]	IEEE 9; 34; 69 bus DNW;	(MO-P)/AMHBMO/Static (1 year)/	Aug. 2013/CLd + SLL
[64]	A. B.	M/[DG +Cap] (L + C + T)	a), b), c), f), k), l), p), q),	[CENS; CSAIDI; ELC; IC_{All}] (↓↓)	115 bus practical Iranian DNW	(MO-P)/IDEA/Static (1 year)/	Dec.–Jan. 2013–14/VLd [Time and Voltage] + TVLL
[65]	A. B.	M/[DG + Cap] (L + C)	a), b), c), f), h), m),	[P-loss (↓↓); VSI (↑↑); SCI (↓↓)]	IEEE 33; Portuguese 94 bus DNW	(MO-P)/Fuzzy MOPSO + FDM/Dynamic (10 years)/	Dec. 2014/FLd + FLL/Uncertainty
[66]	B.	M/(Cap) (L + C + T)	a), b), c), f), h),	[QIC (↓↓); P-loss (↓↓); CCC(↑↑); MiVL (↓↓); MaVL (↑↑)]	51 Bus Test; IEEE 69 Bus DNW	(MO + W)/Fuzzy-GA (MO) approach/Dynamic (20 years)/	Dec. 2015/VLd + MLL
[67]	B.	M/(Cap) (L + C + T)	a), b), c), f), h), l), m), y),	Strategy 1: Minimize cost: [CCP; CCI; OMC; EL] (↓↓) Strategy 2: Technical: [P-loss (↓↓); VMP (↑↑); VUBP (↓↓)]	60 bus real unbalanced Australian MV DNW	(MO + W)/MIP problem with BSFS load flow based PSO method + WSM/Dynamic (30 years)/	Jan. 2016/UBL + TVLL
[68]	A. B.	M/[DG+PPF] (L + C)	a), b), c), f), l), m), w),	[THD; PLHD; ICDGPPF] (↓↓)	IEEE 34 Bus DNW	(MO + W)/ABFO/Static (1 year)/PPF: Passive power filter	Jan. 2016/NL + MLL
[69]	A. B.	M/[DG + RA + D-FACTS](L + C)	a), b), c), f), r),	[OFVC; CLLI] (↓↓)	54 bus test DNW	(MO-P)/MOSOA + max-min approach/Static (1 year)	Apr. 2016/CLd + SLL/
[70]	B. C. D.	M/Fr.(L + C)+ [RA + D-FACTS] (L)	a), b), c), f), p), s),	[OFVC; CLLI] (↓↓)	54 Bus Test DNW	MO-P/MOSOA + max-min approach/Static (1 year)/ADA: Advance distributed automation	May 2016/CLd + SLL/(ADA)

Notes: PT: in Sections 2.1–2.4; DV: Decision Variables (Location, capacity, numbers and types); Constraints in 2.7.4; Objectives in Section 2.5; MO Class in Section 2.6; LdM/LdP in 2.7.5.

Table 3. MO Planning with CRU.

Ref.	PT	(DV) (L, C, N, T)	Major Constraint	Objective Function/Considered Objectives	Test DNW	MO Class/Algorithm/Planning Period (PP)/ Others	Year (Online)/LdM + LdP/Others/
[71]	C. D.	M/(SS, Fr.) (L + C + T)	a), b), c), m), p), r),	[OFVC; ENS] (↓↓)	41 nodes,2 SSs, 73 routes; Radial and Mesh (10 × RF *);	MO-P/NSGA + SPEA, FCM)/Static/ RF * = Reserve feeders for loop	Nov. 2006/CLd + SLL/
[72]	B. C.	M/[(SS, Fr, SSW)] + [M/(Cap)] (L + C)	a), b), c), f), i), m), n),	[IOC; IOBDRA; CIC] (↓↓)	Urban electric DNW expansion planning Radial;	MO + W/ MINLP + GA/Dynamic (5 years)/Main problem into three subproblems	Dec. 2008/CLd + SLL
[73]	C.	M/(SSW) (L)	a), b), c), f), m), p),	[EENS; COD(SSW)] (↓↓)	Rural Billinton; Iranian DNW;	MO + W/ACO + FDM/Static (1 year)	Jan. 2009/CLd + SLL
[74]	A. C.	M/(DG + Fr) (L + C + T)	a), b), c), f), p), q),	[IOC (DG/DER); DSOROC] (↓↓)	UKGDS 355 bus Radial DNW;	MO-P/Hybrid SPEA2 + OPF/Static (New DNW) (20 years)	Mar. 2009/CLd + TVLL
[75]	C. D.	M/[SW + PD] (L + T)	a), b), c), f), h), i), j), l),	[COD; SAIFI and SAIDI] (↓↓)	18 Bus; Practical 51 Section DNW;	MO-P/MACO/Static (1 year) PD *: Protection devices	Mar. 2009/Dist. Load (DL) + PLL
[76]	A. C. D.	M/[(DG + (SS, Fr) + (SSW)] (L + C + T)	a), b), c), r),	Stage I: [(OCS + TOC); CLLI] (↓↓); Stage II: [{(OCS + TOC); CLLI}; P-loss (↓↓); DGPL (↑↑)]	21 bus; 100 bus DNW;	MO-P/MOPSO/Static (1 year)	Aug. 2010/CLd + SLL
[77]	C.	M/(SS + TF + Fr + Br + SSWs)(L + C)	a), b), c), f), p), q), s), u),	[EOI; CENS] (↓↓)	DNW with 180 load buses: 49 exists, 131 added;	MO-P/MINLP + MORTS + GA/Static (1 year)/RTS: Reactive Tabu Search	Jun. 2011/VLd + MLL
[78]	C. D.	M/(A&M SWs *) (L)	a), b), c), f), i), p),	[CIC; SPMC] (↓↓) A&M SWs *: Auto and manual SWs	IEEE 123 bus DNW;	(MO + W)/MSFLA + Fuzzy approach/Static (1 year)/	Oct. 2011/VLd + TVLL
[79]	A. C. D.	M/(DG + SWs + Br.) (L + C + T)	a), b), c), d), f), n), r),	[CEL; NDE; IRC; EIG] (↓↓)	IEEE 33; Actual 177 bus system;	(MO-P)/MOGA/Dynamic (5 years)	Dec. 2011–12/VLd + MLL
[80]	C. D.	M/(Fr + SWs + TL *) (L + C)	a), b), c), f), j), i), p), q),	[OCS; CLLI] (↓↓)TL *: Tie-Line	21 Bus; 54 Bus; 100 Bus DNW;	MO-P/S1: SPEA2-MOPSO; S2: SPEA2-BMOPSO/Static (1 year)	Dec. 2011–12/CLd + SLL
[81]	A. C.	[M/(SS + Fr + DG] (L + C)	a), b), c), f), i), m), n), p), q),	[IOC; CIC] (↓↓)	Urban DNW 30000 Consumers;	MO + W/IGDSEP model as SCMINLP AGA & IAGA / Dynamic (5 years)	Mar. 2012/VLd + TVLL/Wt.: 19
[82]	A. C.	M/(DG + Br) (L + C)	a), b), c), d), f), m),	[IOC; ENS] (↓↓)	Actual DNW 2-SS, 16 LP, 24 Br;	(MO-P)/Hybrid PSO-SFL/Dynamic (4 years)/	Aug. 2012/CLd + MLL/
[83]	C.	M/(Fr + Br) (L + C)	a), b), c), f), r), t),	[IOC; IntC] (↓↓)	21 Bus; 54 Bus; 100 Bus DNW;	MO + W/Dynamic Programming (DynP)/Static (1 year)	Nov. 2012/CLd (BL) + MLL
[84]	C.	M/[SS+SWs + Fr + Br] (L + C)	a), b), c), d), f), m), n), r),	[COD; NSEC(as AIC)] (↓↓)	54 Bus DNW;	MO-P/MO Tabu search (MOTS)/Dynamic (15 years)/	Jun. 2013/VLd + MLL
[85]	C. D.	M/Fr(L + C)] +M/(RA)(L)	a), b), c), f), r),	[OCS; CLLI; P-loss; VD] (↓↓)	54 Bus DNW; 100 Bus DNW;	MO + W/MOSOA/Static (1 year)/ADA	Jun. 2014/CLd + SLL/
[86]	C. D.	M/[RA + SW] (L + C)	a), b), c), p), s),	[OCS; CLLI] (↓↓)	54 Bus DNW;	MO-P/MOSOA + Fuzzy cardinal priority ranking/Static (10 year)/ADA	Apr. 2015/CLd + SLL/
[87]	C.	M/(SWD) (L + C)	a), b), c), f), t),	[1.EC; 2.SAIDI and SAIFI; 3.DGUI] (↓↓) A1: Min [1 + 2 + 3]; A2: Min [1 + (2 + 3)]	94 Bus Portuguese DNW;	MO-P/NSGA-II/Static (1 year)/Approach 2 (A2) > (A1)/	Sep. 2015/CLd + SLL
[88]	A. C.	M/(DG + FCL) (L + C + T)	a), b), c), d), f), g), j), r),	[FCLLDG; VSgL; EC(FCL *)] (↓↓) FCL *: Fault current limiters	Canadian benchmark test; IEEE 69 bus DNW;	(MO-P)/PSO + NLP/Static	Nov. 2015/CLd + SLL/
[89]	A. C.	S/DG [L + C] + S/OLTC(L)	a), b), c), f), i), z),	[VEPB; QPD; VLDG] (↓↓) z = Using dynamic weights.	IEEE 13; IEEE 34 Bus DNW;	MO + W/MOGA/Static	Dec. 2015–16/UBL + TVLL

Note: "*" indicates any additional information about a particular decision variable, constraint and objective, respectively.

Table 4. MO Planning with NTR.

Ref.	PT	(DV) (L, C, N, T)	Major Constraint	Objective Function/Considered Objectives	Test DNW	MO Class/Algorithm/Planning Period (PP)/Others	Year (Online)/LdM + LdP/Others/
[90]	D.	M/(SW St.) (L + T)	a), b), c), f), j), m), v)	[P-loss; Reliability indices: (SAIFI, SAIUI, SAIDI, ENS)] (↓↓)	Civanlar 17 bus; Baran 33 bus; Real 172 bus DNW	MO-P/Micro-GA (mGA)/Static/	Apr. 2009/CLd + SLL
[91]	D.	M/(SW St.) (L + T)	a), b), c), f), i),	[P-loss; CILL] (↓↓)	Actual Medium DNW, 96 Br, 28 SWs.	(MO-P)/Fuzzy MCDM in "Proof of concept" tool/ Static (1 year)	May 2009/CLd + MLL/
[92]	C. D.	M/(Fr + SW St. *) (L + T)	a), b), c), f), y)	[CIC; NLC; SWC] (↓↓) SW St.*: Switch Status	3 Fr, 16 bus; 8 Fr DNW.	MO + W/ Binary PSO (BPSO)/Static (1 year)/	May 2009/VLd + TVLL/
[93]	D.	M/(SW St.) (L + T)	a), b), c), d), f), v)	[NLC; ENS] (↓↓)	IEEE 33; IEEE 123 Bus DNW;	MO-P/BPSO/Static (1 year)/	Apr. 2012/PLd + PLL
[94]	A. C. D.	M/[DG (L+C)] + M/Fr (L)] + TL	a), b), c), h), w)	[VD; P-loss; CEDGP] (↓↓) TL *: Tie-Line	Sample DNW (3 Fr)	MO + W/GA + MCDA weight/Static/DER control	Nov. 2012/CLd + SLL
[95]	D.	M/(SW St.) (L + T)	a), b), c), d), f), i), m), v)	[P-loss; SAIFI] (↓↓)	33 bus; 67 bus TPC;	MO-P/NSGA-II/Static (1 year)	Mar. 2013/CL + BL
[96]	A. C. D.	M/[DG + Br + SW)] (L + C + T)	a), b), c), f), j), l), m), n), r), s), u)	NPV (↓↓) OF1: [SUC (lines); CPL; NRC; O&M; CDG]; NPV (↓↓) OF2: [CDGG; GHGDG]	Test 38; Test 119 Bus DNW;	(MO-P)/(NSGA)/Dynamic (20 year)/	Aug. 2013/PLd + TVLL
[97]	C. D.	M/(Tie-SW + RA) (L + T)	a), b), c), f), j), v)	[P-loss; ENS; IC (Tie-SWs & new devices)] (↓↓)	IEEE 69 Bus Radial DNW	MO-P/NSGA-II+ non dominated MCS/Static (1 year)/	Oct. 2013/VLd + MLL
[98]	A. D.	M/[DG + SW St. *] (L + C + T)	a), b), c), f), v)	[P-loss; OCS; IC; SAIFI; AENS] (↓↓) SW St. *: Switch Status	Baran & Wu 32 bus test DNW	MO-P/SAMBA/Static (1 year)	Jan. 2014/PLd + PLL
[99]	A. B. C. D.	S/[DG + FACTS] + M/[(TL + SW St. *)]; (L + C + T) *	a), b), c), f), v)	[VP(↑↑); P-loss(↓↓); LB(↑↑)] SW St. *: Switch Status	IEEE 33 Bus; TPC Test DNW	MO + W/Fuzzy-ACO/Static/Wt.(1–3): (0.33 each)	Jan. 2015/CLD + MLL/
[100]	A. D.	M/(DG + SW St.] (L + C + T)	a), b), c), f), h), m), v), w)	[P-loss(Br and TFs); OC (SS + DG); CCT] (↓↓)	33 Bus DNW Radial	MO-P/EGSA + FDM/Static/	Mar. 2016/ VLd + TVLL/

Notes: PT: in Sections 2.1–2.4; DV: Decision Variables (Location, capacity, numbers and types); Constraints in Section 2.7.4; Objectives in Section 2.5; MO Class in Section 2.6; LdM, LDP in Section 2.7.5. Also, "*" indicates any additional information about a particular decision variable, constraint and objective, respectively.

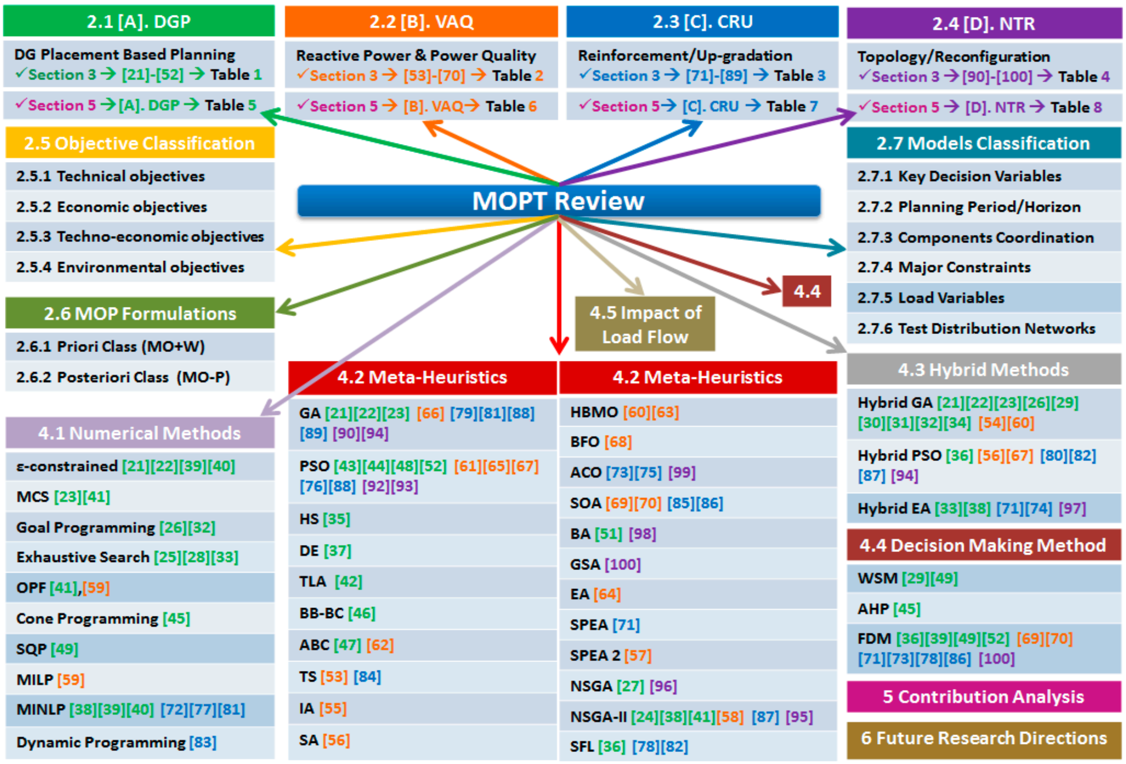

Figure 1. An overarching diagram of the paper.

4. Planning Techniques based on Evaluation Methods in Multi-objective Planning

The methods employed in MOP problems spread across four PT (as indicated in taxonomies of Tables 1–4) can be broadly categorized into numerical, meta-heuristics, hybrid and decision-making methods respectively. In addition, main contributions of reviewed work are shown chronologically in Tables 5–8.

Table 5. The contribution of MODGP-based planning methods and related works. (PTC: Components in planning techniques; MODGP: MO based DG placement).

Ref.	Year	MO	PTC	A	B	C	D	Contribution of MODGP-Based Planning
[21]	2005	4	1	✓	-	-	-	MODGP formulation based on GA and ε constrained method is proposed to solve the best compromise (tradeoff) solution for DM (DISCO).
[22]	2005	3	1	✓	-	-	-	Similarly, with the same formulation (GA and ε constrained method), a double tradeoff method is presented to find the best alternative.
[23]	2007	2	1	✓	-	-	-	MCS embedded in GA planning methodology is proposed to improve the accuracy for stochastic DG integration with tradeoff solution.
[24]	2008	3	1	✓	-	-	-	NSGA-II along with max-min approach solves MODGP problem considering future load uncertainties and risk management
[25]	2008	6	1	✓	-	-	-	EA is employed to solve IMO considering both time-varying generation and demand behavior aiming at various technical impacts of DGP
[26]	2008	2	1	✓	-	-	-	GA with goal programming methodology finds a solution with associated uncertainties among MO and constraints.
[27]	2008	3	1	✓	-	-	-	The proposed NSGA algorithm finds arrangements for wind-based DGs regarding compromise solution among contrasting objectives.
[28]	2009	4	1	✓	-	-	-	An exhaustive search analysis (ES) has presented with IMO for MODGP problem under variable load conditions. GA is also used for comparison of results and advocated for large DNW systems even with suboptimal solutions.
[29]	2010	5	2	✓	-	-	✓	A fuzzy embedded GA is employed to solve fuzzy weighted single objective function employing fuzzy set theory for MODGP.
[30]	2011	5	1	✓	-	-	-	MCS-embedded GA is presented to solve chance constrained programming framework considering future uncertainties of loads/DGs.
[31]	2012	3	1	✓	-	-	-	A hybrid GA-PSO is proposed to solve MODGP problem regarding DG location (with GA) and capacity (with PSO) respectively.
[32]	2012	5	1	✓	-	-	-	A goal attainment method (GoA) has presented, where goal programming transforms multiple objective functions into a single objective function, which is further solved by GA to ensure optimal DG (wind) planning.
[33]	2012	2	1	✓	-	-	-	MODGP problem is solved by two stage heuristic iterative method including clustering (outer) and EA (inner) optimizations respectively, to find time varying voltage magnitude and loss sensitivity factor at each node.
[34]	2013	2	1	✓	-	-	-	The multi-criteria planning model aims to achieve contrasting objectives (cost and reliability) for DGP. GA further finds a set of non-dominant solutions for wind-based DG units sizing, siting, and maintenance schedules.
[35]	2013	2	1	✓	-	-	-	An MO planning framework has developed, namely improved multi-objective harmony search (IMOHS), which can evaluate the DGP.
[36]	2013	3	1	✓	-	-	-	An MO optimization problem for multiple micro-turbines (DG) placement and sizes is solved by hybrid PSO and SFL algorithms based framework, followed by fuzzy decision-making tool to select the most preferred Pareto optimal solution satisfying competing objectives.
[37]	2013	3	1	✓	-	-	-	The methodology based on Pareto frontier differential evolution (PFDE) algorithm is proposed for optimal MODGP (sizing and location).
[38]	2014	2	1	✓	-	-	-	The DGP problem for location, size, and type (REG and PEV) is defined as MO mixed integer nonlinear programming (MINLP), in which an NSGA-II is used to obtain compromise (Pareto frontier) solution for a local distribution company (LDC).
[39]	2014	2	1	✓	-	-	-	The MO probabilistic (mathematical programming) framework has proposed for various DER planning (six DG types, size, and location) that aims at DISCOs contribution in the competitive electricity market. Moreover modified augmented ε-constrained method along with FDM has utilized for best compromise solution among the set of Pareto optimal solutions.
[40]	2014	2	1	✓	-	-	-	MO augmented ε constrained method proposed for DGP planning on short term basis for future DNWs with ANM functionalities.
[41]	2014	2	1	✓	-	-	-	The MOO planning framework based on non-dominated sorting genetic algorithm II (NSGA-II) along with MCS (for uncertain operation scenarios) and OPF, addresses DGP problem of REG and storage integration within DNW.
[42]	2014	3	1	✓	-	-	-	Quasi-oppositional teaching learning-based optimization (QOTLBO) methodology, a variant of TLBO proposed as MOO regarding optimal location and sizing of DGP for solving multi-objective optimal power flow (OPF) problem for radial DNW.
[43]	2014	4,3	1	✓	-	-	-	MOPSO algorithm has been used for MODGP problem satisfying objectives (minimize DISCO cost and maximize DG owner profit) in addition to finding optimal generated electricity prices in a competitive electrical market.
[44]	2014	2	1	✓	-	-	-	An improved MOPSO with preference strategy (IMPSO-PS) is proposed for MODGP with the aim to achieve optimal capacity and locations.

Table 5. *Cont.*

Ref.	Year	MO	PTC	A	B	C	D	Contribution of MODGP-Based Planning
[45]	2014	6	1	✓	-	-	-	Mixed integer second order cone programming (MISOCP) formulation of DGP problem is proposed aiming at optimally allocating dispersed energy storage systems (DSSs) into ADN followed by AHP for DM among multiple objectives.
[46]	2014	4	1	✓	-	-	-	A supervised BB-BC method evaluates minimization of IMO for finding optimal location and capacity of one/more voltage-controlled DG(s).
[47]	2014/15	5	1	✓	-	-	-	Chaotic artificial bee colony (CABC) solves MODGP problem regarding the multi-objective performance index for finding the optimal location of real power DG units and their capacities.
[48]	2015	3	1	✓	-	-	-	An MOPSO based algorithm is presented to find best trade-off solution through multiple objectives under various operational constraints and demand side management (DSM) is justified in DG planning. FDM is used to identify an optimal non-dominated solution.
[49]	2015	2	1	✓	-	-	-	Sequential quadratic programming (SQP) for a set of Pareto front solutions for to find optimal DG sizing and placing. WSM generates a set of acceptable trade-off solutions among contrasting objectives. Fuzzy decision making (FDM) method provides best compromise solutions.
[50]	2015	3	1	✓	-	-	-	A mathematical model of MODGP problem solved by the proposed improved NSGA (INSGA-II). The best solution obtained with FDM.
[51]	2016	3	1	✓	-	-	-	Multi-objective Shuffled Bat algorithm (MOShBAT), a variant of bat algorithm (BA) proposed for the planning of DGs considering various contrasting objectives and showed better results than NSGA-II.
[52]	2016	4	2	✓	✓	-	-	A MOO model for mix penetration (PV and wind-based REGs) and capacitors planning, where MOPSO algorithm produces set of potential solutions after considering all possible trade-offs among distinct objectives and followed by FDM to identify the best non-dominated solution.

Table 6. The contribution of MOVPQ-based planning methods and related works. (MOVPQ: MOP based on VAR compensation and power quality).

Ref.	Year	MO	PTC	A	B	C	D	Contribution of MOVPQ-Based Planning
[53]	2005	2	1	-	✓	-	-	Tabu Search (TS) based approach computes non-dominated solutions to provide decision support for capacitor location problem.
[54]	2007	2	1	-	✓	-	-	GA based fuzzy multi-objective approach is presented for optimal capacitor placement.
[55]	2008	4	1	-	✓	-	-	A two-stage immune algorithm (IA) embedding compromise programming solves the multi-objective capacitor placement problem.
[56]	2009	2	1	-	✓	-	-	Hybrid SA–PSO and IBVT based approach addresses; fixed and switched type capacitor placement, besides finding a valuable trade-off solution.
[57]	2010	3	2	-	✓	✓	-	Strength Pareto evolutionary algorithm (SPEA2) incremented by fuzzy logic solves MO combinatorial optimization problem to address Volt/Var control for distribution systems regarding switched capacitors and automatic voltage regulators (AVR) placement.
[58]	2012	2	1	-	✓	-	-	Elitist NSGA II merged with local search finds best nodes and compensation values of the installed capacitors in MO VAR planning problem.
[59]	2013	2	2	-	✓	✓	-	MILP model is proposed to solve the VR and VRC allocation problem and to obtain Pareto front satisfying multiple objectives.
[60]	2013	3	1	-	✓	-	-	MO capacitor placement problem solved with self-adaptive modified honey bee mating optimization (SAMHBMO), proposed to find Pareto optimal solutions satisfying maximum objectives. Probabilistic load flow (point estimate method or PEM) address associated uncertainties.
[61]	2013	3	1	-	✓	-	-	Accelerated PSO (APSO) based optimization approach solves capacitor planning problem regarding sizing, location, and type.
[62]	2013	3	1	-	✓	-	-	Capacitor (allocation) planning problem for optimal sizing and location is solved by ABC based approach to maximize the required objectives.
[63]	2013	3	1	-	✓	-	-	Two-stage modification method with AMHBMO based approach is proposed to solve the multi-objective capacitor planning problem.
[64]	2014	4	2	✓	✓	-	-	MOF is formulated for simultaneous DG's and capacitor placement and solved by investigated differential evolutionary algorithm (IDEA).

Table 6. *Cont.*

Ref.	Year	MO	PTC	A	B	C	D	Contribution of MOVPQ-Based Planning
[65]	2014	3	2	✓	✓	-	-	Fuzzy MOPSO algorithm is proposed applied to find the best solution of DGs and shunt capacitor banks (SCBs) sizing and placement problem simultaneously with load uncertainty considered as fuzzy data theory. The optimum solution extracted with FDM.
[66]	2015	5	1	-	✓	-	-	GA based fuzzy multi-objective approach solves with maximization of fuzzy MOF for optimum sizing and location of shunt capacitors.
[67]	2016	5,3	1	-	✓	-	-	An improved backward/forward sweep (BSFS) load flow based PSO is proposed to solve mixed integer programming (MIP) problems of both optimal capacitor (delta-connected switched) placement and control to achieve respective objectives in two strategies.
[68]	2016	3	2	✓	✓	-	-	Multi-criteria simultaneous planning with ABFO approach is proposed for PFF and DG (location and size), considering nonlinear loads.
[69]	2016	2	2	✓	✓	-	-	MO seeker optimization algorithm (MOSOA) is proposed planning methodology to integrate distribution automation devices, DGs and D-STATCOMs in advance power distribution network (APDN). "Max–min" approach is selected most suitable trade-off solution.
[70]	2016	2	3	-	✓	✓	✓	MOSOA proposed for planning strategy including distribution automation devices like automatic reclosers (RAs) for reliability and FACTS devices like DSTATCOM; for VAR compensation in ADN. *"Max–min"* approach is applied to select the final trade-off solution.

Table 7. The contribution of MOCRU-based planning methods. (MOCRU: MOP based on MOP based on VAR compensation and power quality.).

Ref.	Year	MO	PTC	A	B	C	D	Contribution of MOCRU-Based Planning
[71]	2006	2	1	-	-	✓	-	MOO methods like non-dominated sorting genetic algorithm (NSGA) and strength Pareto evolutionary algorithm (SPEA) with fuzzy c-means (FCM) solve grid reinforcement planning problem with high/low-reliability solutions for urban/rural cases respectively.
[72]	2008	3	2	-	✓	✓	-	GA based Optimal electric distribution resource planning (OEDSEP) procedure using a hybrid energy hub concept aims at solving optimal device allocation and replacement problem (ODARP) by decomposition into three subproblems to attain multiple objectives.
[73]	2009	2	1	-	-	✓	-	Fuzzy multiobjective model and ant colony optimization (ACO) based approach provides decision support in sectionalizing switch placement (SSP) problem considering real planning requirements in DNW with DGs.
[74]	2009	2	2	✓	-	✓	-	A hybrid method based on strength Pareto evolutionary algorithm (SPEA2) with distribution OPF solves DER placement problem with network reinforcements to assess the trade-off solutions among DER and DSO costs in the long-term grid planning schemes.
[75]	2009	2	2	-	-	✓	✓	The multi-objective ant colony optimization (MACO) applied for placement of switches and protective devices in distribution network addressing Pareto optimal based non-dominated multi-objective solutions.
[76]	2010	2, 4	3	✓	-	✓	✓	Multi-objective PSO-based planning is proposed based on two stages. In the first stage, Pareto-optimality principle is used to obtain tradeoff analysis among two conflicting objectives (total cost and CLLI). In the second stage, all four objectives have optimized. Each solution represents DG (number, location, size, and type), branches (conductor size), sectionalizing switches (number and locations) and network topology.
[77]	2011	2	1	-	-	✓	-	The multi-objective planning (MOP) of primary DNW has formulated as an MINLP. MO-RTS algorithm used to solve the multi-objective planning model for grid reinforcements along with sectionalizing switches (SSWs) placement to minimize costs due to energy not supplied.
[78]	2011	2	2	-	-	✓	✓	A fuzzy multi-objective model presented with modified shuffled frog leaping (MSFLA) algorithm as optimizing tool for planning number and placement of sectionalizing switches in distribution automation system (DASs).
[79]	2011/12	4	3	✓	-	✓	✓	Methodology for active distribution networks (ADN) dynamic expansion planning based on MOGA. Proposed strategy aims at multistage expansion planning under generation and demand uncertainties with options like DG integration, installation of new protection devices, network reconfiguration and rewiring. The solution obtained from proposed method satisfies multiple objectives.
[80]	2011/12	2	2	-	-	✓	✓	A two-step planning strategy is proposed to optimize feeders' allocation (numbers and their routes), sectionalizing switches (number and locations) and tie-lines (number) in DNW. The solution strategy in step 1 consists of SPEA2–MOPSO for SSW allocation and step 2 caters with SPEA2–BMOPSO (binary MOPSO) for tie-line placement.

Table 7. *Cont.*

Ref.	Year	MO	PTC	A	B	C	D	Contribution of MOCRU-Based Planning
[81]	2012	2	2	✓	-	✓	-	Model for MO Integrated Generation and Primary–Secondary Distribution System Expansion Planning (IGDSEP) in the presence of wholesale and retail markets as MINLP problem is divided into six sub-problems and solved with scenario Driven MINLP method with adaptive GA (AGA) and integrated AGA (IAGA).
[82]	2012	2	2	✓	-	✓	-	Multistage distribution network expansion planning (MDEP) problem for DG integration and grid reinforcements is solved with hybrid PSO and Shuffled Frog Leaping (SFL) algorithm to find Pareto optimal solutions satisfying multiple objectives.
[83]	2012	2	1	-	-	✓	-	Optimal feeder routes and conductor size of branches with multi-objective dynamic programming (MODP).
[84]	2013	2	1	-	-	✓	-	Proposed MO tabu search (MOTS) algorithm solves planning problem to check compromise (trade-off) solutions among cost and reliability.
[85]	2014	4	2	-	-	✓	✓	Multi-objective seeker optimization algorithm (MOSOA) is proposed for DSP problem with the simultaneous placement of automatic reclosers (RAs) with solution satisfy maximum conflicting multiple objectives.
[86]	2015	2	2	-	-	✓	✓	MOSOA is proposed for DSP problem with the simultaneous placement of RAs and SSWs to achieve maximum reliability and lower cost.
[87]	2015	3	1	-	-	✓	-	MO planning for optimal placement of switching devices has solved by NSGA-II with two approaches with the aim of satisfying objectives namely DG unavailability, network reliability and equipment cost, with no island network operation.
[88]	2015/16	3	2	✓	-	✓	-	The fault current limiter (FCL) allocation problem with DGs is formulated as multi-objective constrained nonlinear programming (NLP) problem and is solved using PSO to achieve multiple conflicting objectives.
[89]	2016	3	2	✓	-	✓	-	Optimal coordinated voltage control (OCVC) is proposed to solve MOP using Pareto optimization to find the optimal values of voltage of the generators and OLTC, addressing various technical aspects.

Table 8. The contribution of MONTR-based planning methods. (MONTR: MOP based on distribution network reconfigration.).

Ref.	Year	MO	PTC	A	B	C	D	Contribution of MONTR-Based Planning
[90]	2009	5	1	-	-	-	✓	A multi-objective approach based on a micro-genetic algorithm (mGA) aims at trade-offs among reliability indices and power losses (from Pareto front solutions) to obtain radial topologies (reconfiguration) from planning perspective.
[91]	2009	2	1	-	-	-	✓	Fuzzy multi-criteria decision making (MCDM) algorithm is proposed to process information of sources availability at DNW regarding network reconfiguration from the perspective of operational distribution planning.
[92]	2009	3	2	-	-	✓	✓	This paper addresses multi-objective feeder operation optimization problem considering the calculation of interruption costs and impacts of seasonal time variation effects in annual distribution feeders operation planning. The problem is solved with binary PSO (BPSO) to find feeder switching schedule.
[93]	2012	2	1	-	-	-	✓	Reconfiguration problem in an MO framework has solved by BPSO-based search algorithm aim at finding the optimal status of the switches to satisfy objectives (reliability and power loss).
[94]	2012	3	3	✓	-	✓	✓	Weighting method (multi-criteria evaluation) based on GA is proposed to find the optimal up-gradation schemes (including additional feeders) for changing normal closed loop topology to mesh in primary distribution feeders with DGs. The weights can be adjusted by the decision maker to find a solution satisfying required objectives.
[95]	2013	2	1	-	-		✓	NSGA-II solves Pareto optimal reconfiguration problem to attain reconfiguration solution satisfying two objectives.
[96]	2013	5, 2	3	✓	-	✓	✓	MO optimization approach based on NSGA has proposed for multi-year MO planning including DG allocation and network reconfiguration (also future reinforcements).
[97]	2013	3	2	-	-	✓	✓	NSGA-II solves MO network reconfiguration planning problem regarding the tradeoff between minimizing power loss, maximize reliability and minimize investments (tie-switches and protection devices). A non-sequential MCS estimates reliability and protection system response to service restoration (upstream/downstream) to obtain accurate results.
[98]	2014	4	2	✓	-	-	✓	Distribution feeder reconfiguration (DFR) problem is formulated in MO stochastic framework to reinforce reliability and solved with self-adaptive modified bat algorithm (SAMBA) for a feasible solution among contrasting objectives.
[99]	2015	3	4	✓	✓	✓	✓	A fuzzy-ACO-based algorithm has presented for simultaneous NR and allocation of PV and DSTATCOM units.
[100]	2016	3	2	✓	-	-	✓	A secure MOO framework has proposed for network reconfiguration in the presence of micro turbines based DGs. Enhanced gravitational search algorithm (EGSA) algorithm solves the complex MOP followed by fuzzy decision-making tool for optimized Pareto front solution.

4.1. Numerical Methods

(1) *The ε-constrained method*: In this technique, a specific objective function selects as master and others as slaves. Moreover, the slave objective functions considered as new constraints

- *Benefits*: The technique efficiently generates a set of Pareto optimal or non-inferior solutions in MO-based problems.
- *Demerits*: High computation required for greater number of objective functions.
- *Preference*: Enables decision maker select a solution on preference basis.
- *MOPT Ref*: DGP (A) [21,22,39,40].

(2) *Monte Carlo Simulation (MCS)*: The iterative techniques based on use of random numbers.

- *Benefits*: Efficient for problems with less iteration, resulting in efficient processing time.
- *Demerits*: More the complex problem, more iteration and more processing time.
- *Preference*: Mainly deterministic and probabilistic types by behavior and outcome of the random process. Also used as inner optimizations in MO problems.
- *MOPT Ref*: DGP (**A**) [23,41].

(3) *Goal programming (Goal P)*: Suitable for MO formulations aiming at a tradeoff solutions.

- *Benefits*: Simple to implement and aims at a tradeoff solution.
- *Demerits*: Requires very high computation and practically time consuming.
- *Preference*: Several applications in literature.
- *MOPT Ref*: DGP (**A**) [26,32].

(4) *Exhaustive Search (ES)*: Simple problem solving method aims at finding all possible solutions.

- *Benefits*: Simple to implement and determine optimal global solution (of small problems).
- *Demerits*: Requires very high computation and not efficient for large distribution systems.
- *Preference*: ES based optimum solutions compared with the other algorithm and performance is found by relative deviation among two solutions.
- *MOPT Ref*: DGP (A) [25,28,33].

(5) *Optimum power flow (OPF)*: The conventional method is used to solve complex planning problems, aiming at optimal performance of power systems.

- *Benefits*: Better computation efficiency, high precision and use as inner optimizations.
- *Demerits*: Rigid problem formulation and few variants can be inclusion in the calculations.
- *Preference*: Several applications in literature (for high precision optimization problems).
- *MOPT Ref*: DGP (A) [41]; CRU (C) [74].

(6) *Cone programming (Cone P)*: The technique addresses nonlinear convex problems. It aims at minimization of linear objective function over intersection of affine linear manifold intersection and product of (second order quadratic) cones.

- *Benefits*: Efficient computation efficiency and better precision for convex optimizations.
- *Demerits*: May cause inaccurate solutions for real time problem.
- *Preference*: Several applications in literature (for convex optimization problems).
- *MOPT Ref*: DGP (A) [45].

(7) *Sequential quadratic programming (SQP)*: The iterative method is proficient at solving nonlinear formulation with inequality constraints. The procedure involves.

- *Benefits*: Considered as the fastest method to solve nonlinear programming (NLP) problems.
- *Demerits*: Complexity increases with multiple quadratic subproblems at each iteration.
- *Preference*: Few applications in literature (mostly used for DGP optimization problems).
- *MOPT Ref*: DGP (A) [49].

(8) *Mixed integer linear programming (MILP)*: The conventional technique is appropriate to solve problems with linear objective functions, abiding associated constraints.

- *Benefits*: The approach shows excellent convergence properties.
- *Demerits*: The more realistic model experiences more difficulty in finding solutions.
- *Preference*: Applicable to discrete and continuous variables (linear optimization problems).
- MOPT Ref: VPQ (B) [59].

(9) *Mixed integer nonlinear programming (MINLP)*: The conventional numerical technique is a combination of linear programming (LP), mixed integer programming (MIP) and nonlinear programming (NLP), respectively.

- *Benefits*: This approach demonstrates better computation efficiency and accuracy.
- *Demerits*: Difficult to implement nonlinear objective functions and with much iteration.
- *Preference*: Appropriate to address discrete, continuous variables, nonlinear power flow. Also, provides accurate, reliable and efficient solution for MOP formulation.
- *MOPT Ref*: DGP (A) [38–40]; CRU (**C**) [72,77,81].

(10) *Dynamic Programming: (DynP)*: This is is sequential optimization technique based on multiple stages. The technique is capable to address main problems by breaking into sub-problems.

- *Benefits*: The approach addresses concerned problem in efficient and reliable manner.
- *Demerits*: Difficult to implement for large number of objectives.
- *Preference*: Capable to address RT complex problems with less time for optimum solution.
- *MOPT Ref*: CRU (**C**) [83].

4.2. Meta-Heuristics (MH) Methods

(1) *Genetic algorithms (GA)*: A kind of adaptive heuristic search algorithm, based on the concept of natural selection and genetics.

- *Benefits*: Simple, easy to understand, does not depend on the initial solution.
- *Demerits*: More computational time is needed and can converge at local optima due to intensification of parameters in search process.
- *Preference*: Numerous applications, since it does not require complex mathematical knowledge in the implementation of required solution.
- *MOPT Ref*: DGP (A) [21–23]; VPQ (B) [66]; CRU (C) [79,81,88],[89]]; NTR (D) [90,94].

(2) *Particle swarm optimization (PSO)*: In this method, a set of arbitrarily (randomly) activated solutions moves in the search process, aiming at best solution over some iterations.

- *Benefits*: Easy to code, efficient computation time and better convergence than GA.
- *Demerits*: When the problem dimensions increase, the algorithm loses robustness.
- *Preference*: Considerable preference is given in the literature, aiming at large-scale DNs, with modifications in code and efficient tuning with the controller parameters.
- *MOPT Ref*: DGP (A) [43,44,48,52]; VPQ (B) [61,65],[67]]; CRU (C) [76,88]; NTR (D) [92,93].

(3) *Harmony search algorithm (HS)*: The metaheuristic is based on the concept of decision variable (musician) generates (plays) a value (note) for searching a best global optimum (harmony).

- *Benefits*: Easy to implement and offers near optimum solutions in some problems.
- *Demerits*: The standard HS suffers drawbacks (inaccuracy) in finding optimum solutions.
- *Preference*: The drawbacks have been addressed with improved variants, namely improved HS (IHS) and novel global HS (NGHS) respectively.
- *MOPT Ref*: DGP (A) [35].

(4) *Teacher learning algorithm (TLA)*: The method is motivated by the concept of teacher's impact on the results achieved by students in a class and aims a student towards the best qualification.

- *Benefits*: Short simulation times and no parameters are required for the algorithm to work.
- *Demerits*: Nonlinearities and increased iterations for global optima of large scale real DN.
- *Preference*: Capable of finding global or near global optimum solution.
- *MOPT Ref*: DGP (A) [42].

(5) *Big bang big crunch (BB-BC)*: The nature inspired standard BB-BC algorithm consists of two steps. First, the formation of initial candidate solutions spread randomly across the search space. Second, a concurrence operator groups all solutions at only one solution, called "center of mass."

- *Benefits*: Excellent convergence property with less computation time.
- *Demerits*: The improper tuning of system parameters may increase the complexity.
- *Preference*: Applied to nonlinear multidimensional functions, power flow problems (with continuous/discrete control variables) and DGP with good convergence speed.
- *MOPT Ref*: DGP (A) [46].

(6) *Artificial bee colony (ABC)*: An algorithm based on the concept of foraging behavior of honey bees and considers the fact that the food source represents a feasible explanation of the problem. great amount of a food source resembles the characteristics of a converged solution.

- *Benefits*: The approach uses a lesser number of control parameters, better capability to deal with complex multidimensional optimization problems and exhibits good convergence properties.
- *Demerits*: The convergence rate is poor for constrained optimization problems.
- *Preference*: Modified versions of ABC algorithms are proposed for solving real world optimization problems. However, the approach has still not been considered in depth by the researchers.
- *MOPT Ref*: DGP (A) [47]; VPQ (B) [62].

(7) *Tabu search (TS)*: This meta-heuristic optimization technique utilizes adaptive memory to produce the most flexible search behavior. The algorithm operates in sequential way, starting from searching from an initial point and then selecting a new point in the search space as the next current point.

- *Benefits*: Fast convergence properties and easy tuning of the controller parameters.
- *Demerits*: It requires a suitable initial solution. Also, finding an optimal global solution in complex and multi-dimensional problems is not guaranteed.
- *Preference*: The approach is suitable for simple and comparatively less complex problems.
- *MOPT Ref*: VPQ (B) [53]; CRU (C) [77,84].

(8) *Immune algorithm (IA)*: The immune (system) algorithm belongs to the class of AI based meta-heuristics and is based on the concept of human body's defense process against viruses. It starts with a randomly generated population with solutions reproduced at different rates. Later, suitable solutions are duplicated at high rates, followed by mutation at various rates. Finally, a selection operator is applied to produce suitable solutions.

- *Benefits*: The method does not depend on initial solution and is capable of obtaining a global optimum in complex problems with more accuracy than GA.
- *Demerits*: It requires more computation time than GA and PSO. The tuning of the system parameters is a tedious task for real world (MOP) problems.
- *Preference*: The approach utilized in various planning problems in literature.
- *MOPT Ref*: VPQ (B) [55].

(9) *Simulated annealing (SA)*: A stochastic search algorithm motivated by the similarity between the solid annealing procedure and optimization problems. The first metropolis process refers to jumping property that deals with a worse solution having the probability to be accepted as a new solution. Later, a cooling schedule slows down the probability of the worst solution in the search space.

- *Benefits*: Robustness is comparatively high. It does not depend on the initial solution. The algorithm is capable of finding a global optimum solution in combinational and complex (large scale) problems.
- *Demerits*: It requires more computation time than TS. The appropriate tuning of the system parameters is difficult for real world problems, particularly; it is not suitable for multiple planning candidates in large power systems.
- *Preference*: The approach utilized in various asset planning problems in literature.
- *MOPT Ref*: VPQ (B) [56].

(10) *Honey bee mating (HBMO)*: A metaheuristic optimization algorithm inspired by the mating process of honey bees. The method aims at reproducing the mating process between a queen and drones, until new broods are generated, to find the most suitable solution. If the best brood among the brood population is better than the queen, it replaces the queen.

- *Benefits*: It shows suitable performance to solve various complex planning problems.
- *Demerits*: High dependence on adjusting initial parameters and premature convergence resulting in tracking local optimal solution.
- *Preference*: Modified versions of HBMO are utilized to address abovementioned demerits.
- *MOPT Ref*: VPQ (B) [60,63].

(11) *Bacterial foraging (BFO)*: The algorithm is inspired by *E. coli* bacterias' foraging properties, by an activity called "chemotaxis". Simply, the algorithm deals with mimicking the chemotactic movement of (virtual) bacteria in the search space of the problem (food search).

- *Benefits*: Improved BFO variants are developed to improve optimization performance.
- *Demerits*: Poor convergence and decrease in search performance, with increase in search space and problem complexity respectively.
- *Preference*: A few models have developed for solving practical planning problems.
- *MOPT Ref*: VPQ (B) [68].

(12) *Ant colony optimization (ACO)*: This AI method is based on the probabilistic searching behavior of real ants in pursuit of food to find the shortest paths from their nest to a food source (solution).

- *Benefits*: It is easy to understand, simple to code and needs less computation time.
- *Demerits*: Poor convergence, difficult tuning of controller parameters and uncertainty in achieving global optima for simple/complex DN planning problems.
- *Preference*: The technique is utilized in several DN (expansion) planning problems. The deficiency in standard ACO is met with efficient variants, such as mix-max ACO and ant colony search algorithms (ACS), respectively. These variants have better convergence, however, the computation time increases.

- *MOPT Ref*: CRU (**C**) [73,75]; NTR (**D**) [99].

(13) *Bat algorithm (BA)*: This population-based meta-heuristic algorithm mimics a group of bats, searching for the location exhibiting maximum availability of prey. The echo solutions of micro bats represent the most feasible solution.

- *Benefits*: High robustness and better convergence in comparison with GA, PSO, and HS.
- *Demerits*: Difficult tuning of controller parameters and may give inaccurate solutions for real time problems.
- *Preference*: The different variants of technique, notably shuffled-bat algorithm (ShBAT), are used by researchers to solve various planning problems.
- *MOPT Ref*: DGP (A) [51]; NTR (D) [98].

(14) *Evolutionary algorithm (EA)*: This metaheuristic (AI) algorithm is inspired by the concept of biological evolution with operators (reproduction, mutation, recombination, and selection) and implemented by assigning fitnesses to each possible solution.

- *Benefits*: Efficient and robust process to find near-optimal overall solution.
- *Demerits*: Premature convergence, low precision, and possibility of finding local optima.
- *Preference*: The technique has many applications in literature, to solve various planning optimization problems involving integer variables. The variants of this technique predominately include DE, TLA, SOA, GSA, SPEA, SPEA 2, NSGA, NSGA-II, and SFL.
- *MOPT Ref*: VPQ (B) [64].

(15) *Differential evolution (DE)*: An artificial intelligence (AI)-based meta-heuristic based on a population technique (mutation, crossover, and selection) for finding global optimal solutions.

- *Benefits*: Its main features include the ability to solve complex optimization problems.
- *Demerits*: Prone to premature convergence and possibility of falling into local optima.
- *Preference*: Few applications in literature.
- MOPT Ref: DGP (A) [37]; VPQ (B) [64].

(16) *Seeker optimization algorithm (SOA)*: This (meta-heuristic) EA is based on the notion of simulating an individual human's (seeker) searching behavior among a population (seekers), for intelligent solution they search with their memory, experience (learning) and uncertainty reasoning.

- *Benefits*: High robustness and better convergence in comparison with GA and PSO.
- *Demerits*: Requires initial solution and high computation for complex problems.
- *Preference*: The technique has been employed by researchers to solve various planning problems.
- *MOPT Ref*: VPQ (B) [69,70]; CRU (C) [85,86].

(17) *Gravitational search algorithm (GSA)*: This algorithm is based on the law of gravity, where agents' (objects') performance is measured by their masses. Thus, heavier masses show better solutions.

- *Benefits*: Promising results for complex and high dimensional search space problems regarding robustness and convergence, in comparison with GA and PSO.
- *Demerits*: Requires efficient initialization of G-parameter to control search accuracy.
- *Preference*: The technique is not treated in depth to solve various planning problems.
- *MOPT Ref*: NTR (D) [100].

(18) Strength Pareto EA (SPEA): This aims at implementation of elitism, by maintaining an external set of non-dominated (higher fitness) populations (set of solutions), found during the whole iteration loop. The fitness of solutions within a population depends on the best solution in the external set.

- *Benefits*: Well developed to address complex nature and stochastic planning problems.
- *Demerits*: High computation requirements; more time required and need to reduce external number of solutions to a specific population size.
- *Preference*: The method has been considered in various planning problems of complex nature.
- *MOPT Ref*: CRU (C) [71].

(19) *Strength Pareto EA 2 (SPEA 2)*: The algorithm (second generation) addresses the limitations in SPEA 2 (first generation).

- *Benefits*: Improved fitness assignment scheme, precise guidance of the search process and preservation of boundary solutions, better than SPEA.
- *Demerits*: Convergence performance reduces as the search space increases.
- *Preference*: The technique is used to find non-dominated solutions for complex and stochastic-based planning problems.
- *MOPT Ref*: VPQ (B) [57].

(20) *Non-dominated GA (NSGA)*: The algorithm (first generation) aims at employing the notion of selection method, based on classes of dominance of all solutions. The algorithm, in each generation (iteration), indicates individuals (non-dominated solutions) within the population, to form non-dominated solution sets (Pareto front).

- *Benefits*: Well developed to address multi-objective based planning problems.
- *Demerits*: High computational complexity, lack of elitism, need to specify sharing parameters and slow non-dominated sorting procedure.
- *Preference:* To find non-dominated solutions in design, test and planning problems.
- MOPT Ref: DGP (A) [27]; NTR (D) [96].

(21) *Non-dominated GA II (NSGA-II)*: The algorithm (second generation) addresses the limitations in NSGA (first generation), to allow efficient application to constrained planning problems.

- *Benefits*: Efficient constraint management, elitism, parameter-less approach and fast non-dominated sorting procedure, batter than NSGA.
- *Demerits*: Performance of convergence reduces with as the search space increases.
- *Preference*: The technique is employed by researchers to solve complex nature planning problems, aiming at accurate, diverse and well-spread Pareto fronts.
- *MOPT Ref*: DGP (A) [24,38,41]; VPQ (B) [58]; CRU (C) [87]; NTR (D) [95].

(22) *Shuffled frog leaping (SFL)*: This population-based meta-heuristic method is inspired by the concept of mimetic evolution of a group, aiming at the quality of the meme (of an individual) and improves the performance (individual frog) towards a goal (highest food availability).

- *Benefits*: Efficient and better computing performance with global search ability.
- *Demerits*: More computation and premature convergence due to the DN size complexity.
- *Preference*: Several applications in literature and needs to be investigated as a potential candidate for combinational problems, aiming at future distribution concepts.
- *MOPT Ref*: DGP (A) [36]; CRU (C) [78,82].

4.3. Hybrid Methods

The hybrid techniques are developed to address the limitations in the previous techniques. The efficient development of hybrid methods helps to find global optimization solutions. Moreover, these techniques can manage complex (stochastic- and uncertainty-based) optimization problems. However, such methods are comparatively hard to code and have relatively limited example is literature. The prominent MOP-based hybrid methods are the following:

(1) *Hybrid GA*: These methods aim at solving combinational type problems, accommodating inner optimizations and implementing decision making processes to sort out feasible solutions.

- *Benefits*: Better convergence, more precision, and improved performance since high fitness/value chromosomes are used to produce the next generation.
- *Demerits*: Requires more computation time (global optima cannot be reached in a limited time). The linear change of decision variables can result in suboptimal solutions.
- *Preference*: The techniques have employed for optimal solution with maximum objectives.
- *MOPT Ref*: DGP (A): The ε-constrained method [21,22]; MCS [23]; goal programming [26,32]; fuzzy, WSM [29]; MCS, AHP [30]; PSO [31] and multi-criteria stochastic programming model (MSPM) [34]; VPQ (B): GA based fuzzy multi-objective method [54,60].

(2) *Hybrid PSO*: These methods aim at modifications that address the limitations in simple PSO.

- *Benefits*: Better convergence, more precision, and improved optimization than PSO.
- *Demerits*: Requires efficient tuning of several control parameters and the method can suffer from partial optimism.
- *Preference*: These methods results in better performance than standard PSO.
- MOPT Ref: DGP (A): SFL [36]; VPQ (B): SA [56] and mixed integer programming (MIP) [67]; CRU (C): SPEA 2 [80], SFL [82] and nonlinear programming (NLP) [87]; NTR (D): MCDA [94]

(3) *Hybrid EA*: These techniques are employed in the literature to address optimal solutions with decision making in multi-objective planning problems.

- *Benefits*: Highly efficient, robust and quick convergence to find optimal solutions. More suitable for multi-objective planning and decision making problems.
- *Demerits*: The inertia weights are randomly adjusted in the Pareto front. The weighted methods require more knowledge for decision making.
- *Preference*: These methods show promising aspects to address active DP, including storage, REGs, EV, DSM, and DR, stochastic generation, uncertain demands and controllable loads.
- *MOPT Ref*: DGP (A): Two-stage heuristic (ES + clustering techniques) [33] NSGA-II + MINLP [38]; CRU (C): NSGA + SPEA + FDM [71] and SPEA 2 + OPF [74]; NTR (D): NSGA II + MCS-OPF based approach [97].

4.4. Decision Making and Other Methods

The decision-making methods are crucial for finding trade-off solution among a set of solutions in MOP formulations. Notable features are as follows:

- *Benefits*: The method enables decision maker to sort out best possible solution.
- *Demerits*: The weights (weight methods) require extensive knowledge. Also, the results can be specifically weight dependent (in case of IMO).
- *Preference*: FDM is among one of the widely used approaches.
- *MOPT Ref*: DGP (A): WSM [29,49]; AHP [45]; FDM [36,39,49,52]; VPQ (B): Max-min Approach [69,70]; CRU (C): FDM in [71,73,78,86]; NTR (D): FDM in [100] and fuzzy multi-criteria decision making (MCDM) algorithm implemented in "proof of concept" in [91].

4.5. Impact of Load Flow Method

Load flow (LF) or power flow is an important and vital tool for analysis, planning and operation of DNW in steady-state conditions. LF indicates the system variables, which exceed the respective constraints limits. The necessary action must be followed to bring back the system in stable operation zone. In addition, LF and AC based OPF (ACOPF) constitutes an integral part of MOPT problem, as inner optimization. The associated LF (and ACOPF) based solution techniques can be defined by formulation type, solver and initialization. On the basis of literature review, the load flows can be safely classified on the basis of formulation (F), solver (S), and initialization (I), as indicated by (F,S,I). Moreover, interaction among (F,S,I) and impacts of LF (and ACOPF) methods as inner optimization [101] in MOP, has also presented in this sub-section as follows.

4.5.1. Load Flow Formulation (F)

The branch LF models (BLFM) constitute the largest portion of LF formulations. Being inner optimization, LF methods formulates constraints in the main optimization (MOP) problem. The LF methods with usually flat initialization values, solve BLFM formulations, which indicate equality constraints or power/load balance. The prominent technical inequality constraints include voltage limits (between maximum and minimum allowable limits) and branch thermal limits (must be less than the maximum admissible apparent power of the line). LF methods are responsible for operating and retaining the test DNW system within technical inequality constraints.

The ACOPF tool (to solve complex and nonlinear power flow problems) formulates any set of constraints through three types of major formulations, namely polar power–voltage power flow (PSV), rectangular power-voltage power flow (RSV) and rectangular current injection (RIV), respectively [101]. These formulations (which indicate equality constraints) and associated technical constraints are usually solved with MCS, modified LF methods and commercial solvers. Ample details regarding inequality constraints have provided in Section 2.7.4.

4.5.2. Load Flow Solution Methods (S)

The LF solution methods or simple solvers depend on the application of planning problem and type of loads addressed. For load profiles, refer to Tables 1–4, respectively. The solvers can be broadly classified as follows:

(1) *Traditional LF solvers*: The traditional LF solution methods, aiming at solving equality and inequality constraints, predominately include:

- Newton Raphson (NR) as in [48,52,68,79,94].
- Gauss-Seidel (GS) [82].
- Fast decoupling (FDLF) [31].
- Backward/forward sweep (BSFS) LF as in [24,59,63–65,69–71,73,74,77,83–86,91].

(2) *Modified LF solvers*: The modified LF solution methods, aiming at solving equality and inequality constraints, mainly include:

- 3-Phase (Φ)-4-wire BSFS LF as in [23,25,27–29,46,47,72,96].
- Simple (iterative and algebraic) LF as in [50,54,57,58,93,99].
- Numerical based LF as goal attainment method (GoA) in [32], SQP in [49] and MCS in [23], [30,38,39,41,81,97].
- Meta-heuristics (MH) based LF as in [35,55,67,75,76,95].
- Probabilistic LF (PLF) as in simple PLF in [21,22] and 2 m point estimation method (2 m-PEM) as in [60,98].

- Other LF methods and frameworks as in [33,42–44,51,53,66,80,90,92]; in addition to LF frameworks as multi-criteria stochastic planning model (MCSPM) with central limit theorem (CLT) [34] and IBVT in [56].

(3) *Software-based commercial solver packages*: The commercial solvers, aiming at solving nonlinear equality and inequality constraints, notably include:

- Load model synthesis (LOADSYN) [26].
- DIgSILENT® for balanced/unbalanced LF (B/U LF) [36] and static/dynamic modelling [100];
- Voltage stability and optimization (VS&OP) Tool [61,62].
- General algebraic modeling system (GAMS) for modeling mathematical programming models as in [37]. CONOPT solver of GAMS solves the nonlinear optimization problem (NLP) as in [39]. The DICOPT solver of GAMS solves MINLP problem as in [40].
- GUROBI commercial optimization solver; solves linear (LP), quadratic (QP) and quadratic constrained programming (QCP) respectively, as in [45].
- OpenDSS (open electrical power distribution system simulator) software [89].

4.5.3. Initialization (I)

The convergence of solutions depends on an effective initialization method. The initialization methods can be broadly classified on the basis of three prominent types of initializations (or starts) reported in the literature [21–101]. Further details are given later in this section.

- *Flat/Normal/Base/Random Start*: These methods constitute the largest part of initialization methods in the reported literature. Either the load flow initiates flat or starts in BLFM, where the starting voltage is equal to the root (standard/substation/slack bus) voltage. Also, candidate solutions are generated randomly and loads are normally distributed (in the case of PLF). However, these methods have high computation costs.
- *Btheta (Bθ) Start*: This method is a natural extension of the current injection method (CIM) normally considered for optimal dispatch. This method, like flat starts, can require high computation cost.
- *Hot Start*: The initial optimal solution is determined for effective and efficient generation of candidate solutions. The time computation cost can be significantly reduced. Also, more realistic solutions including uncertainty in problems, are addressed in much reduced time.

At each start point, power flow constraints are solved to initialize BLFM, PSV, RSV and RIV formulations. The initialization methods are important in a way that they remain feasible for both equality (formulations) and inequality constraints.

4.5.4. LF Impact with Interaction in MOP Problems

The general LF technique is the arrangement of test problem (DNW size), formulation (F), solver (S) and initialization (I). Moreover, interaction among (F,S,I) and considered test problem (T) as inner optimization (T,F,S,I) [101] needs to be considered in the context of MOP problems. MOP problems mostly consist of inner and outer optimization methods. In MOPT planning problems, efficient LF solutions (with interaction of T,F,S,I) support the main algorithm (outer algorithm) and are followed by a decision-making method. A comprehensive comparison of the impact of LF, on the basis of interactions in MOP problems; is presented in Table 9. The interaction his arranged according to problem types (DGP, VPQ, CRU and NTR), DNW size (T), formulation (F), solver (S) as inner optimization, initialization I (for both inner and outer optimization), main algorithm and DM.

Table 9. Power/Load Flow method impact by interaction in overall MOPT planning problem.

Problem Type	Test Problem (DNW Size)	Formulation (Form)	Solver/Inner Algorithm Method/(LF Method)	Initialization Inner/Main	Main (Outer) Algorithm	Decision Making
[21]	Real Italian	BLFM	Simple PLF (Heuristic)	Normalized	GA + ε constrained	-
[22]	18 Bus	BLFM	Simple PLF (Heuristic)	Normalized	GA + ε constrained	-
[23]	34 Bus	BLFM	3-Phase-4 wire LF/	Flat/Random	GA + MCS	-
[24]	9 Bus	BLFM	BSFS LF with FLd	Flat/Random	NSGA-II	Max-min
[25]	34 Bus	BLFM	3-Phase-4 wire LF (BSFS)	Flat Start	ES	Weight
[26]	34 Bus	BLFM	LOADSYN / FGP	Flat/Random	GA	Weight
[27]	34 Bus	BLFM	3-Phase-4 wire LF (BSFS)	Flat/Random	NSGA	-
[28]	16; 37 Bus	BLFM	3-Phase-4 wire LF (BSFS)	Flat/Random	ES, GA	Weight
[29]	33; 69 Bus	BLFM	3-Phase-4 wire LF (BSFS)	Flat/Random	Fuzzy GA	WSM
[30]	37 Bus	PSV	MCS/CCP	Hot(MCS)/ R	MCS-GA	AHP
[31]	33; 69 Bus	BLFM	Fast decoupled LF (FDLF)	Hot/Random	GA + PSO	Penalty
[32]	25; 33 Bus	BLFM	Goal attainment method	Base/R	GA + Goal P	Weight
[33]	24 Bus	BLFM	Classical LF and LSF	Hot(LSF)/R	2-Stage (MH +ES)	-
[34]	37 Bus	MCPM	MCSPM with CLT	Bθ/Hot	GA + MCOM	-
[35]	33; 69 Bus	BLFM	IMOHS Framework	Random (R)	NGHS-II	Max-min
[36]	33 Bus	BLFM	B/U LF in DIgSILENT®	Base/Hot	PSO + SFL	FDM
[37]	33; 69 Bus	BLFM	GAMS Model as MINLP	Bθ/Random	PFDE Algorithm	-
[38]	38 Bus	PSV	MCS	Random (R)	NSGA-II (MINLP)	-
[39]	9 Bus	RSV/GAMS	CONOPT/MCS	Normalized	AεCM	FDM
[40]	69 Bus	PSV/GAMS	DICOPT	Bθ /Normal	AεCM	-
[41]	13 Bus	PSV	MCS	Bθ/Normal	Fast NSGA-II	-
[42]	69 Bus	BLFM	BIBC and BCBV based LF	Base/Hot	QOTLBO	-
[43]	33 Bus	PSV	Modified branch based LF	Hot (weight)	MOPSO	FDM
[44]	33 Bus	PSV	B/F updated DistFlow LF	Bθ/Hot	IMOPSO-PS	-
[45]	34 Bus	BLFM	GUROBI	Base/Linear	MISOCP	AHP
[46]	69; 123 Bus	BLFM	3-Phase(Φ)-BSFS LF	Flat/Random	S-BB-BC	Weight
[47]	38; 69 Bus	BLFM	3-Φ B/F propagation LF	Flat/Random	CABC	Weight
[48]	28 Bus	BLFM	Newton Raphson (NR)	Flat/Hot	MOPSO	FDM
[49]	15 Bus	BLFM	SQP (Taylor expansion)	Bθ	SQP + WSM	FDM
[50]	33; 292; 588 Bus	PSV	L-Index based LF	Bθ/Random	INSGA-II	FDM
[51]	33 Bus	RIV	3-Φ Current injection LF	Flat/Hot	MOShBAT	-
[52]	28 Bus	BLFM	Newton Raphson (NR)	Flat/Hot	MOPSO	FDM
[53]	94 Bus	BLFM	Forward sweeping LF	Flat/Hot	TS	-
[54]	69 Bus	BLFM	Simple algebraic LF	Flat/Random	Fuzzy-GA	Weight
[55]	69 Bus	BLFM	SA based LF	Base/R	IA	-
[56]	12 Bus	BLFM	IBVT	Random	SA + PSO	-
[57]	69 Bus	BLFM	Algebraic iterative LF	Flat/Hot	SPEA 2	-
[58]	94 Bus	BLFM	Iterative branch based LF	Flat/Random	ENSGA-II	-
[59]	69; 136 Bus	BLFM	BSFS LF	Flat/Linear	MILP Model	-
[60]	9; 34 Bus	BLFM	2 m-PEM	Bθ/Hot	SAMHBMO	-
[61]	34; 118 Bus	BLFM	VS&OP	Flat/Hot	APSO	Weight
[62]	34; 94 Bus	BLFM	VS&OP	Flat/Hot	ABC	Weight
[63]	9; 34; 69 Bus	BLFM	BSFS LF	Bθ/Random	AMHBMO	-
[64]	115 Bus	BLFM	BSFS LF	Flat/Random	IDEA	-
[65]	33; 94 Bus	BLFM	BSFS LF (Harmonics)	Flat/Random	Fuzzy MOPSO	FDM
[66]	51; 69 Bus	BLFM	Compensated line LF	Flat/Hot	Fuzzy-GA	Weight
[67]	60 Bus	BLFM	Improved BSFS (PSO)	Flat/Hot	PSO	WSM
[68]	34 Bus	BLFM	NR	Bθ/Uniform	ABFO	Weight
[69]	54 Bus	PSV	BSFS LF	Flat/Uniform	MOSOA	Max-min
[70]	54 Bus	PSV	BSFS LF	Flat/Hot	MOSOA	Max-min

Table 9. *Cont.*

Problem Type	Test Problem (DNW Size)	Formulation (Form)	Solver/Inner Algorithm Method/(LF Method)	Initialization Inner/Main	Main (Outer) Algorithm	Decision Making
[71]	41 Bus	BLFM	BSFS LF	Flat/Uniform	NSGA + SPEA	FCM
[72]	Urban DNW	BLFM	3-Φ-4 wire LF (BSFS)	Flat/Random	GA + MINLP	Weight
[73]	Rural; Urban	BLFM	Compensated BSFS	Flat/Random	ACO	FDM
[74]	355 Bus	BLFM	BSFS LF	Flat/Random	SPEA 2	-
[75]	18; 51 Bus	TGM	Simple GA based LF	Flat/Random	MACO	-
[76]	21; 100 Bus	BLFM	Penalty factor (GA)	Flat/Random	MOPSO	-
[77]	180 Bus	BLFM	Compensated BSFS	Flat/Random	MORTS	-
[79]	33; 177 Bus	BLFM	NR (Branch exchange)	Flat/Uniform	MOGA	-
[80]	21; 54; 100 Bus	BLFM	Conventional LF	Flat/Random	SPEA2-B/MOPSO	-
[81]	Urban DNW	PSV	MCS	Random (R)	IGDSEP (AGA; IAGA)	Weight
[82]	Actual DNW	BLFM	Gauss Approach	Random (R)	PSO + SFL	-
[83]	21; 54; 100 Bus	BLFM	BSFS LF	Bθ/Hot	DynP	Weight
[84]	54 Bus	BLFM	Compensated BSFS	Bθ/Hot	MOTS	-
[85]	54; 100 Bus	BLFM	BSFS LF	Flat/Hot	MOSOA	Weight
[86]	54 Bus	BLFM	BSFS LF	Flat/Hot	MOSOA	FDM
[89]	13; 34 Bus	BLFM	OpenDSS	Flat/Uniform	MOGA	Weight
[90]	17; 33; 172 Bus	BLFM	Power summation LF	Flat/Uniform	Micro-GA	-
[91]	Actual DNW	BLFM	BSFS LF	Flat/Uniform	MCDM	-
[92]	16 Bus	BLFM	DistFlow B/F update	Flat/Uniform	BPSO	Weight
[93]	33; 123 Bus	BLFM	Simple iterative LF	Flat/Random	BPSO	-
[94]	Sample DNW	BLFM	NR	Flat/Uniform	GA	Weight
[95]	33; 67 Bus	BLFM	Branch exchange MH	Flat/Hot	NSGA-II	-
[96]	38; 119 Bus	BLFM	3-Phase-4 wire (BSFS)	Flat/Uniform	NSGA	-
[97]	69 Bus	BLFM	Non-dominated MCS	Random	NSGA-II	-
[98]	32 Bus	BLFM	2m-PEM	Random	SAMBA	-
[99]	33; 67 Bus	BLFM	Simple iterative LF	Flat/Hot	Fuzzy-ACO	Weight
[100]	33 Bus	BLFM	DIgSILENT® (DPL)	Random	ESGA	FDM

5. Contribution of the Review Work

5.1. Reviewed Work Contributions

The contributions of reviewed work are shown chronologically in Tables 5–8; addressing each PT category under the MOP framework as MODGP, MOVPQ, MOCRU, and MONTR, respectively.

5.2. Assessments of Multi-objective Planning Methods

Among numerical methods, OPF is commonly exploited as an inner optimization algorithm to facilitate high precision, stochastic, efficient time computation and uncertain operation situations. However, the problem formulation is very rigid, and few variations can be incorporated. Dynamic programming (DynP) and exhaustive search (ES) although they promise to find a global optimum solution, however they have not advocated for large distribution systems. Likewise, a major drawback of MCS (being inner optimization) is the high computation time. In comparison, MINLP, SQP, and dynamic programming are the most efficient numerical methods.

Metaheuristic (MH) methods like evolutionary algorithms have been considered as a natural way of addressing complex MOP problems. However, the high computational requirements and possibility of premature convergence towards local optimal solutions need to be addressed with more efficient methods. The simple MH methods require more computation time. Also, more number of functions is required to achieve nearly high quality results. Also, constrained and unconstrained multi-objective problems are difficult to optimize. Similarly, GA and PSO provide near optimal solutions for large distribution systems.

Artificial intelligence (AI)-based metaheuristics (for example ACS, ABC, etc.) and hybrid optimization methods can be consider as promising ways to deal with complex MOP problems more efficiently from a future perspective. The hybrid metaheuristic techniques show robustness (high quality solutions), promises powerful global optimization methods and have ability to address constrained real time planning problems. Furthermore, decision-making methods also need to be considered, aiming at finding optimal weights, for FDNs.

The modified LF methods and software-based LF platforms provide better performance aiming at uncertainty of load and REG generation, in comparison to traditional LF models. Also, they provide generation of various scenarios under all load models, which were limited in conventional methods. The LF impact on the basis of interactions, aiming at MOPT problems have arranged as a big picture, has presented in Table 9. The overall performance comparison of the addressed MOP techniques has been presented in Table 10.

Table 10. Performance comparison of algorithms, applied in multi-objective planning problems.

Algorithm/Methods	Classification/Execution	Compute Cost	Problem/Solution Quality (Optimization)	Parameter Depend	Application in Planning Problems	Others Features
ε-constd.	N/Easy	High ✘	Linear/better ❄	No	Simple ✭	Inner Opt.
MCS	N/Difficult	High ✘	Complex/better ❄	No	Simple ✭/Complex ✭	Inner Opt.
Goal P	N/Difficult	High ✘	Linear/better ❄	No	Simple ✭/Complex ❄	IMO
ES	N/Easy	High ✘	Linear/Excellent ✭	No	Simple ✭	Inner Opt.
OPF	N/Difficult	High ✘	Complex/ Excellent ✭	No	Simple ✭/Complex ❄	Inner Opt.
Cone P	N/Difficult	High ✘	Complex/better ❄	No	Simple ✭/Complex ✘	Convex
SQP	N/Difficult	High ✘	Complex/better ❄	No	Simple ✭/Complex ❄	Fast
MILP	N/Difficult	High ✘	Linear/ Excellent ✭	No	Simple ✭	Linear
MINLP	N/Difficult	High ✘	Complex/better ❄	No	Simple ✭/Complex ❄	Non linear
DynP	N/Difficult	High ✘	Complex/better ❄	No	Simple ✭/Complex ❄	Real Time
GA	MH/Easy	High ✘	Complex/better ❄	No/Yes	Simple ✭/Complex ❄	Variant/AI
PSO	MH/Easy	Average ❄	Complex/better ❄	Yes	Simple ✭/Complex ❄	Variant/AI
HS	MH/Easy	Average ❄	Complex/Average ❄	-	Simple ✭/Complex ✘	Variant/AI
TLA	MH/Average	Low ✭	Complex/Average ❄	No	Complex real world ❄	Nonlinear
BB-BC	MH/Average	Low ✭	Complex/Average ❄	Yes	Complex ❄	Nonlinear
ABC	MH/Average	Average ❄	Complex/Average ❄	Yes	Complex ❄	Nonlinear
TS	MH/Average	Average ❄	Linear/ Excellent ✭	Yes	Simple ✭/Complex ✘	Linear
IA	MH/Difficult	High ✘	Complex/Average ❄	No/Yes	Simple ✭	Variant/AI
SA	MH/Difficult	High ✘	Complex/ Excellent ✭	No/Yes	Complex real world ❄	Tuning
HBMO	MH/Average	Average❄	Complex/Average ❄	Yes	Simple ✭/Complex ❄	Local Opt.
BFO	MH/Average	Average❄	Complex/Poor ✘	-	Simple ✭/Complex ✘	Complex
ACO/ACS	MH/Easy	High ✘	Complex/Average ❄	Yes	Simple ✭/Complex ✘	Variant
BA	MH/Average	Average ❄	Complex/Average ❄	Yes	Complex real world ❄	>PSO, HS
EA	MH/Average	Average ❄	Complex/Average ❄	-	Simple ✭/Complex ❄	Integer
DE	MH/Average	Average ❄	Complex/Average ❄	-	Simple ✭/Complex ❄	Local (AI)
SOA	MH/Difficult	High ✘	Complex/Average ❄	Yes	Simple ✭/Complex ❄	>PSO, GA
GSA	MH/Average	Average❄	Complex/Average ❄	Yes	Complex real world ❄	>PSO, GA
SPEA/2	MH/Difficult	High ✘	Complex/ Excellent ✭	-	Simple ✭/Complex ❄	Variant
NSGA/-II	MH/Difficult	High ✘	Complex/ Excellent ✭	-	Simple ✭/Complex ❄	Variant
SFL	MH/Difficult	High ✘	Complex/ Excellent ✭	-	Simple ✭/Complex ❄	Variant
Hybrids	Hyb/Difficult	High ✘	Complex/ Excellent ✭	Yes	Simple ✭/Complex ✭	Complex
DM	DM/Average	Average ❄	Complex/ Excellent ✭	-	Simple ✭/Complex ❄	FDM (✭)

Notes: Excellent/Easy: ✭, Average/better: ❄, Poor/Difficult: ✘, Numerical: N, Optimization: Opt, Meta-Heuristics: MH, Artificial Intelligence: AI, Hybrid Methods: (Hyb), Decision Making: DM.

6. Requirements for Future Work and Research Directions

The paper presents four planning techniques based on the MO framework with associated classifications, methods, and key information from the viewpoint of their usefulness in MDP. Furthermore, other classifications include four extensive objective categorization, updated decision variables, constraints, and models. Also, fifteen PTC-based problems including interlinked (interdependent) types have illustrated. However, the literature review reveals that there are still several potential research areas from the planning perspective of MO-based frameworks that are research worthy.

6.1. Distribution Network Topology

The topology mostly considered in reviewed works is radial in nature, and other configurations (loop and mesh) have usually been neglected due to cost issues despite their reliable nature.

Furthermore, futuristic distribution mechanisms are expected to be more interconnected in both nature and operation. Hence other configurations must also be evaluated for reliability and other technical perspectives to avoid missing reliable solutions on a cost basis only. The optimal weight allocation in decision making can provide a feasible solution.

6.2. Future Distribution Networks (FDN)

Future/Smart distribution concepts and management models must also be considered from the MOP perspective. The key FDN concepts have been divided along the lines of utility and consumer paradigms. Major FDN concepts on the utility side include looped DNWs, meshed DNWs, micro-grid (MG), clustered or multi MG (MMG), virtual power plants (VPP) and smart cities (SCs), whereas smart homes (SHs) and buildings (SBs) represent FDN models on the consumers' end. Despite classification, designing and planning of FDNs to meet future load demands from the smart grids' perspective needs to be further explored. MOP can be use as a promising tool to exploit this potential research area of FDN from multiple stakeholders' viewpoints. This issue will be addressed in future publications.

6.3. Multi-Obejctive Planning with Optimization Parameters Settings

Since MOP may need large scale problem formulation, a possible way is to efficiently decompose a large problem into sub-problems on the lines of spatial (DNW's size) and time (PP). The inner optimizations parameters (if heuristic methods have been used) can be optimally set by either the planner or adaptively improved with the support of SG technologies (SGTs). Key enabling SGTs may include advanced metering infrastructure (AMI), secure communication link, sensors and demand side management (DSM), favoring both service provider and consumer regarding their decisions and anticipated incentives.

6.4. Prioritization of Weights for Objectives in Future Distribution Networks

Since most of the models and frameworks utilize heuristic methods for evaluation that is time-consuming and associated subjective weighting methods are liable to the deviation. Hence for a quick trade-off solution, planners and researchers must coordinate to find relevant weights from the perspective of requirements and other distribution planning-related issues. SG pilot projects and test beds can provide an opportunity to find accurate weights for each objective in MO problem. Moreover, efforts must be made to improve the speed of optimization processes.

6.5. Active Network Management and Smart Distribution Management System (SDMS)

The active network management (ANM) enables active operation of DNW with support provided with communication, information and automation enable changing of protection settings, topology, and power-flow dynamically. Efforts are required for proposig new methods, aiming at achieving multiple objectives like high REG penetration, power quality, reliability while reducing overall cost and power losses, respectively.

Since DERs are expected to be increased in ADNs and are required to be control by a smart distribution management system (SDMS), since such a system with AMI will allow real-time communication among decision makers for the transaction of useful information and prices makes it naturally a MOP problem in the ADN context. However, an increasing number of DER and loads over a planning horizon respectively adds complexity to SDMS control functionalities. There are several issues of SDMS that needs to be addressed in MOP problems.

A compromise between control issues can be a potential area since central control has high computation requirements and decentralized control requires time-consuming synchronization among local agents to find a compromise solution. Also, addressing complications in load flows with small scale DGs on utility/consumer ends and avoiding delays in command signal propagations; are worthy research areas, in particular, system parameters synchronization (grid, DGs) and contingency analysis under normal and emergency scenarios respectively.

6.6. Islanded Operation with Multi-Type Distributed Generation Units and Modified Topology

Current utility practices discourage islanded operation and recommend indiscriminate disconnection of all DGs connected to a network. Such actions are neither suitable nor preferred in a deregulated and competitive multi-stakeholder electricity markets. Further, islanding with multiple types of DGs in DNW and other concepts (MG, MMG, VPP) must also be evaluated with a change of topology, since interconnected topologies (loop, weakly mesh) are more reliable and serves more consumers in a better way during main grid blackouts.

6.7. Advance Protection System (APS)

The traditional protection systems are more specific towards cost effective solutions like relay-recloser-fuse coordination. However, when the DG penetration exceeds a certain limit, the traditional protection is not technically viable. The protection up gradation is also necessary for future distribution (interconnected) systems having complex power flows. Hence, a suitable trade-off between complexity and economy for any future protection strategy has desired for the distribution mechanism incorporating high DG/DER penetration.

6.8. Dynamic Planning with REGs and High Nonlinear Load Models

The MOP and related planning issues with increasing REG penetration and nonlinear load by high percentage need to be addressed over the multi-stage planning horizon, mainly in the context of FDNs. The major concerns are ensuring system reliability, stability and power quality. Reason being, the simple load models, will not remain technically viable to access the actual benefits.

6.9. Incentive Prioritization for Owner, Investor and Consumer Based Future Market Scenarios

The FDNs in a smart grid environment are expected to have competitive market scenarios and needs maximum stakeholders' participation. Hence incentive-based approaches are required to prioritize facility (DG, devices) owners, investors, and consumers; instead of overall system-wide benefits, to ensure their participation in FDN planning processes.

6.10. Exploiting Real Options

The utilization of real multiple options makes an active research area for the futuristic planning [102]. Prominently, risk-based planning under uncertainty needs to be addressed in MO framework to attain suitable investment strategy under the extreme scenario, from a futuristic point of view.

6.11. Need for Integrated Planning

The literature review reveals that most of researchers have considered planning and (resource) scheduling as separate problems. However, a real-world planning problem needs to be addressed with deeper, wider and aggregated planning approach. The futuristic planning needs to be integrated from startup stage (over planning horizon of several years) aiming at achieving multiple objectives. Followed by efficient resource utilization (days to seasons in a year). Finally, ensure real-time stable operation with anticipated smart technologies (on the time scale of 15 min to one day). Such approach is expected to guarantee optimal planning solution of FDN on long term basis.

6.12. Need for Improved Load Flows

The FDN of future is expected to be interconnected in nature. Hence, there is still room to proposed LF models, which addresses interconnected nature of DNW. Also, new LF models need to be developed considering various types of load models, from the viewpoint of uncertainty (generation and load) and interconnected nature of FDN. The proper formulation, new solvers and hot (improved) initialization of network load/power flows must benefit MOPT in terms of less computation cost and efficient solutions.

7. Conclusions

The MDP has been motivated by various factors and features (ANM, RES, EV, ST, ADA, DR, DSM, etc.), which were limited in traditional planning. The real world planning problems are multi-objective (MO) in nature and involve a large number of stakeholders. MO planning tools can provide compromise solutions among contradictory objectives, satisfy multiple stakeholders, yet address the concerned issues. This paper presents a review of four planning techniques (PT) aim to address MOP problems with associated models and optimization methods under MDP paradigm. The primary aim of this paper is to provide a back ground for FDN planning on the basis of limitations in available works and from the perspectives of MO achievement. The reviewed works consists of 80 recent standard planning papers from various aspects and are organize on the basis of decision variables, attained objectives, abiding constraints, MOP formulations, test systems, load models and year of publications (Section 2). The promising MOPT have classified as DGP, VPQ, CRU, and NTR (Tables 1–4). The MOP planning methods have reviewed into five categories, namely; numerical, meta-heuristic, hybrid, decision-making and load flow methods respectively. Also, classification and interdependence of planning components from four MOPT perspectives, have arranged in (Tables 5–8) with associated contributions from each related work. The LF impact on the basis of interactions, aiming at MOPT problems have arranged as a big picture, has presented in Table 9. The overall performance comparison of techniques (methods) applied for MOP problems have been presented in Table 10. Furthermore, potential future directions in MDP from a MOP perspective have also highlighted. In the future, MOP has several grey research areas in accessing maximum benefits from interconnected network topology, FDN and associated concepts. However, more investigation is needed to carry out realistic (MO) planning by upgrading conventional to smart DNWs or redesign from the beginning. Also, optimal settings of optimization parameters, optimum objectives weights in FDNs, ANM techniques, smart distribution management system (SDMS) and islanded operation with multi-type DGs focusing modified topology need further research attention. In addition, advanced protection schemes (for bidirectional power flows), dynamic planning with high penetration of REGs and nonlinear load models will play an important part in futuristic planning problems. Moreover, maximum incentive-based prioritization given to stakeholders (facility owners, investors, and consumers) needs to be addressed to ensure maximum participation in FDN planning processes. The employment of real investment options concept in MO framework for suitable approach under extreme (worst case scenario) from the futuristic viewpoint is research worthy. Finally, efforts need to be made to proposed integrated planning approaches and new power flow models. Works regarding designing and planning of FDNs, from multiple aspects under MO framework, will be presented in future studies.

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Abbreviations

The following abbreviations have used in this paper:

A	Classification of planning techniques related to DG placement
B	Classification of planning techniques related to VAR and power quality
C	Classification of PT related to component reinforcements/allocations and upgradations
D	Classification of planning techniques related to network topology change or reconfiguration
P	Active power
Q	Reactive power
ABC	Artificial bee colony
ABFO	Adaptive bacterial foraging optimization
AC	Annual cost
ACO	Ant colony optimization
ACS	Ant colony search algorithms
ADA	Advanced distribution automation
AHP	Analytical hierarchal process
AI	Artificial Intelligence
ANM	Active network management
ANSI	Average network security index
AMHBMO	Adaptive modified honey bee mating
APS	Advance protection system
AεCM	Augmented ε constrained method
BA	Bat algorithm
BFO	Bacterial foraging algorithm
BL	Balanced load
BLFM	Branch load flow model
BSFS	Backward/forward sweep load flow
Cap	Capacitor
CABC	Chaotic artificial bee colony
CAC	Capacity adequacy cost
CCC	Current carrying capacity (of branches or feeders)
CCI	Current carrying index (of branches or feeders)
CCT	Critical clearing time
CEDGP	Capacity enhancement with distributed generation penetration
CEL	Cost of energy losses
CENS	Cost of energy not supplied
CIC / CILL	Customer interruption cost/Customer interruption level
CL	Controllable/responsive/flexible load
CLd	Constant load
CLT	Central limit theorem
CLL	Critical load level
CLLI	Contingency load loss index (overall)
CNU	Cost of network upgrading
CVaR	Conditional value at risk
CVR/C	Cost of voltage regulators and variable capacitors
COD	Cost of overall (new and old) devices
Cone P	Cone programming
CPE	Cost of purchased energy (from grid)
CPL	Cost of power losses
CRU	Component reinforcements/allocations and upgradations
CSAIDI	Cost of system average interruption frequency index
CSI	Customer service interruptions
CSM	Capacity security margin (of transformers and feeders)

DE	Differential evolution
DEL	Distributed storage system's energy losses
DER	Distributed energy resources
DISCO	Distribution company
DM	Decision making
DG	Distributed generation penetration level
DGOI	Distributed generation unit's owner income
DGP	Distributed generation unit placement
DGPL	Distributed generation
DGR	Distributed generation unit's reliability
DGUI	Distributed generation unit unavailability index
DNW	Distribution network
DP	Distribution planning
DPL	DIgSILENT programming language
DR	Demand response
DSM	Demand side management
DSS	Distributed storage system
DRP	Demand response provider
DSM	Demand side management
DV	Decision variable
DynP	Dynamic Programming
EA	Evolutionary algorithm
EC	Equipment cost
ECE	External cost of energy (from grid)
EEDG2G	Energy export from DG (REG) to grid
EI	Economic index
EIG	Energy imported from grid
EL	Energy losses
ELC	Energy loss reduction of DG units and capacitors
EMP	Electricity market price (risk based)
ENS	Energy not supplied
EOI	Expansion, operation and maintenance costs
ES	Exhaustive search
ESGA	Enhanced gravitational search algorithm
FACTS	Flexible alternating current transmission system
FCF	Feeder current flow
FDLF	Fast decoupling load flow
FDN	Future distribution network
FGP	Fuzzy goal programming
FCM	Fuzzy clustering method
FCL	Fault current limiter
FCLL	Fault current level
FCLLDG	Fault current level due to distributed generation unit
FDM	Fuzzy decision making
FLd	Fuzzy load
FLL	Fuzzy load level
Fr.	Feeders (of distribution network)
GA	Genetic algorithm
GAMS	General algebraic modeling system
GP	Goal programming
GS	Gauss-Seidel
GHG/ACE	Greenhouse gases/Average (annual) greenhouse gases
GHGE	Greenhouse gases emissions

GHGG	Greenhouse gases emissions from grid
GHGDG	Greenhouse gases emissions from distributed generation units
GSA	Gravitational search algorithm
GRC	Grid reinforcement components
GUC	Grid upgradations with devices/components
HBMO	Honey bee mating algorithm
HS	Harmony search algorithm
hr.	Hours
IA	Immune algorithm
IBVT	Interactive bi-objective programming with the valuable trade off
IC	I (current) line flow limit index
IC_{All}	Investment in distributed generation units and capacitors
ICDGPPF	Investment in distributed generation units and passive power filters
IELOM	Investment in energy losses, operations and maintenance
ILP	Index for active power loss (P-loss index)
ILQ	Index for reactive power loss (Q-loss index)
IMO	Index for multi-objective performance
IMOHS	Improved multi-objective harmony search
IMOPSO-PS	Improved Multi-objective particle swarm optimization with preference strategy
InvC	Investment cost
IntC	Interruption cost
IOC	Investment and operation cost
IRC	Investments in reinforcement cost
ItC	Installation cost of project
IVD	Index for voltage deviation
LB	Load balancing
Ld	Load
LdP	Load profile
LdM	Load model
LF	Load flow
LLI	Line loading index
LOADSYN	Load model synthesis
LV	Low voltage
MaVL	Maximum voltage level limit
MCDA	Multi-criteria decision analysis
MCDM	Multi-criteria decision making
MCS	Monte Carlo Simulations
MCSPM	Multi-criteria stochastic planning model
MDP	Modern distribution planning
MH	Meta-heuristics
MILP	Mixed integer linear programming
MINLP	Mixed integer nonlinear programming
MISOCP	Mixed integer second order cone programming
MiVL	Minimum voltage level limit
MLL	Multiple load level
MnC	Monetary (risk) cost
MODGP	Multi-objective based distributed generation unit placement
MO/MOO	Multi-objective/Multi-objective optimizations
MOP	Multi-objective planning (or Multi-objective based planning)
MOPT	Multi-objective planning techniques
MOshBAT	Multi-objective shuffled bat algorithm
MOSOA	Multi-objective seeker optimization algorithm
MV	Medium voltage

NC	Normally closed switches
NDE	Non-distributed energy
NL	Non-linear/Non-controllable load
NO	Normally open switches
NPL	Network power losses
NPV	Net present value (of components, system and project)
NR	Newton Raphson load flow
NS	Net savings
NSGA	Non-dominated genetic algorithm
NTR	Network (distribution) reconfiguration
OCPL	Overall cost of power losses (during operation)
OCS	Overall complete system cost (including installations, O&M, power losses and reliability)
OF	Objective function
OFVC	Overall fixed and variable costs
OLTC	Online tap changer
OLSSFrLN	Overload (OL) at substation (SS), feeders (Fr) and loads nodes (LN)
OMC	Operation and maintenance cost
OPF	Optimum power flow
PBDG	Power buying from DG owner
PBSS	Power buying from substation (grid)
PBY	Payback years
PC	Penalty coefficient
PEM	Point estimation method
PF	Power filter
PFDE	Pareto frontier differential evolution
ph	Phase
PLd	Probabilistic load
PLF	Probabilistic load flow
PLHD	P (active) power loss based harmonic distortions
PLL	Probabilistic load level
P-loss	Real/resistive power losses
PQ	Power quality
PP	Planning period (horizon)
PSO	Particle swarm optimization
PT	Planning techniques
QCP	Quadratic constrained programming
QIC	Q (reactive) current (I) component
Q-loss	Reactive/inductive power losses
QOTLBO	Quasi oppositional teaching learning-based optimization
QPD	Q (reactive) power deviation
RA	Reclosers-automatic (or Automatic reclosers)
RCC	Reserve capacity of conductor
RCCI	Reserve conductor capacity (RCC) index
REG	Renewable energy generation
SA	Simulated annealing
SAMHBMO	Self-adaptive modified honey bee mating
SAIDI	System average interruption duration index
SAIFI	System average interruption frequency index
SAIUI	System average interruption unavailability index
S-BB-BC	Supervised Big Bang–Big Crunch
SC	Short circuit
SCI	Short circuit index
SCL	Short circuit level

SDMS	Smart distribution management system
SFL	Shuffled frog leaping algorithm
SLL	Single load level
SOA	Seeker optimization algorithm
SOF	Single objective function
SPEA	Strength Pareto evolutionary algorithm
SPMC	Switch purchasing and maintenance cost
SQP	Sequential quadratic programming
SSW	Sectionalizing switches
ST	Storage
STATCOM	Static synchronous compensator
STP	Short term planning
SUC	System upgrade costs
SVC	Static Volt-ampere reactive power (VAR) compensator
SWC	Switching costs
SWD	Switching devices
TDP	Traditional distribution planning
THD	Total harmonic distortions
TLA	Teaching learning algorithm
TLBO	Teaching learning-based optimization
TOC	Total operation cost
TS	Tabu search algorithm
TSIAECP	Two stage immune algorithm embedding compromise programming
TSW	Tie-switches
TVLL	Time-varying load level
TVV	Total voltage variation
UB	Unbalanced combined single and three phase loads
UL	Unbalanced three phase load
VAR	Volt-ampere reactive power
VD	Voltage deviation/drop
VEPB	Voltage error at power buses
VLd	Variable load
VLDG	Voltage level at distributed generation unit
VMP	Voltage magnitude profile
VPI	Voltage profile index
VPQ	Volt-ampere reactive power compensation and power quality
VR	Voltage regulator
VRC	Variable capacitors
VS	Voltage stability
VSI	Voltage stability index
VSL	Voltage stability limit
VSgL	Voltage sag level
VSM	Voltage stability (load-ability) margin
VS&OP	Voltage stability and optimization (tool)
VTHD	Voltage based total harmonic distortions
VUBP	Voltage unbalance profile
WSM	Weighted sum method
Yr.	Years

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