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REVIEW ARTICLE

An Extensive Data-Based Assessment of Optimization Techniques for Distributed Generation Allocation: Conventional to Modern

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Abstract
Distributed generation (DG) is a comprehensive, compact, and salient segment of the centralized power system due to its extensive prospective benefits in constrained/unconstrained power quality parameters. Traditional power plants have their own technical, environmental, and economic diminutions for the expansion of power generation in the distribution network. Furthermore, unreserved fossil fuel escorted the electricity companies towards the renewable resources of energy generation. The enhancement of power quality parameters, cost-saving, and fulfilling the energy demand can be achieved by the integration of optimized DG in the distribution network. This paper presents the conventional to modern mathematical approaches enacted for the objective variables' empowerment via optimization of size and location of DG. The optimization intricacies, parameters, constraints, and benefits are also highlighted in this paper. The exhaustive data-based assessment carried out in this paper is a new work in the literature.

Abbreviations

ALO	Ant-Lion Optimization
ALRPF	Allow reverse power flow
AO	Anyone
AVRPF	Avoid reverse power flow
BCBV	Branch current to bus voltage
BCS	Bilateral Contract Scenario
BDG	Bio gass Distributed Generation
BGA	Binary Genetic Algorithm
BIBC	Bus injection to branch current
BLA	Bi-level Approach
CAC	Considering all constraints
CCT	Critical clearing time
CGA	Continuous Genetic Algorithm
CGSA	Classical Grid Search Algorithm
CL	Constant Load
CML	Commercial Load
COP	Cost Optimization
CPLSM	Combined power loss sensitivity method
CPSO	Clonal Particle Swarm Optimization
DABC	Discrete Artificial Bee Colony
DHPF	Decoupled harmonic power flow
DS	Dispatchable system
ECIM	Equivalent Current Injection Method
EL	Exhaustive Load Flow
ELR	Energy loss reduction
FLC	Fuzzy logic controller
GLBIW	Global Local Best Inertia Weight
GOA	Grasshopper Optimization Algorithm
GSA	Gravitation Search Algorithm
HDG	Hydro DG
HeS	Heuristic search
HL	High load
HPSO	Hybrid Particle Swarm Optimization
IB	Immune based
IGA	Improved Genetic Algorithm
IHRA	Improved Hereford Ranch Algorithm
IL	Industrial load
Itr.	Iteration
IVM	Index Vector Method
LaPF	Lagging power factor
LC	Load Concentration
LCCA	Life cycle cost analysis
LDC	Local distribution company
LePF	Leading power factor
LFC	Limited feeder capacity
LFG	Land fill gas
LI	Loss Incentive
LL	Low load
LLC	Line loading capacity
LLR	Line loss reduction

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LSM	Loss Sensitivity Method
MALO	Multi-objective Ant Lion Optimization
MCPSO	Modified Clonal Particle Swarm Optimization
MFO	Moth-Flame Optimization
MGT	Mini Gas turbine
ML	Medium Load
MMNRES	Multi membered non recombinative evolution strategy
MNM	Modified novel method
MPI	Multi objective performance index
MVO	Multi Verse Optimization
MXL	Mixed load
ND	Non differential
NPr	No preference
NPV	Net profit value
OIW	Constant Inertia Weight
PFR	Power flow reduction
PI	Power system performance index
PP	Probabilistic planning
PR	Pollutant reduction
PSBIT	Power Stabililty Based Index Technique
PSF	Price scaling factor
QR	Quick restoration
RI	Reliability improvement
RIW	Random Inertia Weight
RL	Residential load
RP	Repeated power flow
RPF	Reverse power flow
ΣDG	Number of Distributed Generator
SI	Stability improvement
S_L^0	Peak load
SQP	Sequential Quadratic Programming
TI	Total incentive
Tiv	Time invariant
TLBO	Teaching learning-based Optimization
TP	Traditional planning
TSI	Transient stability improvement
Tv	Time variant
TVIW	Time Varying Inertia Weight
UCO	Uncontrolled output
UFC	Unlimited feeder capacity
Vdm	Maximum voltage drops
VL	Voltage limit
Vpm	V % mean
VSIM	Voltage Sensitivity Index Method
Wc	Clipping wind turbine generation output
W_L	Weightage factor for power loss
WoDG	Without Distributed Generation
WSP	Without solar penetration
Wt	Turning off wind turbine generation output
WTBDG	Wind turbine DG + Bio mass DG
W_{V1}	Weightage factor for voltage deviation
W_{V2}	Weightage factor for voltage variation

1 Introduction

In the modern era, distributed generation (DG) is an indispensable part of the electric power system. It is a futuristic approach for the modern power system due to its enormous advantages (technological benefits, financial benefits, and environmental benefits). The presence of DG in the distribution network enhances the stability and utilization of renewable energy compared to the previous conventional centralized generation (CG). DG bridges the gap between the generation of electric power and day-by-day increasing load demands. These advantages can be achieved by DG selection, site selection, analysis of load demand, renewable energy sources (RES) selection, and optimization for the placement of DG. The integration of DG in the distribution network also facilitates the reduced active power losses and reactive VA losses, enhanced voltage profile, and improved reliability and stability [1]. To create a renewably energized world such a revolutionary approach must be deliberately promoted at political level, social level, and individual levels. The separation from a conventional hierarchy of CG is escorted by the perception, recognition, and dissemination of RES in the distribution network. Moreover, DG unification with the centralized grid generation requires an advanced protection system that can devise the secured implementation to attain promising results despite the presence of various power quality constraints [2, 3].

The relative comparison between CG and DG could be done by the following factors [4]:

(a) *Output Capacity*

The generation capacity of CG is 100 MW-1000 GW while in DG it is up to 300 MW.

(b) *Technology Used*

In CG Hydroelectric plant, thermoelectric plant and nuclear power plant have been used while in DG the electric power has been generated by Diesel engine, Gas engine and RES.

(c) *Location*

CG is situated distant from the consumer and normally established in sector of non-renewable or renewable resources while DG is located near to the consumer facilities.

(d) *Generation to Distribution*

Step-up transformers have been used for high voltage transmission to substation in CG further step-down transformers are used for distribution from substation to distribution having reduced line power losses. DG may or may not be connected to grid for low voltage distribution system.

1.1 Contribution of Paper

In this paper, various types of conventional to modern mathematical optimization approaches to DG allocation are considered for enhancing the power quality parameters, environmental parameters, and financial parameters of the power network in the presence of different constraints.

1.2 Paper Organization

In Section 2, employed aspirations of DG planning have been elaborated. Section 3 presents the optimization approaches (conventional as well as modern mathematical) with methodology, constraints, and optimized results. In Section 4, conclusion of the paper is presented.

2 Employed Aspirations for DG Planning

Multitudinous driving factors have been attained by the optimization of DG allocation and size selection in power system network. The aspirations of DG planning can be recapitulated as technological, economic, and environmental perspectives. The optimization DG allocation benefits are extensively illustrated in Fig. 1.

2.1 Technological Aspect

DG aims to very significant technical advantages which embrace the voltage profile enhancement, active and reactive power losses minimization, power factor optimization (PFO), line loss reduction and network MVA capacity maximization. The various researches for technological advantages are summarized as:

2.1.1 Voltage Profile Enhancement

Voltage profile enhancement (VPE) is an imperative parameter in the power quality of the distribution system. The voltage level is boosted by increasing the penetration level of DG during optimized allocation in the distribution network. In the presence of DG, the VPE is selected as an objective function and the results are significant by providing the bidirectional power flow to/from the power grid during peak hours or valley hours of load [5]. The voltage stability is increased by using the incremental voltage (dv/dp) sensitivities method during the integration of DG [6]. Voltage profile along with voltage stability is also improved by utilizing the positive sequence of voltage ratio [7], power voltage curve [8], and voltage sensitivity index [9]. The voltage sag problem is reduced in a low voltage distribution network during various faults [10]. VPE along with power loss reduction (PLR) is facilitated by considering voltage amplitude as a function of injected power [11], while the max operator is used for such optimization in the Tehran electricity distribution grid [12, 13] and in radial distribution network [14]. The authors proposed a voltage stability index to enhance the voltage level by DG allocation [15]. P–V buses [16] and multiple micro turbines [17] have been incorporated for the improvement of voltage profile and such type of distribution network consist a renewable energy based optimized DG allocation. Voltage rise issue is also encountered with the integration of DG to meet the power requirement during time variant and invariant load [18].

2.1.2 Power Loss Reduction

The integration and optimized allocation of DG in the distribution network enables the minimization of various power losses. Reducing the network losses, reactive power losses, and line loading is done by the optimum sizing and siting of DG in a meshed network [19] and to the load of concentrated buses in ref. [20]. Total energy losses are reduced by active and reactive VA injection at selected bus [9, 10] while real-time solar radiation and atmospheric temperature are considered to reduce the real power losses in a voltage distribution system of Thailand with the contemplation of power quality constraints [15]. A solar photo voltaic (SPV) system is used to reduce power losses with voltage limit consideration [21] while for power injection, DG size of 10–80% of system load demand is selected to diminish the actual power losses [22]. Moreover, actual power losses are decreased by the integration of multiple distributed generation (MDG) systems in continuous and discrete optimization [23]. Transmission line losses are reduced by ECIM which is a function of power quality parameters [24]. However, real power injection and reactive power compensation are done by wind power generation [6]. Total power losses are reduced by computing approximate losses for each bus [25] and compensating real component of branch currents [26]. Real power losses are minimized by using a metaheuristic optimization approach (MHOA) [27]. It is also minimized for hourly power flow with different penetration levels in different operating modes of wind turbines [28]. Annual energy losses are reduced with time-varying characteristics of load curve [29], random behavior of wind speed [30] and intermittent nature of RES [31], avoiding RPF [32], and allowing RPF [33].

2.1.3 Power Factor Optimization

Power factor is also an important power quality parameter which is necessary to optimized in the presence of DG. To

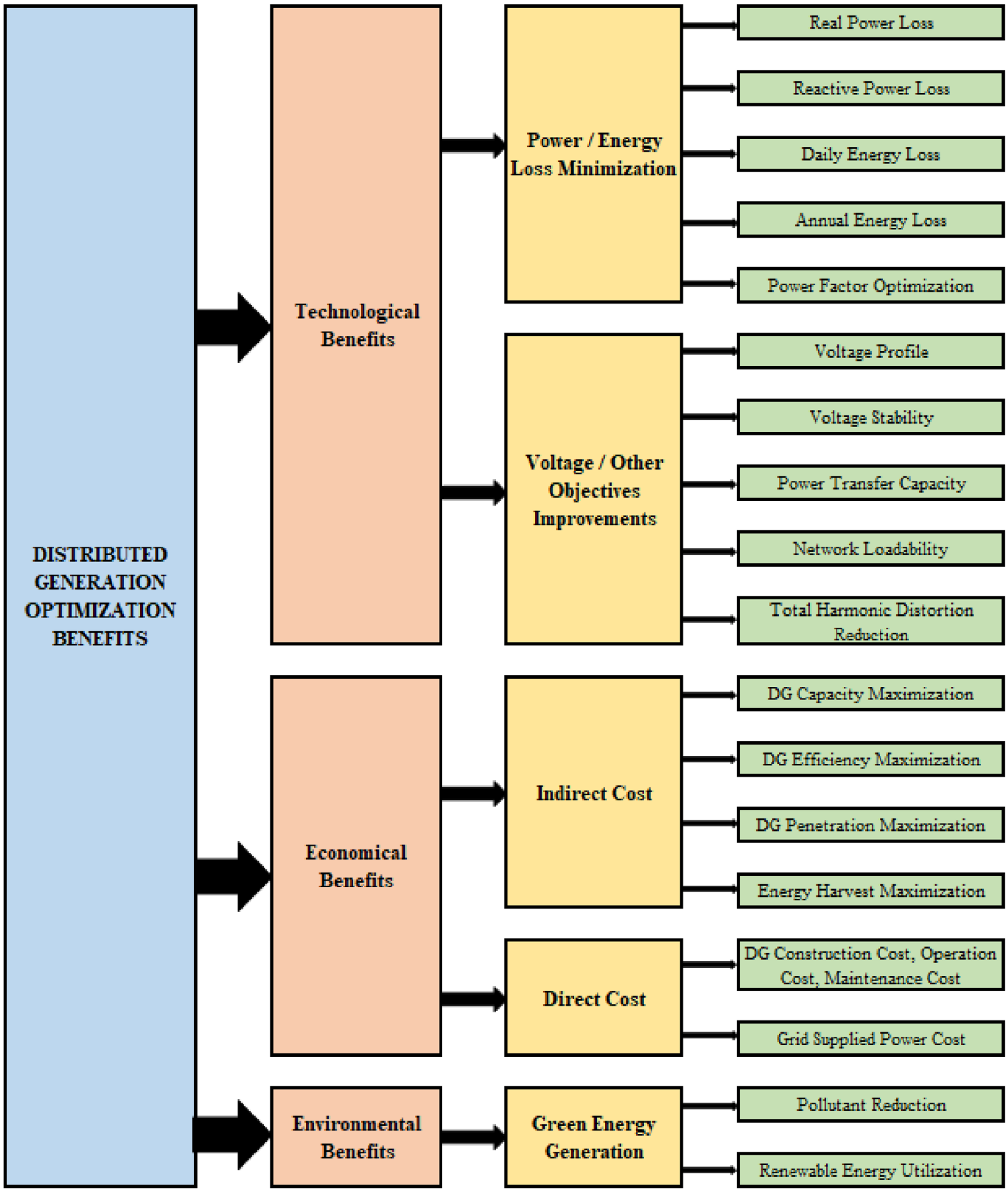


Fig. 1 Benefits of DG optimization

reduce the real power losses, authors optimized the value of power factor by considering the maximum and minimum value of operating power factor while taking inequality boundary conditions, related practical concerns and rounded off issues into account [27]. DG size and power factor is simultaneously optimized by assuming the prespecified constant value of power factor at various load level [29]. Energy losses are reduced by optimizing the power factor in a battery energy storage (BES) integrated SPV system at various load level and the comparison is demonstrated at unity power (UPF), lagging power and leading power factor [34]. Impact of power factor variation is shown on power losses and voltage profile by taking UPF or non UPF of the system [35]. Optimal value of power factor is identified by considering the all-possible values of power factor using curve fitted technique and exact solution method [22]. In [9], a comparative analysis has been shown for UPF and 0.9 lagging power factor with different DG optimization approaches.

2.1.4 Total Harmonic Distortion Reduction

Total harmonic distortion reduction (THDR) is another determined objective of DG planning. The forward/backward sweep approach has been used to optimize the total harmonic distortion (THD) in a distributed system that comprises the amalgamation of passive elements and a harmonic current generator. Moreover, a harmonic spectrum is developed for a nonlinear (NL) load of deviated frequency driver and a convertible speed driver having branch current is a function of harmonic current [31]. THD is optimized in an SPV-based DG system where the various solar radiation levels are considered. THD in voltage profile and current profile have been measured by considering the background harmonics in an 11-kW grid-connected inverter [15].

2.2 Economical Aspect

Cost optimization (COP) is the pillar of the foundation for planning, execution, and maintenance of DG in a distribution system. Total cost (comprises installation cost, maintenance cost, and sag reduction cost) have been reduced by optimum DG allocation and the results are significant [10]. The distribution companies (DisCo)'s cost minimization and profit maximization are exhibited using BLA for DG planning in ref. [36]. DG capital cost with the state-dependent cost is considered in ref. [37] while fuel cost reduction (considering utilization factor) is achieved by the integration of DG in Japan's east power station [38]. The reimbursement time and anticipated profit rate are calculated by forming a multi-objective (MO) DG optimization for the sake of DisCo and owner benefits [39].

2.3 Environmental Aspect

Environment protection has been one of the most crucial aspects of human beings' existence on earth because of the aggressive use of fossil fuels in the traditional power system for meeting the peak demand of end-users. DG could be a prospective measure for the perforation of a natural source of energy into the electrical network of the power system for reducing greenhouse gaseous pollutants emissions and weather change [40]. DG has a great potential for the utilization of RES in power generation and is capable to build a low carbon emission grid. Carbon emission has been calculated for the complete life cycle of DG with the help of the carbon emission intensity factor having a procedure in which the life cycle of the product and pollutant part of the product have been pre-measured. With the penetration of RES in the power system, CO2 emission is reduced up to 1.8 million tons [41].

3 Optimization Approaches

Optimization approaches can be categorized into the following classification; conventional, modern mathematical, and hybrid.

3.1 Conventional Approaches

Conventional approaches of optimization are traditional basic search methods for the optimization of DG parameters. The proposed techniques have been executed by various researchers under this category. The classification of convention algorithm is given in Fig. 2. Moreover, a significant review and data-based assessment of such approaches for DG optimization are conferred in Table 1.

3.1.1 Analytical Method (AM)

In this paper, several AM is reviewed that are used for optimum DG allocation in a distribution network. Total power losses are reduced by an equivalent current injection method in which the BIBC matrix and BCBV have been applied for finding the value of injected current and tested for three distribution systems without considering the admittance matrix and Jacobin matrix [24, 42]. The exact loss formula (ELF) is used for the DG optimization and this method is independent of the type of DG and able to generate the active power and reactive VA [25]. To minimize the energy losses in a three-phase unbalanced system feasible optimization interval (FOI) approach is used and bridging the gap between feeder demand characteristic and SPV based DG (SPVDG) characteristic [32]. DG optimization is done by power injection method (PIM) in a dispatchable system or non-dispatchable system with the consideration of the time-varying nature of the load and supply [29]. FOI technique has been implemented in which the RPF is considered and the power is injected at coupling node followed by the calculation of line losses by Carson equations [35]. An algebraic approach (AA) has been applied for VPE while in [7] an iterative method (IM) has been used for improving the power quality parameters and line loadabilty. In continuation of DG optimization, analytical techniques like a primal–dual interior-point algorithm (MPDIPA) [11], AA [43], multi-objective index (IMO) with self-correction algorithm (SCA) [34], and heuristic curve fitted method (HCFM) [22] are analyzed. In continuation, an IA is used to get the optimum size and location of DG that enhance the reliability and voltage profile of a distribution network. The approach is evaluated

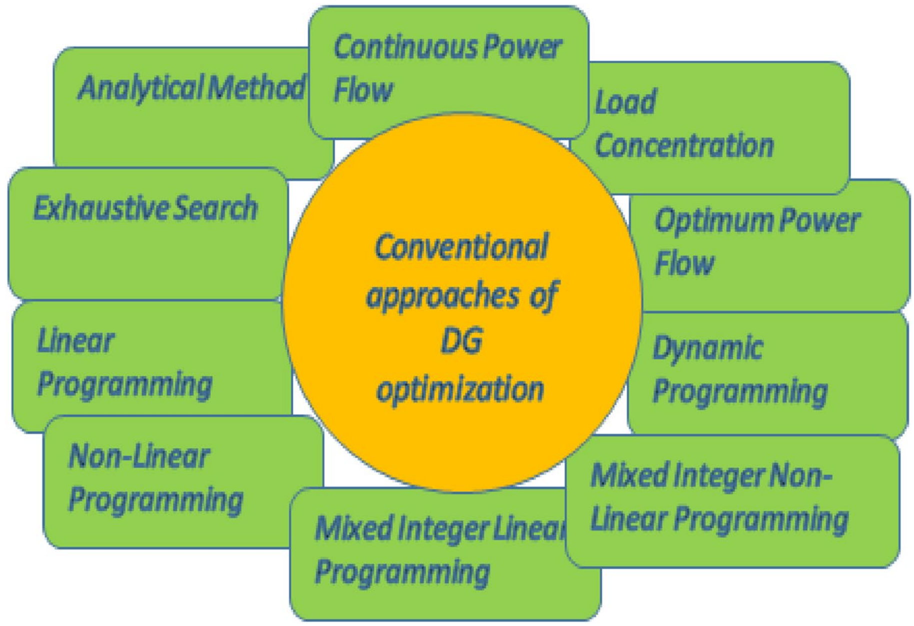


Fig. 2 Conventional approaches of DG optimization

on IEEE 34 bus system and the results are significant on the of different indices [44].

3.1.2 Exhaustive Search (ES)

In [45], the brute force method (BFM) is implemented for the SPVDG system incorporation of MATLAB programming with the consideration of daily load and supply curve without violating the European standard on power quality (EN 50,160 standards). It is like the backward/ forward sweep algorithm includes the large the R/X ratio of long feeder by assuming the π model of a distributed system. A two-stage technique is formed for the DG optimization which is dependent on the supply and load variation, the internal stage consists of ES while the external stage has clustering approach (CA) [46]. Power quality parameters are improved by using the probabilistic approach (PA) [15] and weightage ES [47] by optimal DG allocation. In continuation, Monte Carlo simulation and C language are also used. A Newton–Raphson (N-R) method along with IM has been enacted for the MO optimization problem to improvise the cost-effective power quality parameters [34].

3.1.3 Linear Programming (LP)

The utilization of the distribution network is changed after the dissimilation of DG. The authors presented a methodology for the optimization of DG and getting the maximum harvesting of energy by considering the various power quality and financial constraints. The energy reaping is dependent on DG size, load level, DG location, occurred losses, and financial parameters. Moreover, the limitations which are occurred due to financial concerns are considered to implementing an IM for solving the linear optimization problem [48]. This methodology has the significance to validate the results of nature-inspired optimization techniques. The authors evaluated a genetic algorithm technique for the DG allocation in the actual distribution network of Egypt and the outcomes are justified with the help of LP. Moreover, MO optimization is carried out for optimizing the various parameters of power quality like LLR, SRI, VPE, and PFR [49].

3.1.4 Non-Linear Programming (NLP)

Adaptive reactive power compensation must also be a benefit that would be facilitated in the DG incorporation in the distribution network. Continuing this, the authors demonstrated a DG optimization technique that is based on NLP to solve the MO function. Different objective functions are converted into a single objective function because of power loss reduction and enhanced voltage regulation. It has been highlighted that the application of this optimization technique is valid for different types of DGs by employing the fuzzification technique and adequate weighting scale to facilitate the one-level approach for various objective functions. However, the process of optimization is intended with the help of constraint optimization (CONOPT) which is a tool of general algebraic modeling system (GAMS) software used for nonstop power flow runs [50].

3.1.5 Mixed-Integer Linear Programming (MILP)

In [36], a two-tier approach having the mutual approach among DisCo with the owner has been accomplished. This

Table 1 Data-based assessment of DG optimization by adopted conventional approaches

Ref	Conventional optimization method	Test systems	Different cases	Optimum DG size	Optimum DG location	Strengthened parameters	Compared approaches
[5]	AA	48 km feeder	Vref = 0.94 (p.u.)	144.7 (kVA)	46.8 km	VPE	WoDG
			Vref = 0.95 (p.u.)	292.2 (kVA)	44.8 km		
			Vref = 0.96 (p.u.)	458.3 (kVA)	42.6 km		
			Vref = 0.97 (p.u.)	650 (kVA)	40.1 km		
[7]	IA	IEEE 34	Itr. −1	600 (kVA)	890	PLR, LLC, VPE,	VSIM
			Itr. −2	600 (kVA)	852		
			Itr. −3	1200 (kVA)	814		
[8]	MINLP	IEEE 41	Dispatchable system (0.95 LePF)	4.5 (MVA)	40	VPE	WoDG
			WTDG (0.95 LePF, UPF)	8.8, 1.1 (MVA)	19, 40		
			SPV (0.95 LePF, UPF)	49.7, 1.06, 2.38 (MVA)	19, 28, 40		
[9]	MNM	IEEE 33	UPF	2494.8 (kVA)	6	COP, PLR, VPE	WoDG
		IEEE 69		1832.53 (kVA)	61		
	CPLSM	IEEE 33	UPF	1800 (kVA)	8		
		IEEE 69		1850 (kVA)	61		
	IVM	IEEE 33	UPF	1550 (kVA)	30		
		IEEE 69		1850 (kVA)	61		
	VSIM	IEEE 33	UPF	1000 (kVA)	16		
		IEEE 69		1450 (kVA)	65		
[11]	MPDIPA	IEEE 123	ΣDG = 4	65.37,34.75, 12.17, 31.43 (kW)	60, 36, 57,42	PLR, VPE	WoDG
[15]	PA	IEEE 51	SPV ΣDG = 1	0.8 (MW)	38	PLR, VPE, THDR	AM
			SPV ΣDG = 2	0.7, 0.9 (MW)	38,19		
			SPV ΣDG = 2 with THD	0.7, 0.5 (MW)	38, 19		
[22]	HCFM	IEEE 69	UPF	1900 (kVA)	61	PFO, PLR, VPE	AM
			0.85 LaPF	2300 (kVA)	61		
		IEEE 32	0.85 LaPF	2000 (kVA)	29		
[24]	ECIM	IEEE 12	ΣDG = 1	0.2272 (MW)	9	PLR	Classical grid search Method
		IEEE 34	ΣDG = 1	2.8848 (MW)	21		
		IEEE 69	ΣDG = 1	1.8078 (MW)	61		
[25]	ELF	IEEE 30	ΣDG = 1	3.3 (MW)	12	PLR	Loss sensitivity, Repeated load flow
		IEEE 33	ΣDG = 1	2.49 (MW)	6		
		IEEE 69	ΣDG = 1	1.81 (MW)	61		
[29]	PIM	IEEE 69	BΣDG = 2	0.89, 1.05 (MVA)	62,35	ELR, PFO	WoDG
			WTΣDG = 2	0.86, 0.99 (MVA)	62,35		
			WTBΣDG = 4	0.49, 0.56, 0.71, 0.82 (MVA)	62, 35, 62, 35		
[32]	FOI	IEEE 29	SPV ΣDG = 1	0.2905 (MW)	17	PLR, VPE	WoDG
[33]	FOI	IEEE 29	ΣDG = 1 (ALRPF)	340.4 (kW)	26	PLR, VPE	AVRPF
			ΣDG = 1 (AVRPF)	290.5 (kW)	17		
		IEEE 14	ΣDG = 1 (ALRPF)	803.1 (kW)	9		
			ΣDG = 1 (AVRPF)	601.7 (kW)	7		

Table 1 (continued)

Ref	Conventional optimization method	Test systems	Different cases	Optimum DG size	Optimum DG location	Strengthened parameters	Compared approaches
[34]	IMO & SCA	IEEE 33	SPV + BES at UPF	4.336 (MW) + 1.803 (MW)	12, 20, 24	PFO, PLR, VPE	Standard IEEE 1547
			SPV + BES at LaPF	4.336 (MW) + 1.804 (MW)	12, 20, 24		
[36]	BLA	IEEE 34	HL	1.5 (MW)	21	COP	WoDG
			ML	1.5 (MW)	24		
			LL	1.5 (MW)	21		
[42]	BIBC, BCBV	IEEE 33	Injecting P only	0.981, 0.981, 0.981, 0.325 (MW)	12, 30, 24, 5	PFO, PLR, VPE	Repeated power flow
			Injecting P & Q	1.16, 1.14, 1.13, 0.29 (MW)	30, 11, 24, 31		
		IEEE 69	Injecting P only	1.01, 0.797, 0.511, 0.318 (MW)	61, 62, 17, 50		
			Injecting P & Q	1.23, 0.99, 0.61, 0.88 (MW)	61, 62, 17, 15		
[43]	AM	IEEE 30	ΣDG = 1	15 (MW)	5	PLR	WoDG
[44]	IA	IEEE 33	ΣDG = 2	2.7, 0.39 (MW)	6, 30	VPE, PLR	FFM, CS
[45]	BFM	IEEE 30	ΣDG = 1	1 (MW)	9	PLR	Heuristic search
[46]	CA & ES	24 Node	ΣDG = 5	40, 100, 15, 100, 400 (kW)	4, 7, 9, 11, 13	COP, PLR, VPE	GA, MINLP
[47]	ES	IEEE 6	ΣDG = 2	3.4, 0.85 (MW)	3, 5	PLR, VPE	WoDG
		IEEE 14	ΣDG = 2	25.9, 25.9 (MW)	10, 14		
		IEEE 30	ΣDG = 7	16.194, 8.097, 10.796, 8.097, 5.398, 2.699, 5.398 (MW)	17, 18, 20, 24, 26, 27, 30		
[48]	LP	IEEE 7	BΣDG = 1	8 (MW)	7	COP, PLR, VPE	WoDG
			ΣDG = 1 (LFG)	650 (kW)	3		
			HΣDG = 1, 2, 3	2, 1.5, 0.6 (MW)	2, 3, 2		
			WTGn = 1, 2, 3	4.5, 8.5, 9.4 (MW)	7, 2, 6		
[53]	OPF	IEEE 12	FLCOPF (NPr)	1.8, 30.7, 14.3 (MVA)	1, 10, 11	COP, PLR	IM
			Direct FLCOPF (NPr)	0, 30.9, 17.6 (MVA)	1, 10, 11		
			FLCOPF (CEL-1)	2.6, 30.7, 11.7 (MVA)	1, 10, 11		
			Direct FLCOPF (CEL-1)	20.7, 2.3, 17.7 (MVA)	1, 10, 11		
[54]	FLCOPF	IEEE 12	OPF (NPr)	12.3, 52.3, 38.2 (MVA)	1, 10, 11	COP, PLR	OPF
			FLCOPF (NPr)	13.6, 49.1, 38.4 (MVA)	1, 10, 11		
			OPF (@ bus 1)	34.9, 52, 11.6 (MVA)	1, 10, 11		
			FLCOPF (@ bus 1)	35.9, 48.8, 12.2 (MVA)	1, 10, 11		
[55]	OPF	IEEE 14	ΣDG = 1	202.62 (MW)	4	COP, PLR	WoDG
			ΣDG = 2	195.05 (MW)	4		
			ΣDG = 3	141.28 (MW)	9		

Table 1 (continued)

Ref	Conventional optimization method	Test systems	Different cases	Optimum DG size	Optimum DG location	Strengthened parameters	Compared approaches
			ΣDG = 4	41.94 (MW)	14		
			ΣDG = 5	50.38 (MW)	14		
			ΣDG = 6	42.84 (MW)	14		
			ΣDG = 7	25.33 (MW)	14		
[57]	OPF	IEEE 69	ΣDG = 3 (P = 99%, α = 0.1)	2.6614 (MW)	26, 35, 62	COP, PLR	WODG
			ΣDG = 5 (P = 99%, α = 0.1)	3.9761 (MW)	4, 26, 40, 49, 62		
			ΣDG = 7 (P = 99%, α = 0.1)	5.5305 (MW)	4, 26, 30, 35, 40, 49, 65		
			ΣDG = 9 (P = 99%, α = 0.1)	6.0027 (MW)	4, 13, 17, 26, 30, 40, 49, 58, 52		
			ΣDG = 3 (P = 99.999%, α = 0.01)	2.6614 (MW)	26, 35, 62		
			ΣDG = 5 (P = 99.999%, α = 0.01)	4.0069 (MW)	4, 26, 40, 49, 62		
			ΣDG = 7 (P = 99.999%, α = 0.01)	5.5305 (MW)	4, 26, 30, 35, 40, 49, 65		
			ΣDG = 9 (P = 99.999%, α = 0.01)	6.0027 (MW)	4, 13, 17, 26, 30, 40, 49, 58, 52		
[58]	LC	IEEE 13	LCn @ 5	2, 1 (MW)	5, 11	PLR, VPE	Heuristic search
		IEEE 25	LCn @ 12	2, 2, 2, 0.5(MW)	12, 15, 14, 7		
			LCn @ 17	2, 1.5 (MW)	17, 22		
		IEEE 30	LCn @ 2	50, 50, 50, 10(MW)	2, 9, 6, 28, 13		
[59]	CPF	IEEE 34	ΣDG = 1	25 (MW) and 20 (MVA)r	26	PLR, LLC, VPE	WoDG
			ΣDG = 2	25 (MW) and 20 (MVA)r	26, 33		
			ΣDG = 3	25 (MW) and 20 (MVA)r	26, 33, 17		
[90]	N-R & IS	IEEE 6	ΣDG = 1	6 (MW)	3	COP, PLR, VPE	AA
		IEEE 14	ΣDG = 1	16 (MW)	8		
		IEEE 30	ΣDG = 1	35 (MW)	11		

bi-level MILP approach constitutes the upper level having DG location and central point of power injection while the lower level consists of payment minimization of DisCo to the energy market. A decision-making approach between the owner for profit maximization and DisCo for payment minimization is considered.

3.1.6 Mixed-Integer Non-Linear Programming (MINLP)

The MINLP optimization technique is adopted in various researches [8, 51]. It will affect the DisCo investment planning for transformer purchasing and feeder up-gradation. A pool market model is developed having Lagrangian multiplier (LM) and line loss sensitivity with the consideration of equality and inequality constraints which is optimized by GAMS using a Sparse nonlinear optimizer solver for generation companies and DisCo profit [51]. Beta and Weibull probability distribution functions have been employed to calculate the probabilistic characteristics of natural sources for DG optimization [8].

3.1.7 Dynamic Programming (DP)

Increasing the penetration of renewable energy-based DG in distributed generation is one of the futuristic aspects of energy generation. A reconfiguration of the chronological network has been proposed to reduce the limitation of natural sources. To enhance the power quality parameters, a Markov decision process is adopted to optimize the DG operation. Moreover, the present and future costs are considered to decide every step of the Markov model. Consequently, dynamic programming is used to optimize the proposed recursive model and evaluated on IEEE 33 and IEEE 123 test systems [52].

3.1.8 Optimum Power Flow (OPF)

Several researchers [53, 54, 55, 56, 57] presented the OPF technique for the allocation of DG. CONOPT with a generalized gradient method is used for finding the network generation capacities. For maximizing the generation capacities, the NL optimization executed by finding the multiple local optima is used in a highly meshed reliable system. Initially no contingencies in the problem formulation and solved using scrutiny constrained OPF models then selection of contingency without constraint and include the most violated constraints. In [53, 54], Fault level constraint optimum power flow (FLCOPF) is considered for sinks source concept having bi-level procedures OPF and generation reduction optimization algorithm to solve the quadratic benefit function by considering capacity expansion locations (CELs). For social welfare and profit maximization, local marginal price and short-run marginal price with LM are considered [55]. In continuation of the above social welfare, maximization involves the quadratic curves of benefit, bid, and cost given by DISCOs, seller, and DG owner respectively while profit maximization includes the two-block (inner and outer) approach. OPF technique with genetic algorithm for a variable number of DG [56] and as ordinal optimization (OO) for three-level approach [57] has been executed. Moreover, out of search space, one of all possible solutions is in the top percent α with a probability level of P.

3.1.9 Load Concentration (LC)

In [20], the Kalman filter algorithm is executed for the optimization of DG allocation. This algorithm has the properties of smoothing and noise rejection which are used to solve the linear time-varying equations. Initially, the losses are calculated by the N-R method then the state vector estimation is completed in the measurement update and time update stages which are evaluated by the root mean square error. In [58], the concept of the equivalent load is implemented in two-step approaches of load centroid (LCn) and performance index. Firstly, the equivalent load is calculated then the PI is approachable for finding the active power loss and average node voltage variation.

3.1.10 Continuous Power Flow (CPF)

Referring to the continuation parameters and two levels iterative approach (IA) most sensitive buses have been found for optimum location of DG approaching towards bifurcation point from a stable point. CPF optimized system having predictor and corrector step could be incorporated as a compensator or as a large source for DG units [59].

3.2 Modern Mathematical Approaches

Modern mathematical approaches are basically artificial intelligent techniques founded on the performance of society and nature. Such type of approaches can be predominantly designated as given in Fig. 3. An assessment of modern mathematical approaches for DG optimization is manifested in Table 2.

3.2.1 Evolutionary Programming (EP)

EP is one of the matured artificial intelligence optimization algorithms based on the artificers of real anthology having metamorphosis, contention, and evolution levels which have been used for non-continual, uneven, and undistinguishable optimization problems unlike the conventional methods of optimization. Reactive power planning has been executed using the probability transition rule in [60] comprises the following steps: initialization, statistics, mutation, completion, and determination. The authors demonstrated the EP on 12.66 kV, IEEE 69 test system with two modes of operation involving turning off DG based on wind turbine (WTDG) and clipping of the output using an index-based scheme and sensitivity analysis by keeping the ratio of dispatched wind energy to load (WPDLR) within designated limit [28].

3.2.2 Genetic Algorithm (GA)

GA has the natural assortment that relates to the greater category of EP and has been used to evaluate for the optimum DG allocation in the power system [61]. In continuation, GA has been demonstrated to produce higher grade optimization by leaning on bio-simulated steps like mutation, crossover, and selection. It has been implemented for NL optimization in a Tehran regional electricity company considering the financial objectives that include the pricing of power connectors and the energy which is not provided by the system [14]. Moreover, the linear problem has been optimized for the enhancement of the power quality parameter in the West Delta sub-transmission network [49]. Minimization of

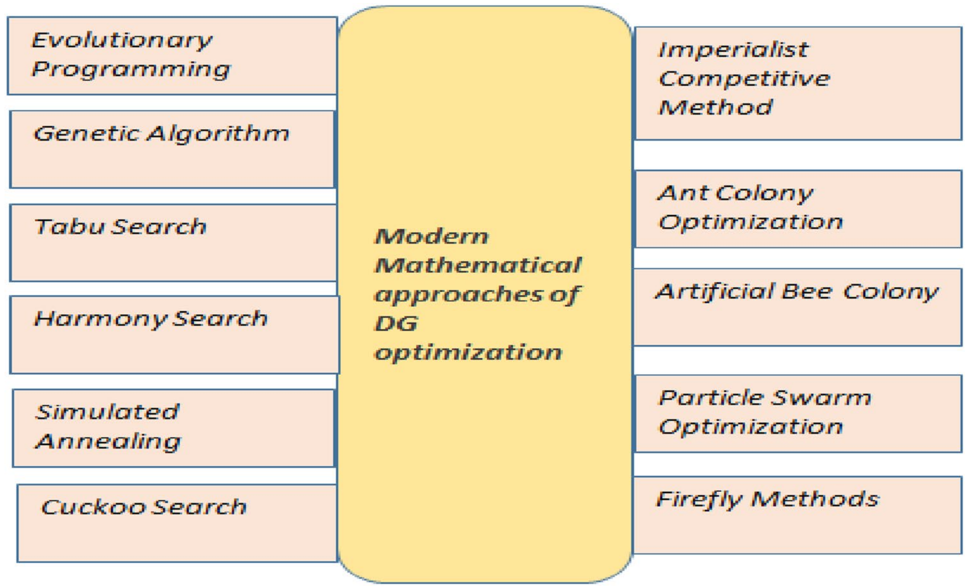


Fig. 3 Modern mathematical approaches of DG optimization

voltage sag effect that is calculated by voltage divider rule with the line loss minimization and cost-saving subjected to the limitations of power flow, voltage level. The optimum size of DG is achieved by a stochastic optimization technique with a point of common coupling consideration during various fault conditions [10]. The various types of load models have been considered for the optimization results with the consideration of source as negative sink and index-based performance evaluation [62]. GA has been integrated with OPF [56] and AM [16] for DG optimization. In [63], step by step approach has been used for the optimization of the size and location of DG in main and sub-network distribution systems using single-step restoration and supplied by utility-owned DG to encounter the power outage problem due to cold load pick up conditions. A non-dominated sorting GA (NSGA) and forward/ backward sweep method have been executed for the renewable DG / nonrenewable DG (NRDG) allocation and size selection in [31]. Zonal division of peak load [64], moment method and central limit theorem [65] have been incorporated with DG planning for the cost, power quality parameters, and reliability optimization. Moreover, SPV and WTDG have been characterized as DG for Weibull reliability, and maintenance costs optimization results in annual operating cost (AOC) minimization.

3.2.3 Tabu Search (TS)

TS was proposed in 1986 that is based on the planning of forbidden moves violating the cycling to form of strong inhibition search in which enough memory is saved for the tabu from down to up in the tabu list. TS technique is employed for the optimization of DG placement considering the residential, commercial, and industrial load having three types of algorithms proceed simultaneously which involves rounding calculation, local minimum finding, and optimum installation respectively [66]. The procedure involves initialization, neighborhood solution, loss calculations, repetition, and updating of the current solution till a maximum number of iterations to get the optimization. If the neighborhood solution is healthier than the present set of values then the neighborhood result is adopted that will satisfy the aspiration in the tabu list. The authors presented a methodology, for the optimization of DG resources and reactive power resources optimization with the involvement of short, intermediate (record best rail solution) and long-term memory (more than 3 successive iterations) having controlled output (CO) and Z scenarios [67]. In this work, the forbidden move i.e., the addition of a new move and deletion of the old one is involved having the updated solution in the next iteration of the tabu list whose length is directly proportional to the better solution.

3.2.4 Harmony Search (HS)

Geem et al. suggested this heuristic technique, is built on imitating the extemporization of the music player for finding the best condition of music by an artistic estimation. Musicologist Tirro and French composer Jean Philippe Rameau documented the history of American Jazz and invented the classical method of harmony examined on Traveling salesman problem (TSP) [68]. Improved multi-objective harmony search (IMOHS) has been suggested for the optimization of DG placement having qualitative comparison with NSGA II. IMOHS includes the search process of novel global HS which includes the mutation probability and excludes the harmony memory considering rate parameters. Mainly two

Table 2 Data-based assessment of DG optimization by adopted modern mathematical approaches

Ref	Modern mathematical optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
[6]	DE	IEEE 6	ΣDG = 2	0.48995, 0.63858 (p.u.)	3, 6	PLR, VPE	0.020545 p.u	Base Care WoDG, BBPSO, MMN-RES
		IEEE 30	ΣDG = 6	0.16362, 0.11973, 0.21795, 0.20327, 0.013192, 0.29578 (p.u.)	16, 18, 19, 23, 25, 27		0.088605 p.u	
[10]	GA	IEEE 34	ΣDG = 4	500 (kW) each	20, 25, 8, 17	COP, PLR, VPE	102.76 (kW)	
		IEEE 30	ΣDG = 5	510 (kW) each	18, 11, 25, 21		104.6 (kW)	
[12]	GA	IEEE 13	V % Mean = 98.823	3200 (kW)	13	PLR, VPE	100.25 (kW)	
			V % Mean = 98.81	1600, 1600 (kW)	13, 9		92.9 (kW)	
[13]	GA	IEEE 13	V % Mean = 98.823	3200 (kW)	13	PLR, VPE	100.25 (kW)	
			V % Mean = 98.81	1600, 1600 (kW)	13, 9		92.9 (kW)	
[18]	GA	IEEE 12	ΣDG = 1 (Tiv)	0.24 (MW)	9	COP, PLR, VPE	0.0046 (MW)	WoDG
			MDG (Tiv)	0.0755, 0.0484, 0.0676, 0.0594 (MW)	6, 8, 9, 10			
			ΣDG = 1 (Tv)	0.13 (MW)	9		0.0035 (MW)	
			MDG (Tv)	0.0401, 0.0601, 0.0401, 0.0267 (MW)	6, 8, 10, 12			
[19]	IHRA	IEEE 6	ΣDG = 4	15 (MW)	2, 3, 4, 6	PLR	0.0498 (MW)	GA
		IEEE 14	ΣDG = 4	26 (MW)			11.12%	
		IEEE 30	ΣDG = 4	28.3 (MW)			9.08%	
[23]	PSO	IEEE 69	ΣDG = 1	1904.2 (kW)	61	PLR	23.9 (kW)	SQP
			ΣDG = 2	1582, 322 (kW)	61, 21		13.6 (kW)	
			ΣDG = 3	1278, 301, 324 (kW)	61, 64, 21		12.8 (kW)	
[27]	ABC	IEEE 69	ΣDG = 1, load = 3802 (kW) + 2694 (kVA)r	2200 (kVA)	61	COP, PFO, PLR	23.9199 (kW)	GA, ELF
			ΣDG = 1, load = 150%	3400 (kVA)	61		54.7271 (kW)	
			MDG, load = 3802 (kW) + 2694 (kVA)r	2100, 600 (kVA)	61, 17		7.99901 (kW)	
			MDG, load = 150%	3200, 900 (kVA)	61, 17		17.9966 (kW)	
			ΣDG = 1 + capacitor (load = 100%)	2200 (kVA), 300 (kVA)r	61, 18		18.5512 (kW)	
			ΣDG = 1 + capacitor load = 150%)	3300 (kVA), 600 (kVA)r	61, 16		42.1286 (kW)	
			Active Power DG (load = 100%)	1800 (kW) + 1350 (kVA)r	61		23.282 (kW)	
			Active Power DG (load = 150%)	2700 (kW) + 1950 (kVA)r	61		53.2194 (kW)	
			DG size is fixed	1000 (kVA)	61		80.29 (kW)	
[28]	EP	IEEE 69	Wc, WPDLR = 0	0.25 (MW) each (1 SPV, 1 WTDG)	53	PLR, VPE	65.69 (MWh)	GA, ES
			Wc, WPDLR = 0.1	0.25 (MW) each (1 SPV, 1 WTDG)	51, 53		51.16 (MWh)	

Table 2 (continued)

Ref	Modern mathematical optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
			Wc, WPDLR = 0.2	0.25 (MW) each (1 SPV, 1 WTDG)	54, 50		44.81 (MWh)	
			Wc, WPDLR = 0.3	0.25 (MW) each (1 SPV, 1 WTDG)	53, 50		42.58 (MWh)	
			Wc, WPDLR = 0.4	0.25 (MW) each (1 SPV, 1 WTDG)	53, 50		42.17 (MWh)	
			Wt, WPDLR = 0	0.25 (MW) each (1 SPV, 1 WTDG)	53		65.69 (MWh)	
			Wt, WPDLR = 0.1	0.25 (MW) each (1 SPV, 1 WTDG)	53, 53		61.4 (MWh)	
			Wt, WPDLR = 0.2	0.25 (MW) each (1 SPV, 1 WTDG)	53, 53		56.04 (MWh)	
			Wt, WPDLR = 0.3	0.25 (MW) each (1 SPV, 1 WTDG)	54, 50		48.17 (MWh)	
			Wt, WPDLR = 0.4	0.25 (MW) each (1 SPV, 1 WTDG)	53, 50		43.79 (MWh)	
			Wc, WPDLR = 0	0.125 (MW) each (2 SPV, 2 WTDG)	53, 54		65.69 (MWh)	
			Wc, WPDLR = 0.1	0.125 (MW) each (2 SPV, 2 WTDG)	53, 54 and 51, 53		51.14 (MWh)	
			Wc, WPDLR = 0.2	0.125 (MW) each (2 SPV, 2 WTDG)	52, 54 and 50, 53		44.7 (MWh)	
			Wc, WPDLR = 0.3	0.125 (MW) each (2 SPV, 2 WTDG)	50, 53 and 50, 53		42.53 (MWh)	
			Wc, WPDLR = 0.4	0.125 (MW) each (2 SPV, 2 WTDG)	53, 54 and 50, 52		42.15 (MWh)	
			Wt, WPDLR = 0	0.125 (MW) each (2 SPV, 2 WTDG)	53, 54		65.69 (MWh)	
			Wt, WPDLR = 0.1	0.125 (MW) each (2 SPV, 2 WTDG)	54, 54 and 53, 53		58.43 (MWh)	
			Wt, WPDLR = 0.2	0.125 (MW) each (2 SPV, 2 WTDG)	52, 54 and 52, 53		48.64 (MWh)	
			Wt, WPDLR = 0.3	0.125 (MW) each (2 SPV, 2 WTDG)	53, 53 and 50, 51		44.27 (MWh)	
			Wt, WPDLR = 0.4	0.125 (MW) each (2 SPV, 2 WTDG)	51, 54 and 50, 53		42.59 (MWh)	
[31]	GA	IEEE 31	NRDG	1.5, 0.5, 1, 1.5, 1.5 (MW)	8,12,13,28,30	PLR, THDR	11,960 (MWh)	WoDG

Table 2 (continued)

Ref	Modern mathematical optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
			NRDG + WTDG	1.5, 0.7, 1.4, 0.6, 0.6 (MW)	8,15,17,20,30		12,784 (MWh)	
			NRDG + SPV	1.15, 0.3, 0.4, 0.85, 0.3 (MW)	12,13,15,17,31,		15,410 (MWh)	
			NRDG + WTDG + SPV	0.3, 1.5, 1.4, 0.8, 1.5 (MW)	6,12,28,30,31		15,121 (MWh)	
[35]	PSO	IEEE 16	ΣDG = 1	12.97 (MW)	9	COP, PFO, PLR, VPE	168.1 (kW)	IAM
			ΣDG = 2	12.97, 5.86 (MW)	9, 6		111.7 (kW)	
			ΣDG = 3	13.1, 5.897, 4.29 (MW)	9, 6, 16		76.4 (kW)	
			ΣDG = 1	2.591 (MW)	6		111.1 (kW)	
			ΣDG = 2	1.002, 1.0195 (MW)	12, 30		87.5 (kW)	
			ΣDG = 3	0.88, 1.0928, 1.0098 (MW)	13, 24, 30		73.2 (kW)	
			ΣDG = 1	1.8062 (MW)	61		78.6 (kW)	
			ΣDG = 2	1.8062, 0.511 (MW)	61, 17		67 (kW)	
			ΣDG = 3	1.8062, 0.511, 0.719 (MW)	61, 17, 50		65.5 (kW)	
[38]	ABC	IEEE 30	ΣDG = 1	200 (MW)	17	COP, PR		Without solar penetration
			ΣDG = 2	136, 97 (MW)	5, 23			
			ΣDG = 3	198, 127, 176 (MW)	14, 22, 23			
			ΣDG = 4	68, 109, 1193, 102 (MW)	11, 13, 26, 29			
[39]	PSO	IEEE 33	ERR = 15%	1, 1, 0.9 (MW)	7, 33, 15	PLR, RI, SI VPE	TLPI = 0.1642 p.u	WoDG
			ERR = 20%	0.9, 0.9, 1 (MW)	6, 32, 14		TLPI = 0.1568 p.u	
			ERR = 25%	0.9, 0.9, 1 (MW)	6, 32, 14		TLPI = 0.1568 p.u	
			ERR = 30%	0.9, 0.9, 1 (MW)	6, 32, 14		TLPI = 0.1568 p.u	
			ERR = 35%	1, 1, 0.9 (MW)	6, 32, 13		TLPI = 0.1479 p.u	
			ERR = 40%	1, 1, 0.9 (MW)	7, 31, 13		TLPI = 0.14665 p.u	
			ERR = 45%	1, 1, 1 (MW)	6, 29, 12		TLPI = 0.162 p.u	
			ERR = 50%	1, 1, 1 (MW)	6, 29, 12		TLPI = 0.1635 p.u	
[49]	GA	IEEE 52	GA (VPE = 24.4%, SRI = 63.1%)	0.3105 p.u	50	LLR, SRI, VPE, PFR	PFR = 42.016%, LLR = 81.5%	LP
			LP (VPE = 24.26%, SRI = 63.075%)	0.3 p.u	50		PFR = 42.709%, LLR = 80.7%	
[62]	GA	IEEE 13	CL	0.63 p.u	7	PLR	0.0161 p.u	WoDG
			IL	0.61 p.u	8		0.0167 p.u	
			RL	0.59 p.u	8		0.0167 p.u	

Table 2 (continued)

Ref	Modern mathematical optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
			CML	0.58 p.u	8		0.0171 p.u	
			MXL	0.62 p.u	8		0.0168 p.u	
		IEEE 37	CL	0.62 p.u	14		0.001889 p.u	
			IL	0.63 p.u	25		0.00166 p.u	
			RL	0.63 p.u	25		0.001664 p.u	
			CML	0.63 p.u	25		0.001646 p.u	
			MXL	0.63 p.u	25		0.001663 p.u	
[63]	GA	IEEE 33	ΣDG = 2	700, 500 (kVA)	10, 31	QR, PLR	-	WoDG
[64]	GA	IEEE 39	MGT	500 (kW)	36	COP, RI	AOC = 141,920 $ / year	WoDG
			MGT	1000 (kW)	19		AOC = 236,520 $ / year	
[65]	GA	IEEE 97	WTΣDG-1	1 (MVA)	Any bus	COP, PR, RI	AOC = 15,000 $ / (MVA)	WoDG
			WTΣDG-2	1.5 (MVA)	Any bus		AOC = 12,750 $ / (MVA)	
			WTΣDG-3	2 (MVA)	Any bus		AOC = 10,500 $ / (MVA)	
			SPV ΣDG-1	16 (MVA)	Any bus		AOC = 20,500 $ / (MVA)	
			SPV ΣDG-2	18 (MVA)	Any bus		AOC = 18,750 $ / (MVA)	
			SPV ΣDG-3	19 (MVA)	Any bus		AOC = 19,625 $ / (MVA)	
[66]	TS	Model 1 (1 S/S, 4 Feeder and 28 Sections)	AL-1 (ΣDG = 10)	4000 (kW)	-	PLR	1725 (kW)	SA
			AL-2 (ΣDG = 10)	4000 (kW)			1823 (kW)	
			AL-3 (ΣDG = 10)	4000 (kW)			1823 (kW)	
		Model 1 (1 S/S, 4 Feeder and 28 Sections)	AL-1 (ΣDG = 20)	4000 (kW)			1211 (kW)	
			AL-2 (ΣDG = 20)	4000 (kW)			1292 (kW)	
			AL-3 (ΣDG = 20)	4000 (kW)			1299 (kW)	

Table 2 (continued)

Ref	Modern mathematical optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
		Model 2 (4 S/S, 6 Feeder and 78 Sections)	AL-2 (ΣDG = 15)	13.7 (kW)			26,554 (kW)	
			AL-3 (ΣDG = 15)	13.7 (kW)			35,250 (kW)	
		Model 2 (4 S/S, 6 Feeder and 78 Sections)	AL-2 (ΣDG = 35)	14.9 (kW)			13,044 (kW)	
			AL-3 (ΣDG = 35)	14.9 (kW)			18,647 (kW)	
[67]	TS	IEEE 33	UCO, SL0 = 3715 + j 2300 (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32	COP, PLR, VPE	54.43 (kW)	
			S_L^1 = 0.8 (3715 + j 2300) (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32		22.87 (kW)	
			S_L^2 = 0.6 (3715 + j 2300) (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32		6.93 (kW)	
			S_L^3 = 0.4 (3715 + j 2300) (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32		5.47 (kW)	
			S_L^4 = 0.2 (3715 + j 2300) (kVA)	275, 325, 150, 100, 450 (kW)	8, 16, 24, 27, 32		17.46 (kW)	
			CO, SL 0 = 3715 + j 2300 (kVA)	275, 400, 75, 50, 500 (kW)	8, 16, 24, 27, 32		50.32 (kW)	
			S_L^1 = 0.8 (3715 + j 2300) (kVA)	275, 400, 75, 50, 500 (kW)	8, 16, 24, 27, 32		21.59 (kW)	
			S_L^2 = 0.6 (3715 + j 2300) (kVA)	275, 400, 75, 50, 500 (kW)	8, 16, 24, 27, 32		7.88 (kW)	
			S_L^3 = 0.4 (3715 + j 2300) (kVA)	275, 225, 75, 50, 325 (kW)	8, 16, 24, 27, 32		3.24 (kW)	
			S_L^4 = 0.2 (3715 + j 2300) (kVA)	175, 75, 75, 50, 125 (kW)	8, 16, 24, 27, 32		0.67 (kW)	
			CO with 300 (kW), 300 (kVA)r Source, SL 0 = 3715 + j 2300 (kVA)	300, 300, 125, 275, 300 (kW)	8, 16, 24, 27, 32		53.1 (kW)	
			S_L^1 = 0.8 (3715 + j 2300) (kVA)	300, 300, 125, 250, 300 (kW)	8, 16, 24, 27, 32		22.7 (kW)	
			S_L^2 = 0.6 (3715 + j 2300) (kVA)	300, 300, 125, 250, 300 (kW)	8, 16, 24, 27, 32		6.83 (kW)	
			S_L^3 = 0.4 (3715 + j 2300) (kVA)	200, 125, 125, 215, 75 (kW)	8, 16, 24, 27, 32		2.68 (kW)	
			S_L^4 = 0.2 (3715 + j 2300) (kVA)	250, 225, 125, 250, 225 (kW)	8, 16, 24, 27, 32		0.8 (kW)	
[69]	HS	IEEE 33	Load = 3.72 (MW), 2.3 (MVA)r	0.9369, 0.6672, 1.0117 (MW)	6, 14, 24, 31	PLR, VPE	0.06783 p.u	GA/ PSO, GA, PSO
		IEEE 69	Load = 3.8 (MW), 2.69 (MVA)r	1.4552, 0.4769, 0.3124 (MW)	61, 64, 21		0.0105 p.u	
[72]	ICM	IEEE 33	ΣDG = 1	200 (kW)	-	PLR	201.38 (kW)	GA
		IEEE 69	ΣDG = 1	200 (kW)			211.45 (kW)	
[73]	ICM	IEEE 69	ΣDG = 3	0.385, 1.186, 1 (MW)	26, 35, 62	PLR	LI = 7.535	GA + OPF, OO, IB, PSO, GA, GAMS, IGA

Table 2 (continued)

Ref	Modern mathematical optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
			ΣDG = 5	1.059, 0.85, 0.873, 0.717, 0.9 (MW)	4, 26, 40, 48, 62		LI = 9.438	
			ΣDG = 7	0.998, 0.686, 0.676, 0.871, 0.719, 0.811, 0.75 (MW)	4, 17, 27, 40, 48, 58, 65		LI = 9.837	
			ΣDG = 9	0.996, 0.752, 0.645, 1.258, 0.496, 0.498, 0.406, 0.855, 0.73 (MW)	4, 17, 27, 30, 35, 41, 50, 58, 65		LI = 9.769	
[74]	ICM	IEEE 33	ZONE-1	941.5 (kW)	30	PLR, VPE	34.52 (kW)	WoDG
			ZONE-2	603.091 (kW)	14		4.82 (kW)	
			ZONE-3	691.607 (kW)	25		2.41 (kW)	
[76]	ABC	IEEE 39	ΣDG = 1	2.5775 (MW)	6	PLR, VPE	105.02(kW)	AM
			ΣDG = 2	1.9707, 0.5757 (MW)	6, 15		89.96(kW)	
			ΣDG = 3	1.7569, 0.5757, 0.7826 (MW)	6, 15, 25		79.25(kW)	
			ΣDG = 4	1.0765, 0.5757, 0.7824, 0.6538 (MW)	6, 15, 25, 32		66.58(kW)	
[77]	ABC	IEEE 33	ΣDG = 1	2.3970 p.u	5	LLC, PLR, VPE	0.06 p.u	WoDG
			ΣDG = 3	1.0645, 0.7322, 0.9823 (p.u.)	29, 13, 23		0.013 p.u	
			ΣDG = 5	1.39, 0.66, 0.52, 0.73,0.74 (p.u.)	1, 24, 14, 7, 30		0.007 p.u	
[78]	PSO	IEEE 12	WTΣDG = 2	336 (kW)	8	PFO, PLR, VPE	14.7 (kVA)	GA, AM, PSBIT
		IEEE 15	WTΣDG = (4 + 3)	1176 (kW)	4, 7		54.8 (kVA)	
		IEEE 33	WTΣDG = (5 + 3 + 5 + 5)	2873 (kW)	7, 16, 24, 30		127.1 (kVA)	
		IEEE 69	WTΣDG = (4 + 2 + 6 + 6 + 4)	3696 (kW)	7, 9, 48, 62, 64		131.3 (kVA)	
		IEEE 12	SPV = (4 + 3)	370 (kW)	5, 10		12..5 (kVA)	
		IEEE 15	SPV = (4 + 4 + 5 + 3 + 4 + 4)	1267 (kW)	5, 6, 8, 9, 12, 15		50.9 (kVA)	
		IEEE 33	SPV = (6 + 6 + 3 + 6 + 6 + 6 + 6 + 6 + 6 + 6)	2693 (kW)	8, 13, 16, 17, 20, 24, 25, 27, 31, 33		127 (kVA)	
		IEEE 69	SPV = (3 + 5 + 5 + 6 + 5 + 6 + 5 + 6 + 6 + 5 + 6)	3062 (kW)	6, 8, 12, 26, 52, 53, 59, 61, 62, 65, 68		148.6 (kVA)	
[81]	CS	IEEE 38	Wv1 = 1 & WL = Wv2 = 0	10, 20, 30, 40 (MW)	18, 8, 27, 36	PLR, VPE		Binary GA, continuous GA, PSO, WoDG
			WL = 1 & Wv1 = Wv2 = 0	10, 20, 30, 40 (MW)	24, 29, 7, 18			

Table 2 (continued)

Ref	Modern mathematical optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
			Wv1 = 1 & WL = Wv1 = 0	10, 20, 30, 40 (MW)	29, 8, 12, 15			
			Wv1 = 0.5 & WL = Wv2 = 0.25	10, 20, 30, 40 (MW)	34, 30, 16, 9			
		IEEE 69	Wv1 = 1 & WL = Wv2 = 0	10, 20, 30, 40 (MW)	30, 44, 59, 29			
			WL = 1 & Wv1 = Wv2 = 0	10, 20, 30, 40 (MW)	58, 51, 38, 19			
			Wv1 = 1 & WL = Wv1 = 0	10, 20, 30, 40 (MW)	32, 68, 63, 31			
			Wv1 = 0.5 & WL = Wv2 = 0.25	10, 20, 30, 40 (MW)	9, 67, 55, 40			
[83]	FF	IEEE 69	ΣDG = 1	1.8753 (MW)	61	PLR, VPE	0.0832 (MW)	GA
			ΣDG = 2	1.7496, 0.9269 (MW)	61, 67		0.0747 (MW)	
[91]	HA	IEEE 9	HL	4, 2, 4, 4 (MVA)	2, 4, 5, 8	COP, PLR	2.42 (MVA)	Bilateral contract scenario
			ML	2, 4, 4 (MVA)	4, 5, 8			
			LL	4, 1, 4, 4 (MVA)	1, 3, 6, 7			
			PSF = 0.7—1.66	4, 4, 4, 3 (MVA)	2, 5, 8, 4			
			PSF = 0.7—1.75	4, 4, 4, 3, 2, 1 (MVA)	2, 5, 8, 4, 7, 1			
[92]	GA	IEEE 16	HL	0.62 p.u	7	PLR	5.76 p.u	WoDG
			ML	0.53 p.u	7		2.63 p.u	
			LL	0.4 p.u	7		1.7 p.u	
		IEEE 37	HL	0.5 p.u	15		14.12 p.u	
			ML	0.47 p.u	15		6.2 p.u	
			LL	0.63 p.u	15		3.45 p.u	
		IEEE 75	HL	0.45 p.u	32		29.93 p.u	
			ML	0.63 p.u	30		13.06 p.u	
			LL	0.59 p.u	30		8.09 p.u	
[93]	MVO	IEEE 33	ΣDG = 1	2500 (kW)	6	VPE, PLR	0.941 (p.u.), 111.01 (kW)	MFO, PSO, HPSO
			ΣDG = 2	852.06, 1156.95 (kW)	13, 30		0.9684 (p.u.), 87.16 (kW)	
[94]	MALO	IEEE 33	ΣDG = 5	220, 50, 30, 20, 1020 (kW)	5, 9, 12, 23, 30	VPE, PLR	0.083, 74.96 kW	WoDG
[95]	PSO	IEEE 33	ΣDG = 5 (OIW)	2.8171 (MW) each	6, 10, 18, 22, 31	VPE, PLR	112.691 (kW)	WoDG
			ΣDG = 5 (RIW)	2.9109 (MW) each			112.558 (kW)	
			ΣDG = 5 (GLBIW)	2.7947 (MW) each			112.719 (kW)	
			ΣDG = 5 (TVIW)	2.8201 (MW) each			112.534 (kW)	
[96]	MCPSO	IEEE 30	ΣDG = 1	46.95 (MW)	23	VPE, PLR	12.93 (MW)	AM, PSO
		IEEE 14	ΣDG = 1	34 (MW)	14		10.093 (MW)	

Table 2 (continued)

Ref	Modern mathematical optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
[97]	PSO	IEEE 34	$\Sigma DG = 1$	3 (MW)	8	VPE, PLR	167 (kW)	WoDG
[98]	CPSO	IEEE 14	$\Sigma DG = 1$	33.95 (MW)	6	VPE, PLR, COP	10.81 (MW)	IA, ELF, PSO

steps namely domination rank and crowding distance are involved in this technique. Out of two harmonies, better harmony is dominated by another harmony, non-dominated harmony is stored in harmony memory while the dominated harmony is not abandoned and got a second chance for extemporization [69].

3.2.5 Simulated Annealing (SA)

In 1983, Kirkpatrick et al. have been researched the SA optimization technique having four steps namely concise configuration, random selection, determining function, and schedule of the annealing process. The authors demonstrated five DG applications to extract the various benefits of DG allocation in the distribution network by using simulated annealing optimization technique. The load flow analysis is used to calculate the voltage drops and power losses having MO function. This technique is evaluated on IEEE 33 test system and concluded the increased penetration of renewable energy in a radial power system. The results exhibited the optimal size and location of DG by considering the number of DG [70].

3.2.6 Imperialist Competitive Method (ICM)

In [71, 72, 73, 74], an optimization technique has been implemented which is based on the nature of imperialistic nature of imperialist for the addiction of imperialism to make an empire. In the whole approach, the colonies approach toward their imperialist then the cost of each empire is calculated to interchange the positions of weaker one to the strongest one till only one empire is exist like the optimized value in DG. In continuation, the profit of distribution network operators is maximized and implemented in the UK under Ofgen which includes power flow constraints, operating limit, voltage profile, feeder capacity, and the number of DG steps with crossover probability and mutation probability function programmed in MATLAB [73]. In [74], losses are calculated by load flow technique in which KVL and KCL are used to measure the upstream voltage resulting in complex power measurement then ICM is implemented for DG optimization in zonal distribution network using islanding operation of the sensitive load.

3.2.7 Ant Colony Optimization (ACO)

ACO technique has been characterized as; initialization, cost function calculation, constraint assignment, feasible state selection, and neighborhood structure with the properties like search, memory storage, feasible neighborhood, termination condition, probabilistic decision, ant routing table, and pheromone update. ACO technique is implemented for restructuring the distribution network framework to minimize power losses. ACO exhibited the characteristic to evade premature stability and trapping in local optima. This technique is tested and implemented on IEEE 33 bus system and the results are significant and power losses are reduced in comparison to without restructuring the distribution network. The convergence time also indicates the faster solution by this technique. Moreover, network losses are reduced from 140 to 110 kW by reconfiguration of DG in the distribution system [75].

3.2.8 Artificial Bee Colony (ABC)

Karboga presented an optimization technique that is based on the communal etiquette of honey bees and encompasses three key components namely food source, searchers, and non-searchers which are having self-organizational behavior depending on alternate feedback, random search, and sharing of information. A bi-level approach having ABC optimization technique is demonstrated on IEEE 33 system for DG allocation. In the first step, DG location is found and this process is followed by the DG size optimization considering 4 different cases to get the possible outcomes in less computation time [76]. Moreover, indexes are introduced in ABC optimization to improve the power quality parameters. In continuation, the authors attracted attention to the reformation of the industrial and commercial processes. The distribution loss index is included with the objective function because of its high presence in Iran [77].

3.2.9 Particle Swarm Optimization (PSO)

In 1995, Kennedy et al. have been investigated PSO technique which is another social behavior simulation to optimization technique comprises the binds between artificial life to bird gathering, fish training and swarming behavior which require only ancient mathematical operators with less memory space and speed. The predecessor involves velocity matching, craziness, cornfield vector, auxiliary variable removal, multidimensional search, distance acceleration and present better version. The foundation of PSO having the pillars of social concept, swarm intelligence principles (proximate, quality, diverse response, stability, and adaptability) and computational behavior. In continuation author also discussed the various modified approach of PSO like multi-objective PSO (MPSO), constraint handling PSO, stretching PSO, cooperative PSO, comprehensive learning PSO and hybrid PSO. Tribal PSO (TPSO) with OO [37], constriction factor PSO [35] and MPSO [39, 78] are executed for renewable source-based DG optimization. Moreover, MPSO has been implemented for optimizing the power quality parameter with a constraint of expected rate of return (ERR) results in terms of total loss power index (TLPI). Synchronous compensator, synchronous generator and synchronous based DG units are used in the optimization process [79]. The continuous and discrete optimization by using N-R method is incorporated for DG optimization and penalty factor calculation [23].

3.2.10 Cuckoo Search (CS)

The researchers Yang et al. have been projected an optimization technique build on the communal bearing of a cuckoo bird in addition to Levy flight conduct for better results due to a good combination of randomization and escalation having fewer constraints CS involves three steps namely cuckoo breeding behavior, Levy flight and search in which a cuckoo bird randomly search the nest, place its egg and if the entertainer bird did not find that egg fit for the nest then the entertainer bird will repudiate the cuckoo's egg. The renewable energy-based DG optimization has been done by the CS algorithm to get technical, financial, and societal advantages. These tests are performed on IEEE 22 and IEEE 69 bus systems having the mono, dual and multi-DG injection. The proposed technology results are efficaciously compared with the established PSO technique [80]. Authors recommended the CS for optimization of the objective function which includes the upgraded voltage profile and abridged power loss with different weightage factors namely; (WL), (WV1), and (WV2) [81]. Moreover, the importance of indices base-voltage evaluation is also highlight in the power quality. The outcomes are significant and compared with well-established GA and PSO. Consequently, the CS technique has the following benefits:

It has the property to cover more distance in step randomization.

- The requirement of optimization parameters is lesser as compared to other approaches so more adaptability is present among the researchers.
- It is inspired by the meta-population approach in which every nest provides a group of solutions.
- The tuned parameters are not dependent on the meeting frequency, so accuracy consideration is not a necessary step.
- It may lead to getting the high acceptance due to its simplicity and robust nature.

3.2.11 Firefly Methods (FFM)

FFM is based on the gleaming etiquettes of a firefly in which three simple assumptions have been followed; all firefly is androgynous and each one produces a flare to attract others, the attraction force is proportional to the brightness and each firefly will attract toward the glower one and in the absence of brighter one then the firefly will take the random step in search space. A modified FFM is used for DG allocation for the active and reactive power compensation along with shunt capacitors. FFM optimization technique considered the four different compensation cases of the distribution network (absence of compensator, presence of shunt capacitor, presence of DG, and presence of integrated DG and shunt capacitor) and evaluated on IEEE 85 test system. The outcomes are significant as compared to PSO and MINLP [82]. Moreover, voltage profile and line losses are considered for the optimization of DG size and allocation. The evaluation has been done on IEEE 69, radial distribution system, and concluded with the results having the same efficacy as in GA [83].

3.3 Hybrid Approaches

In the optimal DG planning, heterogeneous hybrid AI techniques have been proposed by various researchers that are based on the amalgamation of two optimization approaches which work in progression mode or equidistant mode to solve more complex problems. In hybrid category GA is integrated with TS (GATS) [84], PSO (GAPSO) [85], OPF (GAOPF) [86] and fuzzy approach (FZ) [87]. A collateral approach GA and TS is evaluated for the optimization of objective function in the form of GA chromosomes and TS neighbors [84]. For the optimized power quality parameters GAPSO is adopted in which GA is used for the DG allocation and PSO for size optimization with 30 and 20 population size respectively [85]. In GAOPF the decision variables are found using GA and OPF is implemented for the optimum solution. In [88], jumping frog PSO (JFPSO) forwarded the DG location for the optimization of DG by OPF. The deterioration in voltage level has been considered in PSO process followed by the GSA in PSOGSA hybrid optimization technique [89] while the enhanced transient stability is achieved with the cascade process of PSO and shuffled frog leaping (SFL) using CCT index on Dlg SILENT software [17]. Consolidations of FZ with TS (FZTS) has been wielded for the MO, DG optimization [26]. Hybrid optimization techniques are reviewed and summarized in Table 3 based on adopted techniques, test systems, optimized results, and comparison with other optimization techniques.

4 Conclusions

It has been concluded that DG is advantageous for the improvisation of the power system characteristics. It provides numerous optimization techniques implemented in DG allocation with the purpose to meet the limitations. It also acts as a tool to augment the stability, reliability, and consistency of the distribution network. Moreover, it is also to analyze the classification of the intricacies for functioning optimization algorithms. The pictorial taxonomy of data-based assessment of DG optimization approaches are given in Fig. 4.

In this paper, various optimization techniques have been successfully reviewed along with comparative analysis of conventional, modern mathematical and hybrid methods utilized for significant parameters optimization of DG that aims at technological, financial, and environmental benefits with the optimized result parameters. Moreover, conventional approaches are simple, easy to execute and highly précised but agonized due to single objective slow convergence optimization while modern mathematical approaches can solve the multi-objective complex problems, with a smaller number of iterations having some limitations like harder to code, various settling parameters and impetuous convergence. Hybrid optimizations approaches can handle more complex problems with faster convergence but it may undergo complexity including a smaller number of literatures.

Reviewed studies indicate that the integration of renewable energy will maximize the benefits of DG planning in the distribution network but it is also implying the necessity of a reliable assessment tool for renewable energy. The intermittent nature of renewable energy is required to encounter and effective energy storage may lead to the elimination of intermittency.

Additionally, the demand response is also not significantly considered by the researchers. Due to the high cost of the energy storage system, demand response is also a major contributor to the smart distribution system. There is a possibility to develop a system that included the planning and optimal dispatch of renewable DG with energy storage and demand response.

Table 3 Data-based assessment of DG optimization by hybrid approaches

Ref	Hybrid optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
[14]	FZ + AM	IEEE 12	–	0.22 (MW)	9	PLR, VPE	0.01077 (MW)	WoDG
		IEEE 33		2.59 (MW)	6		0.111 (MW)	
		IEEE 69		1.87 (MW)	61		0.0832 (MW)	
[16]	GA + AM	IEEE 4	Vdm = 0.007422 p.u	4000, 3000 (kW)	3,4	COP, RI, VPE	74.26 (kW)	WoDG
			Vdm = 0.007422 p.u	3000, 2000 (kW)	12, 7		129.37 (kW)	
[20]	PSO + SFL	IEEE 33	CL	312.8, 334.4, 323, 279, 200 (kW)	14, 16, 33, 8, 31	PLR, VPE, TSI	0.053273 (MW)	PSO, SFL
			MXL	275.1, 252.3, 306.2, 237.6, 290 (kW)	33, 12, 14, 26, 13		0.055567 (MW)	
[21]	FZ + AM	IEEE 33	VL > ±5%	2.4818 (MW)	6	PLR, VPE	110.6318 (kW)	WoDG
			VL ± 5%	3.15 (MW)	6		115.2 (kW)	
[26]	PSO + FZ	IEEE 33	ΣDG = 1	1.2931 (MW)	32	PLR, VPE	127.0919 (kW)	PSO
			ΣDG = 2	0.3836, 1.1506 (MW)	32, 30		117.3946 (kW)	
			ΣDG = 3	0.2701, 1.1138, 0.1503 (MW)	32, 30, 31		117.3558 (kW)	
			ΣDG = 4	0.2706, 0.8432, 0.1503, 0.5982 (MW)	32, 30, 31, 18		90.4794 (kW)	
[30]	MINLP + OPF	IEEE 41	PP	4.4, 1.1, 2.2 (MW)	19, 23, 40	PLR, VPE	1079.7 (MW)h	WoDG
			TP	6.6, 5.5, 9.9 (MW)	19, 23, 40		1527.2 (MW)h	
[37]	TPSO + OO	IEEE 86	TRIBE PSO (SPV + BDG)	200, 200 (kVA)	61, 85	COP	Total cost = 9,355,000 $	TRIBE PSO, OO
			OO (SPV + BDG)	400, 100 (kVA)	72, 85		9,504,000 $	
			TRIBE PSO + OO (SPV + BDG)	200, 200 (kVA)	61, 82		9,355,000$	
[50]	NLP + OPF	IEEE 34	ΣDG = 2	3112, 6.613 (MW)	17, 18	PLR, VPE	0.279 (MW)	WoDG
[56]	GA + OPF	IEEE 69	ΣDG = 3	2.661 (MW)	26, 35, 62	COP, PLR	TI (£/h) = 8.72	
			ΣDG = 5	4.067 (MW)	4, 26, 35, 40, 62		TI (£/h) = 10.73	
			ΣDG = 7	4.566 (MW)	5, 13, 27, 35, 40, 57, 65		TI (£/h) = 11.27	
			ΣDG = 9	4.833 (MW)	4, 6, 13, 21, 27, 35, 40, 57, 62		TI (£/h) = 11.51	
[79]	PSO + CPF	IEEE 33	ΣDG = 1	3.0317 (MW)	12	PLR	70.949 (kW)	WoDG
			ΣDG = 2	0.9143, 1.5345 (MW)	27, 22		29.82 (kW)	
		IEEE 69	ΣDG = 1	2.2215 (MW)	56		23.594 (kW)	
			ΣDG = 2	0.6247, 2.1213 (MW)	53, 56		7.342 (kW)	
[84]	GA + TS	IEEE 13	BDG	300 (kW)		PLR	84.6 (kW)	GA
			WTDG	200 (kW)			83.5 (kW)	
			SPV	80 (kW)			95.2 (kW)	
		IEEE 34	BDG	200 (kW)			220.9 (kW)	
			WTDG	200 (kW)			195.7 (kW)	
			SPV	200 (kW)			141.4 (kW)	

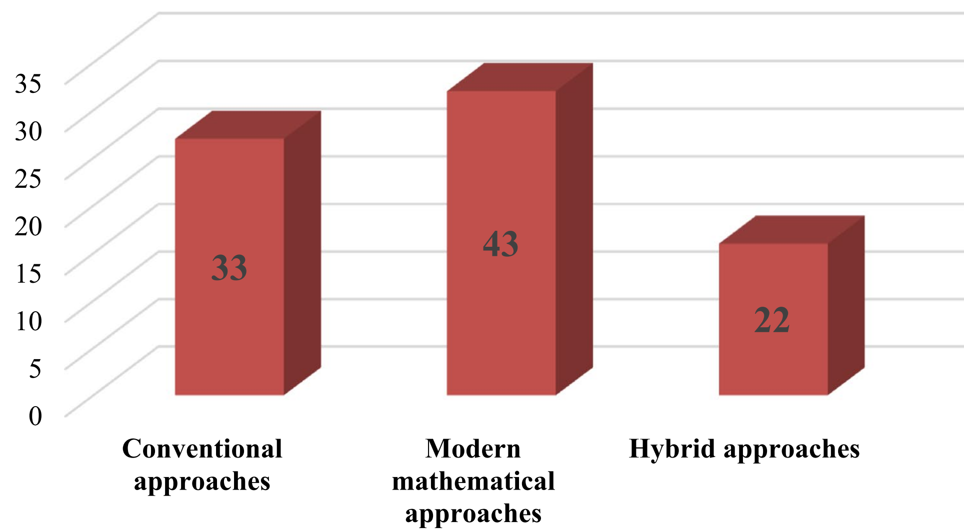
Table 3 (continued)

Ref	Hybrid optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
[85]	GA + PSO	IEEE 33	ΣDG = 4	0.6639, 0.6628, 1.0232, 0.8671 (MW)	32, 14, 24, 26	PLR	0.0682 p.u	GA, PSO
[86]	GA + OPF	IEEE 9	UFC	2 (4 (MVA) & 1 (MVA))	4, 8	COP, PLR	52.73 GWh	MINLP
			LFC	1 (4 & 1), 2 (2 & 1), 1 (1 & 1) (MVA)	2, 4, 7, 1		45.35 GWh	
			CAC	3 (4 & 1), 1 (3 & 1) (MVA)	2, 4, 8, 1		31.55 GWh	
[87]	GA + FZ	IEEE 6	ΣDG = 1	8.5 (MW)	3	COP, PLR	0.112 (MW)	WoDG
		IEEE 30	ΣDG = 2	40, 35 (MW)	10, 6			
[88]	PSO + OPF	IEEE 30	ΣDG = 3	9.75, 9.26, 8.81 (MW)	19, 24, 30	COP, PLR	11.05 (MW)	
			ΣDG = 5	9.95, 7.85, 6.23, 2.01, 7.75 (MW)	7, 19, 24, 26, 30		10.92 (MW)	
			ΣDG = 7	8.78, 7.15, 2, 2, 4.52, 2.01, 7.73 (MW)	7, 19, 21, 23, 24, 26, 30		10.91 (MW)	
			ΣDG = 9	7.78, 5.34, 2, 2, 2, 2, 3.67, 2, 7.21 (MW)	7, 18, 19, 21, 22, 23, 24, 26, 30		10.9 (MW)	
[89]	PSO + GSA	IEEE 69	Test Case 1 (Tiv)	0.2, 1, 1.8 (MW)	21, 49, 61	LLC, PLR, PR, VPE	MPI = 0.5463	PSO, GSA
			Test Case 1 (Tv)	0.9, 0.2, 1.3 (MW)	4, 21, 61		MPI = 0.6014	
			Test Case 2 (Tiv)	0.3, 1.2, 1.8 (MW)	21, 49, 61		MPI = 0.4495	
			Test Case 2 (Tv)	1.3, 1.8, 0.2 (MW)	21, 49, 61		MPI = 0.4909	
			Test Case 3 (Tiv)	1.7, 0.8, 0.8 (MW)	3, 60, 61		MPI = 0.6888	
			Test Case 3 (Tv)	1.6, 0.8, 0.3 (MW)	3, 61, 64		MPI = 0.7131	
			Test Case 3 (Tiv)	0.3, 0.2, 1 (MW)	21, 61, 48		MPI = 0.4771	
			Test Case 3 (Tv)	0.6, 1.5, 0.6 (MW)	50, 61, 47		MPI = 0.5282	
[99]	ABC + TLBO	IEEE 33	WTΣDG-1	2558.5 (kW)	6	VPE, PLR, COP,	67.83 (kW), 35,971$	EA, GA, PSO
			WTΣDG-2	858.3, 1089.1 (kW)	13, 30		28.63 (kW), 15,049$	
			WTΣDG-3	1069.9, 1029.9, 793.8 (kW)	13, 30, 24		11.74 (kW), 6171$	
			SPV ΣDG-1	2590.2 (kW)	6		111.027 (kW), 58,536$	
			SPV ΣDG-2	851.5, 1157.6 (kW)	13, 30		87.16 (kW), 45,814$	
			SPV ΣDG-3	801.7, 1053.6, 1091.3 (kW)	13, 30, 24		72.78 (kW), 38,256$	
[100]	ALO + PSO + FLC	IEEE 33	SPV ΣDG = 2, UPF	385, 2154 (kW)	32, 7	PLR, COP	90.98 (kW), 12,062 $	PSO, ALO + PSO
			WT ΣDG = 2, UPF	951, 696 (kW)	31, 17		89.3 (kW), 8496 $	

Table 3 (continued)

Ref	Hybrid optimization method	Test systems	Different cases	Optimum DG sizes	Optimum DG locations	Strengthened parameters	Optimized results	Compared approaches
			SPV ΣDG = 2, LaPF = 0.85	924 + j1223, 665 + j710 (kVA)	32, 14		47.6 (kW), 8037 $	
			WT ΣDG = 2, LaPF = 0.85	993 + j1667, 606 + j913.5 (kVA)	8, 30		35.5 (kW), 8038 $	
			SPV ΣDG = 2, LePF = 0.85	1669-j413, 1179-j29 (kVA)	7, 30		116 (kW), 13,710 $	
			WT ΣDG = 2, LePF = 0.85	2300 + j273, 934-j38 (kVA)	4, 30		109 (kW), 15,611 $	
[101]	GOA + CS	IEEE 33	ΣDG = 1, Half load = 50%	1716 (kW)	2	VPE, PLR, COP	123.62 (kW), 34.33$	GA, PSO, GOA, CS
		IEEE 33	ΣDG = 1, Full load	926.99 (kW)	24		139.59 (kW), 18.5$	
		IEEE 33	ΣDG = 1, 150% load	926.99 (kW)	24		139.59 (kW), 18.5$	
		IEEE 69	ΣDG = 1, Half load = 50%	1930.7 (kW)	17		141.43 (kW), 38.6 $	
		IEEE 69	ΣDG = 1, Full load	1990.7 (kW)	6		147.66 (kW), 39.8$	
		IEEE 69	ΣDG = 1, 150% load	1890.6 (kW)	12		151.66 (kW), 37.8$	

Fig. 4 Taxonomy for data-based assessment of DG optimization approaches



Declarations

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

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