IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

A comprehensive Review on Evolutionary Optimization Techniques applied for Unit Commitment Problem

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This work was not supported by any form of grant provided by any one funded organization or agency.

ABSTRACT Unit Commitment (UC) is a key task in electric power system operation, aiming at minimizing the total cost of power generation. It is essential to monitor wide range of activities and practices of UC necessary to determine the operating plan of generating units. The UC problem is particularly crucial, when the behavior of loads at every hour interval, is oscillatory and with different operational constraints and environments. Many works have been proposed, with different optimization methods to solve the UC problem. This paper gives a detailed review of the evolutionary optimization techniques, employed for solving UC problem, by collecting them from lots of peer reviewed published papers. This review was carried out under many sections, based on various evolutionary optimization techniques, to help new researchers, dealing with modern UC problem solutions, under different situations of power system.

INDEX TERMS Unit commitment, evolutionary optimization, power balance, load dispatch, operating cost, spinning reserve.

NOMENCLATURE

A. VARIABLES AND CONSTANTS

$\hat{w}_{x,t}$	Actual power output of wind generator all committed units.
CS_{ui}	Cold start-up cost of i^{th} generating unit.
D_h	Load demand in the hour h.
E_i^{max}	Maximum energy delivery of unit i.
E_i^{min}	Minimum energy delivery of unit i.
$F(P_{it})$	Fuel cost of i^{th} generating unit during t^{th} interval.
F_i	Fuel consumption function of unit i.
$F_{max}(i)$	Maximum consumption of total fuel for unit i.
$F_{min}(i)$	Minimum consumption of total fuel for unit i.
HS_{ui}	Hot start-up cost of i^{th} generating unit.
$I(i,t)$	Commitment status of unit i at time t.
$M_{DT,j}$	Minimum down time of unit j.
$M_{UT,j}$	Minimum up time of unit j.
N	Total number of units.
N_B	Number of buses.
N_L	Number of transmission lines.
$P(i,t)$	Power generation of unit i at time t.
P_D^t	System load demand at time t.
$P_{i\,max}$	Allowable maximum output of generator i.
$P_{i\,min}$	Allowable minimum output of generator i.
P_{it}	Output power of i^{th} generator at t^{th} hour in MW.
$P_{min,n}$	Minimum power generated by all committed units.
P_{rt}	Reserve power of i^{th} generator at t^{th} hour in MW.
P_R^t	Spinning reserve at time t.
P_{sk}	Slack bus generation output at k^{th} hour.
r	Probability that the reserve is called and generated.
$R(i,t)$	Level of spinning reserve of unit i at time t.
RD_i	Ramp down rates of unit i.
R_{pt}	Forecasted reserve price at t^{th} hour/MW.
RU_i	Ramp up rates of unit i.
S_l^{max}	Maximum transmission power of line l.
S_{pt}	Forecasted spot price at t^{th} hour in/MW.
ST_i	Startup cost is given for i^{th} generating unit.
T	Total number of hours.

φ_k^{max} Maximum phase angle of k^{th} transmission line.
φ_k^{min} Minimum phase angle of k^{th} transmission line.

B. ABBREVIATIONS

ACO Ant Colony Optimization.
AFSA Artificial Fish Swarm Algorithm.
AHN Augmented Hopfield Network.
ALHN Augmented Lagrange Hopfield Network.
ANN Artificial Neural Network.
AQEA Advanced Quantum EA.
ASSA Absolutely Stochastic SA.
BCPSO Binary Clustered PSO.
BDE Binary Differential Evolution.
BFA Bacteria Foraging Algorithm.
BHC Binary Hill Climbing.
BSFLA Binary Shuffled Frog Leaping Algorithm.
CCA Cooperative Co-Evolutionary Algorithm.
CIGA Chaotic Immune GA.
CLP Constraint Logic Programming.
CPSO Chaotic Particle Swarm Optimization.
CSA Cuckoo Search Algorithm.
DBDE Discrete binary DE.
DD Dual Decomposition.
DE Differential Evolution.
DP Dynamic Programming.
EA Evolutionary Algorithm.
ED Economic Dispatch.
ELPSO Elite Particle Swarm Optimization.
EP Evolutionary Programming.
EPL Extended Priority List.
EPSO Enhanced Particle Swarm Optimization.
ES Evolutionary Strategy.
ES Expert System.
ESA Enhanced Simulated Annealing.
FA Firefly Algorithm.
HTBPSO Hybrid Topology Binary Particle Swarm Optimization.
IA Immune Algorithm.
IBPSO Improved Binary Particle Swarm Optimization.
IBSFLA Improved Binary Shuffled Frog Leaping Algorithm.
ICGA Integer-Coded Genetic Algorithm.
IDE Improved Differential Evolution.
ILR Improved Lagrangian Relaxation.
ISAPSO Improved Simulated Annealing Particle Swarm Optimization.
LP Linear Programming.
LR Lagrangian Relaxation.
LSA Local Search Algorithm.
MACO Memory Bounded Ant Colony Optimization.
MAEA Meta-modal Assisted Evolutionary Algorithm.
MBDE Memetic Binary Differential Evolution.
MILP Mixed Integer Linear Programming.
MRCGA Matrix Real-Coded Genetic Algorithm.
MSSA Modified Salp Swarm Algorithm.
NP Network Programming.
NSGA-II Non-dominated Sorting Genetic Algorithm –II.
NUWD Non-Uniform Weight vector Distribution.
PL Priority List.
PRGA Parallel Repaired Genetic Algorithm.
PSO Particle Swarm Optimization.
QBPSO Quantum inspired Binary Particle Swarm Optimization.
QEA Quantum Evolutionary Algorithm.
RSA Random Search Algorithm.
SA Simulated Annealing.
SADE Self Adaptive Differential Evolution.
SDP Semi Definite Programming.
SFLA Shuffled Frog Leaping Algorithm.
SQP Sequential Quadratic Programming.
SSGA Steady State Genetic Algorithm
TS Tabu Search.
UC Unit Commitment.
UWD Uniform Weight vector Distribution.
WLS Wide Local Search.

I. INTRODUCTION

The Unit Commitment (UC) problem is related to the trustworthy operating state of power system network, intended for the functioning status of thermal units as well as the power dispatch, which involves distributing the system load demand to the committed thermal units [1]. Thermal power generation plays an important role in the majority of the grid connected power systems, to provide towering-quality electric power, to consumers in a profitable and secured mode [2]. The use of the most favorable working plan is to meet the power demand, at the least fuel price, by means of the best possible mix up of dissimilar power plants [3],[4]. It is possible to meet the necessary power demand under more than a few operating plans, with on/off position of generating units, over a short term scheduling, with the prospect of reducing total generation cost while at the same time, gratifying coupling constraints of spinning reserve and power balance, in addition to corporeal and outfitted constraints of every individual unit [5], [6].

A variety of conventional/predictable techniques was carried out from the past studies to solve UC problems under a variety of dimensions, bordering on Probabilistic techniques [7], [8], Security constrained multi-area method [9], Storage and delivery constrained method [10], Priority List (PL) [11]-[14], Linear Programming (LP) [15], [16], Mixed Integer LP (MILP) [17]-[21], Sequential Lagrangian MILP [22], Tighter Approximated MILP [23], Tight MILP [24], Tight and Compact MILP [25], [26], Tight Polyhedral MILP [27], Strengthened MILP [28], Fuzzy based MILP [29], [30], Computationally Efficient MILP [31], Dynamic Programming (DP) [32]-[35], Decomposition based DP [36], Enhanced DP [37], Multi-Pass DP [38], Dynamic Regrouping based Sequential DP [39], Dual Optimization DP [40], Dual Decomposition (DD) based Sequential Quadratic Programming (SQP) [41], Semi Definite

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Programming (SDP) [42], [43], Lagrangian Relaxation (LR) [44]-[55], Adaptive LR [56], LR with Lagrange Multiplier (LM) Updating [57], LM based Sensitive Index [58], Lagrangian Reduction Search Range [59], Lagrangian heuristics based on disaggregated bundle technique [60], Augmented Lagrangian (AL) approach [61], [62], Decomposition Method [63]-[65], Hybrid Decomposition [66], Integer Programming (IP) [67], Adaptive IP [68], Projected Mixed IP [69], Monte Carlo [70], Branch and Bound Algorithm [71], Modified Sub-gradient method [72], Benders Decomposition [73]-[75], Outer Approximation (OA) [76], OA and Outer Inner Approximation [77] and Tighter Relaxation [78], [79].

There are key difficulties, to resolve the UC problems, by incorporating these classical approaches like deprived convergence, computation intricacy to handle multi-objective functions with many constraints, to achieve efficient results. Nontraditional artificial intelligence based optimization approaches like Network Programming (NP) [80], Tabu Search (TS) [81], Hybrid fuzzy based TS [82], Heuristic search techniques [83]-[85], Simulated Annealing (SA) [86]-[89], Twofold SA [90],[91], Adaptive SA [92], Enhanced SA [93],[94], Stochastic SA [95],[96], Ant Colony Optimization (ACO) [97],[98], ACO with Random Perturbation [99], Memory Bounded ACO [100], Nodal ACO [101], Hybrid Taguchi ACO [102], Fuzzy Logic [103]-[107], Fuzzy based SA [108],[109], Fuzzy DP [110], Fuzzy Hierarchical Bi-Level Modelling [111], Artificial Neural Network (ANN) [112]-[119], Hybrid ANN [120]-[122], Hopfield ANN [123]-[127], Expert System [128]-[131] and Quasi-Oppositional Teaching Learning Algorithm [132], could cope with the convergence properties, intricacy of computational operation and give innovative solutions against conservative methods. Every traditional and non- traditional technique has diverse properties, merits and demerits. The key advantages and disadvantages of some traditional and non- traditional methods, focused on this section, are given in Table 1.

Aside from the above techniques, there is an additional class of numerical methods, applicable to the UC problem called evolutionary optimization techniques, which have greater capability to search for superior results of intricate optimization problems. However, these techniques necessitate a substantial quantity of computational time, to come across the near-global minimum, particularly for a large-scale UC problem.

The main objective of this paper was to present comprehensive review, about the different evolutionary optimization techniques, to deal with various dimensions of UC problems, under different constraints and environments. Summarization of reviews, extracts from the referred publications of leading international journals, names of international journals, along with their publishers, are listed in Table 2. Also the number of articles published since 1973 related to UC problems displayed in Fig. 1 based on the list of journals given in Table 2. The contributions of this paper include the following:

1. Clear reviews about the UC problem, with different evolutionary optimization techniques like GA (section II. A), PSO (section II. B), EA (section II. C), EP (section II. D), DE (section II. E), SFLA (section II. F), FA (section II. G), other evolutionary optimization techniques (section II. H) and hybrid evolutionary optimization techniques (section II. I) are presented.

2. The constraint implementation, tool of simulation, hardware used to run simulations and the test and practicing systems used to validate of results, focused in the references, have been captured and tabularized.

3. The distinguished features of every proposed work focused on the references related to evolutionary optimization techniques, have been captured and tabularized.

The rest of the paper is ordered as follows. Section II, explains about the general backdrop of UC problem, including a variety of equality and inequality constraints focused in the references. Section III, describes the review of different evolutionary optimization techniques, germane to UC problem focused on the references. Finally, section IV, concludes this paper.

II. COMMON BACKDROP CONCERNING UC PROBLEM

UC is an extremely important optimization assignment since the best possible scheduling of commitment, can reduce the enormous amount of total production costs while overcoming a variety of unit and system constraints. UC problem solutions are implemented for both stochastic and deterministic loads. The configuration of UC problem, with on/off scheduling of generating units, is represented in Fig. 2. Owing to the poor accuracy of results obtained from stochastic loads, the constraints of stochastic UC models are changed into the determinate form and then the formulation solution can be done by any of the customary optimization algorithms.

Two types of analysis, like data envelopment analysis and principal component analysis are applied to deterministic loads, to provide definite and unique solutions. The input and output variables are defined in the first analysis and minimum number of variables is in the second analysis. The different types of objective functions, related to UC problem under different circumstances, are as follows.

A. TRADITIONAL FUEL BASED CIRCUMSTANCE

The Traditional UC is an optimization problem which can be mathematically formulated as:

$$Min \sum_{t=1}^{T}\sum_{i=0}^{N} F(P_{it}).U_{it} + ST \,.\, U_{it} + SD \,.\, U_{it} \qquad (1)$$

There are three costs to minimize from the equation (1). The term (P_{it}) denotes the generation of unit i at time t, and $\mathrm{F}(P_{it})$ denotes the fuel cost of the unit i at time t and the terms $\mathrm{ST}\,.\,\mathrm{U_{it}}$ and $\mathrm{SD}\,.\,U_{it}$ represent the start up and shutdown costs respectively.

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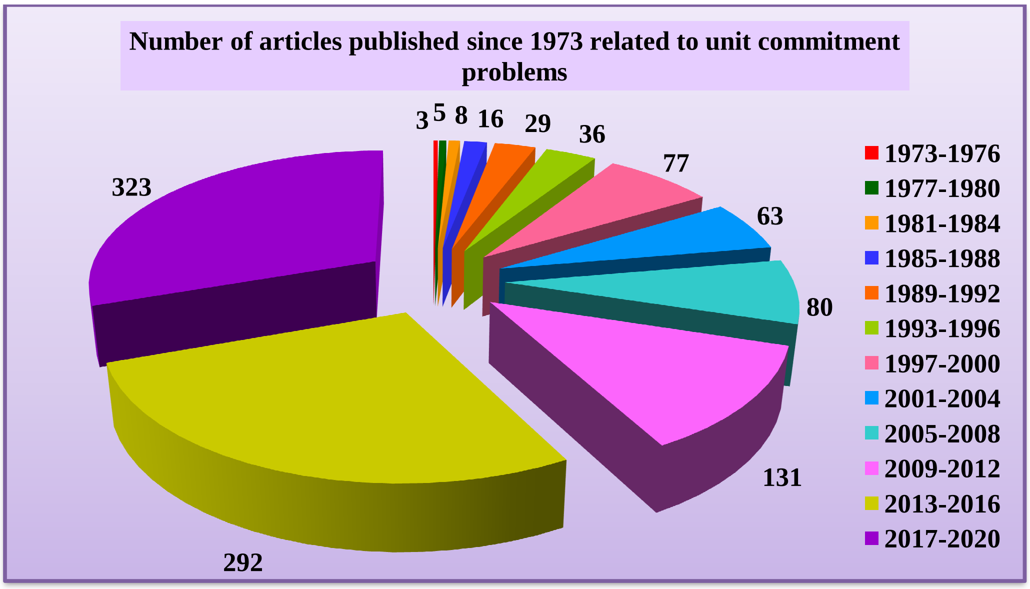

FIGURE 1. Number of articles published since 1973 related to unit commitment problems.

The production cost of the operating generators, which is basically a convex function, is called fuel cost. The cost equation, for a unit *i*, can be represented in a quadratic form as:

$$F(P_{it}) = a_i + b_i \,.\, P_{it} + c_i \,.\, P_{it}^2 \tag{2}$$

where,
a_i,b_i, and c_i are fuel cost coefficients of i^{th} generating units. The startup cost of ith generating unit can be articulated by:

$$ST_i = \begin{cases} HS_{ui}, & T_{i,off}^{t} \le T_{i,down} + T_{i,cold} \\ CS_{ui}, & T_{i,off}^{t} \ge T_{i,down} + T_{i,cold} \end{cases} \tag{3}$$

where
HS_{ui}: Hot start-up cost of ith generating unit.
CS_{ui}: Cold start-up cost of ith generating unit.

In standard systems, the archetypal value of the shut down cost is zero and it is considered as a fixed cost and given by:

$$SD \,.\, U_{it} = KP_{it} \tag{4}$$

where K = Incremental shut-down cost.

B. STOCHASTIC BASED CIRCUMSTANCE

Stochastic circumstance is one wherein arbitrariness is incorporated either in the objective function or in the constraints. According to the realistic requirement like probability-constrained and anticipation programming, several types of hesitant programming methods can be implemented, to carry out the stochastic optimization. Owing to the large scale integration of renewable resources like solar and wind, etc., ambiguity occurs in power systems at the present time. Therefore, for the successful and consistent operation of the system, the demand and supply may as well be different within a stochastic environment. Problem formulation of the UC, based on the stochastic based environment is given by:

$$min \sum_{t=1}^{N}\left[\sum_{t=1}^{T}\left(C_i P_{i,t} + C_{i,t,U} + C_{i,t,D}\right)\right] + M\sum_{x=1}^{N}\sum_{t=1}^{T}\left(\widehat{w}_{x,t} - w_{x,t}\right), \tag{5}$$

Subjected to,

$$\sum_{i=1}^{N} P_{i,t} + \sum_{x=1}^{N_W} W_{x,t} = D_t(t = 1,2,\dots,T), \tag{6}$$

$$P_{l,min} \le \sum_{i=1}^{N} G_{l-1} P_{i,t} + \sum_{x=1}^{N_W} G_{l-x} w_{x,t} - \sum_{i=1}^{x} G_{l-i} D_{i,t} \le P_{l,max}, \tag{7}$$

$$g_l\left(I_{i,t}\right) \le 0, \tag{8}$$

$$g_r\left(P_{i,t}, I_{i,t}\right) \le 0, \tag{9}$$

$$g_c\left(C_{i,t,U}, C_{i,t,D}, I_{i,t}\right) \le 0, \tag{10}$$

$$0 \le w_{x,t} \le \widehat{w}_{x,t}, \tag{11}$$

$$I_{i,t} P_{i,t} \le P_{i,t} \le I_{i,t} P_{i,max} \tag{12}$$

where
$W_{x,t}$ = Power dispatched at wind farm *x* and time interval *t*.
$\widehat{w}_{x,t}$ = Actual power output of wind generator.
$\boldsymbol{\widehat{w}_{x,t} - w_{x,t}}$ = Wind power spillage.
It seems that $\widehat{w}_{k,t}$ is an arbitrary parameter and hence $\widehat{w}_{x,t} - w_{x,t}$ is an arbitrary variable. The stochastic environment based UC is formulated with the assumption of wind spilled.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3010275, IEEE Access

TABLE 1. Key advantages and disadvantages of classical and non-classical approaches focused in literature.

Algorithm	Ref. No.	Advantages	Disadvantages
Linear Programming	[15-31]	• Offers an information base for optimum allocation of inadequate resources. • Helps to making adjustments according to the altering conditions. • Helps to solving the multi- dimensional problems. • Simple and easy to understand. • Analyses the problems in more flexibility and adaptive. • Provides better quality of decision.	• Cannot resolve the problems in which variables cannot be stated quantitatively. • The factor of uncertainty is not considered in this method. • Extremely mathematical and complicated. • To specify an objective function in mathematical form is not a trouble-free task. • Impracticable to solve nonlinear functions.
Dynamic Programming	[32-40]	• Stores preceding values to keep away from the multiple calculations • This recursive procedure does not have memory. • Convenient to use again the partial covered subordinate solutions.	• Must be keeping the track of the number of partial solutions. • Not capable of resolving non-integer constraint based problems.
Sequential Quadratic Programming	[41]	• Usually necessitates the smallest number of functions and gradient evaluations. • Does not try to gratify the equalities at every iteration	• Usually infringes nonlinear constraints until convergence, frequently by huge quantities. • Requires a good quadratic programming solver.
Semi-Definite Programming	[42-43]	• Speedy and significant for seed methods. • It is a convex problem and therefore, has no local minima/maxima. • Easy to be implemented.	• Lack of the relative numerical precision of an optimal solution • Poor accuracy.
Lagrangian Relaxation	[44-62]	• It basically produces sub-problems that can be solved in parallel. • Equations are simple to keep in mind. • Fewer numbers of variables involved. • Computer programs are incredibly easy to encode.	• Slower convergence. • Do not give any bounds on the quality of the solution. • It can oscillate and fail to converge if the slave problems are also uniform.
Decomposition Method	[63-66]	• Easy to implement • Less computing time is required to run the program	• There is no way to be sure that every essential component has been captured and appropriately related.
Integer Programming	[67-69]	• Easier way in terms of time, cost and effort that might be required to derive an integer solution. • Possible to model any of the variables and constraints. • More flexibility and realistic.	• Does not satisfy all given constraints. • More complicated to model and solve
Monte Carlo	[70]	• Does not disturb the continuing activities of the real system. • More general than mathematical models. • More sensible replication of a system than mathematical analysis. • Effective to analyze transient conditions over mathematical techniques	• Poor reliability. • Less accuracy than mathematical analysis. • Needs more computation time to run complex problems
Branch-and-Bound Algorithm	[71]	• It finds the minimum path in place of finding the minimum descendant, so there should not be any recurrence. • Less time complexity.	• The load balancing aspects make parallelization difficult. • Capable of running with small size network only.
Modified Sub-gradient Method	[72]	• Inexpensive iteration process and does not need second derivatives. • Extremely simple for minimizing convex non differentiable functions.	• Slower convergence. • Poor tuning process.
Benders Decomposition	[73-75]	• Obliging tool for solving process design problems. • Alternates between the solution of relaxed master problems and convex nonlinear sub-problems.	• Not free from local optima.
Outer Approximation and Outer-Inner Approximation	[76-77]	• Good performance of the approximate computation of the projection.	• Very complicated to solve the large size models.
Tighter Relaxation Method	[78-79]	• Transaction with additional variables in the higher dimensional space, in addition to supplementary constraints • Simple and to adoptable to computers	• Slower progress than the contra methods • Extremely enormous and tough to solve.
Network Programming	[80]	• Powerful, flexible and intuitive. • Updated information only can be sent. • Quick solution obtained. • They have naturally integer solutions.	• Cannot devise the extensive range of models.

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TABLE 1. Key advantages and disadvantages of classical and non-classical approaches focused in literature (Continued).

Algorithm	Ref. No.	Advantages	Disadvantages
Tabu Search	[81-82]	• Convenient to apply for both continuous and discrete solution spaces. • Permits non-improving solution to be accepted in order to escape from a local optimum.	• Numerous parameters to be determined. • Large number of iterations is required. • Complicated to find global optimum and depends on parameter settings.
Heuristic Methods	[83-85]	• Easy to implement and learn. • Does not stop at local optimum. • Efficient to solve.	• Complexity in computation and need much more computation time. • Heuristic evaluations are insecurely structured and therefore, run the risk of finding one-time, low-priority problems.
Simulated Annealing	[86-96]	• Coding is simple even for complex problems. • Cost functions and arbitrary systems are easy to deal.	• There are a small number of local minima. • Necessitates a few other complementary methods to find an optimal solution.
Ant Colony Optimization	[97-102]	• Can be used in dynamic applications. • Inherent parallelism. • Well-organized for some problems similar to Travelling Salesman Problem.	• Difficult to understand the theoretical analysis. • Needs more convergence time.
Fuzzy Logic	[103-111]	• Gives effective solution to complex problems. • Interpretability and simplicity. • It can handle problems with imprecise and incomplete data, and it can model nonlinear functions of arbitrary complexity. • The algorithms are often quite understandable. • Sometimes it uses only approximate data and hence simple sensors can be used.	• It is difficult to develop fuzzy rules and membership functions. • Outputs can be interpreted in a number of ways, making analysis difficult. • It requires lot of data and expertise to develop a fuzzy system.
Neural Net works	[112-127]	• Suitable to model complex functions. • Easy to implement. • Ease of use and learnt by example, and very little user domain-specific expertise needed.	• It cannot be retrained. If add data later, this is almost impossible to add to an existing network. • Handling of time series data is a very complicated task. • Intricate network structure.
Expert System	[128-131]	• Holds and maintains momentous levels of information. • Centralizes the decision making process. • Makes things more efficient by reducing the time needed to solve problems. • Decreases the number of human errors. • Provides tactical and relative advantages that may create problems for competitors. • Provides reliable answers for cyclic decisions, processes and tasks.	• No common sense used in making decisions. • Not capable of explaining the logic and reasoning behind a decision. • It is not simple to automate complex processes. • There is no suppleness and capability to adapt to changing environments. • Errors may occur in the knowledge base, and could lead to incorrect decisions.
Quasi-Oppositional Teaching Learning based Algorithm	[132]	• It is consistent, precise and robust. • Appropriate crossover and mutation rate is not required. • It gives improved performance with less computational time for the problems with high dimensions	• It converges quickly, if proper precaution is not taken. • It gives a near optimal solution earlier than an optimal one in a limited iteration cycles

TABLE 2. List of referred journals with publishers used in this review.

S. No.	Journal Name	Publishers
1	Applied Energy	Elsevier
2	Applied Mathematical Modelling	Elsevier
3	Applied Soft Computing	Elsevier
4	Computers & Electrical Engineering	Elsevier
5	Electric Power Components and Systems	Taylor & Francis
6	Electric Power Systems Research	Elsevier
7	Electrical Power and Energy Systems	Elsevier
8	Energy	Elsevier
9	Energies	MDPI Publications
10	Energy Conversion and Management	Elsevier
11	Engineering Optimization	Taylor & Francis
12	European Journal of Operational Research	Elsevier
13	Expert Systems with Applications	Elsevier
14	IEEE Access	The Institute of Electrical and Electronics Engineers
15	IEEE Transactions on Automatic Control	The Institute of Electrical and Electronics Engineers
16	IEEE Transactions on Energy Conversion	The Institute of Electrical and Electronics Engineers

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TABLE 2. List of referred journals with publishers used in this review (Continued).

S. No.	Journal Name	Publishers
17	IEEE Transactions on Industrial Informatics	The Institute of Electrical and Electronics Engineers
18	IEEE Transactions on Industry Applications,	The Institute of Electrical and Electronics Engineers
19	IEEE Transactions on Neural Networks and Learning Systems,	The Institute of Electrical and Electronics Engineers
20	IEEE Transactions on Power Apparatus and Systems	The Institute of Electrical and Electronics Engineers
21	IEEE Transactions on Power Systems	The Institute of Electrical and Electronics Engineers
22	IEEE Transactions on Systems, Man, and Cybernetics	The Institute of Electrical and Electronics Engineers
23	IEEJ Transactions on Electrical and Electronic Engineering	Wiley Interscience
24	IET Generation, Transmission & Distribution	The Institution of Engineering and Technology
25	Informatica	Vilnius University Institute of Mathematics and Informatics, Lithuania
26	Information Sciences	Elsevier
27	International Journal of Ambient Energy	Taylor & Francis
28	International Journal of Applied Mathematics and Computer Science	Institute of Control and Computation Engineering, University of Zielona Gora
29	International Journal of Energy Sector Management	Emerald Publishing Limited
30	International Journal of Modelling and Simulation	Taylor & Francis
31	International Journal of Systems Science	Taylor & Francis
32	International Transactions on Electrical Energy Systems	John Wiley & Sons
33	Journal of Circuits, Systems, and Computers	World Scientific Publishing Company
34	Journal of Electrical Engineering	De Gruyter, Slovakia
35	Journal of Electrical Engineering and Technology	The Korean Institute of Electrical Engineers
36	Journal of Electrical Systems	Engineering and Scientific Research Groups
37	Journal of Heuristics	Kluwer Academic Publishers
38	Journal of Information and Optimization Sciences	Taylor & Francis
39	Journal of the Chinese Institute of Engineers	Taylor & Francis
40	Knowledge Based Systems	Elsevier
41	Mathematical Problems in Engineering	Hindawi Publishing Corporation
42	Measurement and Control	SAGE Publications
43	Microprocessors and Microsystems	Elsevier
44	Neural Computing & Applications	Springer
45	Neurocomputing	Elsevier
46	Nonlinear Analysis, Theory. Methods & Applications	Pergamon Elsevier
47	Operational Research	Springer
48	Simulation Practice and Theory	Elsevier
49	Soft Computing	Springer
50	Swarm and Evolutionary Computation	Elsevier
51	The Hong Kong Institution of Engineers Transactions	Taylor & Francis
52	The Scientific World Journal	Hindawi Publishing Corporation
53	Turkish Journal of Electrical Engineering & Computer Sciences	TUBITAK (Scientific and Technological Research Council of Turkey)
54	WSEAS Transactions on Computers	World Scientific and Engineering Academy and Society
55	WSEAS Transactions on Power Systems	World Scientific and Engineering Academy and Society
56	WSEAS Transactions on Systems	World Scientific and Engineering Academy and Society

Equation (5) consists of the objective function of operation and start-up/shut down costs of thermal generators, as well as the predictable wind power spillage; Equation (6) corresponds to system power balance constraints. Equation (7) corresponds to DC transmission constraints. The term g_I in equation (8) indicates the constraints, linked only with integer variables, like minimum online/ offline time limits. The term g_r in equation (9) denotes ramping-up and ramping-down constraints. The term g_c in equation (10) represents constraints for start-up/shut down costs. Equations (11) and (12) represent the upper and lower limits of wind and thermal generators' real power output.

C. PROFIT BASED CIRCUMSTANCE

The chief goal of this profit based circumstance is to maximize the profit of the providers, who partake in the energy brokerage. Role of self-governing system operator is to match the power demand and supply and it establishes the rivalry among the generation companies. Consequently, the profit is maximized by suppliers to schedule their units as said by the predicted power cost. The difference between revenue and the total fuel cost is called the profit of generating company. Both the revenue and total fuel cost are calculated on the basis, the predicted values of reserve power, price and power demand. Consequently, predicted reserves and powers of the generating company play an imperative role in profit maximization. Problem formulation of the profit based UC is given by:

Maximize. Profit (P) = Available revenue (R_a) – Total operating cost (C_t)

Or

$Maximize.(C_t - R_a)$

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The available revenue and total operating cost can be calculated by:

$$R_a = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(P_{it}\ .\ S_{pt}\right).\ U_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} r\ .\ R_{pt}\ .\ P_{rt}\ .\ U_{it} \quad (13)$$

where

P_{it} : Output power of i^th^ generator at t^th^ hour in MW.
S_{pt} : Forecasted spot price at t^th^ hour/MW.
U_{it} : ON/OFF status of the unit.
r: Probability that the reserve is called and generated.
R_{pt} : Forecasted reserve price at t^th^ hour/MW.
P_{rt} : Reserve power of i^th^ generator at t^th^ hour in MW.
N: Total number of units.
T: Total number of hours.

The sum of fuel cost for both power and reserve power generation, $F(P_{it} + P_{rt})$ and startup cost of all units is called total operating cost of the system.

$$\mathrm{C_t} = (1-\mathrm{r})\sum_{i=1}^{N}\sum_{t=1}^{T} F(P_{it}).U_{it} + r\sum_{i=1}^{N}\sum_{t=1}^{T} F(P_{it} + P_{rt})\ .\ U_{it} + ST\ .\ U_{it} \quad (14)$$

where,

$F(P_{it})$: Fuel cost of i^{th} generating unit during t^{th} interval, is given in equation (2).
ST : Startup cost is given for i^{th} generating unit in equation (3).

D. VARIOUS CONSTRAINTS INVOLVED IN UC PROBLEM

A variety of UC related problems are related to numerous constraints, like total generated power to meet the load demand, sufficient spinning reserve to cover any deficits in a generation, loading of each unit to be within its minimum and maximum permissible limits, minimum up and down times of each unit to be observed and unit availability constraints like unit being available or not available, running condition, and initial status. Implementation of various constraints, simulation tool, hardware and validity of results used in reference papers, associated with evolutionary optimization techniques, are listed in Table 3. The various constraints involved in UC are as follows:

1) SYSTEM POWER BALANCE/LOAD BALANCE CONSTRAINTS

The generated power from all committed units must be sufficient to meet the system power demand, as articulated by:

$$\sum_{i=1}^{N} P_i^t u_i^t = P_D^t\ ,\ \ for\ t = 1,2,\ldots,T. \quad (15)$$

where P_D^t is system load demand at time t.

2) SYSTEM SPINNING RESERVE CONSTRAINTS

In an attempt to minimize the chance of load disruption, spinning reserve ought to be available in the power system and specified in terms of surplus megawatt capacity, as articulated by:

$$\sum_{i=1}^{N} u_i^t P_{i\,max} \geq P_D^t + P_R^t \quad (16)$$

where P_R^t is spinning reserve at time t.

3) GENERATOR CAPACITY CONSTRAINTS

The generated power of units must be in their maximum and minimum boundaries, as shown below:

$$P_{i\,min} \leq P_i \leq P_{i\,max}\ , for\ i = 1,2,\ldots,n. \quad (17)$$

where $P_{i\,min}$ and $P_{i\,max}$ are the allowable minimum and maximum output of generator i, respectively.

4) RAMP LIMIT CONSTRAINTS

Because of the confines of thermal stress and mechanical characteristics of a generating unit, the real operating range of all online units is limited by their ramp rate limits, as shown below:

$$\begin{aligned} P_{i\,max}(t) &= min(P_{i\,max}, P_i^{t-1} + \tau\ .RU_i) \\ P_{i\,min}(t) &= max(P_{i\,min}, P_i^{t-1} + \tau\ .RD_i) \end{aligned}, \quad (18)$$

where RU_i and RD_i are the ramp up and ramp down rates of unit i , respectively.

5) MINIMUM UP AND DOWN TIME CONSTRAINTS

If any unit is once committed or de-committed, it cannot be turned on or off right away. The minimum up and down time constraints point out that a unit must be on/off during a definite number of hours, in accordance with shutdown or start-up respectively. These constraints are expressed by:

$$u_{j,t} = \begin{cases} 1 & if\ 1 \leq T_{ON\ j,t-1} < M_{UT,j} \\ 0 & if\ 1 \leq T_{OFF\ j,t-1} < M_{DT,j} \\ 0\ or\ 1 & otherwise \end{cases} \quad (19)$$

where,

$T_{ON\ j,t}$ is the duration for which unit j is continuously on-line at hour t.
$M_{UT,j}$ and $M_{DT,j}$ are the minimum up and down time of unit j.

6) FUEL COST CONSTRAINTS

The fuel cost has to be limited to a particular range, for every hour, in the time period. The equation is expressed as:

$$F_{min}(i) \leq \sum_{t=1}^{T} F_i(P(i,t)I(i,t) + R(i,t)I(i,t) + N(i,t)) \leq F_{max}(i) \quad (20)$$

where

$F_{min}(i)$ = Minimum consumption of total fuel for unit i.
F_i = Fuel consumption function of unit i.
$P(i,t)$ = Power generation of unit i at time t.
$I(i,t)$ = Commitment status of unit i at time t.
$R(i,t)$ = Level of spinning reserve of unit i at time t.

$N(i,t)$ = Level of non-spinning reserve of unit i at time t.
$F_{max}(i)$ = Maximum consumption of total fuel for unit i.

7) NETWORK SECURITY CONSTRAINTS

Transmission capacity limit, the line flows and bus voltage magnitude constraints are grouped into system network security constraints, under steady state operation of power system and expressed as:

(a) Transmission capacity constraints

$$|S_l(t)| \leq S_l^{max}, l \in N_L \tag{21}$$

where
S_l^{max} = Maximum transmission power of line l.
N_L = Number of transmission lines.

(*b) Transmission line flow constraints*

$$\varphi_k^{min} \leq \varphi_k \leq \varphi_k^{max}; k = 1,2, \ldots, N_L \tag{22}$$

where
φ_k^{min}= Minimum phase angle of kth transmission line.
φ_k^{max}= Maximum phase angle of kth transmission line.

(c) Bus voltage magnitude constraints:

$$V_k^{min} \leq V_k \leq V_k^{max}, k \in N_B \tag{23}$$

where
V_k^{min}= Minimum voltage limit of bus k.
V_k^{max}= Maximum voltage limit of bus k.
N_B= Number of buses.

8) OTHER CONSTRAINTS

The following constraints are also called sub constraints and they are not often implemented, for the application of UC problem.

(a) Energy constraints – They are observed in UC problem, with energy contracts which couples generation decisions over the time perspective. It can be formulated as follows:

$$E_i^{min} \leq \sum_{t=1}^{T} P_{i,t} U_{i,t} \leq E_i^{max} \tag{24}$$

where
E_i^{min} = Minimum energy delivery of unit i.
E_i^{max}= Maximum energy delivery of unit i.

(b) Must run/down constraints - Based on the temporary maintenance and fuel aspects this constraint enforces units in or out of service.

(c) Crew constraints – It is not possible to turn on more than one unit at the same time in a power plant while starting up owing to deficient crew members.

(d) Initial operating status of generating units:
The preliminary operating status of each unit ought to take the previous day's schedule into account, so that each unit satisfies its minimum up/downtime.

(e) Slack bus constraint:

$$P_{sk\,(min)} \leq P_{sk} \leq P_{sk\,(max)} \tag{25}$$

where
P_{sk}= Slack bus generation output at kth hour.

(f) Emission constraint – Based on polluting gases emitted by burning fuel to be limited and expressed by the following equation

$$\sum_{i=1}^{N} \sum_{t=1}^{I} H_i(P_i(t)) \leq E_{limit} \tag{26}$$

where
$H_{P_i(t)}$=Quadratic function connected with some types of emission.

(g) Minimum loading constraint – It is based on the following equation

$$\sum_{n=1}^{N} P_{min,n} \leq D_h \tag{27}$$

where,
$P_{min.n}$= Minimum power generated by all committed units.
D_h= Load demand in the hour h.

III. REVIEW OF UC PROBLEM DEALT WITH BY EVOLUTIONARY OPTIMIZATION TECHNIQUES

Evolutionary optimization techniques are devised to solve superior dimensional problems and they are proved to be better than traditional optimization techniques, to solve multi dimensional UC problems. However, these methods require a considerable quantity of computational time to arrive at the near-global minimum, particularly for a major UC problem. Numerous researchers have examined an assortment of evolutionary optimization techniques, related to UC problem, in diverse dimensions. This paper proposes to present a complete review of the UC problem, integrated with numerous types of evolutionary optimization techniques like UC problem incorporated with GA [133-159], UC problem incorporated with PSO [160-170], UC problem incorporated with EA [171-177], UC problem incorporated with EP [178-183], UC problem incorporated with DE [184-190], UC problem incorporated with SFLA [191-193], UC problem incorporated with FA [194-199], UC problem incorporated with other evolutionary optimization techniques like BFA [200], FSA [201-202] and CSA [203], UC problem incorporated with Hybrid evolutionary optimization techniques [204-244], in the subsequent sections. Distinctive features of the references, connected to evolutionary optimization techniques, are captured and showed in Table 4, including the year of the publication.

A. UC PROBLEM INCORPORATED WITH GA

Sheble and Maifield proposed the UC problem incorporating GA, for 24 hour commitment schedule with six generators [133]. Two types of loading procedure (load 1 and load 2) are implemented to acquire the results intended for 24 hour schedule. Load 1 procedure represents that all generating units are in the off state, in the initial scheduling period and on state, in the final scheduling period. Load 2 procedure represents that all generating units are in off state, at first scheduling period and all need not be at on state during the final scheduling period. The fuel price for every UC schedule is premeditated, by the sum of the

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cost of ED intended for every hour. Sheble and Maifield [136] also presented a domain specific mutation based GA for UC problem, with three different electric utilities and the effectiveness of this approach is compared with the Lagrangian relaxation method.

A new forced mutation operator is introduced with GA based thermal UC, subject to demand, generating capacity, reserve and minimum up/down time constraints [134]. The penalty methods, incorporated with GA were constructed [135] and these methods were used to meet the various constraints like surplus generation, system demand, minimum up and down time, and spinning reserve. A GA based UC solution, incorporated with a changing quantity function and two sets of problem specific operators is also presented [137]. At first set, Swap-window and window-mutation operators are presented. Swap-mutation and swap-window hill climb operators are implemented in the second additional set. Yang et al framed a solution through GA, in juxtaposition with the means of constraint handling techniques. The on-off status of units are represented by the binary strings, contained in the entrenched minimum up and down time constraints [138] and developed a parallel GA in terms of sequential GA, master-slave and dual-direction ring based parallel GA, implemented in an eight-processor based transputer network [139].

A Dynamic Programming Crossover (DPX), to explore the gene sets without any repair algorithms or penalty functions in the constrained search space is discussed by Cai and Lo [140]. Three types of fitness functions and the Roulette Wheel Parent Selection Algorithm based selection technique are also designed and executed. A genetic algorithm based constrained optimization, with a precise changing fitness function method, is proposed to solve the cutting stock and unit commitment problems [141]. In this method, an active way fitness function is integrated with the constraints of the problem and formed by altering penalty terms. The penalty factors are reserved low down on the initial stage of evolution of GA, to make things easier for the search. The search competence of this optimization process is reinforced by some supplementary operators like Swap-Window, Window-Mutation, Swap-Mutation and Swap-Window Hill-Climbing operators.

A new Parallel Repaired GA (PRGA) was framed by Arroyo et al [142], to resolve UC problem, with three diverse optimization methods like Global Parallelization (planned to speed up the performance of the GA and lessen the computational time), Coarse-Grained Parallelization (to amplify the effect of mutation and crossover operators for escaping from local optima) and Hybrid Parallelization (combination of the Global and Coarse-Grained Parallelization) of GA. The performance of this planned method was evaluated by a technologically advanced LR algorithm. A new problem specific operator was introduced by Swarup and Yamashiro [143], to correct and mend the process of desecrated schedule, and it was classified into two types bit change operator and minimum up/down time operator. The bit position was modified by the bit change operator like change bit '101' to '111' or '010' to '000', with a sure quantity of probability. The bits were re-ordered by the minimum up/downtime operator, to satisfy the minimum up/down time constraints. The same author also proposes a similar approach [147], incorporating randomized operators in UC schedule, akin to without any operator, with bit operator and with bit and string operator modes.

A two level GA algorithm was presented, to resolve UC problem, subject to spinning reserve, generation limit, energy and minimum up/down time constraints [144]. The on/off status of generating units was determined by the higher level GA. The ED was contracted with the lower level GA. Taylor expansion based varying λ-technique was also projected in this technique, to overcome the oscillation effect between minimum and maximum MW limits. Chen and Wang have presented a new cooperative co-evolutionary algorithm (CCA), by combining the framework of basic LR with traditional GA [145]. Two level approaches are formulated in this approach, by optimizing the Lagrange multipliers through a sub-gradient based stochastic optimization level in the first level (also called high level) and the UC schedule is solving with GA in the second level (also called low level). The heat consumption (in one million British thermal units - MBTU) is chosen as the objective of the optimization process instead of fuel cost and the cost per unit heat consumption ratio is taken as 6:1 (cost of six units of nuclear heat equals that of one unit of coal heat).

A unit level crossover [146] was implemented to attain the better scheduling, by maintaining the initial half of the bits and swaps the second half of the bits, by means of arbitrarily selected units. The mutation probability ranged from 0.004 to 0.024. Best and worst cost, with an average time of this approach is also presented and compared with a simple GA. Three special operators like unit exchange/copying operator (performing chromosome operation to avoid the violation constraints), Excessive-reserve elimination operator (improve the performance of UC schedule) and Chromosome length augmentation (ability to increase the length of chromosome in order to include the necessary new cycles) were introduced in an Integer Coded GA (ICGA) based UC problem, to reduce the size of chromosome [148]. Dudek presented a mutation method, incorporating GA and its probability, dependant on the requirement of meeting the load demand of the units, start-up and production costs [149]. The proposed transposition operator helps to swap the chromosome sections that encode the conditions of two randomly selected units. The generation schedule is symbolized by a real number matrix based chromosome and the feasible solution is achieved by the proposed repairing mechanism [150].

An encoding-decoding scheme and representation of floating point chromosome were designed to reduce the complexity of minimum up/down time constraint handling [151] and some of the specific crossover and mutation operators like arithmetic crossover, simple two-point crossover, uniform crossover, Gaussian mutation, Cauchy mutation and boundary mutation were also designed and implemented. In [152], two stages are proposed - transmission line flow limit by GA, presented in the primary stage and the actual power generation limit constraint on line phase angle, in the secondary stage. The line flows and losses are calculated by a decoupled load flow model. A parallel structure based GA is presented to solve thermal UC problem, subjected to customary constraints [153].

A deterministic selection (a compulsory approach wherein individuals, with enhanced fitness, are crossed with those of poorer fitness) and an annular crossover (chromosome symbolized as a ring to swap of genetic information flanked by two individuals) were implemented in [154]. The actual and integer part of UC problem is solved by a single algorithm called a binary-real coded GA, incorporating generated power range (ramp rate) constraint [155]. Real and binary part of this proposed method determines the quantity of generating power through committed units and their scheduling respectively. A new untypical genetic operator (transportation) [156] which functions is by means of single chromosome and produces offspring through swapping chromosome splinters that encode every one decision variables of two arbitrarily selected units.

A memetic, multi-objective evolutionary optimization method is presented, with a combination of local search algorithm with non-dominated sorting GA-II (NSGA-II), which is proposed for the main problem and a weighed-sum, lambda-iteration method is used to resolve the sub-problem of power dispatch [157]. The emission objective is considered in overall environmental UC problem, by formulating the multi-objective function amalgamated with two UC sub-problems. The design is equipped with two local search strategies and one local search operator. On/off schedule of this method is identified through the global search by NSGA-II and a priority list method, which is used to generate the on/off schedule solution by means of the initial population of chromosomes in NSGA-II.

In [158], two optimizers are used in the enhanced version like real coded GA and MILP, to solve UC and ED of micro grids. With this approach, the formulation of strategies, inputs and constraints are initially obtained by MILP, with simple algorithm settings and then interfaced with the CPLEX software package. An event-driving age behavior of lithium-ion battery storage system model has also been implemented in this investigated energy management system approach, for control of reactive power, peak power shedding and load shifting purposes. Five main micro-grid operations policies like cost effective operation, grid supporting mode, maximum islanding degree, eco-friendly operation and malfunctioning policy have also been incorporated. Jo and Kim proposed to solve the UC problem, through an improved GA technique. An uncertainty integration method was introduced in this approach, to assemble the most excellent combination of wind and solar units, by Monte Carlo simulation [159]. The probability of crossover and initial mutation values are given as 0.7 and 0.2 respectively. A modified approximation process and repair operators were also used in this approach.

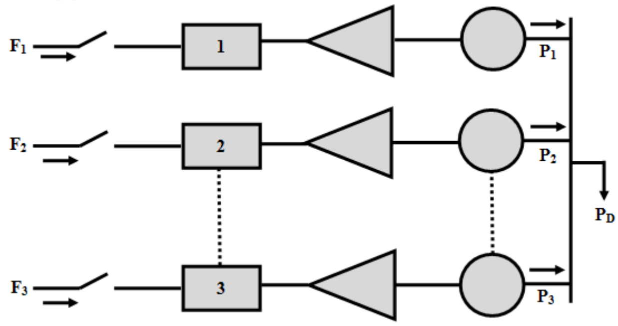

FIGURE 2. **Basic representation of unit commitment.**

B. UC PROBLEM INCORPORATED WITH PSO

More particles information was used in an enhanced adaptation scheme, with improved social interaction based PSO, to control the operation of mutation for effective search [160]. An 'iteration best' index integrated with PSO called Iteration PSO (IPSO) was presented by Lee and Chen for getting better fineness of solution and reducing the computational time, to resolve UC problem with probabilistic reserve, subjected to customary constraints [161]. The spinning reserve level is appraised by the effect of fuel cost, in addition to outage cost considered in the UC problem.

A priority list, based on strategies of heuristic search and unit characteristics, to mend the leading constraints helps to enhance the improved discrete binary PSO incorporated with lambda-iteration technique, called an improved binary PSO (IBPSO) was presented by Yuan et al [162]. Three stages have been suggested to solve the UC problem, in addition to ED problems, like the amalgamation of discrete binary PSO with priority list, executed to commit the units to gratify spinning reserve, ignoring the minimum up/down time constraints in the first stage. Violations of minimum up/down time constraints, in addition to de-committing excessive spinning reserve, repaired by a heuristic search algorithm in the second stage. Finally, the solution of ED is obtained by the lambda-iteration technique.

Wang and Singh [163] framed a mixed-integer PSO (MIPSO), to resolve UC problem, by considering the generator outages, subjected to four essential constraints. The unit selection is indicated by position values in binary numbers and those representing an output of each unit, in real numbers. A new set of individuals was created by PSO, combined with GA operators from upper potential individuals and further refining them to give close to the best concluding solution [164]. In this approach, PSO is customized to run in multi-population background and everyone is hereditary, from preceding population, through applying GA operators. The entire work is performed with three cases (case 1: only thermal units, case 2: thermal units, with wind and solar energy, without battery, case 3: thermal units, with wind and solar energy, with battery).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3010275, IEEE Access

TABLE 3. Implementation of constraints, simulation tool, hardware and validation of results used in reference papers associated to evolutionary optimization techniques.

Ref. No.	Constraints Used															Simulation Tool Used	Hardware Used	Cases
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O			
[133]	√	√	√	√	-	-	-	-	-	-	-	-	-	-	-	C- language	DEC (Digital Equipment Corporation) Station Computer	6- unit system
[134]	√	√	√		√	-	-	-	-	-	-	-	-	-	-	FORTRAN 77	NG	10- unit system
[135]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	NG	IBM PC (Model 80 386)	9- unit system
[136]	-	-	-	-	√	√	√	-	-	-	-	-	-	-	-	NG	Sun Sparc Station LX	Big Edison Electric Company, Municipal Electric Company and Rural Electric Exchange having 9-generators each
[137]	√	-	√	√	√	√	√	-	-	-	-	-	-	-	√	NG	HP APOLLO-720, 50 MHz Work station	10-, 20-, 40-, 60-, 80- and 100 unit test cases
[138]	√	√	√	√	√	-	√	√	-	-	-	-	-	-	-	Turbo C language,	IBM- PC486-66.	Taiwan Power 38-unit practical system
[139]	√	√	√	√	√	-	-	√	-	-	-	-	-	-	-	Express C language	Inmos T800-G25S Transputer with PC-486-66	Taiwan Power 38-unit practical system
[140]	-	-	-	-	-	√	√	-	-	-	-	-	-	-	-	NG	SUN SPARC workstation 10	NG
[141]	√	-	√	-	√	-	-	-	-	-	-	-	-	-	-	NG	HP Apollo 720 workstation	10- and 20- unit systems.
[142]	√	-	-	√	√	-	-	-	-	-	-	-	-	-	-	Fortran 90 with Message Passing Interface	DEC- Alpha 21164 processor with 128 MB of RAM	Real case of mainland Spain 45- generating units
[143]	√	√	√	-	√	√	√	-	-	-	-	-	-	-	-	C- Language	HP-UX 9000 Engineering Work Station (EWS)	10- unit system
[144]	√	√	-	-	√	-	-	-	√	-	-	-	-	-	-	NG	Pentium II 400 PC	10- unit system
[145]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	NG	Pentium-II-26 Microcomputer	IEEE RTS-96 test system
[146]	√	√	√	-	√	-	-	√	-	-	-	-	-	-	-	NG	Pentium–IV,1.5GHz Processor	10- unit system
[147]	√	√	√	-	√	-	√	-	-	-	-	-	-	-	-	C- Language	HP-UX 9000 Engineering Work Station (EWS)	10- unit system
[148]	√	-	√	√	-	√	√	-	-	-	-	-	-	-	-	NG	Intel P-IV, 1.60 GHz with 512-MB of RAM	10-, 20-, 40-, 60-, 80- and 100-units
[149]	√	√	-	-	√	-	√	-	-	-	-	-	-	-	-	MATLAB	Pentium III, 800MHz PC	3- and 12-unit cases
[150]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	Visual C++	Intel P- IV, 1.4 GHz CPU with 256-MB of RAM.	38-unit system
[151]	√	√	√	√	√	√	√	√	-	-	-	-	-	-	√	NG	IBM-PC with P-II, 300 MHz Processor with 128 MB of RAM	20-,40-,60-,80- and 100-unit cases

TABLE 3. Implementation of constraints, simulation tool, hardware and validation of results used in reference papers associated to evolutionary optimization techniques (Continued).

Ref. No.	Constraints Used															Simulation Tool Used	Hardware Used	Cases
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O			
[152]	√	√	√	-	√	-	√	-	-	√	√	-	-	-	-	NG	NG	Indian utility 66-bus system comprising 12 generators and 93 transmission lines and 100-unit systems
[153]	√	√	√	-	√	-	√	-	-	-	-	-	-	-	-	C- Language	Intel Duo core 1.8 GHz Processor based PC with 2.0 GB of RAM.	10- and 20-unit systems
[154]	√	√	√	√	√	-	-	-	-	-	-	√	-	-	√	NG	NG	10- and 45-unit systems
[155]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	C- Language	HCL desk-top 2.9 GHz, 2.0 GB of RAM Processor by Fedora 8 Linux environment	10-unit system up to 100-units
[156]	√	√	-	-	√	-	√	-	-	-	-	-	-	-	-	MATLAB	NG	12 -unit system
[157]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB	Intel Core i5, 3.4 GHz Processor based PC with 4.0 GB of RAM	10-unit system up to 100-units
[158]	-	-	-	-	-	-	√	-	-	-	-	-	√	-	-	MATPOWER	NG	22-bus radial LV micro-grid
[159]	√	-	√	-	√	√	√	-	-	-	-	-	-	-	-	MATLAB	Intel quad-core, 3.2 GHz processor with 8 of GB RAM	10-, 20-, 40-, 60-, 80- and 100-unit cases
[160]	√	√	√	√	-	-	-	-	-	-	-	-	-	-	-	MATLAB 6.5	Pentium IV, 2.0 G Computer	20-, 40-, 60-, 80- and 100-units
[161]	√	√	-	√	√	-	√	-	-	-	-	-	-	-	-	NG	IBM-Pentium-IV, 2.8 GHz PC	48-unit system
[162]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	√	C++ 6.0 language	Intel Pentium-IV, 1.5 GHz processor with 128 MB of RAM	20, 40, 60, 80 and 100-units
[163]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	NG	NG	10-unit system
[164]	√	√	√	√	√	√	-	-	-	-	-	-	-	-	-	Visual C++	Pentium-IV processor with 512 MB of RAM	10-unit system up to 100-units
[165]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB 6.5	NG	IEEE 30-bus system
[166]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	√	NG	NG	10-unit system up to 100-units
[167]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	Visual C++ 6.0	Pentium-IV, 2.0 GHz Processor based PC with 512 MB of RAM	10-unit system up to 100-units
[168]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	NG	Pentium-IV, 2.6 GHz Processor with 2.0 GB of RAM	10-, 20-, 40-, 60-, 80- and 100-unit cases
[169]	-	√	√	-	√	-	√	-	-	-	-	-	√	-	-	FORTRAN 90	Intel Pentium-IV, 1.66 GHz processor with 2 GB of RAM	10-, 12-, 14-, 20- and 40-unit cases
[170]	√	-	-	√	√	-	-	-	-	-	-	-	-	-	-	NG	NG	10- unit system
[171]	√	√	-	-	-	-	√	-	-	-	-	-	-	-	-	NG	Intel Core 2, 2.20 GHz Processor	10-unit system

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Ref. No.	Constraints Used															Simulation Tool Used	Hardware Used	Cases
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O			
[172]	√	√	√	√	√	-	√	-	-	-	-	-	-	-	-	NG	Pentium-IV, 2.0 GHz Processor	10-unit system up to 100-units
[173]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	MATLAB	Intel Core, 2.39 GB processor with 1.99 GB of RAM	10-unit system up to 100-units
[174]	-	-	-	√	-	-	√	-	-	-	-	-	-	-	-	NG	Intel Core 2, 2.20 GHz Processor	6-unit system
[175]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	MATLAB	INTEL CORE2 DUO, 2.66 GHz Processor with 1.95 GB of RAM	10-, 20-, 40-, 60-, 80- and 100-unit cases
[176]	-	-	-	-	-	-	√	-	-	-	-	-	-	-	-	NG	NG	4- unit and 6- unit system
[177]	√	√	-	√	√	-	√	-	-	-	-	-	-	-	-	MATLAB	Intel core i7, 3.07GHz processor with 8 GB RAM	10-, 12-, 14-, 20- and 40-unit cases IEEE-RTS -24-bus
[178]	-	-	√	-	√	-	√	-	-	-	-	-	-	-	√	NG	NG	10-, 20-, 40-, 60-, 80- and 100-unit cases
[179]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	NG	Sun Sparc work Station 10	90 thermal units
[180]	√	-	√	√	√	-	-	√	-	-	-	-	-	-	-	MATLAB	NG	10-, 23- and 34-unit systems
[181]	√	-	√	-	√	-	-	√	-	-	-	-	-	-	-	MATLAB	NG	10-, 23- and 34-unit systems
[182]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	NG	NG	Indian-utility 11-unit, three IEEE hydro-thermal test cases like 25-units (22 thermal and 3 hydro units), 44-units (32 thermal and 12 hydro units) and 65-units (45 thermal and 20 hydro units)
[183]	√	-	√	-	√	-	-	√	-	-	-	-	-	-	-	NG	NG	10-, 23- and 34-unit systems
[184]	√	-	√	√	√	-	-	-	-	-	-	-	-	-	√	NG	NG	10-, 23- and 34-unit systems
[185]	√	√	-	-	√	-	√	-	-	-	-	-	-	-	-	NG	NG	4-unit, 10-unit and 8-unit Turkish interconnected system
[186]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	√	Visual C++	Pentium-IV, 2.4 GHz Processor based PC with 256 MB of RAM	10-unit system up to 100-units
[187]	√	√	√	-	√	-	-	√	-	-	-	-	-	-	-	C++ language	PCD32m-Pentium-IV-2.4G Processor based PC	10-, 20-, 40-, 60-, 80- and 100-unit cases
[188]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	Turbo C and MATLAB R2007a	Intel Dual Core, 2.4 GHz, 1.0 GB of RAM Processor	6-unit (IEEE 30-bus) and 10-unit systems
[189]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	C- language Executed in Linux 8.0 environment	HC1, 2.9 GHz Processor with 2.0 GB of RAM	10-, 20-, 40-, 60-, 80- and 100-unit cases
[190]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	√	NG	NG	10-, 20-, 40-, 60-, 80- and 100-unit cases
[191]	√	-	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB	Pentium-IV Processor based PC with 512 MB of RAM	10-, 20-, 40-, 60-, 80- and 100-unit cases

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Ref. No.	Constraints Used A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Simulation Tool Used	Hardware Used	Cases
[192]	√	-	√	-	√	-	-	-	-	-	-	-	-	-	-	NG	NG	10-unit system
[193]	-	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB 2011	NG	IEEE 14- bus, 30- bus, 57-bus and 118-bus systems
[194]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB 7.01	Pentium-IV, 3.2 GHz Processor based PC with 1.0 GB of RAM	IEEE RTS 24-unit system
[195]	√	√	√	√	√	-	-	-	-	-	√	-	-	-	-	MATLAB 7.01	Pentium-IV, 3.2 GHz Processor with 1.0 GB of RAM	IEEE RTS 24-bus system
[196]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	NG	NG	3-unit, 12-unit, 17-unit, 26-unit and 38-unit generator systems
[197]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB 7.01.	Pentium-IV, 3.2 GHz Processor with 2.0 GB of RAM	100-unit system, IEEE RTS 24-bus system and IEEE 118 bus system and Tai-power 38-unit system
[198]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB	Pentium-IV, 3.40 GHz Processor with 1.0 GB of RAM	100-unit system, an IEEE 118-bus system and a 38-bus Taiwan practical system
[199]	√	√	√	-	√	√	√	-	-	-	-	-	-	-	-	MATLAB	NG	10- unit system
[200]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	NG	Intel Pentium-IV, 2.0 GHz Processor based PC with 512 MB of RAM	10-, 20-, 40-, 60-, 80- and 100-unit cases
[201]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	NG	NG	10-unit system up to 100-units
[202]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB 7.9	Intel Core2-Duo, 2.20 GHz Processor	10-unit system up to 100-units
[203]	√	-	√	√	√	-	√	-	-	-	-	-	-	-	-	MATLAB 2016a	Intel core i5, 2.30GHz processor with 4 GB RAM	4- unit system
[204]	-	√	-	√	√	-	-	-	-	-	-	-	-	-	-	NG	IBM PC-486, 33 MHz Processor	43-unit Taiwan power system
[205]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	√	NG	DEC-AXP 4610 Processor	110-unit system
[206]	√	√	-	-	-	-	-	-	-	-	-	-	-	-	-	NG	NG	10-unit system
[207]	√	√	√	-	-	-	-	-	-	-	-	-	-	-	-	NG	NG	10-unit and 26-unit systems
[208]	√	√	√	-	√	-	-	√	-	-	-	-	-	-	√	NG	NG	10-unit and 26-unit systems
[209]	√	√	√	-	√	√	-	-	-	-	-	-	-	-	-	Turbo C language	486DX2-66 Compatible PC	10-, 20-, 40-, 60-, 80- and 100-unit cases
[210]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	√	NG	NG	5-, 10- and 26 generating units
[211]	√	√	√	√	√	√	√	-	-	-	-	-	-	-	-	Turbo C language	486DX2-66 compatible PC	10- and 20- unit system, Tai-power 40-unit system
[212]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	NG	NG	10-unit system
[213]	-	√	√	√	√	√	√	√	-	-	-	-	-	-	-	Visual C++	Pentium III-MMX PC with 450 MHz Processor	10-, 20- and 30-units
[214]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	NG	Dell DIM 4100, 1GHz Processor	10-unit system up to 100-units
[215]	√	√	√	-	√	-	-	√	-	-	-	-	-	-	√	NG	NG	10-unit system

TABLE 3. Implementation of constraints, simulation tool, hardware and validation of results used in reference papers associated to evolutionary optimization techniques (Continued).

Ref. No.	Constraints Used															Simulation Tool Used	Hardware Used	Cases
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O			
[216]	√	√	√	√	√	√	-	-	-	-	-	-	√	-	-	C++ language	NG	IEEE-118 bus system
[217]	√	√	√	-	√	-	-	√	-	-	-	-	-	-	-	Visual C++	Pentium-III MMX, 450 MHz Processor based PC	10-, 20- and 30-units
[218]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	Visual Basic	NG	10-unit system
[219]	√	√	√	√	√	-	-	√	-	-	√	-	-	-	√	NG	NG	10- and 20- unit system, Tai-power 38-unit system
[220]	√	-	√	-	√	-	√	√	-	-	-	-	-	-	-	MATLAB	NG	10-, 24- and 36-unit systems
[221]	√	√	√	√	√	-	-	√	-	-	-	-	-	-	-	NG	Pentium-IV, 2.0 GHz Processor based PC	10-, 20-, 40-, 60-, 80- and 100-unit cases
[222]	√	√	√	-	√	-	-	-	-	-	√	-	-	-	-	NG	NG	14-bus system and modified IEEE 30-bus system
[223]	√	-	-	-	√	-	-	-	-	-	-	-	-	√	-	NG	NG	Wujiangdu hydropower station comprising with 5-units
[224]	√	√	√	-	√	-	√	-	-	-	-	-	-	-	-	MATLAB 7.4	Pentium-IV, 3.0 GHz Processor based PC with 1.0 GB of RAM	10-, 20-, 40-, 60-, 80- and 100-unit cases
[225]	√	√	√	√	√	-	-	√	-	-	-	-	-	-	-	MATLAB	Intel Core 2 Quad, 2.4 GHz processor based PC	10-, 20-, 40-, 60-, 80- and 100-unit cases, Tai-power 40-unit system
[226]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	Visual C++	Pentium-IV Processor with512 MB of RAM	10-unit system up to 100-units
[227]	√	√	√	√	√	√	-	-	-	-	-	-	√	-	-	C++ language	Intel Pentium IV Processor based PC with 512 MB of RAM	10-unit system up to 100-units
[228]	√	√	√	√	-	-	√	-	-	-	-	-	-	-	-	MATLAB 7.01	Intel Pentium-IV, 3.2 GHz processor with 1 GB RAM	6-, 10-, 26- and 40- unit cases
[229]	√	√	-	√	√	-	√	-	-	-	-	-	-	-	-	MATLAB	AMD Core, 3.01 GHz computer with 4.0 GB of RAM	10-unit system, revised IEEE 118-bus system comprising of 33 conventional units
[230]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	MATLAB	Intel Core2 Duo Processor with 4 GB of RAM	IEEE 14-bus
[231]	√	√	√	√	√	-	√	-	-	-	-	-	-	-	-	Java	Intel Core i5-3210M, 2.5 GHz Processor based note book computer with 6.14 GB DDR3-1600 memory	10-, 20-, 40-, 60-, 80- and 100-unit cases,
[232]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	√	C- Language	Intel XEON, 3.10 GHz Processor with 4.0 GB of RAM	10-, 20-, 40-, 60-, 80- and 100-unit cases,
[233]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB R2012a	Pentium-IV, 2.8 GHz Processor with 2.0 GB of RAM	10-unit system up to 100-units, 38-unit Tai-power practical case

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Ref. No.	Constraints Used															Simulation Tool Used	Hardware Used	Cases
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O			
[234]	√	√	√	-	√	-	-	-	-	-	-	-	√	-	-	C-Language	Intel-3.10GHz Processor based PC	10-unit system up to 100-units
[235]	√	√	√	-	√	-	-	√	-	-	-	-	-	-	√	MATLAB 7.12	NG	IEEE 14-bus, IEEE 30-bus and a 10-unit test model
[236]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	-	MATLAB 2014a	Intel core i5-3470, 3.20GHz processor with 8 GB RAM	10- unit system
[237]	√	√	√	-	√	-	-	√	-	-	-	-	-	-	√	MATLAB R2013a	NG	4-, 10-, 20- and 40-unit cases
[238]	√	√	√	-	√	-	-	-	-	-	-	-	-	-	-	MATLAB R2013a	Intel core i5-3470S, 2.90GHz processor with 4 GB RAM	IEEE 30-bus system
[239]	√	√	√	√	√	-	-	-	-	-	-	-	-	-	√	FORTRAN 90	Intel core i5-2410 M, 2.30GHz processor with 4 GB RAM	10-, 40- and 100- unit cases
[240]	√	√	√	-	√	-	√	-	-	-	-	-	-	-	-	NG	NG	5-, 6-, 10- and 26- unit cases
[241]	√	-	√	-	-	√	-	-	-	-	-	-	√	√	-	MATLAB	NG	6- and 10- unit cases
[242]	√	√	√	√	√	√	-	-	-	-	-	-	-	-	-	NG	NG	10- unit system
[243]	-	√	-	√	√	√	√	-	-	-	-	-	-	-	-	MATLAB R2018a	Intel core i7, 2.5GHz processor with 8 GB RAM	188-bus transmission system with 33-bus distribution system in five cases
[244]	√	√	√	√	√	√	√	-	-	-	-	-	-	-	-	MATLAB	Tower server with 24 cores, 48 threads and 64GB RAM	4- and 10- unit cases

(NG = Not given; A = Power balance/Load demand constraints; B = Generator/Unit capacity constraints; C = System/Unit spinning reserve constraints; D = Ramp limit constraints; E = Minimum up/down time constraints; F = Fuel cost constraints; G = Start-up/shutdown cost constraints; H = Must run/unavailability/fixed output/Crew constraints; I = Energy constraints; J = Slack bus constraint; K = Transmission capacity/line flow/bus voltage magnitude constraints; L = Minimum loading constraint; M = Emission constraints; N = Hydro constraints; O = Unit initial/de-rating status constraints)

TABLE 4. Projected algorithms with the distinctive features in reference papers connected to evolutionary optimization techniques.

Reference Number	Algorithm used	Distinguished features	Year of publication
[133]	GA	• The fuel price of every UC schedule was planned by the summation of the cost of ED intended for every hour.	1994
[134]	GA	• A new forced mutation operator was implemented in this work.	1995
[135]	GA incorporated with penalty methods	• The penalty methods were used to impose the various constraints, like surplus generation, system demand, minimum up and down time, and spinning reserve.	1996
[136]	Domain specific mutation based GA	• Results were obtained from three different practical electric utilities, like Big Edison Electric Company, Municipal Electric Company and Rural Electric Exchange having nine generators each.	1996
[137]	Problem specific operators based GA	• Two sets of specific additional operators were handled. • Swap-window and window-mutation operators were presented in the first set. Swap-mutation and swap-window hill climb operators were handled in second set.	1996
[138]	GA	• The on-off states of units were represented by, the binary strings contains with well-established minimum up and down time constraints.	1996
[139]	Parallel GA	• A new technique was presented, to insert the minimum up/down time constraints in the binary representation.	1997

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TABLE 4. Projected algorithms with the distinctive features in reference papers connected to evolutionary optimization techniques (Continued).

Reference Number	Algorithm used	Distinguished features	Year of publication
[140]	GA	• The gene sets in the constrained search space finding out by the Dynamic Programming Crossover (DPX), without using any penalty functions or repair algorithms.	1997
[141]	GA	• A new precise varying fitness function technique was implemented, to integrate the problem's constraints into the fitness function, as penalty terms. It varies with the generation index, resulting in an altering fitness function to make possible position of the general area of the global optimum.	1998
[142]	Parallel Repaired GA	• Three different optimization methods, like global parallelization (planned to speed up the performance of GA and lessen the computational time), coarse-grained parallelization (make to amplify the effect of mutation and crossover operators for escaping from local optima) and hybrid parallelization (combination of the global and coarse-grained parallelization) were implemented.	2002
[143]	GA	• A new problem specific operator was introduced to correct and repair the process of desecrated schedule. • The problem specific operator was classified, as bit change operator and Minimum up/down time operator.	2002
[144]	GA	• Taylor expansion based varying λ-technique was projected, to overcome the oscillatory effect between minimum and maximum MW limits	2002
[145]	LR combined with GA	• Two level approaches was formulated, one to optimize the Lagrange multipliers through a sub-gradient based stochastic optimization level in the first level (also called high level) and the UC schedule, is solved with GA in the second level (also called low level).	2002
[146]	Two level crossover based GA	• Single point crossover was applied in two ways (maintaining the initial half of the bits and swaps the second half of the bits by means of arbitrarily selected units), to achieve better scheduling.	2003
[147]	GA	• Randomized bit operators are employed, to satisfy the time dependent constraints.	2003
[148]	Integer-Coded GA	• Three special operators were proposed, like unit exchange/copying operator (performing chromosome operation to avoid the violation constraints), excessive-reserve elimination operator (improve the performance of UC schedule) and chromosome length augmentation (ability to increase the length of chromosome in order to include the necessary new cycles).	2004
[149]	GA with specialized search operators	• The mutation method and its probability is dependent on the requirement to meet the load demand of the units, start-up and production costs.	2004
[150]	Matrix real-coded GA	• The generation schedule has been symbolized by, a real number matrix based chromosome and the feasible solution was achieved by the repairing mechanism. • The window mutation operator is also used to enhance the searching performance.	2006
[151]	Floating-point GA	• Specific crossover and mutation operators, like arithmetic crossover, simple two-point crossover, uniform crossover, Gaussian mutation, Cauchy mutation and boundary mutation were designed and used.	2007
[152]	GA	• It can be solved by customary constraints, excluding transmission line flow limit by GA presented in the primary stage. • The line flow violations were minimized and committed unit schedule with GA based optimal power flow, subjected to actual power generation limit constraint and phase angle was focused in the second stage.	2010
[153]	Parallel structure based GA	• An intelligent mutation was projected for the best solution. If over committed is considered, then the more pricey units are de-committed or else those are committed.	2011
[154]	Annular crossover GA	• A deterministic selection (a compulsory approach wherein individuals with enhanced fitness are crossed by those of poorer fitness) and an annular crossover (chromosome symbolized as a ring to swap of genetic information flanked by two individuals) were implemented.	2011
[155]	Binary-real coded GA	• Real and binary part determines the quantity of generating power through committed units and their scheduling respectively.	2013
[156]	GA	• A new untypical genetic operator (transportation) is introduced in this work, functioned by single chromosome and produces offspring through swapping chromosome splinters that encode every one decision variables of two arbitrarily selected units.	2013
[157]	NSGA-II combined with LSA	• A combination of local search algorithm with non-dominated sorting GA-II (NSGA-II) is proposed for the main problem and a weighed-sum lambda-iteration method is used to resolve the sub-problem of power dispatch. • The design of UC problem is equipped with two local search strategies and one local search operator.	2013
[158]	Real coded GA and MILP	• The different case specific and flexible sub operators were developed by an enhanced real coded GA, used as the first optimizer. The second optimizer was the decomposition of the mixed integer, nonlinear programming (MINLP) into MILP, to handle the topological constraints.	2018

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TABLE 4. Projected algorithms with the distinctive features in reference papers connected to evolutionary optimization techniques (Continued).

Reference Number	Algorithm used	Distinguished features	Year of publication
[159]	Improved GA	• Minimum up and down constraints were considered by the repairing operator, to modify the infeasible solution. Infeasible solution was approximated by the approximation operator under the satisfaction conditions of spinning reserve and demand constraints.	2018
[160]	Improved social interaction based PSO	• The convergence is assured by using a new adaptive strategy for selecting parameters and adopts the orthogonal design to produce a preliminary population that are sprinkled uniformly over viable solution space.	2006
[161]	Iteration PSO	• Spinning reserve level is appraised by the effect of fuel cost, in addition to outage cost, considered in UC problem.	2007
[162]	Improved binary PSO	• The amalgamation of discrete binary PSO with priority list is executed to commit the units to gratify spinning reserve, ignoring the minimum up/down time constraints in the first stage. • Violations of minimum up/down time constraints, in addition to de-commit excessive spinning reserve, are repaired by a heuristic search algorithm in second stage. • Finally, the solution of ED is obtained by the lambda-iteration technique.	2009
[163]	Mixed-integer PSO	• The unit selection is indicated by position values is binary numbers and those representing an output of each unit are real numbers.	2009
[164]	Advanced PSO	• A new set of individuals is created by PSO combined with GA operators from upper potential individuals and further refines them to give close to the best concluding solution.	2009
[165]	PSO	• The profit based unit commitment problem is solved by using a variety of PSO techniques such as chaotic PSO, new PSO and dispersed PSO.	2010
[166]	PSO	• Two iterative control loops are proposed, to control the eventual terminate of the search procedure and evolutionary procedure respectively.	2010
[167]	Enhanced PSO	• Three stages are framed to calculate the start-up cost of UC. In the first stage, units are committed to satisfy spinning reserve through the combination of discrete binary PSO and priority list, without allowing for minimum up/down time constraints. • The violations in minimum up/down time constraints are repaired by a heuristic search algorithm in second stage. • Finally, the ED problem is solved by the lambda-iteration method and the start-up cost of UC is calculated as of the total production cost of ED problems.	2011
[168]	Time variant acceleration coefficients based PSO	• Integer and binary coding are planned to satisfy the minimum up/down time and spinning reserve constraints respectively. • The ability of global search is enhanced by changing the acceleration coefficients c1 and c2 effectively, by which either c1 is greater than c2 (at the beginning of optimization process) or c1 is less than c2 (at the time of increasing the iterations).	2015
[169]	Binary PSO and PSO	• CHP model was framed as a mixed integer model and hence both binary PSO and regular PSO methods were employed, to deal with binary and real variables respectively.	2019
[170]	Improved PSO	• The conventional PSO was improved through bird-flocking simulation in two-dimensional space and it was incorporated with time varying inertia weight, which is capable of locating faster rate good solution.	2019
[171]	Two-level two-objective EA	• A new strategy is framed for the coarsening of UC problem, solved by EA, under a low level optimization (coarse-grained UC problem). • Solutions obtained from low level are injected into high level population of EA for further refinement called high level optimization (fine-grained UC problem).	2009
[172]	Improved Quantum EA	• Two effectual techniques are initiated and compared with an ordinary quantum evolutionary algorithm. • In the first technique, the quantum bits (Q-bits) are updated by a simple rotation gate in which determines the rotation angle without lookup table information used in an ordinary QEA. • Due to the solution quality and convergence speed, the magnitude of rotation angle is determined by decreasing the rotating angle approach is proposed in the second technique.	2009
[173]	Quantum Inspired EA	• The ED of each UC schedule is computed by lambda-iteration technique to determine the optimal output of the generation and UC schedule is solved by QEA approach.	2009
[174]	Meta-modal assisted EA	• Monte Carlo simulation is carried out, to compute the cost function value of each population member of EA	2010
[175]	Advanced Quantum Inspired EA	• Single-search, group-search and multi-observation techniques are presented. • In a single-search process, individual quantum bit (Q-bit) is updated by quantum gates (Q-gates), which are determined by its observed solution and the best solution of its own is recorded. • In a group-search process, observed solution determines the Q- gate updating and the best solution is found among all the Q-bit individuals.	2011

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TABLE 4. Projected algorithms with the distinctive features in reference papers connected to evolutionary optimization techniques (Continued).

Reference Number	Algorithm used	Distinguished features	Year of publication
[176]	EA	• A well-organized and groundbreaking depiction of chromosome is introduced as the integer numbers are like decision variables matching to the conversion of binary to decimal situations to meet every hour demand.	2011
[177]	EA with PL	• During the evolution, the derived varieties of schedules have been engaged in implementing a plurality of PL in the heuristic mechanism.	2018
[178]	EP	• An overall UC schedule is coded as a cord of symbols and out looked as a candidate for replication. • Preliminary populations of such candidates are arbitrarily produced, to shape the base of succeeding generations.	1999
[179]	LR based EP	• The preliminary solution of schedule is achieved by LR and is enhanced this opening point by EP so as to discontinue needless units and re-dispatch load.	1999
[180]	TS based EP	• The algorithm is based on annealing NN and the load demand is taken as a control parameter, by a TS approach, to enhance the superiority of the solution. • To keep away from the entrapment from local minima, the input of TS is given as of the EP algorithm based offspring, with refined initial status and the final status is selected by evolutionary strategy.	2004
[181]	SA based EP	• Each schedule is shaped by committing all the units in keeping with their initial status. • A haphazard re-commitment is carried out regarding the minimum down time of the particular unit.	2007
[182]	SA entrenched EP	• The optimal point is found by EP technique and SA is entrenched in EP, to make quick best point convergence	2011
[183]	TS based EP	• A selection routine procedure is engaged to eradicate the possible schedules. The trail is made to correct the unwanted mutations, prior to the best solution is selected by evolutionary scheme.	2011
[184]	DE	• Two adaptations of DE (Boolean logic and Integer-coded) are projected with two implementations. • OR/XOR-type Boolean logic on variable strings is executed in the first implementation, through binary coding of the selected variables. The second execution uses integer coding of the UC variables	2008
[185]	SSGA combined with BDE	• Formulated an evolutionary algorithm, comprising three evolutionary algorithms, named steady state GA (SSGA), evolutionary strategy (ES) and DE, to solve UC problem.	2008
[186]	Discrete binary DE	• The combined approach of DBDE with PL is helps to commit generating units, without considering minimum up/down time constraints, at the first stage. • In second stage, the violations found in minimum up/down time are repaired by a heuristic algorithm, in addition to de-commit excessive units, based on the schedule obtained from the first stage. • In the final stage, the optimal solution obtained from the above stages is additionally improved by a gray zone modification algorithm, with heuristic unit substitution search technique.	2009
[187]	Improved DE	• In the acceleration operation (if required), the present individuals are artificially pushed toward a better point, since no improvement was found in the present generation under crossover and mutation operation. • In the migration operation (if required), a newly diverse population of individuals is regenerated in order to enhance the possibility of the use of smaller population size, since no improvement was found in the best fitness of the present generation	2010
[188]	Self adaptive DE	• The combination of committed and de-committed generating units are decided and selected, by using GA during every hour. • These GA based pre-committed schedule of generating units, are optimized by projecting SADE approach	2012
[189]	Binary-real coded DE	• Unit scheduling procedure is determined by binary part of this method and quantity of power generation of committed units is determined by the real part of this approach.	2012
[190]	Modified Binary DE	• The fundamental difference between the standard DE and proposed MBDE, lies in the mutation strategy and initialization phase. • According to the information, drawn out from the parent vectors by means of mutation operators, it builds the multiple probability models, at every iteration.	2018
[191]	SFLA	• The minimum up/down time constraints are directly coded, without considering a penalty function method and start-up costs are modelled in two values (both cold start and hot start) stair case function. • Total operating cost over a scheduling period is the first term of the objective function and violations in system constraints are penalized by penalty function, noted as a second term of the objective function.	2011

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TABLE 4. Projected algorithms with the distinctive features in reference papers connected to evolutionary optimization techniques (Continued).

Reference Number	Algorithm used	Distinguished features	Year of publication
[192]	Binary and improved binary SFLA	• A novel binary version of SFLA is introduced by ISFLA encoded in discrete space. The capability of BSFLA is tested with twelve bench mark functions.	2013
[193]	Improved SFLA	• The commitment schedule is given by the main problem, with minimum emission level and up/down time constraint satisfaction and this schedule is taken by the sub-problem to solve ED, emission dispatch and combining both of them to depend on the weighing factor, given to each constraint, to dispatch the real power among the committed units.	2014
[194]	Fuzzy adaptive FA	• The 24 hour UC scheduling is obtained by binary coded FA and the fuzzy designed variable is tuned by real coded FA to maximize the fitness function. • Lambda-iteration method is also used to obtain the ED problem.	2012
[195]	Binary-real coded FA	• Three stages are framed, with the evaluation of reliability being modelled by generator outage disturbance. • In the first stage, binary coded FA based, reliability constrained UC problem is obtained. The optimal power flow problem is executed through real coded FA in the next stage. In the third stage, search ability and the repair strategies are incorporated by both algorithms, given in the first two stages. • Loss of probability index is projected to recognize the reliability of the system.	2012
[196]	Binary-real coded FA	• A new binary coded FA is planned to resolve the UC problem and the real coded FA is used to resolve the ED problem. • A tan-h function is initiated in the binary-coded FA to enhance the likelihood of the flipping status of the binary variable, thus getting better the quality of solution and plummeting the computational time of UC problem.	2013
[197]	Fuzzy tuned FA	• The contradictory functions are devised as a single objective function, by means of fuzzy weighted optimal deviation. • The fuzzy membership design variables are tuned via real coded FA. • Separate parameter settings are used, in each case study, in terms of binary and real coded approach.	2013
[198]	FA with multiple workers optimization	• Global search is attained by means of the local search performed by individual workers procedure. • The size of the cluster from the distributed model is configured between 10 to 15 nodes. Out of these, one can be assumed as master node and others are called multiple workers.	2016
[199]	Modified FA	• Larger random number offered improved searching ability in the beginning stage. In the final stage, smaller random number provided enhanced convergence.	2020
[200]	BFA	• The penalty functions are not required to handle the minimum up/down time constraints by using integer coding of the approach which helps to minimize the simulation time.	2009
[201]	Improved artificial fish swarm algorithm FSA	• Searching performance of this optimization method is enhanced by introducing a new intelligent mutation operator, similar to the GA	2013
[202]	Binary FSA	• Two strategies like strategy-A (payment for power delivered) and strategy-B (payment to reserve allocated) are included and simulated in this approach for power selling and reserve, using different generator unit combinations	2015
[203]	Improved Binary CSA	• A crossover operator was used in local exploitation, with mutation of the present solution and the levy flight was used in global exploration with random characteristics. The best solution of this method was updated at every end of the iteration process.	2018
[204]	Hybrid GA with NN and DP	• This method has three features like to keep away from network learning stagnation, minimize the computation time and diminish the uncertain states in NN output	1997
[205]	Hybrid GA	• A hybrid GA, incorporated with a speedy priority list, ordering scheme, to resolve the generator scheduling.	1997
[206]	Hybrid GA – LR method	• The proposed GA-LR is implemented with two alternative ways. • In the first way, the GA plays the main role of solution with LR as a part of the GA process like initial population. • The LR method uses the GA to update the Lagrange multipliers, in the course of solution, in a second way.	1997
[207]	Hybrid GA-TS method	• The genetic algorithm solution is coded as a blend between binary and decimal depiction. • A fitness function is created from the total operating cost of the generating units without penalty terms.	1999
[208]	Hybrid GA, with TS and SA	• The role of TS is to generate new members in population of GA, incorporated in reproduction phase. • Similarly, the role of SA is to improve the rate of convergence of the GA, by testing the population members after every generation	1999

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TABLE 4. Projected algorithms with the distinctive features in reference papers connected to evolutionary optimization techniques (Continued).

Reference Number	Algorithm used	Distinguished features	Year of publication
[209]	Hybrid LR-GA	• In the initial stage, a two stage dynamic programming based search, for the minimum constrained Lagrangian function, under stable Lagrangian multipliers. • The maximization of the Lagrangian function respecting its multipliers, is adjusted by the GA in subsequent stages. • A new uniform crossover technique is to create two new offspring chromosomes, by means of swap over the bits between parent chromosomes through a randomly generated mask	2000
[210]	Hybrid GA	• The choice of the merit-order method is planned for the hybridization process, with a simple implementation, fast computation and predictable results.	2002
[211]	Hybrid annealing GA	• Two main features are focused like SA, incorporating quasi-equilibrium control, based on genetic operator, including population based state transition and Boltzmann type selection operator, incorporated with GA	2002
[212]	Hybrid PSO	• UC problem is solved by both real and binary valued PSO, run in parallel. • Four strategies are used to obtain the results like (i) through standard PSO, (ii) through PSO with differential mutation, (iii) through PSO with decreasing of the inertia weight in a linear manner and (iv) through standard PSO but instead of reinitializing the particle values while violating the generating constraints.	2003
[213]	Hybrid Chaos immune GA with Fuzzy system	• The search process is prevented by chaos search to keep away from premature convergence and the fuzzy system implemented to decide the ratio of crossover and mutation values, to avoid the excessive convergence time. • The ability of global search enhancement and increase of search speed is achieved by immune antigen memory and identification function	2004
[214]	Hybrid PSO-LR approach	• The structure of LR is based on dual optimization process like to decompose a problem into one master and more manageable sub-problems. • DP method is used to solve these sub problems and maintain the connection between them, maintained by Lagrange multipliers which are updated by PSO	2004
[215]	Hybrid Fuzzy based GA	• The spinning reserve quantity and load demand error are considered as two inputs of fuzzy model. • Similarly, penalty factor and fuzzy load demand are considered as two outputs. • The initial population of GA is created by a set of randomly generated feasible solutions and the forecasted load demand is estimated by applying fuzzy logic rules	2004
[216]	Hybrid LR-GA	• The wind down coupling constraints (time period, coupling of either units or both), hooked on the objective function through Lagrange multipliers and then updated by GA, to overcome the convergence difficulties of LR. • Dual optimization procedure is implemented to relax the coupled constraints called cost and profit based Lagrangian functions	2004
[217]	Hybrid Chaos search Immune GA with Fuzzy system	• A GA based logistic equation can produce a number of areas of near-best solutions to uphold solution difference keeping away from early convergence. • Such logistic equation is used to frame the chaos search queue method. Ability of partial search in chaotic immune GA (CIGA) is increased by the auto regulation unbiased mechanism of the immune system, to produce the correct quantity of antibodies, with restraint and promotes the individual density in CIGA	2006
[218]	Hybrid PSO	• The UC problem is handled by BPSO, as RCPSO resolves the ED problem and both algorithms are run concurrently.	2006
[219]	Hybrid Fuzzy adaptive PSO	• The equilibrium flanked by local and universal searching capabilities is augmented by adopting the fuzzy IF/THEN rules, to vigorously regulate the inertia weight.	2007
[220]	Hybrid GA with TS	• The new scheduled constraints in UC problem are checked and the status of new population (generated by GA) is also improved and updated by TS algorithm.	2009
[221]	Hybrid Quantum inspired binary PSO	• The combination of conventional BPSO with a superposition of conditions, in addition to quantum bit is planned. • The Q-bit individuals are updated by a combination of coordinate rotation gate, through a dynamic rotation angle (used to determine the rotation angle magnitude), to improve the capability of the search process.	2010
[222]	Hybrid Chaotic PSO	• Two types of processes have been carried out as like in the first process, the projected real coded CPSO is realized, to optimize the solution problems with continuous variables. • The binary coded CPSO is implemented to solve the problems, with discrete variables found in the second process.	2011
[223]	Hybrid PSO embedded with TS	• Two types of PSO approach are put into practice like discrete binary PSO and conventional PSO, which could solve the UC and ED problems respectively and joint with parallel optimization. • Supple memory system of TS is used to enhance the PSO and to conquer the hasty convergence of conservative PSO.	2011

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TABLE 4. Projected algorithms with the distinctive features in reference papers connected to evolutionary optimization techniques (Continued).

Reference Number	Algorithm used	Distinguished features	Year of publication
[224]	Hybrid Chemotactic PSO-DE with LR	• It is based on the combined function of BFA, PSO and DE respectively, and updated by Lagrange multipliers of LR, to get better its performance. • DE-LR method is also proposed in this paper for the same problem solution.	2012
[225]	Hybrid Expert system with Elite PSO	• All constraints are handled by ES and utilized as a pre-dispatch tool in the beginning, to produce a healthy swarm. Then the optimal solution of the problem is acquired by the combination of both ES and EPSO	2012
[226]	Hybrid Fuzzy controlled binary clustered PSO	• The preliminary population is created by the particles in the framework of PSO, which are generated by a weighted priority list and clustering procedure of these solutions, based on their fitness values. • Degree of acceptance for the uncertainties like spinning reserve, total production cost and forecasted load demand are determined by fuzzy membership functions and allocating membership degree based on error margin. • The fuzzified individual membership function variables are amassed and integrated with the fitness value to give the adequacy measurement of an exacting candidate schedule.	2012
[227]	Hybrid advanced fuzzy controlled binary PSO	• Load demand, spinning reserve and production cost are fuzzified, by turning over membership degree depending on error margin. • The amassed membership function, which combines the individual membership functions of fuzzified variables, is integrated with the fitness value, to offer the suitability measurement of a particular candidate schedule. • A dynamic probabilistic mutation operator is implemented on the individual solutions, based on their connected fitness values.	2012
[228]	Hybrid Fuzzy assisted CSA	• To choose the best solution, fitness sharing incorporated with fuzzification mechanism, was introduced in this technique that could serve the next generation.	2012
[229]	Bi-random simulation based Hybrid GA	• Three stages of UC problem are framed as like the resolve of a day-ahead UC decision (first stage), the resolve of the intraday UC adjustment decision of sub-fast start units (second stage) and the resolve of UC decision of sub-fast start units (third stage) respectively. • The day-ahead UC decision is solved by GA and the UCED sub-problem (under the group of each hour-ahead forecasted wind power and real wind power scenario) is solved by MILP method	2014
[230]	Hybrid gradient GA	• Three strategies are implemented the first strategy is rooted in the use of fuzzy logic method, the second one relies on the use of genetic algorithm, and the third strategy uses a hybrid optimization method, gradient-genetic algorithm.	2014
[231]	Hybrid enhanced LR-PSO	• De-commitment heuristics of generating units and reserve repair procedure are proposed.	2014
[232]	Hybrid GA-DE	• Two problem specific variation operators (swap window mutation and window mutation operators) and local search operators (swap mutation and swap-window hill climb operators) are implemented, to keep away from a premature convergence	2015
[233]	Hybrid adaptive bacterial foraging with GA	• This method is derived from the combination of BFA and GA, with adaptive stopping criterion, which can be used to choose the maximum number of iterations on the enhancement of the objective function.	2015
[234]	Hybrid GA with DE	• A new hybrid strategy between GA and DE is framed within the structure of MOEA/D, such that the binary and continuous variables are evolved by GA and DE respectively. • The performance of this method is enhanced by the implementation of a new analogous island model, rooted in a mixture of MOEA/D with uniform and non- uniform weight vector distribution scheme.	2015
[235]	Hybrid PSO-GWO	• The swarm position is firstly updated by NPSO algorithm and then further updated by GWO algorithm	2016
[236]	Hybrid binary PSO with SADE	• The priority sequence of both UC and charging/discharging dispatch of plug-in electric vehicles was obtained, by using a dual priority list method.	2017
[237]	Hybrid DE with RSA	• A set of random solutions was generated by making the position of individual solutions uniformly at random and then the new solutions were generated until the maximum number of iterations was reached.	2017
[238]	Hybrid DE with RSA	• The crossover and mutation were used, to update the solution vector, till the optimal global solution was obtained.	2017
[239]	Hybrid MBDE with BHC	• The universal solution, searched by the BDE algorithm was improved, by memetic BDE algorithm. The fine tuning solutions were obtained by accelerating the local search through BHC algorithm.	2019
[240]	Hybrid DA with PSO	• The position of velocity is controlled by a sigmoid function, within the suitable range, to be used as a probability. The position change is described by comparing with the random uniformly generated numbers between 0 and 1.	2019

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TABLE 4. Projected algorithms with the distinctive features in reference papers connected to evolutionary optimization techniques (Continued).

Reference Number	Algorithm used	Distinguished features	Year of publication
[241]	Hybrid MSSA-ANN-PSO	• The hunting behaviour of original Salp Swarm Algorithm (SSA), for one more position on population, is to obtain the best step leader position, by means of using mutation and crossover mechanism. The best speed factor and speed of the wind were optimized by the prediction procedures of ANN. In this procedure, the wind speed and wind probability were taken as the input and output of the network, respectively.	2019
[242]	Hybrid GA with SA	• An additive and divisive hierarchical clustering algorithm was implemented, to control the increasing and decreasing manner of the load respectively, incorporated with the hybrid technique of GA and SA, to solve the UC problem. The premature convergence was eliminated by replacing weaker strings (having a lower fitness value), with strong strings processed by SA, to enhance the performance of combined GA.	2019
[243]	Hybrid PSO with DE	• The population of PSO is updated by both PSO and DE. The velocity and position particles are updated by PSO and PSO, with DE, respectively, which helps to improve the convergence speed and solve large scale optimization problems.	2020
[244]	Hybrid Improved SA with PSO	• The upper layer UC problem was solved by the elitist strategy PSO, combined with binary and SA process. The interior point method was used, to solve the lower level UC problem, after dimension reduction.	2020

Raglend et al [165] discussed a profit based UC, incorporated with a few PSO techniques like chaotic PSO, and dispersed PSO. The optimization approach has an adaptive particle size, which means that the necessity of number of duty cycles, by each unit, is determined throughout the optimization process [166]. This process starts with a number of tribes and ultimately evolves to explore the entire problem space. Each particle in a tribe is aided by a set of associates in its neighborhood. The global solution of this process is determined by tribal location and communication between other tribes. Two iterative control loops are also implemented, to control the eventual terminate of the search procedure and evolutionary procedure respectively.

An enhanced discrete binary PSO, incorporated with lambda-iteration method, improved by priority list rooted in unit characteristics called enhanced PSO, has been proposed with three stages, to calculate start-up cost of UC. In the first stage, units are committed to satisfy spinning reserve through the combination of discrete binary PSO and priority list, without allowing for minimum up/down time constraints. The violations in minimum up/down time constraints are repaired by a heuristic search algorithm in the second stage. Finally, the ED problem is solved by the lambda-iteration method and the start-up cost of UC is calculated as the total production cost of ED problems [167]. In time variant acceleration coefficients, based PSO approach [168], the ability of global search is enhanced by changing the acceleration coefficients c_1 and c_2 effectively, either c_1 is greater than c_2 (at the beginning of optimization process) or c_1 is less than c_2 (at the time of increasing the iterations).

The dual operating mode called CHP (combined heat and power units), along with heat and thermal units based UC problem, was formulated by Anand and Dhillon, by incorporating binary PSO with PSO [169]. In this approach, the dual mode CHP and heat and power units would formulate the multi objective profit and economic based model of CHP-UC problem, obtained in the first attempt. In the second attempt, both binary and regular PSO techniques were applied to the mixed integer UC problem. The best and non-dominated solution was obtained, by using the cardinal priority ranking method in the third attempt. Finally, the effectiveness of the dual mode CHP unit was inspected on multi objective profit and economic based models, to deal with the cost, along with the pollutant emission.

An improved version of PSO with a simplified method was presented by Darvishan et al, to solve UC problem. It was subject to some of the key constraints with the uncertainty of load demand, modeled by a chance-constrained programming. It replaced the power balance equations, one for every period with the joint chance constraint, which bounds the least value of the probability together, to meet all the power balance constraints [170].

C. UC PROBLEM INCORPORATED WITH EA

A two-level, two-objective evolutionary algorithm was proposed in the platform of generic multi-level optimization, called Evolutionary Algorithm System (EASY), developed by the laboratory of thermal turbo-mechanics, National Technical University of Athens, to resolve UC problem [171]. The first objective of this approach was to cover the distribution of the power demand over a scheduling horizon, without considering the total operating cost. Minimize the risk of not fulfilling feasible variation in demand was the second objective. A strategy is framed for the coarsening of UC problem, solved by EA, in low level optimization (coarse-grained UC problem). The solutions obtained from low level are injected into high level population of EA, for further refinement, called high level optimization (fine-grained UC problem). The same author(s) have also proposed a meta-modal assisted EA, with probabilistic outages, based on two-level evolutionary strategy to minimize the total operating cost [174]. Monte Carlo simulation is carried out, to compute the cost function value of each population member of EA. Simulation of this method is obtained from the same platform, given in [171].

A novel evolutionary algorithm, inspired by the concept and principles (quantum bit and the superposition of states) of quantum computing, named improved Quantum Evolutionary Algorithm (QEA), is discussed [172]. Two effectual techniques are initiated in this approach compared to an ordinary quantum evolutionary algorithm. In the first technique, the quantum bits (Q-bits) are updated by a simple rotation gate, which determines the rotation angle without lookup table information, used in an ordinary QEA. Due to the solution quality and convergence speed, the magnitude of rotation angle is determined by decreasing the rotating angle approach in the second technique. Another QEA approach is presented in [173], to determine the optimal output of the generation and UC schedule.

A new priority list based initialization method and a special quantum bit (Q-bit) expression were developed for ensuring initial search area diversity, to improve the efficiency of solution probing [175]. Single-search, group-search and multi-observation techniques are also incorporated in this approach. In a single-search process, individual quantum bit (Q-bit) is updated by quantum gates (Q-gates), which are determined by its observed solution and the best solution of its own is recorded. In a group-search process, observed solution determines the Q- gate updating and the best solution is found among all the Q-bit individuals. A well-organized and groundbreaking depiction of chromosome is introduced, as the integer numbers are like decision variables, matching the conversion of binary to decimal situations, to meet the every hour demand [176].

An EA, combined with PL method, was proposed by Tsalavoutis et al, to solve UC problem. It dealt with customary sub problems, through a simple transformation by avoiding binary variables [177]. The performance of this approach was improved by an elitist mutation operator introduced in this approach, to avoid the premature convergence of the proposed technique. The heuristic repair mechanism was also included in this work, which utilizes the information offered by the PL of the generating units.

D. UC PROBLEM INCORPORATED WITH EP

Juste et al [178] proposed an uncomplicated solution of UC problem by incorporating EP method, subjected to initial unit status, minimum up/down time and start up cost constraints. The preliminary solution of schedule is achieved by LR, which enhanced this opening point by EP, in order to discontinue needless units and re-dispatch load found in a coalesced LR and EP [179]. In the EP based TS approach, based on annealing NN, the load demand is taken as a control parameter by TS approach to enhance the superiority of the solution [180]. To ward off the entrapment from local minima, the input of TS is given as the EP algorithm based offspring, with refined initial status and the final status is selected by evolutionary strategy. The same author(s) also presented an EP based SA approach, to solve UC problem [181]. The effectiveness of this approach was tested and compared with the same case studies and algorithms respectively.

A hydrothermal UC problem, incorporated with SA and entrenched EP approach (EP-SA), was planned by Christober Asir Rajan [182], subject to customary constraints. In this approach, the optimal point is found by EP technique and SA is assisted by EP to make quick best point convergence. The same author also presented an EP-TS approach, with cooling and banking constraints, to solve UC problem solution [183].

E. UC PROBLEM INCORPORATED WITH DE

Patra et al [184] projected a DE based solution, subjected to ramp limit constraints and developed with binary code and integer code implementations. The reserve of the demand is considered as 10% for all cases. The higher and lesser ramp limits are considered as equal and the ramp rate is given as 20% of the maximum output per hour. The total production cost and CPU time for all unit cases are compared with some other optimization methods. The total production cost, including and excluding ramp rate constraints, was also compared with binary coded DE and integer coded DE for all unit cases. An evolutionary algorithm, comprising three evolutionary algorithms like steady state GA (SSGA), evolutionary strategy (ES) and DE, was formulated [185]. During the every iteration of SSGA approach, only one offspring is generated in the EA loop and existing one individual in the population is replaced by a new one, which helps to keep the size of population constant. Two point crossover and self adaptation mutation were chosen in SSGA and ES approaches respectively.

Constraint handling procedure is effectively done in a discrete binary DE (DBDE) approach [186], using unit characteristics based PL and HS strategies, to enhance this technique. Three stages are implemented in this UC problem method. The combined approach of DBDE with PL helps to commit generating units, without considering minimum up/down time constraints, in the first stage. In the second stage, violations found in minimum up/down time are repaired by, a heuristic algorithm in addition to de-committing excessive units based on the schedule obtained from the first stage. In the final stage, the optimal solution, obtained from the above stages, is additionally improved by a gray zone modification algorithm, with heuristic unit substitution search technique.

An Improved DE, incorporated with acceleration and migration operation, was presented by Chang [187]. During the acceleration operation (if required), the present individuals are artificially pushed toward a better point owing to any improvement not found in the present generation under crossover and mutation operation. During the migration operation (if required), a newly diverse population of individuals is regenerated, in order to enhance the possibility of the use of smaller population size, due to any improvement not found in the best fitness of the present generation.

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Surekha et al [188] framed a combination of GA and self adaptive DE (SADE) approach. The combination of committed and de-committed generating units are decided and selected, using GA during every hour. These GA based pre-committed schedule of generating units are optimized by projecting the SADE approach. A binary-real coded DE is presented in [189], which incorporated a number of repairing mechanisms to make fast searching process. Unit scheduling procedure is determined by binary part of this method and quantity of power generation of committed units is determined by the real part of this approach.

The binary mutant vectors were generated by a probability estimator operator, proposed in a modified binary DE (MBDE) based UC problem, by Dhaliwal and Dhillon [190]. In this approach, unit scheduling and power allocated to commit units, were performed by five different priority methods. Three performance indicators like standard deviation, total operating cost and success rate were also considered in this approach. The results were obtained through Wilcoxon signed rank test.

F. UC PROBLEM INCORPORATED WITH SFLA

An integer-coded evolutionary optimization technique, called SFLA with two term objective functions was framed by Ebrahimi et al [191]. In this approach, the minimum up/down time constraints are directly coded, without considering a penalty function method and start-up costs are modelled in two values (both cold start and hot start), stair case function. Total operating cost, over a scheduling period, is the first term and the violation in system constraints are penalized by penalty function in the second term.

A binary and improved binary shuffled frog leaping algorithm (BSFLA and IBSFLA) based approach was presented by Barati and Farsangi [192]. It was a new binary version of SFLA, called ISFLA, encoded in discrete space. The capability of BSFLA is tested with twelve bench mark functions. The total cost of proposed methods, found in this paper, was evaluated with twenty-five diverse optimization methods. Anitha et al [193] attempted a multi-objective evolutionary approach, named improved SFLA, to resolve the combined emission constrained UC problem, subjected to regular constraints. The commitment schedule is given by the main problem, with minimum emission level and up/down time constraint satisfaction and this schedule is taken by the sub-problem to solve ED and emission dispatch. It depends on the weighing factor given to each constraint, to dispatch the real power, among the committed units.

G. UC PROBLEM INCORPORATED WITH FA

System reliability level and fuel cost were simultaneously optimized, in a multi-objective UC problem, using fuzzy adaptive FA, by Chandrasekaran and Simon [194], called fuzzy adapted firefly lambda optimization. In this approach, the 24 hour UC scheduling is obtained by binary coded FA and the fuzzy designed variable is tuned by real coded FA, to maximize the fitness function. The Lambda-iteration method is also used to obtain the ED problem. The same authors proposed another UC problem, based on the same algorithm, tuned by fuzzy membership function, subjected to customary constraints with the same methodology [195].

A reliability and network constrained UC problem, incorporating binary-real coded FA, based on the flashing behaviour of fireflies, was presented by Chandrasekaran and Simon [196]. Three stages are framed in this approach, with the evaluation of reliability being modeled by generator outage disturbance. In the first stage, binary coded FA based reliability constrained UC problem is obtained. The optimal power flow problem is executed through real coded FA in the next stage. In the third stage, search ability and the repair strategies are incorporated by both algorithms, given in the first two stages. Loss of probability index is also employed to recognize the reliability of the system. The same approach, subjected to customary constraints, was tested with five case studies [197]. A global search is attained by means of the local search, performed by individual workers [198]. The size of the cluster of the distributed model is configured between 10 to 15 nodes. Out of these, one can be assumed as master node and others are called multiple workers.

A combination of PL and modified FA was proposed by Hussein and Jaber, to solve the UC problem, in two steps, using PL (on/off cases of units provided in the first step), combined with modified FA (load scheduling between units provided in the second step) [199]. In this approach, the randomization parameter was not kept constant and it can be decreased linearly with iterations, with respect to their initial and final values.

H. UC PROBLEM INCORPORATED WITH OTHER EVOLUTIONARY OPTIMIZATION TECHNIQUES

A new integer coded algorithm, consisting of the foraging behaviour of E-coli bacteria, called BFA was proposed by Eslamian et al [200]. The penalty functions are not required to handle the minimum up/down time constraints, by using integer coding of the approach, which helps to minimize the simulation time. A new implicit reserve constraint UC problem, incorporated with an improved artificial fish swarm algorithm, was proposed by Han et al [201]. In this approach, the spinning reserve constraint is not given openly but totally in the transaction between outage loss and cost. The searching performance of this optimization method is enhanced by introducing a new intelligent mutation operator, similar to the GA. A swap move based local search and cyclic re-initialization operators, were introduced and integrated with the Binary Fish Swarm algorithm, to avoid trapping behaviour at a local optimum solution [202]. Feasible search space is kept by adopting a repairing mechanism of minimum up/down constraints. Two strategies like strategy-A (payment for power delivered) and strategy-B (payment to reserve allocated) are included and simulated in this approach for power selling and reserve, using different generator unit combinations.

Zhao et al proposed an improved binary CSA method, to solve UC problem, with the help of a new priority list, designed by a new heuristic search method, based on the minimum output with average fuel cost [203]. To choose the right search direction in an iterative process, a new binary updating mechanism was incorporated in this approach. The infeasible solutions were repaired by a greedy method, which contains three main stages like meeting minimum up/down and spinning reserve constraints and de-committing surplus units. The maximum iteration count and population size, proposed in this method were 200 and 10 respectively, with the threshold value set at 0.7.

I. UC PROBLEM INCORPORATED WITH HYBRID EVOLUTIONARY OPTIMIZATION TECHNIQUES

A new approach, formulated with GA incorporating NN and DP, to solve thermal UC problem was proposed by Huang and Huang [204]. Initially, a feasible set of commitment schedule for generators is devised by genetic enhanced NN and optimized by DP method. This hybrid approach has three features keeping away from network learning stagnation, minimizing the computation time and diminishing the uncertain states in NN output. The multi-layered perceptrons are taken as a NN model and the objective function in a multi-stage process is minimized by DP method.

A large scale UC problem was framed by Orero and Irving [205], through a hybrid GA, incorporated with a speedy priority list, ordering scheme to resolve the generator scheduling. Two alternative ways are used to implement a hybrid GA-LR method of UC problem. In the first way, the GA plays the main role of solution with LR as a part of the GA process like initial population. The LR method uses the GA to update the Lagrange multipliers, in the course of solution in the second way [206].

A mixed binary and decimal code based, hybrid GA-TS method, was used to accelerate the search and put aside the memory space, subjected to customary constraints [207]. The generation and evaluation of the initial population and the fitness function determination are attained through GA. The generation of new population members is acquired via TS. The integration of GA, TS and SA algorithms was proposed to solve UC problem [208]. The role of TS is to generate new members in the population of GA, incorporated in reproduction phase. Similarly, the role of SA is to improve the rate of convergence of GA, by testing the population members, after every generation.

The application of GA joint, with Lagrangian Relaxation (LR) method, called LRGA was proposed by Cheng et al [209]. In the initial stage of this approach, there is a two stage dynamic programming based, search for the minimum constrained Lagrangian function, under stable Lagrangian multipliers. The maximization of the Lagrangian function, regarding its multipliers, is attuned by the GA in subsequent stages. A new uniform crossover technique is adopted, to create two new offspring chromosomes, by means of swap over the bits between parent chromosomes through a randomly generated mask. A priority list scheme based, hybrid GA, with some notable merits like predictable results, less computation time and simplification was proposed by Paranjothi and Balaji [210].

A hybrid annealing GA was proposed by Cheng et al with two stages named SA search stage and GA evolution stage [211]. The Quasi-population creation, in numerous search paths, is generated by the execution of iterative generate and test procedure, in each stage. Two main features are also akin to SA incorporating with quasi-equilibrium control, based on genetic operator, including population based state transition and Boltzmann type selection operator, incorporated with GA. A hybrid version of PSO is presented to resolve UC problem, subjected to the formulation of normal constraints based on the simple alteration like functioning on binary problems which are conservatively optimized by GA [212].

The search process is prevented by the chaos search, in the combination of GA and IA, called Hybrid Chaos Search Immune Genetic Algorithm and Fuzzy System, to prevent from premature convergence and the fuzzy system implemented to decide the ratio of crossover and mutation values, to avoid the excessive convergence time. The ability of global search enhancement and increase a search speed is achieved by immune antigen memory and identification function [213]. The structure of LR is based on dual optimization process, to decompose a problem into one master and more manageable sub-problems. DP method is used to solve these sub problems and the connection between them is maintained by Lagrange multipliers, which are updated by PSO [214].

A new fuzzy unit commitment model, incorporated with GA, called Fuzzy GA (FZGA) was proposed by Mantawy [215]. In this approach, the spinning reserve quantity and load demand error are considered as two inputs of the fuzzy model. Similarly, penalty factor and fuzzy load demand are considered as two outputs. The initial population of GA is created by a set of randomly generated feasible solutions and the forecasted load demand is estimated by applying fuzzy logic rules. Yamin and Shahidehpour proposed a hybrid LR-GA technique [216], with the wind down coupling constraints (time period, coupling of either units or both), hooked on the objective function through Lagrange multipliers and then updated by GA, to overcome the convergence difficulties of LR. The dual optimization procedure is implemented by relaxing the coupled constraints, called cost and profit based Lagrangian functions.

With the combination of Immune algorithm (IA) and GA, added to chaos search and fuzzy system, a GA based logistic equation can produce a number of areas of near-best solutions, to uphold solution difference to prevent from early convergence. Such logistic equation is used to frame the chaos search queue method. Ability of partial search in Chaotic Immune GA (CIGA), is increased by the auto regulation, unbiased mechanism of the immune system, to

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produce the correct quantity of antibodies with restraint and promotes the individual density in CIGA. The long convergence time of this approach is evaded by the proportion of crossover and mutation values, to make certain variations in the populations, during the search period through the fuzzy system [217].

A combination of binary PSO and real coded PSO [218] is designed, to solve UC problem and ED problem respectively, with concurrent run. In a fuzzy adaptive PSO approach, the equilibrium flanked by local and universal searching capabilities is augmented by adopting the fuzzy IF/THEN rules to vigorously regulate the inertia weight [219]. In the GA based TS (GA-TS) technique [220], the new scheduled constraints in UC problem are checked and the status of new population (generated by GA) is also improved and updated by TS algorithm.

A quantum inspired binary PSO (BPSO) based technique, called QBPSO algorithm is intended for UC solution, subjected to associated system and unit constraints [221]. The combination of conventional BPSO with a superposition of conditions, in addition to quantum bit, is proposed in this QBPSO approach. The Q-bit individuals are updated by a combination of coordinate rotation gate through a dynamic rotation angle (used to determine the rotation angle magnitude), to improve the capability of the search process.

An efficient tent-map based, hybrid Chaotic PSO (CPSO) algorithm [222], incorporated these two types of process. In the first process, the projected real coded CPSO is realized to optimize the solution problems, with continuous variables. The binary coded CPSO is implemented to solve the problems, with discrete variables, found in the second process. Chaotic map and turbulence process are also involved in this approach, to avoid the premature convergence of PSO and flee from local minima.

An improved PSO, embedded with TS (PSO-TS) optimization method, is presented with some more different constraints like water balance, turbine discharge capacity and minimum/maximum reservoir level constraints [223]. Two types of PSO approach are put into practice, akin to discrete binary PSO and conventional PSO, which solve the UC and ED problems respectively and combined with parallel optimization. A supple memory system of TS is used, to enhance the PSO and conquer the hasty convergence of conservative PSO.

Three different evolutionary optimization methods are integrated with each other called Chemotactic PSO-DE (CPSO-DE), based on the combined function of BFA, PSO and DE and updated by Lagrange multipliers of LR [224]. A two-level hierarchical approach, with an expert system (ES) and Elite PSO (ELPSO), was presented by Chen [225], with all constraints handled by ES and utilized as a pre-dispatch tool in the beginning, to produce a healthy swarm. Then the optimal solution of the problem is realized by the combination of both ES and ELPSO.

In an advanced fuzzy controlled, binary clustered PSO, based on multi-population approach [226], the preliminary population is created by the particles in the framework of PSO, which are generated by a weighted priority list and the clustering procedure of these solutions is based on their fitness values. The degree of acceptance, for the uncertainties like spinning reserve, total production cost and forecasted load demand is determined by fuzzy membership functions and allocating membership degree, based on error margin. The fuzzified individual membership function variables are amassed and integrated with the fitness value, to give the adequacy measurement of an exacting candidate schedule.

A fuzzy function controlled multi-population based Binary Clustered PSO (BCPSO) was presented by Chakraborty et al [227]. A multi-objective, fuzzy assisted, hybrid Cuckoo Search Algorithm (CSA) technique was proposed by Chandrasekaran, to solve the UC problem [228]. The efficiency of this approach was due to both binary (for solving ED) and real (for solving UC) coded CSA. Consequently, the performance improvement was obtained by introducing a tan-h function. The boundary values of fuzzy design variables were tuned by the real coded CSA and thus in every iteration, the fitness of best solution was evaluated.

Three stages of UC problem like the resolve of a day-ahead UC decision (first stage), the resolve of the intraday UC adjustment decision of the sub-fast start units (second stage) and the resolve of UC decision of sub-fast start units (third stage) were formulated by Zhang et al [229]. A classic gradient method united with GA, was presented by Marrouchi and Saber, who made a comparative study, by way of fuzzy logic and GA [230]. The strength of LR and PSO methods were considered and a new hybrid algorithm called enhanced LRPSO (ELRPSO) was proposed by Yu and Zhang [231].

In a hybrid GA and DE (hGADE), the search capability of the hybridized variants was enhanced by incorporating the initial heuristic generation of population and a replacement strategy, based on infeasible solution preservation in the population [232]. Two problems specific, variation operators (swap window mutation and window mutation operators) and local search operators (swap mutation and swap-window hill climb operators) were implemented to prevent from a premature convergence. The proposed evaluation procedure is divided into four case studies. In the first case, a heuristic initialization strategy is incorporated to improve the effectiveness of hGADE variants (hGADE/r1 and hGADE/cur1). GA is hybridized with these two classical variants of DE and parameter tuning is conducted in the second case. The variants of hGADE are validated, with some other approaches, in the third case. In the fourth case, the combination of two variants is implemented, to further amplify the performance of this proposed approach. A hybrid adaptive bacterial foraging, with GA (HABFGA) method was examined by Elattar [233], with the combination of BFA and GA, with adaptive stopping criterion.

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Trivedi et al [234] proposed an enhanced version of Multi-objective Evolutionary Algorithm based on Decomposition method (MOEA/D) and incorporated with DE (MOEA/D-DE) to solve economic/emission UC problem. A new hybrid strategy between GA and DE is framed, within the structure of MOEA/D, so that the binary and continuous variables are evolved by GA and DE respectively. The performance of this approach is enhanced by the implementation of a new analogous island model, based on a mixture of MOEA/D, with uniform and non-uniform weight vector distribution scheme.

Two new optimization approaches were posited to solve single area UC problem, named swarm intelligence based new PSO (NPSO) and a hybrid approach of PSO and Grey-Wolf Optimization (PSO-GWO) [235]. The swarm position was firstly updated by NPSO and then further updated by GWO algorithm. A new parallel-series meta-heuristic, hybrid optimization technique was proposed by Yang et al, to solve the UC problem, by including the demand side management of plug-in electric vehicles charging/discharging and renewable generations, subject to customary constraints. In this approach, a hybrid topology binary PSO (HTBPSO), coordinated with Self-Adaptive DE (SADE) and a lambda iteration technique, was implemented to solve the complex hybrid UC problems [236]. This methodology has three important sections, including two algorithms running in parallel and linked with a series running algorithm. Initially, the HTBPSO algorithm was used to determine the on/off status of thermal units, in a 24 hour plan, operating in parallel with the SADE algorithm, to determine the load shaping demand side management of plug-in electric vehicles, in an hour based horizon, throughout a day. Then both algorithms were operated in series, with a lambda iteration technique, to optimize the power generation, in real value, for the ED problem. A hybrid DE, with Random Search Algorithm (RSA) based, single area UC problem was presented by Kamboj et al, subject to customary constraints, to enhance the ability of exploitation and universal performance [237]. In this approach, the RSA was implemented to perform the random population search for global and stochastic optimization problem. The same authors proposed the same methodology of optimization process, subject to import/export and tie line constraints [238].

A new mutation strategy based, Memetic Binary DE (MBDE) algorithm, was hybridized with a Binary Hill Climbing (BHC) algorithm, was proposed by Dhaliwal and Dhillon, to solve UC problem, subject to customary constraints. In this approach, the combined MBDE and BHC were used as global and local search operators respectively, to improve the exploration and exploitation aspect [239]. A new unit de-commitment plan was also presented, to de-commit the needless generating units, by prioritizing of generating units and total profit. The power allocation of the committed generating units was done by using a priority method based, simple algorithm. Two meta-heuristic techniques called, Dragonfly Algorithm (DA) and PSO, were hybridized to solve a mixed integer UC problem, was presented by Khunkitti et al, in an improved version [240]. In this approach, the sigmoid function was also implemented, to find the optimum operating status of generating units. A PL method, based on the average production cost of a generating unit was also incorporated in this proposed work.

A new multi-objective, hybrid combined technique of Modified Salp Swarm Algorithm (MSSA) and ANN, assisted with PSO, was proposed to solve EED problem, related to hydro, wind and thermal units [241]. The optimal combination of the thermal generator unit was created by MSSA, with the customary objective functions like minimum fuel and emission. The probability factor of wind speed was proposed by combining PSO and ANN techniques. In this approach, the optimization process of MSSA was executed by the combination of thermal generators, based on the pumped storage units and the uncertainty of wind power. The generating units were classified into a variety of clusters, by formulating a new approach to UC problem, by combining a hybridized method of GE with SA, was suggested by Reddy et al, subject to customary constraints [242]. This approach has been classified into three stages. In the beginning stage, the base load, intermittent load, semi-peak load and peak load were formed into clusters and all the generating units were separated into the corresponding clusters, based on their operating costs. The operating costs were obtained by the hybrid of GA and SA techniques. Solution of UC was obtained by, incorporating additive cluster algorithm, in the second stage, for increasing the load pattern. In the third stage, solution of UC was obtained, by incorporating divisive cluster algorithm, for decreasing the load pattern. A new hybrid version of PSO, incorporating DE, is used to solve coordinated security constrained, UC (SCUC), based on transmission system operators (TSO) and distribution system operators (DSO), proposed in [243]. In this approach, the coordination strategy has been formulated by analytical target cascading technique (ATC), with large scale distributed energy resources and the direct current optimum power flow technique, used as a sub problem of ATC. The objective function (with penalties) of TSO has been decomposed into the objective functions of coordinator and TSO and helps it to reduce the quantity of quadratic equations.

A two layer structure based algorithm was proposed, to solve UC problem, subject to customary constraints. It was based on the improved hybrid version of SA with PSO, called ISAPSO, combined with elitist strategy, binarization method and unique layering mechanism [244]. An elitist strategy was introduced in this approach, which enhanced the search of the current optimal solution at every iteration process of the algorithm, to reduce the complexity function. In this approach, the UC problem was divided by the proposed method, into two layers, to solve the sub-problem of this algorithm. The elitist PSO with SA and the binarization method was framed, to obtain wide search range with faster convergence in the upper layer. The optimal solution, for each individual in the upper layer, was calculated by the convex optimization approach in the lower layer.

IV. CONCLUSION

Evolutionary optimization techniques play a crucial role in solving all types of UC problems, owing to their substantial quantity of computational time and speedy convergence characteristics, over other traditional optimization techniques. This paper has compiled review of the past literature, associated with UC problems, with reference to various types of evolutionary optimization techniques in a multi directional way. This tabulation of review was extracted from several research articles, published in the past decades, through a number of refereed journals. Implementation of a variety of constraints related to UC problems reported in the literature are recapitulated and tabularized. The distinctive features of projected evolutionary optimization techniques, given in the reference papers associated with UC problems, are also summarized and tabulated. It could assist new researchers with a concise idea, about the use of evolutionary optimization techniques, in power system UC problems.

From the literature review, it can be found that the number of researchers in UC problem using evolutionary optimization techniques is increasing considerably. It is clearly indicated that, the performance of evolutionary algorithm in power system optimization task is highly encouraging. Being a successful and reliable tool, the evolutionary algorithm can be exploited for other power system optimization problems like economic load dispatch, optimal power flow, optimal reactive power dispatch etc.

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3010275, IEEE Access

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