Received June 21, 2017, accepted July 9, 2017, date of publication July 18, 2017, date of current version August 8, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2728683

Selecting a Meta-Heuristic Technique for Smart Micro-Grid Optimization Problem: A Comprehensive Analysis

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ABSTRACT In current epoch, the economic operation of micro-grid under soaring renewable energy integration has become a major concern in the smart grid environment. There are several meta-heuristic optimization techniques available under different categories in literature. One of the most difficult tasks in cost minimization of micro-grid is to select the best suitable optimization technique. To resolve the problem of selecting a suitable optimization technique, a rigorous review of six meta-heuristic algorithms (Whale Optimization, Fire Fly, Particle Swarm Optimization, Differential Evaluation, Genetic Algorithm, and Teaching Learning-based Optimization) selected from three categories (Swarm Intelligence, Evolutionary Algorithms, and Teaching Learning) is conducted. It presents, a comparative analysis using different performance indicators for standard benchmark functions and proposed a smart micro-grid (SMG) operation cost minimization problem. A proposed SMG is modeled which incorporates utility connected power resources, e.g., wind turbine, photovoltaic, fuel cell, micro-turbine, battery storage, electric vehicle technology, and diesel power generator. The proposed work will help researchers and engineers to select an appropriate optimization method to solve micro-grid optimization problems with constraints. This paper concludes with a detailed review of micro-grid operation cost minimization techniques based on an exhaustive survey and implementation.

INDEX TERMS Smart micro-grid, meta-heuristic optimization techniques, electric vehicle technology, fuel cell.

ABBREVIATIONS

BES	Battery Energy Storage
BEV	Battery Electric Vehicle
PBEV	Plug-in Battery Electric Vehicle
DG	Distributed Generator
FX	Fixed Cost
FCTs	Fuel Cell Technologies
FCEV	Fuel Cell Electric Vehicle
FCPG	Fuel Cell Power Generator
GA	Genetic Algorithm
MG	Micro-Grid
MGCO	Micro-Grid Central Operator
MT	Micro-Turbine
OR	Operating Reserve
PSO	Particle Swarm Optimization
IBA	Improved Bat Algorithm
SPV	Solar Photo-Voltaic
RES	Renewable Energy Source
SMG	Smart Micro-grid
EVTs	Electric Vehicle Technologies
V2G	Vehicle to Grid
V2H	Vehicle to House
G2V	Grid to Vehicle
PC	Personal Computer
Std_dev	Standard deviation
TCPD	Total Cost Per Day
Li-ion	Lithium ion
WT	Wind Turbine
DiG	Diesel Generator
EMS	Energy Management System
NSGA-II	Non-dominated Sorting Genetic Algorithm II

NOMENCLATURE

$Bid_{BES,t}$, $Bid_{grid,t}$, $Bid_{FC,t}$, $Bid_{MT,t}$, $Bid_{iWT,t}$, $Bid_{iPV,t}$, $Bid_{FCEV,t}$	Bid of BES, utility, FC, MT, WT, PV, and FCEV at time step t, correspondingly in € ct/kW h
MC_{BES}, FX_{BES} MC_{BEV}, FX_{BEV} MC_{PHEV}, FX_{PHEV}	Repair and constant cost for BES, BEV and PHEV, correspondingly in €ct/kW h
IR	Interest-rate for battery installation on loan
LT	Life span of the batteries in years
NT	Operation duration in hours
OR_t	Required generating backup minutes in kW
OM_{DG}	Constant repair and operation cost of DGs in €ct
OM_{MT}, OM_{FC}, OM_{iWT}, OM_{iPV}, OM_{FCEV}	Constant repair and operation cost of MT, FC, WT, PV, FCEV correspondingly in €ct/kW h
$P_{grid,max}$, $P_{grid,min}$ $P_{BES,max}$, $P_{BES,min}$ $P_{BEV,max}$, $P_{BEV,min}$ $P_{PHEV,max}$, $P_{PHEV,min}$ $P_{FCEV,max}$, $P_{FCEV,min}$ $P_{FC,max}$, $P_{FC,min}$ $P_{MT,max}$, $P_{MT,min}$	Maximum and minimum generation of power for utility, BES, BEV, PHEV, FCEV, FC and MT in (kW)
$P_{Demand,t}$	Power demand at time step t in kW
C_f	Diesel Fuel Price (€ct/l)
P_{DiG}	Power output of diesel generator
tax	Rate of tax for grid
η_{charge}, $\eta_{discharge}$	Charging and discharging efficiency of different batteries
$C_{BES,max}$, $C_{BES,min}$ $C_{BEV,max}$, $C_{BEV,min}$ $C_{PHEV,max}$, $C_{PHEV,min}$	Maximum and minimum capacity of BES, BEV and PHEV in kW h
$C_{BES,t}$ $C_{BEV,t}$ $C_{PHEV,t}$	Stored energy in BES, BEV and PHEV
$Cost_{grid,t}$	Supply cost with the grid in upstream mode at time step t in €ct
$Cost_{DG,t}$, $Cost_{BEV,t}$ $Cost_{BES,t}$, $Cost_{PHEV,t}$ $Cost_{DiG,t}$	Cost of operation and fuel of DGs, BEV, BES, PHEV and DiG at time step t, correspondingly in €ct
C	Overall cost in €ct
$P_{grid,t}$, $P_{MT,t}$, $P_{BES,t}$ $P_{iPV,t}$, $P_{FC,t}$, $P_{FCEV,t}$, $P_{iWT,t}$, $P_{PHEV,t}$ $P_{BEV,t}$, $P_{DiG,t}$	Generated power of grid, MT, BES, PV, FC, FCEV,WT, PHEV, BEV and DiG correspondingly in kW
$\underline{P}_{BEV,t}$; $\overline{P}_{BEV,t}$ $\underline{P}_{BES,t}$; $\overline{P}_{BES,t}$ $\underline{P}_{PHEV,t}$; $\overline{P}_{PHEV,t}$	Maximum discharging and charging rates of BEV, BES and PHEV at time t, correspondingly in kW
$SUC_{MT,t}$, $SUC_{FC,t}$, $SUC_{FCEV,t}$	start up cost for MT, FC, and FCEV at time step t, correspondingly in €ct
$TCPD_{BEV}$, $TCPD_{BES}$ $TCPD_{PHEV}$	Per day overall cost of BEV, BES and PHEV, correspondingly in €ct
$u_{MT,t}$, $u_{BES,t}$, $u_{BEV,t}$ $u_{FC,t}$, $u_{PHEV,t}$ $u_{DiG,t}$	On/Off status of MT, BES, BEV, FC, PHEV and DiG attime step t, correspondingly
t	t^{th} time step (h)

I. INTRODUCTION

As world transit from the conventional grid system to the smart grid system, renewable energy sources' incorporation has become the key issue in the present environment. In accordance with the International Energy Agency prediction, power production by renewable power resources will be almost three times in between 2010 to 2035. It will contribute 31% of the globe's entire power production, in which solar, wind and hydro will provide 7.5%, 25% and 50% respectively, of the overall renewable power production by 2035. The intermittency and climate dependency of renewable power resources make their interconnection more complex and difficult. Various energy storage devices are used to solve above mentioned problems of intermittency and weather dependency with renewable. Hence inside the smart grid environment, the development of micro grid is a great solution for integration of renewable energy sources. It has numerous advantages such as energy loss-reduction, reliability and enhancement of energy management.

Micro-grid consists of different renewable power resources like wind, SPV and micro turbines. It also incorporates latest generation technologies such as fuel cell technologies and combined heat and power (CHP) technology. To solve the above-discussed intermittency problem of renewable energy, storage devices, for example, battery energy storage system, electric vehicle technology and flywheel storage system can be used. Micro-gird provides a better solution as compared to the distributed generation sources due to their better coordination and control. It can be used as islanded mode and gird connected mode as per requirement. Hence inside micro-grid, the operation, control and coordination problem are of great importance. Further, similar to the conventional grid, micro-grid also required some cost which is related to its generation, maintenance and operation; consequently, many researches are focused on the micro-grid cost minimization problem.

Various meta-heuristic techniques are developed by researchers to solve the micro-grid cost minimization problem. Population dependent meta-heuristic optimization techniques have two main classifications: swarm intelligence (SI) and evolutionary algorithms (EA). A number of renowned evolutionary techniques are as follows: Evolution Strategy (ES), Genetic Algorithm (GA), Differential Evolution (DE), Evolution Programming (EP), etc. Various swarm intelligence dependent techniques are as follows:

Firefly (FF), Shuffled Frog Leaping (SFL), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), etc. In addition to above mentioned meta-heuristic optimization techniques, different natural phenomena based methods are also available, e.g., Gravitational Search (GSA), Harmony Search (HS) algorithm, Flower Pollination (FPA), Biogeography-Based Optimization (BBO), etc.

Meta-heuristic techniques need no gradient information. Meta-heuristics have the capability to recover from local optima due to their inherent stochasticity; consequently, it can better tackle uncertainties in objectives. It can tackle multiple objectives with only a few algorithmic changes. Normally, meta-heuristics techniques are probabilistic in nature and controlled by common parameters, e.g., population, elite population size, the number of generations, etc. In addition to these parameters, different methods require specific control parameters, e.g., GA utilizes the probability of mutation and crossover, operator selection, etc; PSO employs weight of inertia, cognitive and social factors; ABC makes use of the number of different type of bees i.e. onlooker, employed, scout and their limits. In the same way, different techniques require separate tuning of their specific parameters. In these techniques, parameter's tuning is an extremely critical issue, because it's directly affects the performance of techniques. Improper tuning may result in increased computation time or local optima. Table 1 presented the time line for the evaluation of different meta-heuristic techniques.

In this paper, the authors have focused on the problem of choosing the appropriate meta-heuristic optimization technique for the minimization of operation cost. To identify the best algorithm, different meta-heuristic techniques (PSO, GA, FF, DE, TLBO and WO) from three different categories (swarm intelligence, evolutionary algorithms and teaching learning) are considered and compared. These optimization methods are compared by using nineteen standard test functions from three different categories (uni-model, multi-model, composite) as well as a micro-grid frame work. MG consists of different energy sources such as PV, WT, BES, MT, FC, DiG and EVT. The problem of micro-grid operation cost minimization is solved for two different cases (charging mode of batteries and discharging mode of batteries) using these optimization techniques. The comparison of different optimization methods for various standard test functions is accomplished using the following parameters: mean and standard deviation of fitness value, average fitness value for different population, convergence characteristics for different population, trajectory (fitness value of the first search agents with respect to the number of iterations for any algorithm) and the capability to explore the search space. In comparative analysis of SMG, two different cases are considered and each case is observed for the following parameters: average, best, worst and standard deviation of optimized operation cost (fitness value), convergence characteristics for different population, variation of best fitness value with respect to increase in population size and power generated by different energy sources for different population size.

TABLE 1. List of meta-heuristic algorithms (1975-2016) [79].

Year	Method	Developed by
1975	Genetic Algorithm (GA)	Holland
1977	Scatter Search (SS)	Glover
1980	Genetic Programming	Smith
1983	Simulated Annealing (SA)	Kirkpatrick et al.
1986	Tabu Search (TS)	Glover & McMillan
1986	Artificial Immune System (AIS)	Farmer et al.
1989	Memetic Algorithm	Moscato
1992	Ant Colony Algorithm (ACO)	Dorigo
1993	Multi-Objective GA (MOGA)	Fonseca & Fleming
1994	Reactive Search Optimization (RSO)	Battiti and Tecchiolli
1995	Particle Swarm Optimization (PSO)	Kennedy and Eberhart
1997	Differential Evolution (DE)	Storn and Price
1997	Cross Entropy Method (CEM)	Rubinstein
1999	POPMUSIC	Taillard and Voss
2001	Harmony Search (HS)	Geem et al.
2001	Bootstrap Algorithm (BA)	Hanseth and Aanestad
2004	Bees Optimization (BO)	Nakrani and Tovey
2005	Glowworm Swarm Optimization (GSO)	Krishnanand and Ghose
2005	Artificial Bee Colony (ABC)	Karaboga
2006	Honey-bee Mating Optimization (HMO)	Haddad et al.
2007	Intelligent Water Drops (IWD)	Hamed Shah-Hosseini
2007	Imperialist Competitive Algorithm (ICA)	Atashpaz-Gargari & Lucas
2008	Firefly Algorithm (FA)	Yang
2008	Monkey Search (MS)	Mucherino and Seref
2009	League Championship Algorithm (LCA)	Husseinzadeh- Kashan
2009	Gravitational Search Algorithm (GSA)	Rashedi et al.
2009	Cuckoo Search (CS)	Yang and Deb
2010	Bat Algorithm (BA)	Yang
2011	Galaxy-based Search Algorithm (GbSA)	Shah-Hosseini
2011	Spiral Optimization (SO)	Tamura and Yasuda
2011	Teaching-Learning-Based Optimization (TLBO)	Rao et al.
2012	Krill Herd (KH)	Gandomi and Alavi
2012	Differential Search Algorithm (DSA)	Çivicioglu
2013	Grey Wolf Optimizer (GWO)	Seyedali Mirjalili
2014	Water Wave Optimization (WWO)	Zheng
2015	Ant Lion Optimization (ALO)	Seyedali Mirjalili
2016	Whale Optimization (WO)	Seyedali Mirjalili

The structure of the paper is as follows. The next section provides the literature review. In section 3, the problem is formulated along with its constraint. Section 4 describes a set of nineteen standard benchmark functions from three different categories. The proposed SMG system and the two specific cases are described in the section 5. The comparative analysis of different optimization methods using standard test functions and proposed SMG system is provided in the section 6, which is followed by the concluding remarks.

II. LITERATURE REVIEW

Micro-grid optimization problem is a complex and real world problem. Generally, micro-grid is the combination of various renewable energy sources (solar, wind) along with energy storage system (BES, EVT) and diesel generator. Mathematical methods such as linear and integer programming are cumbersome and require more time to provide the optimal solution of real world problem, whereas meta-heuristic techniques provide the optimal solutions for practical problems in less time. Thus, this section presents the comprehensive review of micro-grid system with different technologies such as battery energy storage, electric vehicle technology, and diesel generator. Additionally, it also focuses on the current development in utilization of GA, PSO, DE, TLBO, FF and WO meta-heuristic algorithms in power system optimization problems.

A. MICRO-GRID TECHNOLOGIES

There are various technologies that can be incorporated in MG to enhance the performance and stability of the MG system. These technologies are as follows:

1) MICRO-GIRD WITH RENEWABLE ENERGY SOURCES AND/OR BATTERY ENERGY STORAGE SYSTEM

Currently, there is a lot of development in the field of micro-gird technology with battery energy storage system. Thompson *et al.* [1] presented a method for optimizing investment in the data centre's battery storage capacity. Sharma et al. [2] proposed a grey wolf optimisation based cost minimisation problem to find out optimal capacity of BES in the operation of MG. Krishnamurthy and Kwasinski [3] discussed the resiliency of micro-grid power supply in severe conditions. Further, distribution-architecture's characteristics, the effect of power electronic device interfaces, energy storage, and lifelines are also presented. Xu *et al.* [4] presented an engineering experience from battery energy storage system (BES) projects that require design and implementation of specialized power conversion systems (a fast-response, automatic power converter and the controller). Liu *et al.* [5] proposed an optimal coordinated planning strategy in addition to the optimization of energy sources capacity in micro-grid. Khodabakhsh and Sirouspour [6] developed two different techniques for online rolling horizon optimal control of an energy storage system in a utility linked micro-grid, which is subject to uncertainty in load and electricity pricing. Shen *et al.* [7] presented an energy-management scheme for MG containing renewable battery storage, diesel generators, PV, wind and different demands. Guo *et al.* [8] addressed a bi-level structure for the optimal working of a MG e.g. EV parking deck with on-site renewable power production by the roof-top PV system. Hassanzadehfard *et al.* [9] employed the battery packs as long term storages and ultra-capacitors as short-term storages for the frequency control of utility connected micro-grid. Alharbi and Bhattacharya [10] developed a model to calculate the optimal power rating and energy capacity of BES for coordinated operation of micro-grid. Graditi et al. [80] carried out the technical and economical evaluation for installing different types of battery technologies to lower the electricity cost for a customer-side application. Ippolito et al. [81] developed a bidirectional converter to connect and control the utility grid with renewable energy sources and battery storage systems. Silvestre *et al.* [82] presented a multi-objective generalized framework for optimal sizing of distributed energy resources in micro-grids by using an indicator based swarm approach. Graditi *et al.* [83] presented an optimal energy dispatch problem, which is having directly controlled and shiftable loads. It is solved by glow worm swarm particles optimization algorithm. Takeuchi *et al.* [84] described an optimal scheduling methodology to determine the operating schedule of an energy network for minimizing CO_2 emission and energy costs. Favuzza *et al.* [85] applied an ant colony search for electrical distribution systems management problem. Gamarra and Guerrero [86] reviewed the technical literature about optimization techniques applied to micro-grid planning.

2) ELECTRIC VEHICLE TECHNOLOGY

The advancement of Electric vehicle technology has a great impact on micro-grid operation, as it can be used for both, backup and demand. Melhem *et al.* [11] proposed a residential energy management in smart grid considering renewable power sources and V2G integration. They presented an integration of distributed power sources in the smart gird in an urban context. Yu *et al.* [12] focused on the investigation of EV movability to effect demand response management (DRM) of V2G technology in the smart grid environment. They presented a model of V2G mobile energy system, which is dynamic in nature and can travel across several cities. Hence, EVs can work as power suppliers between various cities. Laureri *et al.* [13] discussed the techniques for integration of electric vehicle in smart grids. An optimization technique is utilized to minimize the total costs of smart grid. Paterakis *et al.* [14] proposed the optimal operation of a neighbourhood of smart households in terms of minimizing the total energy procurement cost. For that purpose Bi-directional power flow is considered both for household and neighbourhood level. Li *et al.* [15] proposed an online methodology to perform cost-aware scheduling of EV demands and provides power to micro-grids. They developed a stochastic optimization formulation to minimize the time-average charge of a micro-grid, purchase cost of electricity from utility, discharging and charging cost associate with batteries, renewable harvesting charge and pollutant's emission charge. Yao *et al.* [16] proposed a charging scheme on a real-time basis to manage the EV charging and incorporated demand response schemes in the parking station.

a: PLUG IN ELECTRIC VEHICLE (PHEV)

Odeim *et al.* [17] investigated the optimization of a power management scheme of a battery/super-capacitor/fuel cell hybrid vehicular system, both offline and in real time mode. For offline mode, dynamic programming and pontryagin's minimum principle are used. Online mode incorporates a multi-objective genetic algorithm. Xu [18] proposed a consensus technique based an optimum charging rate controlling scheme for PEV, which is used for apportioning existing charging energy. It lines up each PEV's interest with the system's gain. The developed approach was implemented on multi-agent network structure. Vinot *et al.* [19] proposed a universal optimization method for designing the power-split hybrid electric vehicles (PS-HEVs) with an electric variable transmission (EVT). Further, GA is implemented to optimize parameters of the network. For demand response and user adaptation in smart grid networks, Fan [87] proposed a distributed framework with a novel charging method for plug-in hybrid electric vehicles (PHEVs).

b: FUEL CELL ELECTRIC VEHICLE (FCEV)

Ettihir *et al.* [21] addressed the strategy of energy management for FCEV. For fuel cell system the maximum power and efficiency points are varying with operating condition but unique in nature. Further, for tracking both maximum power and efficiency, they developed an extremum seeking process (ESP). Chakraborty et al. [23] proposed a FCEV which incorporates current-fed full-bridge bidirectional voltage doubler with secondary-assisted device voltage clamping and zero current commutation. For a fuel cell/battery hybrid bus, Hu et al. [24] proposed the concurrent optimum element sizing and power management scheme. Further, Hu et al. [25] proposed a multi-constraint optimization method for fuel-cell hybrid bus and presented its soundness and effectiveness using a case study. Morales-Morales et al. [26] analysed various restrictions that enforce the existence of uncertainty in the design of optimum EMSs for FCEV.

3) FUEL CELL TECHNOLOGY

Fuel cell is the recent technology, which has been incorporated in the micro-gird system. Patterson *et al.* [20] explored the workability and cost feasibility of a hybrid grid connected micro-grid that employs the aggregation of batteries, PV and FC systems. Zhang *et al.* [22] studied hybrid power supply of aluminium air fuel cell and the super capacitor. The matching parameters are analysed and calculated. In addition, the hybrid power energy allocation strategy is developed. At last, the power performance simulation is carried out by the authors. For islanded MG which contains PV/BES/FC-electrolyser, Sun et al. [27] proposed an EMS with modified droop control. Ramírez-Murillo *et al.* [28] realized a power system, which is serial-parallel hybrid (SPH) in nature. It contains an auxiliary storage, FC and the current-controlled dc-dc converter. Thale *et al.* [29] proposed a reconfigurable micro-grid architecture containing PV, WT, FC and micro-hydro based RES.

4) DIESEL GENERATOR INCORPORATED MICRO-GRID

Diesel generators are important elements inside the micro-grid system; these are used as backup energy sources. Vidyanandan and Senroy [30] presented a strategy of control for regulating frequency in a WT and DiG supplied MG. Tang *et al.* [31] developed a power allocation strategy for seawater desalination load, batteries, and DiGs. Further a multi-objective optimization problem for optimal operation of micro-grid is solved using NSGA-II. Hajar *et al.* [32] applied an optimization algorithm on micro-grid with distributed generation and renewable energy. Three different energy hubs (renewable energy, diesel engines, and batteries) are integrated in this study. Mohamed and Koivo [33] presented the scheme for cost optimization and optimal operating strategy for MG. In addition to this an emissions reduction scheme is also discussed. Afshar *et al.* [34] proposed the optimum design for a standalone micro-grid system with diesel generator.

B. META-HEURISTIC TECHNIQUES BASED MICRO-GRID OPTIMIZATION

Meta-heuristic techniques are strong and flexible methods that have efficiently handled practical micro-grid optimization problems. GA, PSO, DE, TLBO, FF and WO are widely utilized to solve the various electrical optimization problems including micro-grid operation cost minimization. Some of the latest researches, which utilized above mentioned algorithms, are as follows:

1) GENETIC ALGORITHM

Holland introduced the Genetic algorithms to understand the adaptive processes of natural systems [88]. GA is associated with the binary and other types of representations. It utilizes two operators' crossover and mutation to encourage diversity. Further, it uses the probabilistic selection methods. In GA, the parents are replaced methodically by their offspring. The mutation is bit flipping while the crossover operator is based on the uniform or n-point crossover. A fixed probability p_m is applied to the mutation operator. The GA is applied on numerous power system optimization problems as follows:

Jayadev and Shanti Swarup [35] proposed a commercial MG containing one PV, one BES and two DiG with the hypothesis that the main grid utilizes dynamic pricing. For the formulation of objective function, discontinuous functions are used which is solved by GA. A real-time EMS was proposed by Vergara *et al.* [36] for a MG. A multi-objective optimization problem is formed and solved by using the NSGA-II. Siqi *et al.* [37] developed a coordinated operational system of hybrid storage and DiG. It incorporates the running characteristics of DiG and hybrid storage. Further, for optimizing the power, adaptive genetic algorithm (AGA) is utilized. For power flow and demand side management optimization in a micro grid, Santis *et al.* [38] presented an application of computational intelligence methods. Along with this, hybrid fuzzy-GA paradigm is used for time-of-use cost management. For confirming the precision and validity of the mathematical modelling of a new environmental and economic dispatch of SMG, Liao *et al.* [39] used the quantum genetic algorithm. Changsong *et al.* [40] proposed a novel micro-grid power trading model to find out an optimum schedule for all available units over a planning horizon. The METM utilized genetic algorithm (GA) to assist the micro-grid scheduling. A control scheme is presented by Zolfaghari *et al.* [41] to enhance the load sharing among inverter-based DGs in MG. GA tuned proportional-integral (PI) controller is used for this purpose. Shi *et al.* [42] proposed a multi-objective optimization problem for construction of energy sources, storage and interruptible load in MG. The problem is solved by employing improved NSGA-II. Deng *et al.* [43] studied and modelled a micro-grid including a WT, PV and a CHP system with FCs and MT. GA is used to solve the optimum model and an operation strategy. For cost effective and reliable micro-grid, Nasser and Reji [44] proposed an optimum design scheme. For optimization, a hybrid Genetic Particle Swarm Optimization is utilized. Eldessouky and Gabbar [45] presented micro-grid (MG) optimization using GA. The algorithm's aim is to find out the optimum size of combined wind and gas generator to satisfy a given key performance indices (KPIs). Shariatzadeh *et al.* [46] applied GA and PSO for reconfiguration of SMPS.

2) PARTICLE SWARM OPTIMIZATION

The PSO consists of a population of particles, known as a swarm, with each member of the swarm being associated with a position vector x_t and a velocity vector v_t. The size of these vectors is equal to the dimension of the search space. The term velocity (v_t) at any iteration t indicates the directional distance that the particle has covered in the $(t-1)^{th}$ iteration. The directional velocity of any particle is calculated on the basis of a particle personal best 'pbest' (p_l) and swarm's global best 'gbest' (p_g) [89].

The following equations describe the velocity and position update for i^{th} particle at any iteration t:

$$v_{i,t+1} = wv_{i,t} + c_1 r_1 .* \left(p_{l,i} - x_{i,t}\right) + c_2 r_2 .* \left(p_g - x_{i,t}\right)$$

Here, r_1 and r_2 are random vectors (in range [0, 1]), and w, c_1 and c_2 are pre-specified constants. The operator ".$*$" signifies element to element multiplication of two vectors.

The next position of any particle is computed on the basis of previous position and current velocity.

$$x_{i,t+1} = x_{i,t} + v_{i,t+1}$$

The PSO is applied on various power system optimization problems as follows:

Saber and Venayagamoorthy [47] proposed a SMG optimization with controllable demands by PSO. Cao *et al.* [48] proposed an economic dispatch of MG which depends on enhanced PSO. Chen *et al.* [49] realized the basic economic dispatch function of the system based on PSO, which aims at minimizing the operating costs. Chen *et al.* [50] developed an upgraded PSO technique with adaptive weight and acceleration coefficients for solving the economic, environmental and health dispatch model of a micro-grid. An economic operation of micro-grid under an uncertain framework is studied by Liang *et al.* [51]. A micro-grid scheduling strategy is developed on the basis of Roulette Wheel Mechanism and Probability Density Functions. Further, PSO is used to find the optimum solution. Yang *et al.* [52] proposed an enhanced PSO technique for HOME-EMS, which incorporates load response in a smart grid. Hao *et al.* [53] studied a distinctive utility connected MG, which contains WT, hydro power, BES and local demand. First its mathematical algorithm is constructed and then PSO is applied to solve the optimal operation problem. An *et al.* [54] proposed a novel operating cost optimization method for a building with an integrated MG linked to the utility. Further, a piecemeal decision algorithm and a PSO algorithm were utilized to produce a charging and discharging rate's schemes for BESs. Elamine *et al.* [55] presented a multi-agent structural design for SMG, which is based on wind power forecast. It utilizes neural network, which is trained by hybrid PSO and back-propagation technique. Liang *et al.* [56] studied the multi-objective optimum scheduling problem in a vague structure. The probability distribution function and roulette wheel mechanism are used to develop the scenarios and multi-objective PSO is used to coordinate between them.

3) DIFFERENTIAL EVOLUTION

Storn and Price [90] proposed a robust and easily parallelizable technique DE to solve the global optimization problems. DE is population based meta-heuristic technique, which starts with randomly initialized solution vectors. To modify an existing solution in the population, DE utilized the difference vector of two randomly chosen members. The weight of a difference vector is a user-defined constant parameter ($F > 0$):

$$v_{i,t+1} = x_{(r_1,t)} + F.(x_{r_2,t} - x_{r_3,t})$$

At each generation t, it is ensured that r_1, r_2 and r_3 are different from each other and also from i. The resultant vector v_i is called a mutant vector of x_i. The DE is applied on various power system optimization problems as follows:

Tiwari and Srivastava [57] proposed a differential evolution technique based EMS to optimize the working of a micro-grid with RES. Shuai *et al.* [58] proposed a distinctive islanded MG system. Differential evolution is used to optimize the operation cost. Wu *et al.* [59] described the use of a multi-objective self-adaptive differential evolution algorithm for the concurrent optimization of element sizing and control scheme in parallel EVs. Fan *et al.* [60] proposed a real time pricing, controllable load and a meta-heuristic technique based multi-objective optimization model for household micro-grids to minimize the electricity bill cost and reduce the difference between the temperature of heating, ventilation and air conditioning. Basu *et al.* [61] proposed the planned scheduling for economic energy sharing in a CHP based MG using DE technique.

4) TEACHER LEARNING BASED OPTIMIZATION (TLBO)

TLBO simulates the teaching-learning process of the class room. It is a population-based algorithm and does not require any algorithm-dependent parameters. The common control parameters required by TLBO are the number of generations and population size [91].

The function of TLBO is categorised into two phases, 'Teacher phase' and 'Learner phase'.

a: TEACHER PHASE

On the basis of his/her capabilities, teacher attempts to enhance the mean performance of the group of students in their concerned subject. At i^{th} iteration, let there be n number of learners, m number of subjects, and $M_{j,i}$ be the mean performance of the learners in a particular subject j. $X_{total-kbest,i}$ is the best overall performance by considering all the subjects together. k_{best} is the result of best learner. The learner having best performance is selected as a teacher. The difference between the performance of each subject of a teacher and current mean performance of corresponding subject is formulated as:

$$Difference\_Mean_{j,k,i} = r_i(X_{j,kbest,i} - T_F M_{j,i})$$

Where, $X_{j,kbest,i}$ is the best learner's result in subject j. T_F is the teaching factor, and r_i is the random number in the range [0, 1]. The value of T_F is given as,

$$T_F = round[1 + rand(0, 1)\{2 - 1\}]$$

In the teaching phase, the existing solution is updated as:

$$X'_{j,k,i} = X_{j,k,i} + Difference\_Mean_{j,k,i}$$

Where, $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$.

b: LEARNER PHASE

In the learner phase, learners enhance their knowledge by interacting randomly with other learners. A less knowledgeable learner learns new things from more knowledgeable learners. For n population size, the learning process is as follows:

P and Q learners are selected randomly such that $X'_{total-P,i} \neq X'_{total-Q,i}$, where, $X'_{total-P,i}$ and $X'_{total-Q,i}$ are the updated function values of $X_{total-P,i}$ and $X_{total-Q,i}$ of P and Q respectively at the end of teacher phase:

$$\begin{aligned} X''_{j,P,i} &= X'_{j,P,i} + r_i(X'_{j,P,i} - X'_{j,Q,i}), \\ &\qquad if\ X'_{total-P,i} < X'_{total-Q,i} \\ X''_{j,P,i} &= X'_{j,P,i} + r_i(X'_{j,Q,i} - X'_{j,P,i}), \\ &\qquad if\ X'_{total-Q,I} < X'_{total-P,i} \end{aligned}$$

$X''_{j,P,I}$ is accepted if it provides a better value of function. The TLBO is applied on various power system optimization problems as follows:

Veltman *et al.* [62] proposed a prediction interval modelling tuned by an improved TLBO for load forecasting in MGs. Dixit and Roy [63] presented the impact of PEVs on automatic generation control using the TLBO technique. Yammani *et al.* [64] developed a modified TLBO technique to find out the optimum placement and size of distributed RESs units in the distribution network. Rani *et al.* [65] applied TLBO to resolve a multi-objective problem of the economic and emission scheduling.

5) FIREFLY OPTIMIZATION

Firefly Algorithm (FF) is a nature inspired meta-heuristic optimization algorithm, which is motivated from the conduct of fireflies [92]. FF depends on three basic rules:

i) All fireflies are attracted to each other with disregard to gender.
ii) Attractiveness is correlated with brightness (light emission) such that bright flies attract less bright flies, and in absence of brighter flies they move randomly.
iii) The brightness is proportional to the objective function.

The movement of a firefly i is attracted to another more attractive (brighter) firefly j is determined by

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} \left(x_j - x_i\right) + \alpha \epsilon_i$$

Where β_0 is attractiveness at distance zero, $r_{ij} = \left\| x_i - x_j \right\|$ is the distance between any two fireflies i and j at distance x_i and x_j, respectively, ϵ_i is a vector of random numbers drawn from a Gaussian distribution or uniform distribution and α being the randomization parameter. The FF is applied on power system optimization problems as follows:

Odeim *et al.* [17] investigated the optimization of a power management scheme of a battery/super-capacitor/fuel cell hybrid vehicular system.

6) WHALE OPTIMIZATION

Whale Optimization Algorithm (WO) is a nature inspired meta-heuristic optimization algorithm, which is encouraged from the behaviour of Humpback whales [93]. The WO algorithm is working on the following rules:

a: ENCIRCLING PREY

Humpback whales can identify the position of prey and encircle them. As per the activities of humpback whales the WO assumes that the current best solution is the objective prey or near to the optimum. Other search agents will renew their position towards the best agent, as represented by the following equations:

$$\begin{aligned} \vec{D} &= \left| \vec{C} . \vec{X^*}(t) - \vec{X}(t) \right| \\ \vec{X}(t+1) &= \vec{X^*}(t) - \vec{A} . \vec{D} \\ \vec{A} &= 2\vec{a} . \vec{r} - \vec{a} \\ \vec{C} &= 2 . \vec{r} \end{aligned}$$

where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, X^* is the position vector of the best solution obtained so far, $\overrightarrow{X}$ is the position vector, || is the absolute value, and '•' is an element-by-element multiplication, $\overrightarrow{a}$ is linearly decreased from 2 to 0 over the course of iterations and $\overrightarrow{r}$ is a random vector in [0, 1].

b: BUBBLE-NET ATTACKING METHOD

Humpback whales swim about the prey within a shrinking circle and along a spiral-shaped path, concurrently. The authors have assumed that there is a 50% probability (p) of either the shrinking encircling mechanism or the spiral model to update the location of whales through optimization. The mathematical model is as follows:

$$\overrightarrow{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \overrightarrow{A}.\overrightarrow{D} \, if p < 0.5 \\ \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) \, if p \geq 0.5 \end{cases}$$

Where p is a random number in [0, 1], b is a constant to define the shape of the logarithmic spiral and l is a random number in [−1, 1].

c: SEARCH FOR PREY

This method highlights exploration and allows the WO algorithm to achieve a global search. The mathematical model is as follows:

$$\overrightarrow{D} = |\overrightarrow{C}.\overrightarrow{X_{rand}} - \overrightarrow{X}(t)|$$
$$\overrightarrow{X}(t+1) = \overrightarrow{X_{rand}} - \overrightarrow{A}.\overrightarrow{D}$$

Where $\overrightarrow{X_{rand}}$ is a random position vector.

The WO algorithm starts with a set of random solutions. In every iteration, the search agents revise their positions with regard to either a randomly chosen search agent or the best solution obtained so far. The WO is applied on power system optimization problems as follows:

Reddy *et al.* [68] utilized whale optimization algorithm (WOA) to determine the optimal distributed generation size. Trivedi *et al.* [69] presented the solution of an emission constraint environment dispatch problem with MG by using whale optimization algorithm.

III. PROBLEM FORMULATION

Selecting a suitable method to solve the cost minimization problem of SMG, the proposed problem is formulated as follows:

The formulation of the economic operation problem of SMG (EOSMG) is illustrated as follows:

Minimization of total cost of SMG is given by Eq.1.

$$MinC(X) = \sum_{t=1}^{NT} c_t + OM_{DG} + CTCPD + C_f \sum_{i=1}^{N} \left(aP^2_{DiG(i)} + bP_{DiG(i)} + c\right) \quad (1)$$

where cumulative total cost per day for batteries is the summation of total cost per day for BES, BEV and PHEV.

$$CTCPD = TCPD_{BES} + TCPD_{BEV} + TCPD_{PHEV}$$

c_t is the summation of the supply cost of grid, operation and fuel cost of DG, BES, BEV, PHEV, as well as start up cost of FC, MT and FCEV, as shown in

$$c_t = Cost_{grid,t} + Cost_{DG,t} + Cost_{BES,t} + Cost_{BEV,t} + Cost_{PHEV,t} + SUC_{FC,t} + SUC_{MT,t} + SUC_{FCEV,t} \quad (2)$$

Supply cost of the grid is defined by

$$Cost_{grid,t} = \begin{cases} Bid_{grid,t}P_{grid,t} & if \ P_{grid,t} > 0 \\ (1-tax)\,Bid_{grid,t}P_{grid,t} & if \ P_{grid,t} < 0 \\ 0 & if \ P_{grid,t} = 0 \end{cases} \quad (3)$$

The operation and fuel cost of the distributed generators are presented by

$$Cost_{DG,t} = Bid_{MT,t}P_{MT,t}u_{MT,t} + Bid_{FC,t}P_{FC,t}u_{FC,t} + Bid_{FCEV,t}P_{FCEV,t}u_{FCEV,t} + Bid_{PVi,t}P_{PVi,t} + Bid_{WTi,t}P_{WTi,t} \quad (4)$$

The start up cost of FC, FCEV and MT are provided, respectively, in

$$SUC_{FC,t} = Start_{FC} * \max\left(0, u_{FC,t} - u_{FC,t-1}\right) \quad (5)$$

$$SUC_{FCEV,t} = Start_{FCEV} * \max\left(0, u_{FCEV,t} - u_{FCEV,t-1}\right) \quad (6)$$

$$SUC_{MT,t} = Start_{MT} * \max\left(0, u_{MT,t} - u_{MT,t-1}\right) \quad (7)$$

The constant repair and operation cost of distributed generators are presented by

$$OM_{DG} = (OM_{MT} + OM_{FC} + OM_{FCEV} + OM_{PVi} + OM_{WTi}) * NT \quad (8)$$

The overall charges of the SMG consist of the operation charges of BES, BEV, PHEV, FCEV and utility, fuel and OM charges of DGs and DiGs, the start-up charges of FCEV, MT and FC in addition cumulative per day overall cost of batteries, which is used in BES, BEV and PHEV (*CTCPD*). The cost of batteries contains the single-time constant cost (FX) and the yearly repair cost (MC). Overall cost of the battery is $(FC + MC)*C_{max}$, where C_{max} is the battery's size. The time window selected for this work is a day; therefore, the operation cost is computed over 24 hours and *TCPD* is required in €ct/day. The *TCPDs* of mounted batteries in €ct/day can be achieved using the following equations [70]:

$$TCPD_{BES} = \frac{C_{BES,max}}{365}\left(\frac{IR(1+IR)^{LT}}{(1+IR)^{LT}-1}FC_{BES} + MC_{BES}\right) \quad (9)$$

$$TCPD_{BEV} = \frac{C_{BEV,max}}{365}\left(\frac{IR(1+IR)^{LT}}{(1+IR)^{LT}-1}FC_{BEV} + MC_{BEV}\right) \quad (10)$$

$$TCPD_{PHEV} = \frac{C_{PHEV,max}}{365}\left(\frac{IR(1+IR)^{LT}}{(1+IR)^{LT}-1} \times FC_{PHEV} + MC_{PHEV}\right) \quad (11)$$

TABLE 2(A). Constraints.

Constraint	Formulation
Electrical demand balance	It mandates that the total power generation should always be equal to load plus losses of the system (in this work losses are neglected) $P_{grid,t} + P_{MT,t}u_{MT,t} + P_{FC,t}u_{FC,t} + P_{PVi,t} + P_{WTi,t} + P_{BES,t}u_{BES,t} + P_{BEV,t}u_{BEV,t} + P_{PHEV,t}u_{PHEV,t} + P_{FCEV,t}u_{FCEV,t} + P_{DiG(i)} = P_{Demand,t} \quad ,t = 1, \ldots\ldots, NT$ (12)
Dispatchable DGs constraints	It provides the power output limits of various DGs; i.e. they should generate power with specified limit. $P_{FC,min} \le P_{FC,t} \le P_{FC,max}$,$t = 1, \ldots\ldots, NT$ (13) $P_{MT,min} \le P_{MT,t} \le P_{MT,max}$,$t = 1, \ldots\ldots, NT$ (14) $P_{FCEV,min} \le P_{FCEV,t} \le P_{FCEV,max}$,$t = 1, \ldots\ldots, NT$
BES constraints	It provides the minimum and maximum, charging and discharging rate of BES. Discharging mode [20]: $C_{BES,t+1} = max\left\{\left(C_{BES,t} - \frac{\Delta t P_{BES,t}}{\eta_{discharge}}\right), C_{BES,min}\right\}, t = 1, \ldots\ldots, NT$ (16) $\underline{P_{BES,t}} \le P_{BES,t} \le \overline{P_{BES,t}} \quad ,t = 1, \ldots\ldots, NT$ (17) *Charging mode:* $C_{BES,t+1} = min\{(C_{BES,t} - \Delta t P_{BES,t}\eta_{charge}), C_{BES,max}\}, t = 1, \ldots\ldots, NT$ (18) $\underline{P_{BES,t}} \le P_{BES,t} \le \overline{P_{BES,t}} \quad , t = 1, \ldots\ldots, NT$ (19) *Where* $\overline{P_{BES,t}} = min\left\{\frac{P_{BES,max}(C_{BES,t} - C_{BES,min})\eta_{discharge}}{\Delta t}\right\}, t = 1, \ldots\ldots, NT$ (20) $\underline{P_{BES,t}} = max\{P_{BES,min}(C_{BES,t} - C_{BES,max})/\eta_{charge}\Delta t\}, t = 1, \ldots\ldots, NT$ (21)
Grid Constraints	Gird supply should provide within the specified limits presented by equation (34) $P_{grid,min} \le P_{grid,t} \le P_{grid,max}$ (34)
Diesel Generator Constraints	Diesel generator should produced electric power within specified limits presented by equation (35) $0 \le P_{Dig(i)} \le P_{Dig(i)}^{max}$ (35)

TABLE 2(B). Constraint.

Constraint	Formulation
BEV Constraints	It provides the minimum and maximum, charging and discharging rate of BEV. Discharging mode: $C_{BEV,t+1} = max\left\{\left(C_{BEV,t} - \frac{\Delta t P_{BEV,t}}{\eta_{discharge}}\right), C_{BEV,min}\right\}, t = 1, \ldots\ldots, NT$ (22) $\underline{P_{BEV,t}} \le P_{BES,t} \le \overline{P_{BEV,t}} \quad ,t = 1, \ldots\ldots, NT \quad , t = 1, \ldots\ldots, NT$ (23) *Charging mode:* $C_{BEV,t+1} = min\{(C_{BEV,t} - \Delta t P_{BEV,t}\eta_{charge}), C_{BEV,max}\}, t = 1, \ldots\ldots, NT$ (24) $\underline{P_{BEV,t}} \le P_{BES,t} \le \overline{P_{BEV,t}} \quad ,t = 1, \ldots\ldots, NT \quad , t = 1, \ldots\ldots, NT$ (25) *Where* $\overline{P_{BEV,t}} = min\left\{\frac{P_{BEV,max}(C_{BEV,t} - C_{BEV,min})\eta_{discharge}}{\Delta t}\right\}, t = 1, \ldots\ldots, NT$ (26) $\underline{P_{BEV,t}} = max\{P_{BEV,min}(C_{BEV,t} - C_{BEV,max})/\eta_{charge}\Delta t\} \quad ,t = 1, \ldots\ldots, NT$ (27)
PHEV constraints	It provides the minimum and maximum, charging and discharging rate of PHEV. Discharging mode: $C_{PHEV,t+1} = max\left\{\left(C_{PHEV,t} - \frac{\Delta t P_{PHEV,t}}{\eta_{discharge}}\right), C_{PHEV,min}\right\}, t = 1, \ldots\ldots, NT$ (28) $\underline{P_{PHEV,t}} \le P_{PHEV,t} \le \overline{P_{PHEV,t}} \quad , t = 1, \ldots\ldots, NT$ (29) *Charging mode:* $C_{PHEV,t+1} = min\{(C_{PHEV,t} - \Delta t P_{PHEV,t}\eta_{charge}), C_{PHEV,max}\}, t = 1, \ldots\ldots, NT$ (30) $\underline{P_{PHEV,t}} \le P_{PHEV,t} \le \overline{P_{PHEV,t}} \quad ,t = 1, \ldots\ldots, NT$ (31) *Where,* $\overline{P_{PHEV,t}} = min\left\{\frac{P_{PHEV,max}(C_{PHEV,t} - C_{PHEV,min})\eta_{discharge}}{\Delta t}\right\}, t = 1, \ldots\ldots, NT$ (32) $\underline{P_{PHEV,t}} = max\{P_{PHEV,min}(C_{PHEV,t} - C_{PHEV,max})/\eta_{charge}\Delta t\}, t = 1, \ldots\ldots, NT$ (33)
Operating Reserve Constraints	In SMG systems, reliability is achieved by acquiring the energy storage, e.g. BES, EVTs and operating reserves. In each time step, operating reserve (OR) is the addition of standby generation capacity of turned on BES, EVTs, FC, MT, DiG and Grid. It can be supplied to the SMG in less than 10 min and defined by the (36) $P_{FC,max}u_{FC,t} + P_{MT,max}u_{MT,t} + P_{grid,max} + \overline{P_{BES,t}}u_{BES,t} + \overline{P_{BEV,t}}u_{BEV,t} + \overline{P_{PHEV,t}}u_{PHEV,t} + \overline{P_{FCEV,t}}u_{FCEV,t} + P_{DiG(i)} \ge OR_t + P_{Demand,t}$, $t = 1, \ldots\ldots, NT$ (36) Where, OR_t is the 10-min OR requirement at time t.

The proposed cost minimization problem is subjected to the constraints presented in Table 2(A) and 2(B). The limits of the constraints are presented in Table 7 in Appendix A.

IV. STANDARD FUNCTIONS

To select the appropriate meta-heuristic technique, a set of nineteen standard functions from three different categories (uni-model, multi-model, composite) are selected and applied on various algorithms. These standard functions are presented in Tables 8(A), 8(B) and 8(C) in Appendix B.

V. SYSTEM DESCRIPTION

To select the suitable algorithm for the proposed problem, six algorithms are applied on an advanced SMG object system as shown in Fig. 1. There are different DGs (MT, FC, PV, WT), Li-ion BES and DiG in the adopted SMG. In addition, the proposed SMG system consists of EVTs (BEV, PHEV, and FCEV) technology. In this problem formulation, FCEV is considered as a DG source. Appendix A provides the details of generation limits and coefficients used in the present work.

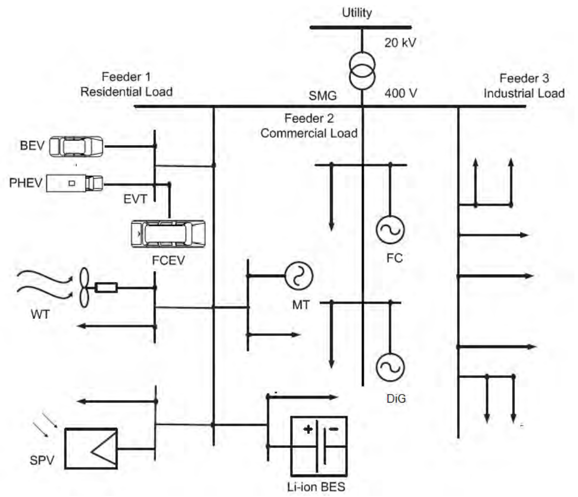


FIGURE 1. SMG system.

If the SMG under study has MT, FC, FCEV, PV, WT, BES, BEV, PHEV and DiG then the location of m^{th} search agent X_m can be characterized as (37), shown at the bottom of this page. More information regarding the implementation of SMG can be referred from [70], [71], [75]. All DGs generate active power at the unity power factor in the current work. The FX and MT charges, for mounting and operation of batteries used in BES, BEV and PHEV, are assumed to be 465 (€ct/ kWh) and 15 (€ct/ kWh) [13]. The LT and IR for funding the batteries of BES, BEV and PHEV are correspondingly 3 and 0.06. The tax is considered as 10% in this work. The charging and discharging rate of batteries are equal and kept at 90%. Let the minimum capacities to be 10% of the maximum capacities of the batteries. The maximum capacities of batteries are set to 500 kWh. For a time horizon of one day with hourly time step, the EOSMG studies are performed. A PC with 2.4 GHz Intel i5-4210U CPU and 4 GB RAM is used to simulate the techniques in MATLAB. The operation reserve and forecasted values of load demand are given in Fig 2. This figure shows the forecasted value of variable load for 24 hours. It is supplied by the different energy sources of MG. This variable load requirement is due to the fact that the patterns of energy utilization by industrial, commercial and domestic customers are different. Fig. 2 also presents the operating reserve requirement in addition to the standby reserve capacity of MG sources and the utility. It will be supplied during unavailability of the supply from the main gird.

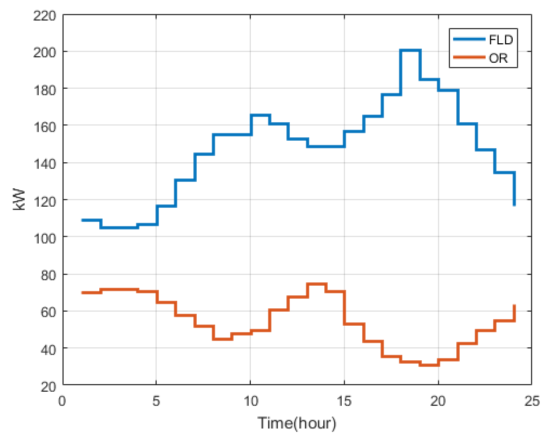


FIGURE 2. Forecasted load demand (FLD) and operating reserve (OR).

To verify the performance of different techniques, they are frequently applied on the considered problem of EOSMG for 30 independent trials. The important variables of different algorithms include the maximum number of iterations and population size. In this work, four different population numbers are selected i.e. 25, 50, 100 and 200. The maximum number of iterations is 500. For comparative analysis, the algorithms WO, FF, PSO, DE, GA and TLBO are considered. The sequential optimization strategy (i.e., one-by-one parameter) is used to tune one parameter at a time, and its optimal value is determined empirically. For FF, attraction coefficient, mutation coefficient and mutation coefficient damping ratio are 2, 0.2 and 0.98, respectively. For PSO local learning coefficient and global learning coefficient are selected

$$X_m = [x_{m,1} x_{m,2} \ldots \ldots x_{m,D}] \times \begin{bmatrix} C_{BESmax,1}, C_{BESmax,2}, \cdots, C_{BESmax,s1}, C_{BEVmax,1}, C_{BEVmax,2}, \cdots, C_{BEVmax,s2} \\ C_{PHEVmax,1}, C_{PHEVmax,2}, \cdots, C_{PHEVmax,s3}, P^m_{MT,1}, P^m_{MT,2}, \ldots, P^m_{MT,T}, \\ P^m_{FC,1}, P^m_{FC,2}, \ldots, P^m_{FC,T}, P^m_{FCEV,1}, P^m_{FCEV,2}, \ldots, P^m_{FCEV,T} \\ P^m_{PV,1}, P^m_{PV,2}, \ldots, P^m_{PV,T}, P^m_{WT,1}, P^m_{WT,2}, \ldots, P^m_{WT,T} \\ P^m_{BES,1}, P^m_{BES,2}, \ldots, P^m_{BES,T}, P^m_{BEV,1}, P^m_{BEV,2}, \ldots, P^m_{BEV,T} \\ P^m_{PHEV,1}, P^m_{PHEV,2}, \ldots, P^m_{PHEV,T}, P^m_{Grid,1}, P^m_{Grid,2}, \ldots, P^m_{Grid,T} \\ P^m_{DiG,1}, P^m_{DiG,2}, \ldots, P^m_{DiG,T}, u^m_{MT,1}, u^m_{MT,2}, \ldots, u^m_{MT,T}, \\ u^m_{FC,1}, u^m_{FC,2}, \ldots, u^m_{FC,T} \\ u^m_{FCEV,1}, u^m_{FCEV,2}, \ldots, u^m_{FCEV,T}, u^m_{PV,1}, u^m_{PV,2}, \ldots, u^m_{PV,T} \\ u^m_{WT,1}, u^m_{WT,2}, \ldots, u^m_{WT,T}, u^m_{BES,1}, u^m_{BES,2}, \ldots, u^m_{BES,T} \\ u^m_{BEV,1}, u^m_{BEV,2}, \ldots, u^m_{BEV,T}, u^m_{PHEV,1}, u^m_{PHEV,2}, \ldots, u^m_{PHEV,T} \\ u^m_{Grid,1}, u^m_{Grid,2}, \ldots, u^m_{Grid,T}, u^m_{DiG,1}, u^m_{DiG,2}, \ldots, u^m_{DiG,T} \end{bmatrix} \quad (37)$$

TABLE 3(A). Standard function optimal values (30 trials).

Function	Optimization Method			
	WO		FF	
	Mean	Std dev	Mean	Std dev
F1	1.41E −30	4 .91E −30	3.962E-02	1.449E-02
F2	1.06E −21	2.39E −21	5.035E-02	1.235E-02
F3	5.39E −07	2.93E −06	4.927E-02	1.941E-02
F4	7.258E-02	3.975E-01	1.455E-01	3.117E-02
F5	2.787E+01	7.636E-01	2.176E+00	1.447E+00
F6	3.116E+00	5.324E-01	5.873E-02	1.448E-02
F7	1.425E-03	0.000E+00	**8.530E-04**	**5.040E-04**
F8	−5.080E+03	6.958E+02	1.246E+03	3.533E+02
F9	**0.000E+00**	**0.000E+00**	2.635E-01	1.828E-01
F10	7.404E+00	9.898E+00	1.683E-01	5.080E-02
F11	2.890E-04	1.586E-03	9.982E-02	2.447E-02
F12	3.397E-01	2.149E-01	1.261E-01	2.632E-01
F13	1.889E+00	2.661E-01	2.130E-03	1.238E-03
F14	5.688E-01	5.059E-01	1.502E+02	9.716E+01
F15	7.531E+01	4.308E+01	3.145E+02	9.293E+01
F16	**5.5 66E+01**	2.188E+01	7.345E+02	2.040E+02
F17	**5.3 84E+01**	2.162E+01	8.186E+02	1.100E+02
F18	7.7 81E+01	5.203E+01	1.335E+02	2.156E+02
F19	**5.788E+01**	3.445E+01	8.622E+02	1.260E+02

TABLE 3(B). Standard function optimal values (30 trials).

Function	Optimization Method			
	PSO		DE	
	Mean	Std dev	Mean	Std dev
F1	1.360E-04	2.020E-04	8.2E −14	5.9E −14
F2	4.214E-02	4.542E-02	1.5E −09	9.9E −10
F3	7.013E+01	2.212E+01	6.8E −11	7.4E −11
F4	1.086E+00	3.170E-01	**0.000E+00**	**0.000E+00**
F5	9.672E+01	6.012E+01	**0.000E+00**	**0.000E+00**
F6	1.020E-04	8.28E−05	**0.000E+00**	**0.000E+00**
F7	1.229E-01	4.496E-02	4.630E-03	1.200E-03
F8	−4.842E+03	1.153E+03	−11080.1	5.747E+02
F9	4.670E+01	1.163E+01	6.920E+01	3.880E+01
F10	2.760E-01	5.090E-01	9.7E −08	4.2E −08
F11	9.215E-03	7.724E-03	**0.000E+00**	**0.000E+00**
F12	6.917E-03	2.630E-02	**7.9E −15**	**8E −15**
F13	6.675E-03	8.907E-03	**5.1E −14**	**4.8E −14**
F14	1.000E+02	8.165E+01	**6.75E −2**	**1.11E −1**
F15	1.559E+02	1.318E+01	2.876E+01	8.628E+00
F16	1.720E+02	3.277E+01	1.444E+02	**1.940E+01**
F17	3.143E+02	2.007E+01	3.249E+02	**1.478E+01**
F18	8.345E+01	1.011E+02	1.079E+01	2.604E+00
F19	8.614E+02	1.258E+02	4.909E+02	3.946E+01

TABLE 3(C). Standard function optimal values (30 trials).

Function	Optimization Methods			
	GA		TLBO	
	Mean	Std dev	Mean	Std dev
F1	1.188E-01	1.256E-01	**0.000E+00**	**0.000E+00**
F2	1.452E-01	5.323E-02	**0.000E+00**	**0.000E+00**
F3	1.390E-01	1.212E-01	**3.250E-27**	**8.210E-27**
F4	1.580E-01	8.620E-01	3.960E-253	4.240E-253
F5	7.142E-01	9.727E-01	2.666E+01	2.940E-01
F6	1.679E-01	8.686E-01	2.740E-09	5.360E-09
F7	1.007E-02	3.263E-03	1.710E-02	8.950E-03
F8	**-2.092E+03**	**2.472E+00**	-1.231E+04	2.210E+02
F9	6.593E-01	8.158E-01	1.870E-12	6.660E-12
F10	9.561E-01	8.077E-01	**3.550E-15**	**8.320E-31**
F11	4.878E-01	2.178E-01	**0.000E+00**	**0.000E+00**
F12	1.108E-01	2.152E-03	6.160E-03	2.340E-02
F13	1.290E-01	6.885E-02	6.160E-03	2.340E-02
F14	1.146E+02	2.696E+01	3.119E-01	3.042E-01
F15	9.546E+01	**7.163E+00**	**1.702E+01**	7.219E+00
F16	3.254E+02	5.167E+01	1.238E+02	6.039E+01
F17	4.663E+02	2.957E+01	2.944E+02	3.158E+01
F18	9.037E+01	1.373E+01	**5.182E+00**	**1.617E+00**
F19	5.212E+02	**2.799E+01**	2.302E+02	4.837E+01

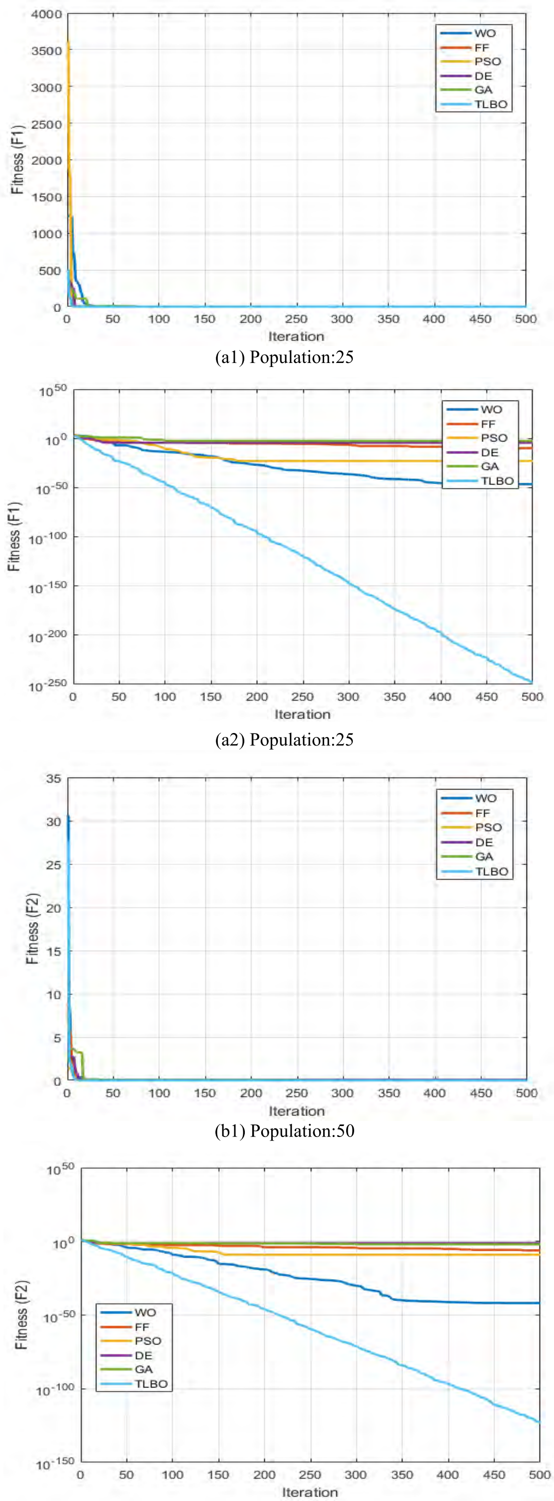
as 1.5 and 2, respectively. The inertia weight damping ratio is selected as 0.99. For DE upper and lower bound of scaling factor and cross over probability are 0.8, 0.2 and 0.2, respectively. For GA, mutation rate, population size and crossover rate are considered as 0.1, 50, and 0.7, correspondingly. To identify an effective algorithm, two different cases of the proposed formulation are considered. For the first case, all batteries are connected to the system at no charge condition. In this case, these batteries are connected as loads to the SMG. The Second case considered all connected batteries in charged condition. Hence all batteries worked as energy sources.

A. CASE 1: CHARGING MODE OF DIFFERENT BATTERIES

In this case, the Li-ion batteries are added in the form of BES, BEV and PHEV in SMG test system; although, it is the elementary component of the SMG. The key advantage of the batteries in the SMG is to retain reliability, make possible the incorporation of renewable energy sources, and enhance the quality of power [73], [76], [77]. The Li-ion batteries commit during the time period when there is no charge; therefore, the discharging is limited to the charging in the preceding hours. To observe effectiveness of the batteries with appropriate and optimum capacity, maximum sizes of batteries ($CBES_{max}$, $CBEV_{max}$, $CPHEV_{max}$) are considered as the control parameters.

A DiG set is incorporated in the micro-grid system. The diesel fuel price C_f is 1.33 (€ct/l). The values of DiG's fuel consumption curve parameters a, b, c are 0.246, 0.0815, and 0.4333, respectively.

In the above case, the EOSMG is solved for the system to minimize the total operation cost and find the economical size of batteries as well as the optimal output of FC, MT, WT, PV, FCEV, BEV, PHEV, BES, DiG and GRID. The mathematical optimum output of EVTs, DGs, DiG, utility and BES are calculated by six algorithms and provided in Fig 9(A). It must be noted that the economical sizes of BES, BEV and PHEV in this work are 50 kWh each. The results obtained by different algorithms, depicted in Table 4. The divergence characteristic of six algorithms is presented in Fig. 7(A).



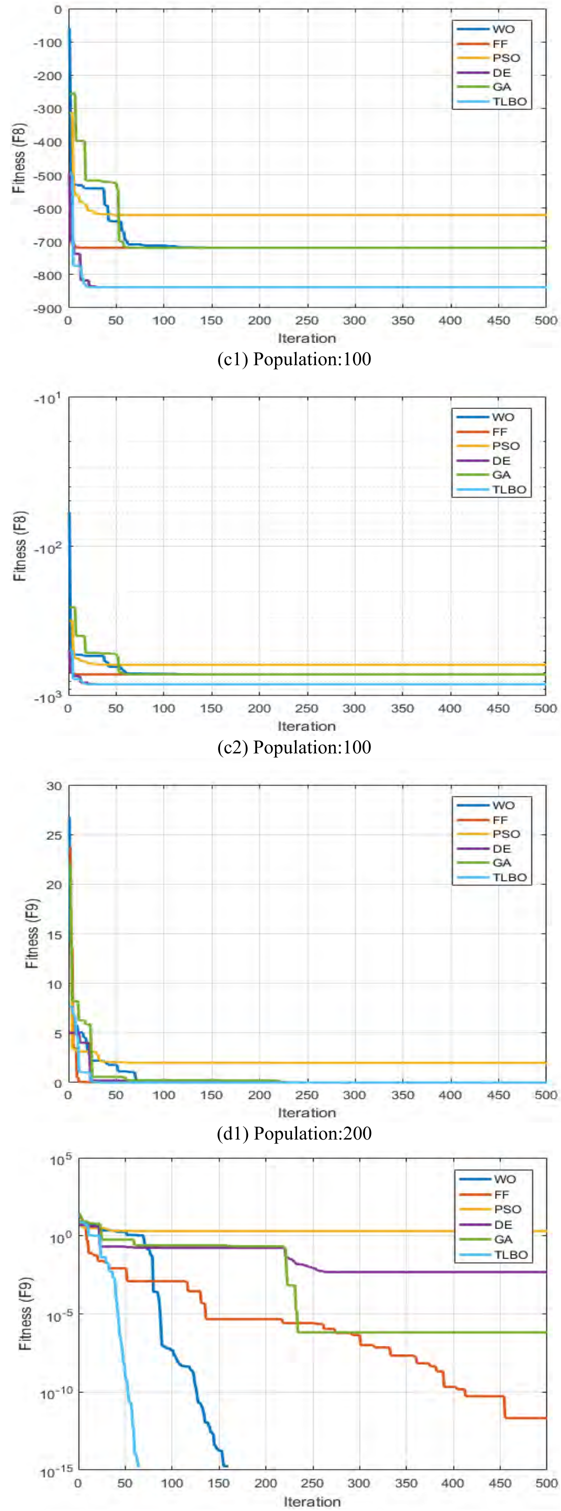
(a1) Population:25

(a2) Population:25

(b1) Population:50

(b2) Population:50

FIGURE 3(A). Convergence curve of selected algorithm on different population. (a1) Population:25. (a2) Population:25. (b1) Population:50. (b2) Population:50.



(c1) Population:100

(c2) Population:100

(d1) Population:200

(d2) Population:200

FIGURE 3(B). Convergence curve of selected algorithm on different population. (c1) Population:100. (c2) Population:100. (d1) Population:200. (d2) Population:200.

B. CASE 2: DISCHARGING MODE OF BATTERIES

In this case, all the batteries are fully charged, the optimal power output of MT, FC, BES, BEV, PHEV, FCEV, PV, WT, DiG and power grid for six algorithms in the SMG are shown in Fig. 9(B). Due to economical power supplied by batteries, it is beneficial for EOSMG to purchase power from BES and EVTs. In this case, the system considers batteries of optimum size 50 kWh. A comparative analysis among different

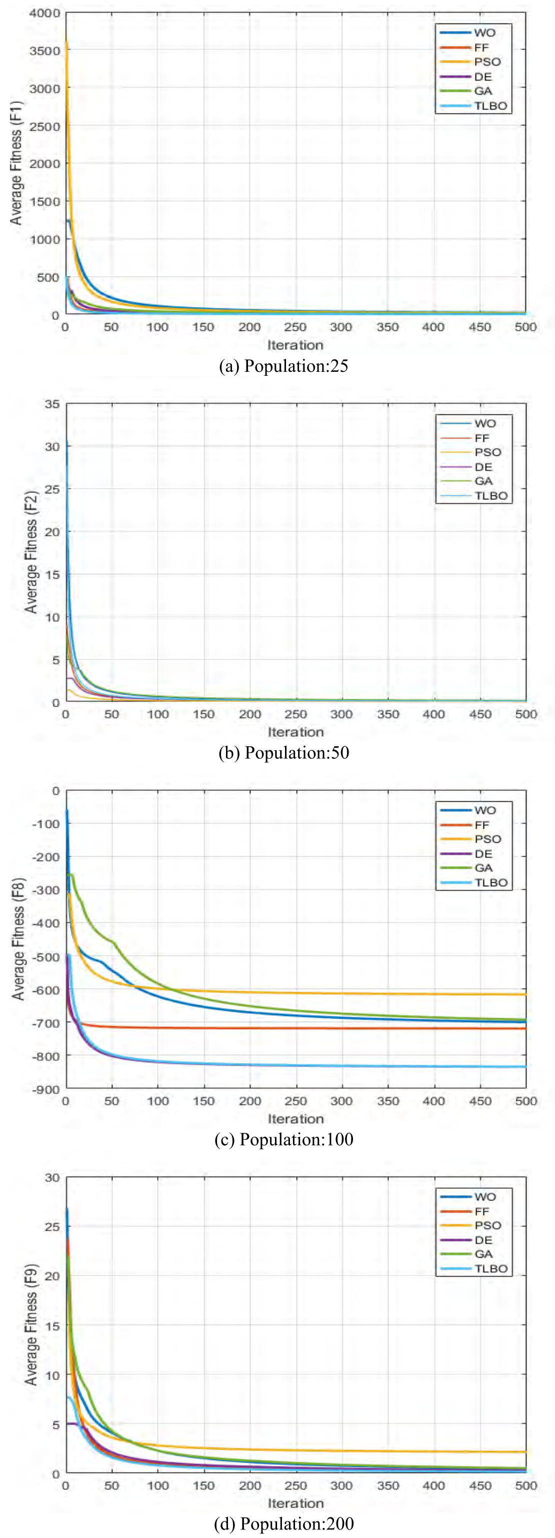


FIGURE 4. Average fitness values on different population. (a) Population:25. (b) Population:50. (c) Population:100. (d) Population:200.

algorithms on optimal operation costs for 25, 50, 100 and 200 population sizes is also presented. The results obtained by different algorithms and their convergence characteristic are shown in Table 5 and Fig. 7(B), respectively.

TABLE 4. Case I.

Algorithm Name	Result Criteria	Population Size			
		25	50	100	200
WO	Avg	1895.962	1884.372	1872.538	1866.909
	Best	1857.268	1812.25	1801.815	1809.16
	Worst	1922.766	1922.652	1922.652	1889.725
	Std Dev	26.10433	32.09542	34.6155	20.02034
FF	Avg	1336.425	1324.982	1271.721	1319.819
	Best	**1310.512**	**1255.266**	**1243.399**	1280.419
	Worst	1409.943	1379.061	1301.979	1391.419
	Std Dev	37.61483	48.89212	20.56732	32.41049
PSO	Avg	1561.667	1488.155	1455.332	1486.473
	Best	1474.172	1384.653	1387.701	1366.182
	Worst	1630.049	1663.96	1540.646	1670.344
	Std Dev	46.07841	69.87589	48.30058	97.61517
DE	Avg	1404.373	1429.614	1447.885	1470.274
	Best	1328.212	1358.216	1418.74	1457.831
	Worst	1445.983	1486.497	1472.376	1479.262
	Std Dev	36.79459	43.20021	19.32837	5.021147
GA	Avg	1617.909	1599.23	1551.728	1462.649
	Best	1553.311	1490.201	1472.198	1430.426
	Worst	1658.022	1662.603	1640.682	1505.002
	Std Dev	28.91071	47.20861	52.82723	32.87075
TLBO	Avg	1539.588	1487.463	1459.77	1393.955
	Best	1441.732	1355.387	1372.707	**1263.903**
	Worst	1693.091	1652.032	1578.852	1519.195
	Std Dev	90.71279	82.39088	68.37556	79.34193

VI. COMPARATIVE ANALYSIS

For selecting suitable meta-heuristic technique, all the algorithms are first applied on nineteen standard test functions. These functions are presented in Appendix A2, A3 and A4. These functions are categorized as uni-model, multi-model and composite functions. Table 3(A), 3(B), and 3(C) summarized the results obtained from the different algorithms on standard functions for 30 trials. The comparison among six algorithms on different standard functions is based on their mean and standard deviation. In the first category of benchmark functions (i.e. uni-modal): the minimum mean values and standard deviation of functions F1, F2 and F3 are obtained by TLBO; F4, F5 and F6 are obtained by DE; F7 is obtained by FF. For the second category of benchmark functions (i.e. multi-modal): the minimum mean values and standard deviation of functions F8 is obtained by GA; F9 is obtained by WO; F10 and F11 are obtained by TLBO; F11, F12 and F13 are obtained by DE. For the third category (i.e. composite benchmark functions): the minimum mean values of functions F14 is obtained by DE; F15 and F18 are obtained by TLBO; F16, F17 and F19 are obtained by WO. Whereas

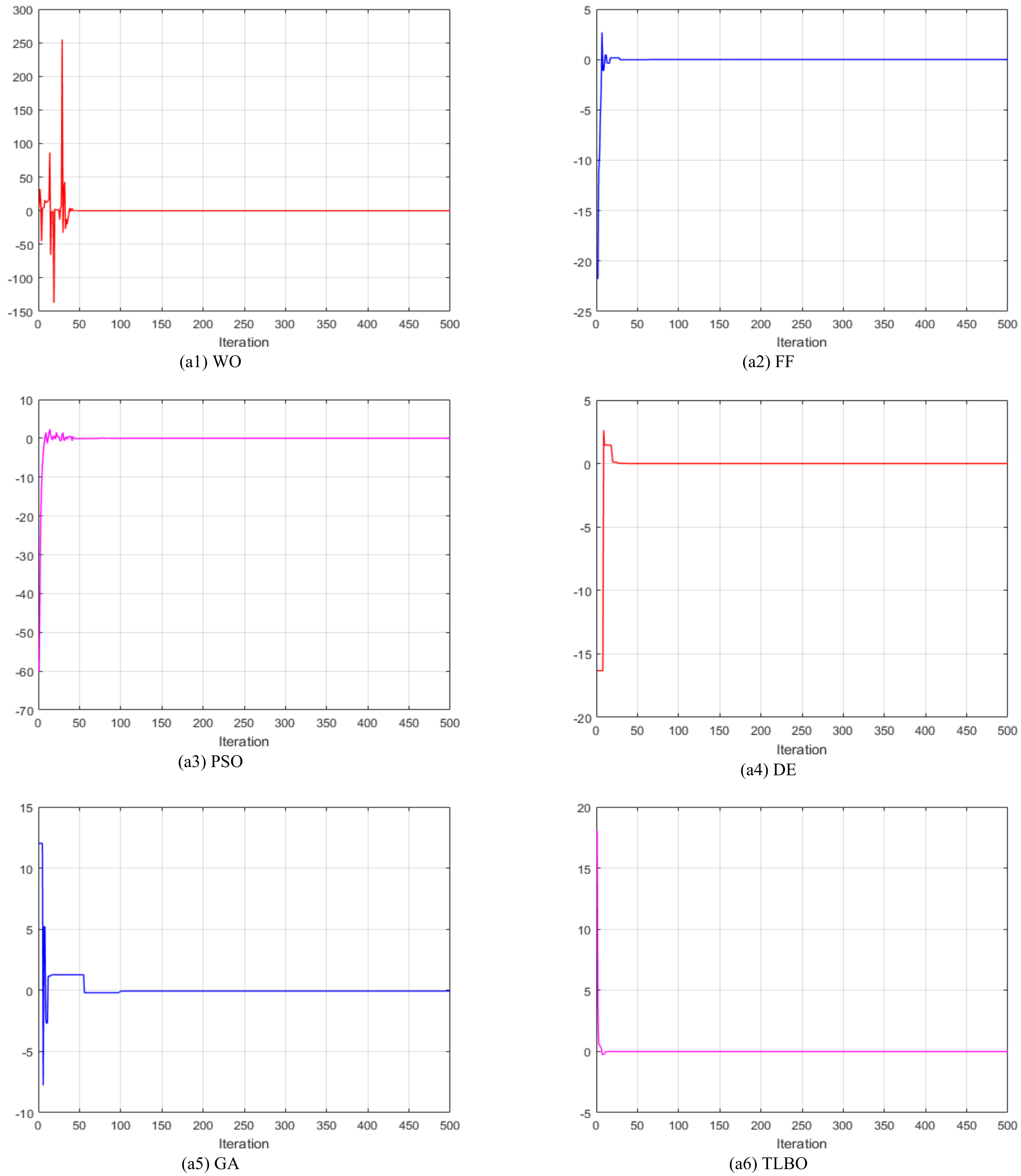


FIGURE 5(A1). Trajectory of F1 (a1-a6) for different algorithm. (a1) WO. (a2) FF. (a3) PSO. (a4) DE. (a5) GA. (a6) TLBO.

for the third category (i.e. composite benchmark functions): the standard deviations of functions F14, F16 and F17 are obtained by DE; F15 and F19 are obtained by GA; F18 is obtained by TLBO. From the above analysis, it is observed that for the uni-modal benchmark functions the performance of TLBO and DE is better and stable; for the multi-modal benchmark function the performance of DE is best and the second best is TLBO as well as their performance are stable; for the composite benchmark functions the performance of WO is best, but their standard deviations are not least, i.e. it's performance is not stable (there is a lot of fluctuation in the computed mean values).

Fig. 3(A) and (B) presents the comparison of convergence characteristics for different algorithms for four standard

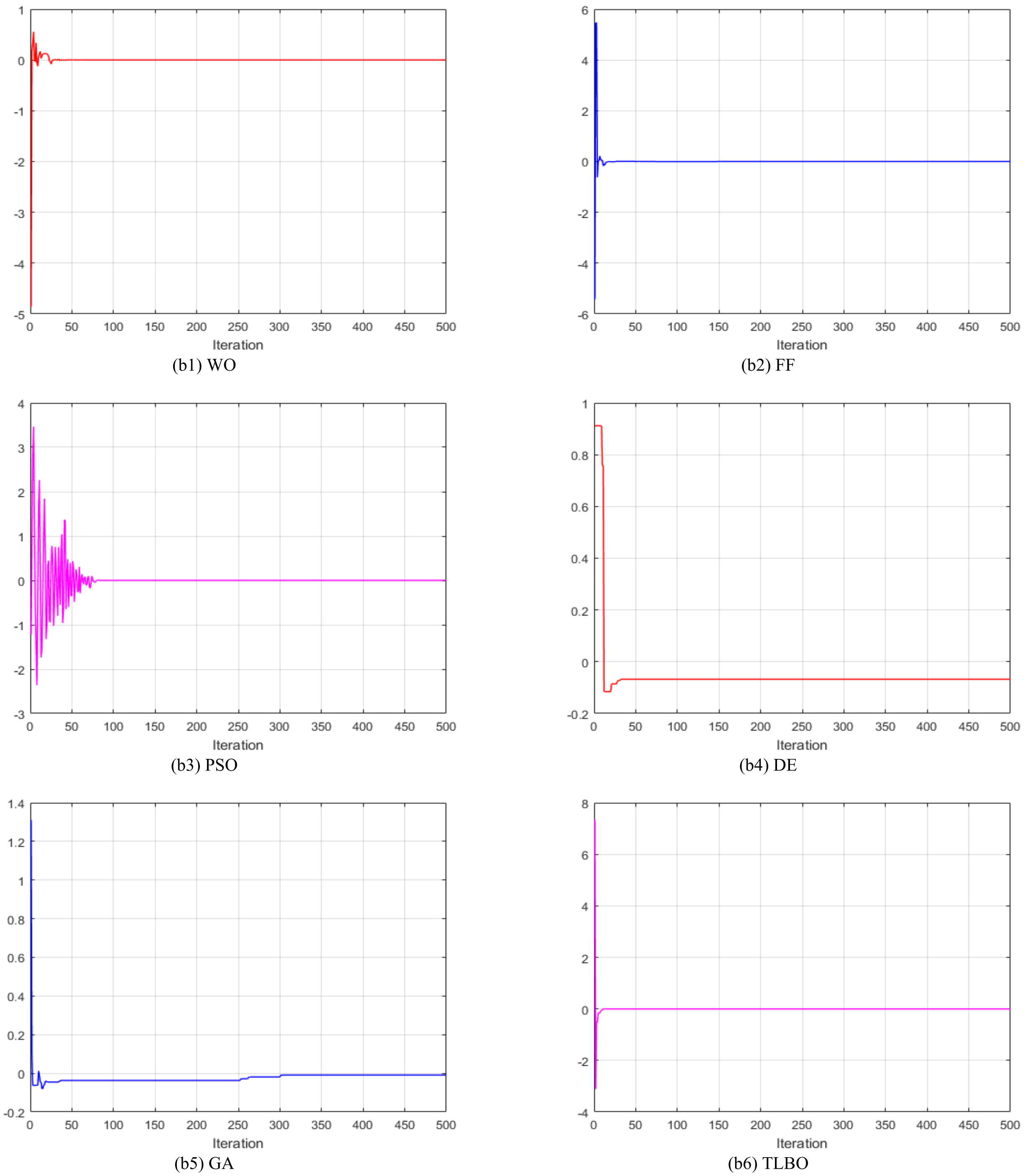


FIGURE 5(A2). **Trajectory of F2 (b1-b6) for different algorithm. (b1) WO. (b2) FF. (b3) PSO. (b4) DE. (b5) GA. (b6) TLBO.**

functions (F1, F2, F8 and F9) under two categories (uni-modal and multi modal). To increase the clarity and understandability of the convergence of different algorithms, two different types of convergence graphs are generated: the first, normal plot of fitness value with respect to the number of iterations; the second, semi-log of fitness with respect to the number of iterations. From Figs. 3(A-a1), 3(A-a2), 3(A-b1), 3(A-b2), 3(B-d1) and 3(B-d2), it is clear that the fastest convergence of F1, F2 and F9 is provided by the TLBO algorithm, which is followed by the WO algorithm. Similarly, from Figs. 3 (B-c1) and 3 (B-c2), it is clear that the fastest convergence of F8 is obtained by the TLBO algorithm, which is followed by the DE algorithm.

Fig. 4(a) to 4(d) represents the comparison of average fitness value for different algorithms on four standard functions (F1, F2, F8 and F9) under two categories (uni-modal and

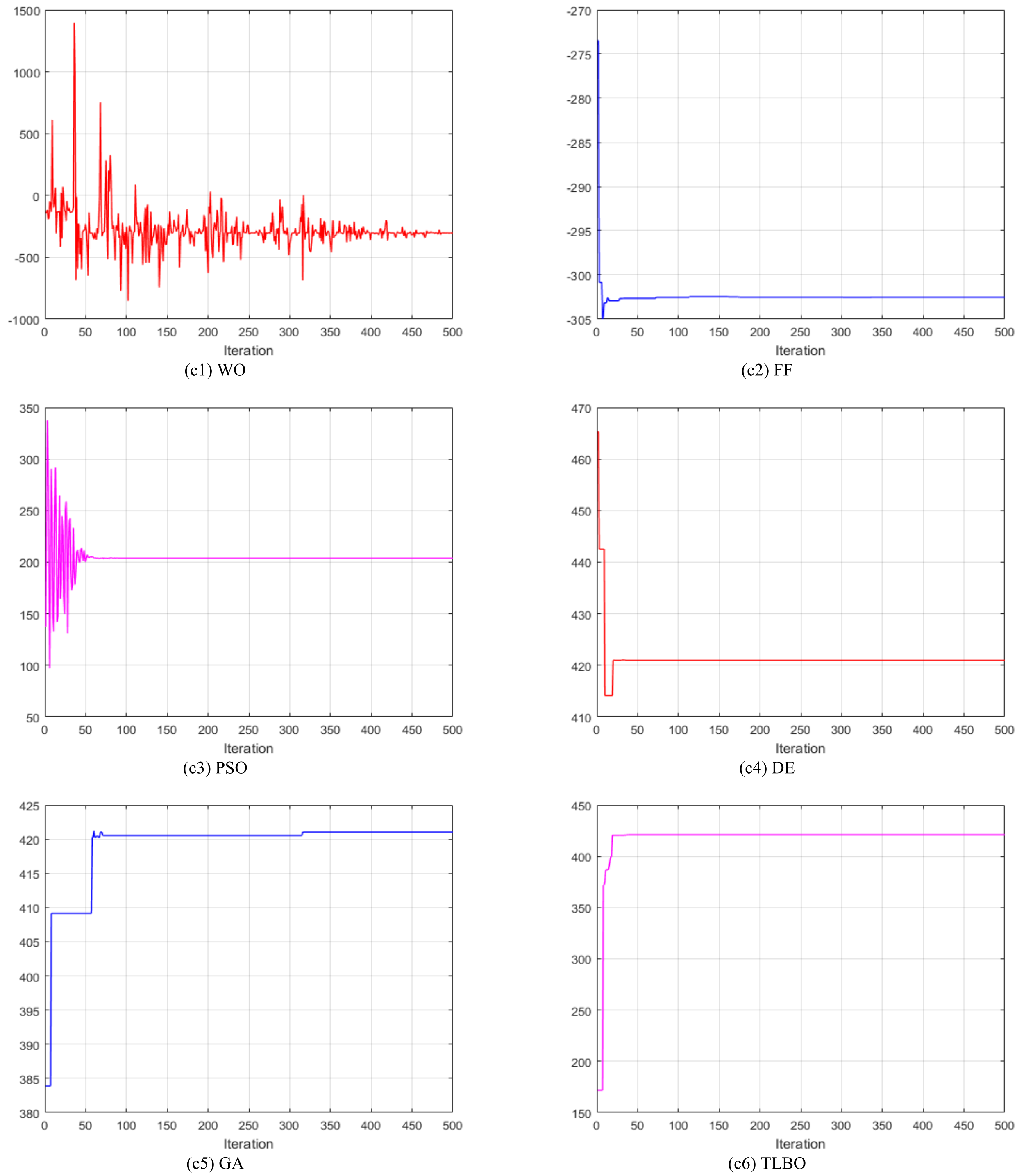


FIGURE 5(B1). Trajectory of F8 (c1-c6) for different algorithm. (c1) WO. (c2) FF. (c3) PSO. (c4) DE. (c5) GA. (c6) TLBO.

multi modal). To show the comparative analysis among the average fitness value of four functions (F1, F2, F8 and F9) with respect to the number of iterations for six algorithms, five search agents are considered. From Figs. 4(a) and 4(d), it is apparent that the minimum average value for F1 and F9 is provided by the TLBO algorithm, which is followed by the FF algorithm. This reflects that all the search agents of TLBO as well as FF are competent to search the optimal search space rather than other algorithms. Similarly, from Fig. 4(b) the minimum average fitness value for function F2 is obtained by the PSO algorithm, which is followed by FF algorithm. This reflects that all the search agents of PSO as well as

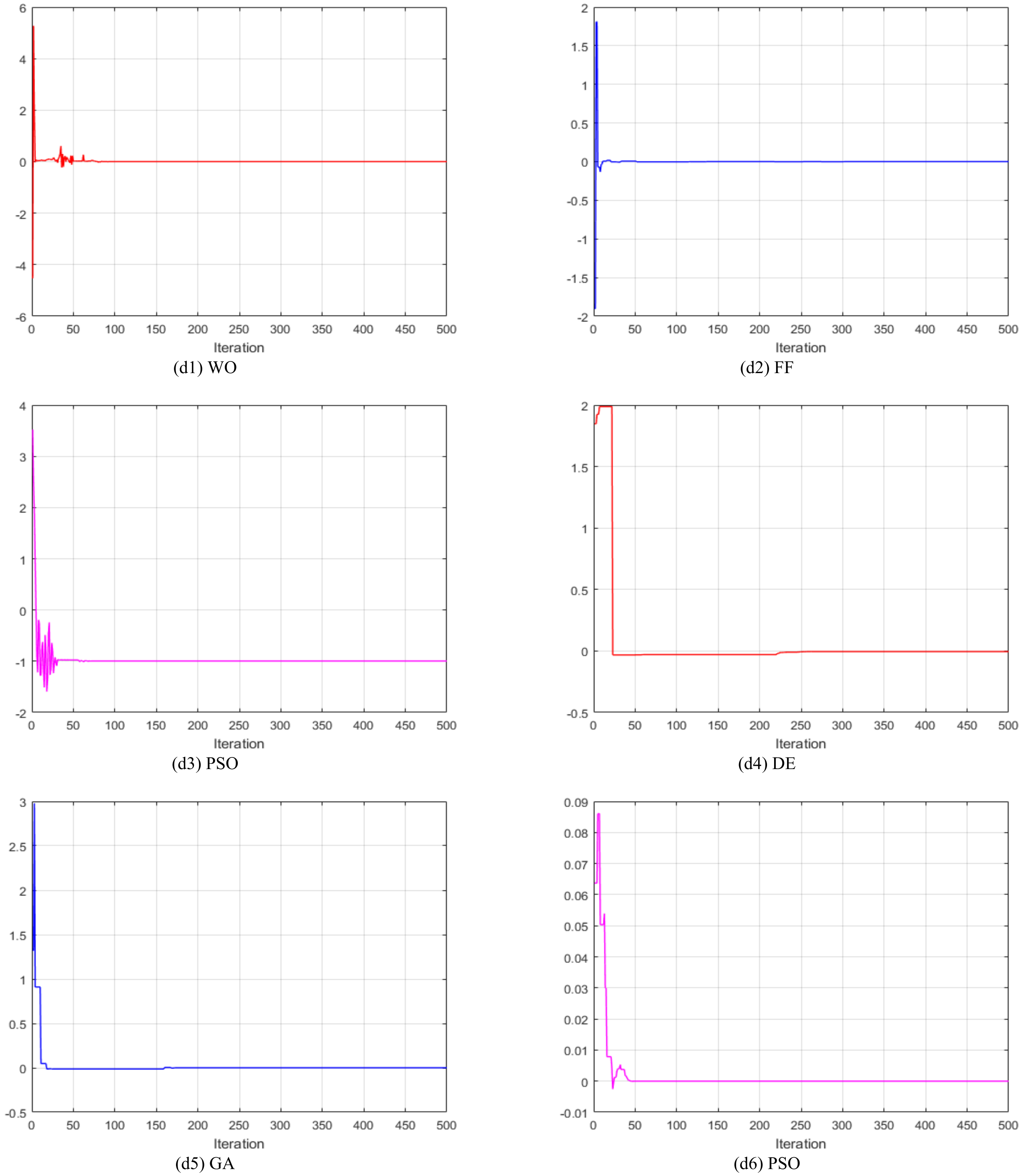
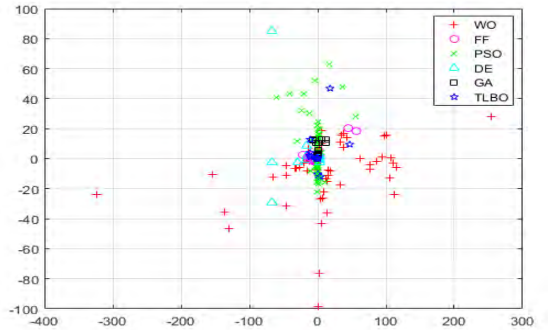


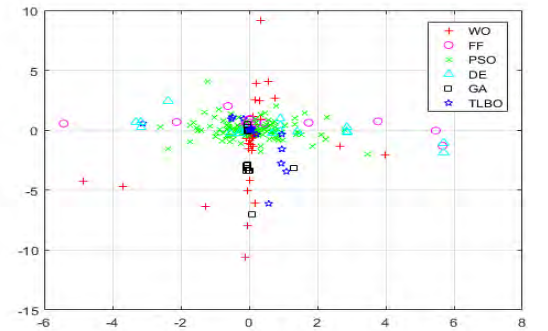
FIGURE 5(B2). **Trajectory of F9 (d1-d6) for different algorithm. (d1) WO. (d2) FF. (d3) PSO. (d4) DE. (d5) GA. (d6) PSO.**

FF are capable to search the optimal search space rather than other algorithms. Similarly, for F8, Fig.4(c) presents the minimum average fitness value obtained by the TLBO, which is followed by the DE. This reflects that all the search agents of TLBO as well as DE are capable to search the optimal search space rather than other algorithms. It is concluded from the above analysis that all the search agents of TLBO are best capable to explore the optimal search space.

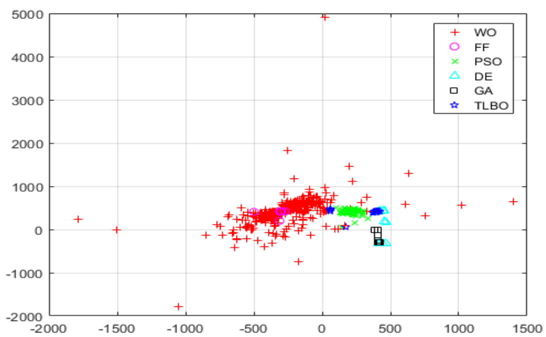
Fig. 5(A1), 5(A2), 5(B1) and 5(B2) provides the comparison among six algorithms based on the trajectory of the first search agent, which is obtained by using standard benchmark function F1, F2, F8 and F9. Sub graphs (a1) to (a6) of



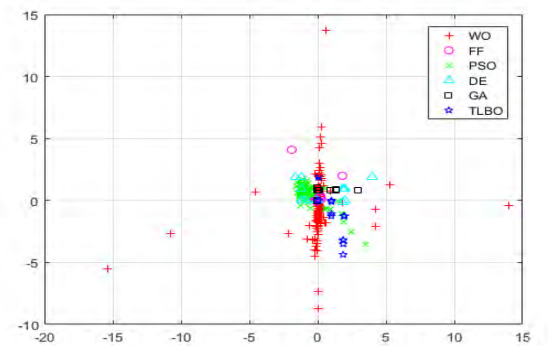
(a) F1



(b) F2



(c) F8



(d) F9

FIGURE 6. Search Space history of first two agents for different algorithms. (a) F1. (b) F2. (c) F8. (d) F9.

Fig. 5(A1) and (b1) to (b6) of Fig. 5(A2) provides the efforts made by the first search agents of six search algorithms for F1 and F2. Similarly, sub graphs, (c1) to (c6) of Fig. 5(B1)

TABLE 5. Case II.

ALGORITHM NAME	RESULT CRITERIA	POPULATION SIZE			
		25	50	100	200
WO	AVG	2148.452	2138.521	2118.811	2111.898
	BEST	2114.415	2112.901	2098.861	2103.331
	WORST	2164.356	2164.356	2131.201	2112.901
	STD DEV	18.28651	25.61983	10.8966	2.855636
FF	AVG	1684.281	1611.481	1566.495	1513.902
	BEST	**1625.751**	**1590.586**	**1501.22**	**1502.00**
	WORST	1737.844	1657.686	1597.962	1555.111
	STD DEV	48.40549	23.43579	32.86659	17.7379
PSO	AVG	1859.08	1815.539	1755.705	1738.688
	BEST	1774.527	1762.98	1712.208	1609.353
	WORST	1978.663	1916.539	1818.515	1843.296
	STD DEV	62.08434	44.70922	26.37133	52.67522
DE	AVG	1692.248	1689.152	1718.008	1744.151
	BEST	1640.878	1631.78	1672.833	1721.302
	WORST	1733.647	1748.117	1752.595	1824.784
	STD DEV	25.93265	41.02138	22.51057	31.38304
GA	AVG	1928.792	1854.813	1804.834	1772.96
	BEST	1885.948	1769.807	1738.579	1665.428
	WORST	1968.639	1945.736	1855.596	1844.432
	STD DEV	25.36623	46.44801	32.4359	58.08054
TLBO	AVG	1826.229	1774.724	1726.649	1687.12
	BEST	1768.313	1695.442	1597.565	1580.295
	WORST	1980.203	1913.987	1854.628	1766.095
	STD DEV	68.26358	80.37166	65.30852	47.52199

and (d1) to (d6) of Fig. 5(B2) present the efforts made by the first search agents of six search algorithms for F8 and F9. The Trajectory is the fitness value of the first search agents with respect to the number of iterations for any algorithm. The analysis of Fig. 5(A1), 5(A2), 5(B1) and 5(B2) is as follows:

- For F1 and F8, the effort made by the first search agent of WO is the maximum and TLBO is the minimum
- For F2, the effort made by the first search agent of PSO is the maximum and TLBO is the minimum
- For F9, the effort made by the first search agent of PSO is the maximum and FF is the minimum

It is observed from the above analysis that the overall effort made by the first search agent of TLBO is least.

One more important comparative analysis based on the search space history of different algorithms for four standard functions (F1, F2, F8 and F9) is presented in Fig. 6. From the sub Figures (a) to (d) of Fig. 6, it is observed that the exploration capability of WO is the best whereas of GA is the worst. Therefore, it is concluded that WO explores a wide range of search space and do not get stuck in the local minima, whereas GA explores the least range of search space and easily get stuck in the local minima.

TABLE 6. Characteristics of selected meta- heuristic algorithms.

MEASURES	FF	GA	WO	PSO	TLBO	DE
Input Parameters	• Variation of attractiveness • Distance between two files. step size • Light absorption coefficient	• Crossover rate • Mutation rate • Population size	• Population size • Number of generations	• Population size • Velocity of each particle and maximum change • Learning factors, • Inertia weight • position of the best and current particle	• Population size • Number of generations	• upper bound of scaling factor • lower bound of scaling factor • cross over probability
Convergence Rate	Fast	Fast	Very Fast	Rapid but less than GA	Fast	Average
Intensification and Diversification Component	• Attraction • Mutation • Mutation coefficient damping	• Crossover • Mutation • Natural selection	• Search of pray • Bubble-net attacking	• Local search • fitness	• Teacher phase • Learner phase • Learner's result	• Scaling • Cross over • Mutation • Natural selection
Pros	• Less complex and easy to implement • automatic subdivision • able to deal with multimodality • tuned to control the randomness • Deal with non-linear, problems • Good initial solution is not required	• Suitable for solving various type of optimization problems • Provide globally best solution in most of the problems • Easy to integrate with different techniques • Easy to drive for real and binary search space	• High exploration ability due to position updating algorithm • High local optima avoidance • High convergence speed	• Simple organization • Implementation is easy • Quick performance • Adjustment is require to few parameters • Global search approach is efficient • Dependency on initial points is very small	• Requires only the common control parameters (population and generations) • Algorithm-specific control parameters are not require • Easy to implemented • Simple structure	• More stable • Easily applicable on wide variety of real valued problems despite noisy, multi-modal, multi-dimensional space
Cons	• Computational efforts are increased greatly if tuning of algorithm-specific parameters are improper • High dependency of algorithm-specific parameters leads to local optimal solution • Complexity for combinatorial optimisation • Higher execution time	• For selection and cross over it uses complex operators • Results are unpredicted • Convergence rate are premature • Trapped into local optima • Run-time is long • Local search is weak • Difficult encoding scheme • Slow convergence rate • Finding sub-optimal solution • Stability and convergence depends on crossover and mutation rates	• At large number of variables and higher constraints get trapped in a local optimum	• Convergence rate is slow • Problem in selecting Parameter • High probability to trap in a local optima • For complex multimodal problems poor exploration characteristic • Once trapped into local optima it is difficult to come out from this situation • Weak local search	• For finding optimal solution, search is not efficient in large space	• Highly dependent on tuning of the algorithm-specific parameters • High dependency of algorithm-specific parameters leads to local optimal solution • a greater degree of computational complexity for combinatorial problems
Applications	• Digital image processing and compression • Fault detection and feature selection • Trail neural network • Semantic Web Composition • Classification and Clustering • Rigid Image Registration Problems • Parameter Optimization of SVM	• Scheduling • Chemical Engineering and Chemistry • Medicine, Image Processing • Data Analysis and Mining • Physics and Geometry • Finance and Economics • Communication and Networking • Electrical Engineering	• structural engineering • thermal engineering • constrained mechanical design optimization • Scheduling • Cost reduction	• Machine Learning • Function Optimization • Geometry and Physics • Operations Research • Chemistry, Chemical Engineering, • Electrical Engineering and Circuit Design	• Digital signal processing • constrained mechanical design optimization problems • thermal engineering • civil engineering, structural engineering, • computer engineering • physics, biotechnology • economics	• Engineering, Structural Optimization, and Design • Chemistry, Chemical Engineering • Scheduling, • Function Optimization, Electrical Engineering and Circuit Design

From the observations of Figs. 3–6 it is concluded that:

- It is observed from the analysis of Fig. 3 that fastest convergence for most of the standard function is obtained by the TLBO
- It is clear from the analysis of Fig. 4 that all the search agents of TLBO are best capable to explore the optimal search space
- It is derived from the analysis of Fig. 5 that the effort made by the first search agent of TLBO is least
- As per the observation of Fig. 6, WO explores a wide range of search space than other algorithms.

On the basis of the above aggregation it is concluded that the performance of TLBO is the best in most of the cases among the selected six meta-heuristic techniques.

Apart from the comparison on different standard functions, another comparison is made on EOSMG problem under four different population sizes i.e. 25, 50, 100 and 200. For this comparative analysis, a SMG cost minimization problem is proposed and different algorithms are applied on this problem under two different cases. For the first case, all the batteries are connected to the system at no charge condition. In this case, these batteries are connected as loads to the micro grid. The Second case considered all connected batteries in charged condition. Hence all batteries worked as energy sources.

Case 1: For case one, the results are summarized in Table 4. From the results it is extracted that on most of the population sizes, i.e. 25, 50 and 100, FF algorithm provided the best results, while on the population size of 200, TLBO computed the best results. Table 4 presents a comparison among the results obtained by different techniques for EOSMG under four criteria, i.e. average value, the best value, the worst value and standard deviation. From the results it is clear that at population size 25, 50 and 100, FF algorithm provides the best values i.e. 1310.512, 1255.266 and 1243.399 €ct/day, respectively, while at population size 200, TLBO generates the optimum solution (1262.903 €ct/day). By comparing the results obtained for standard test functions and EOSMG, one can observe that on standard functions WO and/or TLBO compute the best results, but for the complex optimization problem (EOSMG) with a large number of variables and constraints rather than WO and TLBO, FF gives the most optimum results.

Fig. 7(A) presents the comparison of convergence characteristics of different algorithms for the EOSMG problem under case 1. From the sub Figures (a), (b), (c) and (d) of

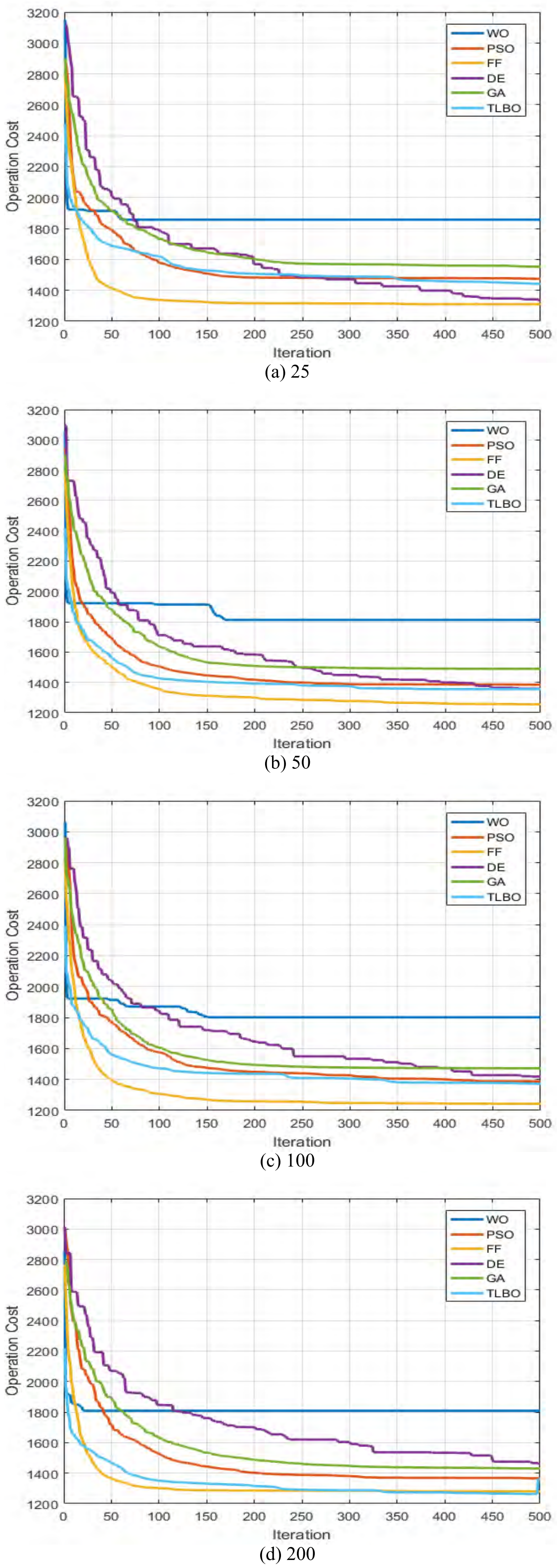


FIGURE 7(A). **Convergence curves for case 1 at various population sizes. (a) 25. (b) 50. (c) 100. (d) 200.**

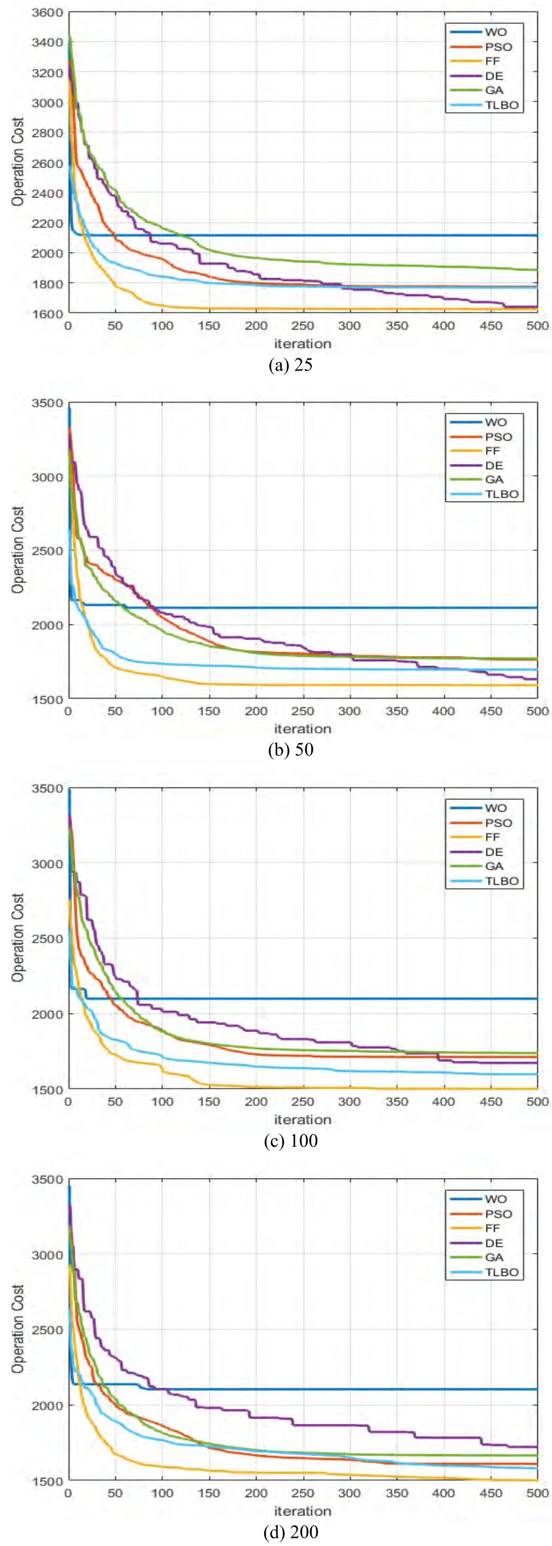


FIGURE 7(B). **Convergence curves for case 2 at various population sizes. (a) 25. (b) 50. (c) 100. (d) 200.**

Fig. 7(A), the analysis made from the convergence sub graphs at different population sizes (25, 50, 100 and 200) are as follows:

- For the population size 25, the convergence of FF and TLBO is better than the other algorithms
- For the population sizes 50 and 100, the convergence of FF and GA is better than the other algorithms

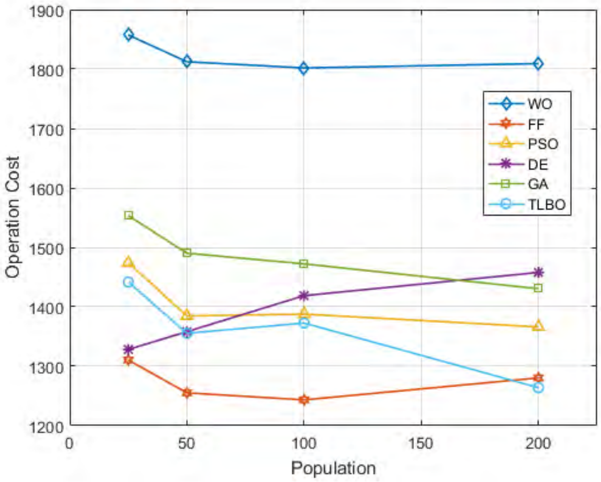


FIGURE 8(A). Variation of best cost with respect to population for case 1.

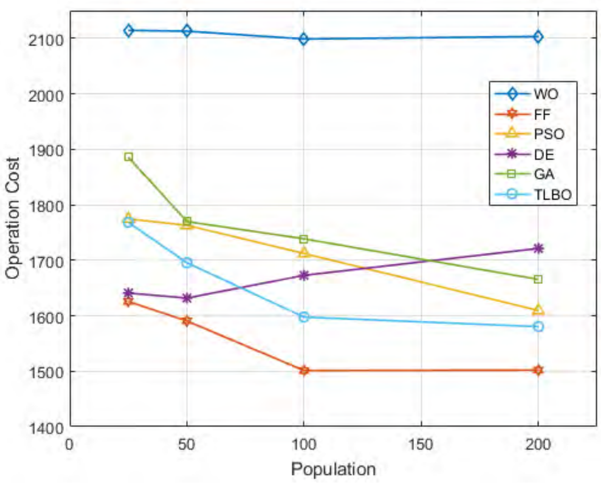


FIGURE 8(B). Variation of best cost with respect to population for case 2.

- For the population size 200, the convergence of WO and TLBO is better than the other algorithms

From the above analysis it is concluded that under case 1 i.e. charging mode of batteries, the convergence of FF is faster than other algorithms for the different population sizes.

A critical comparative analysis based on the increment in population size is presented in Fig. 8(A). By the observation of graph in Fig. 8(A), it is clear that with the increment in population size, the performance of DE is imparted while the performance of GA is improved. For WO and FF, the performance is improved for increment in the population size from 25 to 100, but it deteriorates at 200. The performances of PSO and TLBO are unstable with an increase in population size.

Fig. 9(A) summarizes the power generation by different energy sources for six algorithms, under the first case. Further power output for different population sizes i.e. 25, 50, 100 and 200 are presented by the sub graphs (a) to (f) of Fig. 9(A). The positive value of graphs shows the power production while the negative value presents the power consumption. According to Fig. 9(A) and 9(B), an opportunity is available for BES, BEV and PHEV that they economically stores energy by purchasing power from the power grid and then

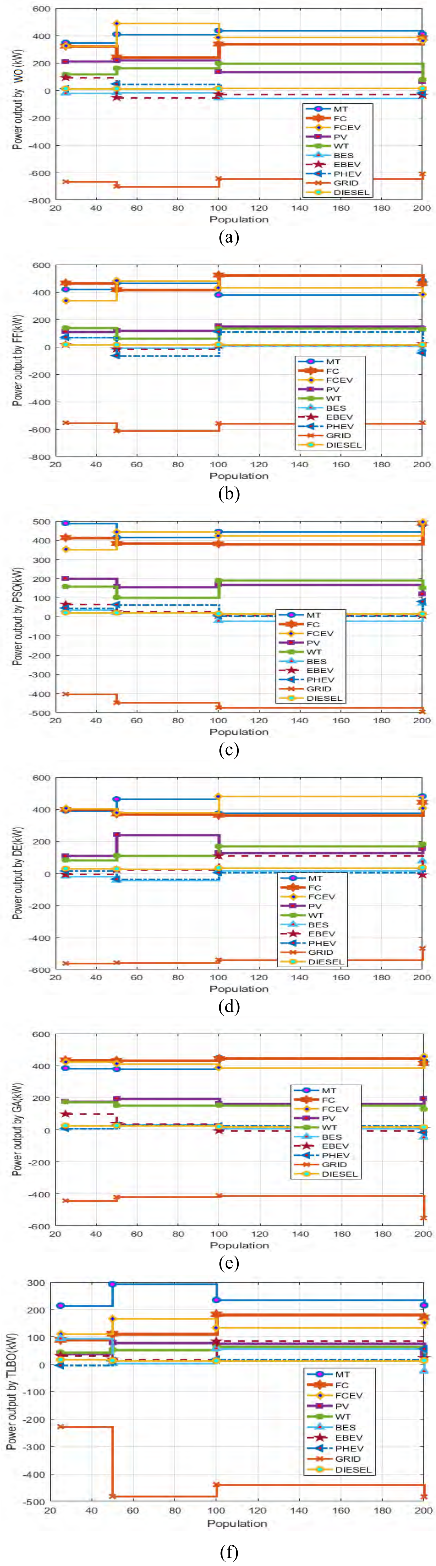


FIGURE 9(A). Optimal power output for case 1.

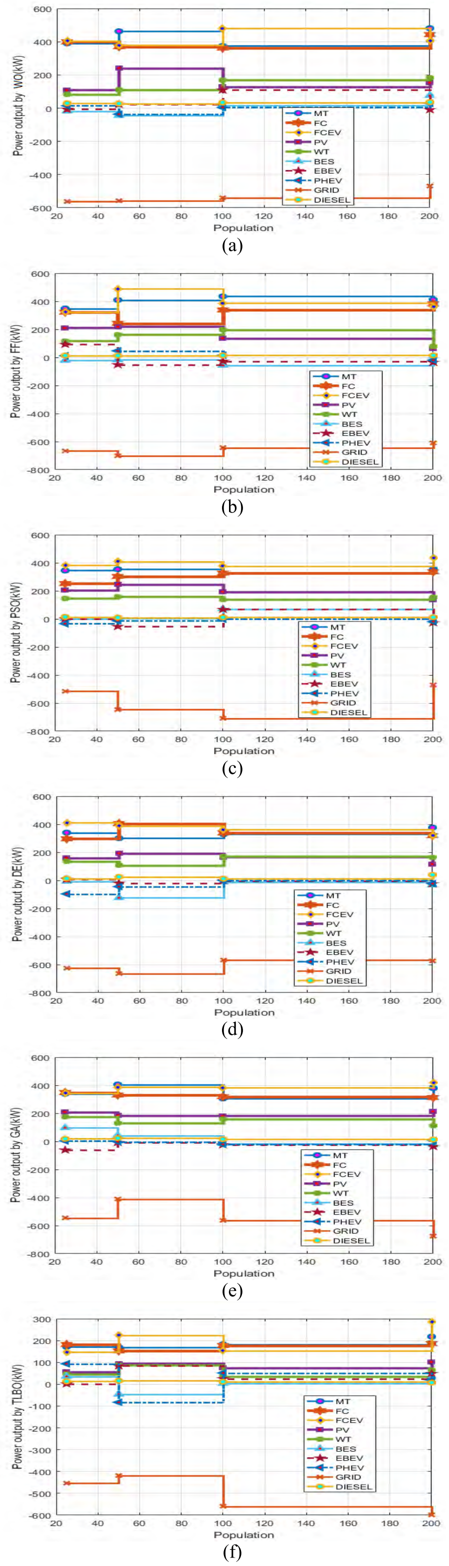


FIGURE 9(B). Optimal power output for case 2.

selling that power back into the power grid during the peak load demand.

In Fig. 9(A) and 9(B), negative value reflects the consumption of power, whereas positive value shows the generation of power.

As per the observation of Fig. 9(A), under all the meta-heuristic algorithms, the renewable energy sources along with fuel cell technology (FC and FCEV) generate electric power and supply back to the grid. Further, batteries used in BES, BEV and PHEV are storing energy in this case (negative sign of power). In case 1, FF provides the minimum cost for micro-grid operation, therefore the generation by different energy sources computed by FF algorithm is optimal generation. Hence for the population of 25, 50, 100 and 200 the optimal generations are 1092.57, 864.6112, 1207.583, and 1009.798 MW with respect to the optimal costs 1310.512, 1255.266, 1243.399, and 1280.419 €ct/day.

Case 2: In the second case, it is assumed that all batteries are in charged condition and will ready to supply electricity to the grid. Table 5 presents a comparison among the results obtained by different techniques for EOSMG under four criteria. From the results, it is clear that at population size 25, 50, 100 and 200, FF algorithm provides the optimal costs i.e. 1625.751, 1590.586, 1501.22 and 1502.0 €ct/day, respectively.

By comparing the results obtained for standard test functions and EOSMG, it is observed that on standard functions WO and/or TLBO compute the best results, but for the complex optimization problem with a large number of variables and constraints rather than WO and TLBO, FF gives the most optimum results.

Fig. 7(B) presents the comparison of the convergence characteristics of different algorithms for the EOSMG problem under case 2. From the sub Figures (a), (b), (c) and (d) of Fig. 7(B), for the population sizes of 25, 50, 100 and 200, the analysis made from the convergence sub graphs are as follows:

- For population sizes 25, 50 and 100, the convergence of WO and FF is better than the other algorithms
- For population size 200, the convergence of WO and GA is better than the other algorithms

From the above analysis it is concluded that under case 2, i.e. the discharging mode of batteries, the convergence of WO and FF is faster than other algorithms for the different population sizes.

A comparative cost variation analysis with respect to population size among different methods is presented in Fig. 8(B). From Fig. 8(B), it is clear that with the increment in population size, the performances of PSO, GA and TLBO are improved, while for WO and FF, the performance is improved from 25 to 100, but deteriorates at 200. The performance of DE is unstable with an increase in population size.

Fig. 9(B) summarizes power generation by the different energy sources for six algorithms, under the second case. Further, power output for different population sizes i.e. 25, 50, 100 and 200 are presented by the sub graphs (a) to (f) of Fig.9(B). From Fig. 9(B), it is clear that all renewable energy sources along with FC technology generate power. Additionally, batteries supply back energy to the gird with positive sign of power. Also in case 2, FF provides the minimum cost for micro-grid operation, therefore the generation by different energy sources computed by FF algorithm is optimal generation. Hence for the population of 25, 50, 100 and 200, the optimal generations are 751.931, 812.585, 769.386, and 654.67 MW with respect to the optimal costs 1625.751, 1590.586, 1501.22, and 1502.00 €ct/day.

Apart from analytical analysis, Table 6 provides the theoretical comparison of different properties of six meta–heuristic techniques. This comparison is based on different factors such as input parameters, convergence, intensification and diversification component, advantages, drawbacks and applications.

VII. CONCLUSION

Currently, there is a continuously increasing demand of electrical energy. Therefore, along with conventional energy sources, the renewable energy sources have also been integrated in the system to fulfill the electrical energy demand. Micro-gird technology provides a platform to integrate all types of renewable and non-conventional energy sources. For the efficient utilization of MG technology, the economic operation and control problem of micro-grid should be optimized. Due to a large availability of optimization techniques, the selection process of appropriate technique is cumbersome.

A comprehensive analysis of optimal economic operation and control problem of SMG using different meta-heuristics techniques (WO, PSO, FF, DE, GA and TLBO) is performed to select an appropriate optimization technique.

To analyze available meta-heuristic techniques, nineteen standard test functions under three different categories, i.e. uni-modal, multi model and composite, are selected. Additionally, a smart micro-grid system with MT, FC, PV, WT, BES, EVTs and Diesel Generator is proposed to show the comparison of an EOSMG problem. Optimization methods from three different categories (SI, EA and TL) are compared on different performance parameters to show their effectiveness. Two different comparisons are presented, the first, for standard functions and the second, for a developed problem. Individual source generations are also provided.

The percentage of minimum mean values of fitness, for different nineteen standard functions, obtained by the WO, FF, PSO, DE, GA and TLBO are 21.05, 5.26, 0, 36.84, 5.26 and 36.84 respectively. The percentage of minimum standard deviation of fitness, for different nineteen standard functions, obtained by the WO, FF, PSO, DE, GA and TLBO are 5.26, 5.26, 0, 47.36, 15.78 and 31.57 respectively. It is clear from the comparison of mean value, standard deviation, percentage of minimum mean values and standard deviation of fitness for different standard functions that the performance of TLBO and DE is better and stable with respect to other algorithms.

As per the convergence characteristic's analysis of different algorithms, it is observed that TLBO technique has the fastest convergence. All the search agents of TLBO are best capable to explore the optimal search space. It is observed that WO explores a wide range of search space and easily get stuck in the local minima. It is concluded from the analysis of different algorithms on various standard functions that the overall performance of TLBO is better than the other algorithms.

Further, the comparisons of different algorithms for two separate cases of developed EOSMG optimization problem framework are presented.

For case 1, at population sizes 25, 50 and 100, FF algorithm provides the best values i.e. 1310.512, 1255.266 and 1243.399 €ct/day, respectively, while at population size 200, TLBO generates the optimum solution (1262.903 €ct/day). The convergence of FF is faster than other algorithms for the different population sizes. It is observed that with the increment in population size, the performance of DE is impairing while the performance of GA is improving. For WO and FF, the performance is improved for increment in the population size from 25 to 100, but it deteriorates at 200. The performances of PSO and TLBO are unstable with an increase in population size.

For case2, at population sizes 25, 50, 100 and 200, FF algorithm provides the best values i.e. 1625.751, 1590.586, 1501.22 and 1502.0 €ct/day, respectively. The convergence of WO and FF is faster than other algorithms for the different population sizes. It is clear that with the increment in population size, the performances of PSO, GA and TLBO are improving, while for WO and FF the performance are improved from 25 to 100, but it deteriorates at 200. The performance of DE is unstable with an increase in population size.

The comparison of different algorithms for two separate cases of developed EOSMG optimization problem

TABLE 7. Constraints limit and Bids of the DGs, Utility, BES, Dig and EVTs.

Type	Min. Power (kW)	Max. Power (kW)	Bid (€ct/kW h)	OM (€ct/kW h)	Start-up (€ct)
MT	6	30	0.457	0.0446	0.96
FC	3	30	0.294	0.08618	1.65
FCEV	3	30	0.294	0.08618	1.65
PV	0	25	2.584	0.2082	0
WT	0	15	1.073	0.5250	0
BES	-30	30	0.380	-	0
BEV	-30	30	0.380	-	0
PHEV	-30	30	0.380	-	0
Grid	-30	30	-	-	-
DiG	0	20	-	-	-

TABLE 8(A). Uni-modal benchmark functions.

Functions	Range	f_{min}
$F_1(x) = \sum_{i=1}^{n} x_1^2$	[-100, 100]	0
$F_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} x_i$	[-10, 10]	0
$F_3(x) = \sum_{i=1}^{n} (\sum_{j-1}^{i} x_j)^2$	[-100, 100]	0
$F_4(x) = \max_i\{\lvert x_i \rvert, 1 \le i \le n\}$	[-100, 100]	0
$F_5(x)=\sum_{i=1}^{n-1} [100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	[-30, 30]	0
$F_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	[-100, 100]	0
$F_7(x)=\sum_{i=1}^{n} ix_1^4 +\text{random}[0, 1)$	[-1.28, 1.28]	0

TABLE 8(B). Composite benchmark functions.

Functions	Range	f_{min}
$F_{14}(CF1)$: $f_1, f_2, f_3, \dots, f_{10} = Sphere\ Function$ $[\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_{10}] = [1,1,1,\dots,1]$ $[\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_{10}] =$ $[{}^5/_{100}, {}^5/_{100}, {}^5/_{100}, \dots, {}^5/_{100}]$	[-5, 5]	0
$F_{15}(CF2)$: $f_1, f_2, f_3, \dots, f_{10} = Griewank's\ Function$ $[\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_{10}] = [1,1,1,\dots,1]$ $[\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_{10}] =$ $[{}^5/_{100}, {}^5/_{100}, {}^5/_{100}, \dots, {}^5/_{100}$	[-5, 5]	0
$F_{16}(CF3)$: $f_1, f_2, f_3, \dots, f_{10} = Griewank's\ Function$ $[\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_{10}] = [1,1,1,\dots,1]$ $[\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_{10}] = [1,1,1,\dots,1]$	[-5, 5]	0
$F_{17}(CF4)$: $f_1, f_2 = Ackley'sFunction$ $f_3, f_4 = Rastrigin's\ Function$ $f_5, f_6 = Weierstrass\ Function$ $f_7, f_8 = Griewank's\ Function$ $f_9, f_{10} = Sphere\ Function$ $[\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_{10}] = [1,1,1,\dots,1]$ $[\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_{10}] =$ $[{}^5/_{32}, {}^5/_{32}, 1, 1, {}^5/_{0.5}, {}^5/_{0.5},$ ${}^5/_{100}, {}^5/_{100}, {}^5/_{100}, {}^5/_{100}]$	[-5,	0
$F_{18}(CF5)$: $f_1, f_2 = Rastrigin's\ Function$ $f_3, f_4 = Weierstrass\ Function$ $f_5, f_6 = Griewank's\ Function$ $f_7, f_8 = Ackley's\ Function$ $f_9, f_{10} = Sphere\ Function$ $[\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_{10}] = [1,1,1,\dots,1]$ $[\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_{10}] =$ $[{}^1/_5, {}^1/_5, {}^5/_{0.5}, {}^5/_{0.5}, {}^5/_{100},$ ${}^5/_{100}, {}^5/_{32}, {}^5/_{32}, {}^5/_{100}, {}^5/_{100}]$	[-5, 5]	0
$F_{19}(CF6)$: $f_1, f_2 = Rastrigin's\ Function$ $f_3, f_4 = Weierstrass\ Function$ $f_5, f_6 = Griewank's\ Function$ $f_7, f_8 = Ackley's\ Function$ $f_9, f_{10} = Sphere\ Function$ $[\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_{10}] =$ $[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1]$ $[\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_{10}] =$ $[0.1 * {}^1/_5, 0.2 * {}^1/_5, 0.3 * {}^5/_{0.5},$ $0.4 * {}^5/_{0.5}, 0.5 * {}^5/_{100}, 0.6 * {}^5/_{100},$ $0.7 * {}^5/_{32}, 0.8 * {}^5/_{32}, 0.9 * {}^5/_{100},$ $1 * {}^5/_{100}]$	[-5, 5]	0

framework reflects that the performance of FF is superior to other methods. It is concluded that algorithms of swarm intelligence category are better fitted to solve such cost minimization problems.

TABLE 8(C). Multimodal benchmark functions.

Functions	Range	f_{min}
$F_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{x_i})$	[-500, 500]	-1.68E+3
$F_9(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10]$	[-5.12, 5.12]	0
$F_{10}(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	[-32, 32]	0
$F_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[-600, 600]	0
$F_{12}(x) = \frac{\pi}{n}\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] + (y_n - 1)^2\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	[-50, 50]	0
$F_{13}(x) = 0.1\{\sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2[1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	[-50, 50]	0

This work will help researchers to select an appropriate optimization method to solve MG cost minimization problems with constraints. This study may also be helpful for the commercial utilization of MG. In addition to this other optimization techniques may also be considered for further study. The futuristic enhancement of the current work may be to develop an algorithm which can provide better results on both standard as well as practical formulations. There is an open problem to formulate such a standard function which can help to select a suitable optimization method for cost minimization problems.

APPENDIX A

Constraints limits used in this study are shown in Table 7.

APPENDIX B

Standard functions used in this study are shown in Table 8(A)–(c).

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