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Enhanced Velocity Differential Evolutionary Particle Swarm Optimization for Optimal Scheduling of a Distributed Energy Resources With Uncertain Scenarios

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ABSTRACT In the MicroGrid environment, the high penetration of uncertain energy sources such as solar Photovoltaics (PVs), Energy Storage Systems (ESSs), Demand Response (DR) programs, Vehicles to Grid (V2G or G2V) and Electricity Markets make the Energy Resource Management (ERM) problem highly complex. All such complexities should be addressed while maximizing income and minimizing the total operating costs of aggregators that accumulate all types of available energy resources from the MicroGrid system. Due to the presence of mixed-integer, discrete variables and non-linear network constraints, it is sometimes very difficult to solve such problem using traditional optimization methods. This paper proposes a new metaheuristic optimization technique entitled the ''Enhanced Velocity Differential Evolutionary Particle Swarm Optimization'' (EVDEPSO) algorithm to tackle the ERM problem. Its key feature is the updation of the Velocity by the terms named as Enhanced Velocity, Cooperation and Stochastic Uni-Random Distribution and position by the term Deceleration Factor. The performance of the proposed method is measured by a case study comprises of 100 scenarios of a 25-bus MicroGrid with high penetration of aforementioned energy sources. IEEE Computational Intelligence Society organized the competition on the above mentioned problem, in which EVDEPSO secured a second rank. The results of EVDEPSO are compared with the competition participated optimization algorithms. It also compared with well-known optimization algorithms such as Variable Neighborhood Search and Differential Evolutionary Particle Swarm Optimization. The comparison results show that the performance of EVDEPSO is superior in terms of the Ranking Index (R.I) and Average Ranking Index (A.R.I) as compared to the aforementioned algorithms. For effective comparative analysis of algorithms, standard statistical test named as One-Way ANOVA and Tukey Test is used. The results of this test also prove the effectiveness of EVDEPSO algorithm as compared to all tested algorithms.

INDEX TERMS Enhanced velocity differential evolutionary particle swarm optimization, distributed energy resource management, smart grid, electric vehicles, demand response, electricity market, energy storage.

SYMBOLS

SYMBOLS	**Description**
DiG	Conventional DG units
Sup	External power suppliers
Solar	Solar Generation (PV) units
ST	Energy Storage Systems (ESSs)
Ev	Electric vehicles(Ev)
Ms	Electricity Markets
LD	Load
SE	Scenario
T	Total number of periods
t	Time slot
O.C	Operation cost of aggregator (m.u.)
$Minimize\_f$	Minimize Objective function (m.u.)
Income	Income of aggregator (m.u.)
N_B	Total buses
N_{SE}	Total Scenarios
N_P	Total Population
$N_{iteration}$	Total Iterations
N_{DiG}	Total DG units
N^i_{DiG}	Total connected DG units to bus i
N_{Solar}	Total PV units

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N^{i}_{Solar} Total connected PV units to bus i
N_{LD} Total loads
N^{i}_{LD} Total loads LD connected to bus i
N_{K} Total lines
N_{ST} Total storage units
N^{i}_{ST} Total storage units ST connected to bus i
N_{Sup} Total external power suppliers
N^{i}_{Sup} Total connected Sup connected to bus i
N_{Ev} Total electric vehicles Evs
N^{i}_{Ev} Total electric vehicles connected to bus i
$\eta_{Cha(Ev)}$ Charge mode Grid-to-Vehicle(G2V) efficiency of Ev
$\eta_{Dis(Ev)}$ Discharge mode Vehicle-to-Grid(V2G) efficiency of Ev
$\eta_{Cha(ST)}$ Storage charge efficiency of ST in charge mode
$\eta_{Dis(ST)}$ Storage discharge efficiency of ST in discharge mode
$C_{DiG(DiG,t)}$ Cost of DiG unit generation in time slot t (m.u./kWh)
$C_{Sup(Sup,t)}$ Cost of Sup generation in time slot t (m.u./kWh)
$C_{Solar(Solar,t)}$ Cost of Solar generation in time slot t (m.u./kWh)
$C_{Dis(ST,t)}$ Discharge cost of ST in time slot t (m.u./kWh)
$C_{Dis(Ev,t)}$ Discharge cost of Ev in time slot t (m.u./kWh)
$C_{GC(DiG,t)}$ Curtail generation power cost of DiG unit in time slot t (m.u./kWh)
$C_{NSLoad(LD,t)}$ Non-supplied cost of LD load in time slot t (m.u./kWh)
$C_{CutDR(LD,t)}$ Demand response curtailment cost of LD load in time slot t (m.u./kWh)
$P^{i}_{Cha(ST,t,SE)}$ Real power storage charge of ST at bus i in time slot t for SE scenario (kW)
$P^{i}_{Cha(Ev,t,SE)}$ Real power storage charge of Ev at bus i in time slot t for SE scenario (kW)
$P_{ChaLimit(ST,t,SE)}$ Maximum real power charge limit of ST in time slot t for SE scenari(kW)
$P_{ChaLimit(Ev,t,SE)}$ Maximum real power charge limit of Ev in time slot t for SE scenario (kW)
$P_{CutLD(LD,t,SE)}$ Demand response real power curtailment of load LD in time slot t for SE scenario (kW)
$P^{i}_{CutLD(LD,t,SE)}$ Demand response real power curtailment of load LD at bus i in time slot t for SE scenario (kW)
$P_{Dis(ST,t,SE)}$ Real power discharge of ST in time slot t for SE scenario (kW)
$P^{i}_{Dis(ST,t,SE)}$ Real power discharge of ST at bus i in time slot t for SE scenario (kW)
$P_{Dis(Ev,t,SE)}$ Real power discharge of Ev in time slot t for SE scenario (kW)
$P^{i}_{Dis(Ev,t,SE)}$ Real power discharge of Ev at bus i in time slot t for SE scenario (kW)
$P_{DisLimit(ST,t,SE)}$ Maximum real power discharge limit of ST in time slot t for SE scenario (kW)
$P_{DisLimit(Ev,t,SE)}$ Maximum real power discharge limit of Ev in time slot t for SE scenario (kW)
$P_{DiG(DiG,t)}$ Generation of real power by DiG unit in time slot t (kW)
$P^{i}_{DiG(DiG,t)}$ Generation of real power by DiG unit at bus i in time slot t (kW)
$P_{Di(t)}$ Demand of real power at bus i in slot t (kW)
$P_{DiGMax(DiG,t)}$ Maximum generation of real power by DiG unit in time slot t (kW)
$P_{DiGMin(DiG,t)}$ Minimum generation of real power by DiG unit in time slot t (kW)
$P_{GC(DiG,t,SE)}$ Generation curtailment power by DiG unit in time slot t for SE scenario (kW)
$P^{i}_{GC(DiG,t,SE)}$ Generation curtailment power by DiG unit at bus in time slot t for SE scenario (kW)
$P_{Gi(t)}$ Generation of real power at bus i in time slot t (kW)
$P^{i}_{Load(LD,t,SE)}$ Load LD demand of real power at bus i in time slot t for SE scenario (kW)
$P_{MaxCutDR(LD,t)}$ Maximum DR curtailment of load LD in time slot t (kW)
$P_{NSLoad(LD,t)}$ Non-supplied demand of real power for load LD in time slot t (kW)
$P^{i}_{NSLoad(LD,t,SE)}$ Non-supplied demand of real power for load LD at bus i in time slot t for SE scenario(kW)
$P_{Sell(Ms,t)}$ Real power sell to market Ms in time slot t (kW)
$P^{i}_{Sell(Ms,t,SE)}$ Real power sell to market Ms at bus i in time slot t for SE scenario (kW)
$P_{Sup(Sup,t)}$ Generation of real power by Sup in time slot t (kW)
$P^{i}_{Sup(Sup,t)}$ Generation of real power by Sup at bus i in time slot t (kW)
$P_{Sup\_MaxLimit(Sup,t)}$ Maximum generation limit of real power of external supplier Sup in time slot t (kW)
$Q_{Sup\_MaxLimit(Sup,t)}$ Maximum generation limit of reactive power of external supplier Sup in time slot t (kVAr)
$Q^{i}_{DiG(DiG,t)}$ Generation of reactive power by DG unit at bus i in time slot t (kVAr)

$Q_{Di(t)}$	Demand of reactive power at bus i in slot t (kVAr)
$Q_{DiGMax(DiG,t)}$	Maximum generation of reactive power by DG unit in time slot t (kVAr)
$Q_{DiGMin(DiG,t)}$	Minimum generation of reactive power by DG unit in time slot t (kVAr)
$Q_{Gi(t)}$	Reactive power generation at bus i in slot t(kVAr)
$Q^{i}_{Load(LD,t,SE)}$	Demand of reactive power of load LD at bus i in time slot t for SE scenario(kVAr)
$Q^{i}_{NSLoad(LD,t,SE)}$	Non-supplied demand of reactive power for load LD at bus i in time slot t for SE scenario(kVAr)
$Q^{i}_{Sup(Sup,t)}$	Reactive power generation of the external supplier Sup at bus i in time slot t (kVAr)
Ap^{max}_{Lk}	Maximum apparent power flow permissible in line k connecting bus i and j (kVA)
$E_{BatCap(ST)}$	Battery capacity of ST (kWh)
$E_{BatCap(Ev)}$	Battery capacity of Ev (kWh)
$E_{MinCha(ST,t,SE)}$	Guaranteed minimum stored energy in storage ST for SE scenario (kWh)
$E_{MinCha(Ev,t,SE)}$	Guaranteed minimum stored energy in Ev for SE scenario at the end of time slot t (kWh)
$E_{Stored(ST,t,SE)}$	Energy stored in ST for SE scenario at the end of time slot t (kWh)
$E_{Stored(Ev,t,SE)}$	Energy stored in Ev for SE scenario at the end of time slot t (kWh)
$E_{Trip(Ev,t,SE)}$	Energy consumption during a tour of the electric vehicle Ev in slot t for SE scenario (kWh)
$\theta_{ij(t,SE)}$	Voltage angle between bus i and j in time slot t for SE scenario (rad)
θ^{max}_{i}	Maximum allowable angle of voltage at bus i in (rad)
θ^{min}_{i}	Minimum allowable angle of voltage at bus i (rad)
B_{ij}	In the admittance matrix, the imaginary part of the element corresponds to row i and column j(S)
G_{ii}	In admittance matrix,the real part of the diagonal element corresponding to row i (S)
G_{ij}	In admittance matrix,the real part of the element corresponding to row i and column j (S)
L^{i}	Line set connected to the bus i
$\overline{U_{i(t,SE)}}$	Voltage phasor at bus i in time slot t for scenario SE (V)
$\overline{U_{j(t,SE)}}$	Voltage phasor at bus j in time slot t for scenario SE (V)
$U_{i(t,SE)}$	Voltage magnitude at bus i in time slot t for scenario SE (V)
$U_{j(t,SE)}$	Voltage magnitude at bus j in time slot t for scenario SE (V)
U^{max}_{i}	Maximum voltage limit at bus i (V)
U^{min}_{i}	Minimum voltage limit at bus i (V)
$X_{Cha(ST,t,SE)}$	Storage unit ST binary variable associated with power charge in time slot t for SE scenario
$X_{Cha(Ev,t,SE)}$	Electric vehicle Ev binary variable associated with power charge in time slot t for SE scenario
$X_{CutDR(LD,t,SE)}$	DR curtailment binary variable of Load LD in time slot t for SE scenario
$X_{Dis(ST,t,SE)}$	Storage unit ST binary variable associated with power discharge in time slot t for SE scenario
$X_{Dis(Ev,t,SE)}$	Electric vehicle Ev binary variable associated with power discharge in time slot t for SE scenario
$X_{DiG(DiG,t,SE)}$	Conventional DG unit DiG binary variable related to connected or disconnected in time slot t for SE scenario
$X_{Solar(Solar,t,SE)}$	Solar binary variable related to connected or disconnected in time slot t for SE scenario
$\overline{Ad_{ij}}$	Series admittance phasor of line that connect bus i and j (S)
$\overline{Ad_{sh\_i}}$	Shunt admittance phasor of line that connected to bus i (S)
$\overline{Ad_{sh\_j}}$	Shunt admittance phasor of line that connected to bus j (S)

I. INTRODUCTION

In a microgrid environment, the increasing penetration of Distributed Energy Resources (DERs), including renewable resources such as photovoltaic, V2G (Vehicle to Grid), Energy Storage Systems (ESSs), Demand Response programs (DR) and the electricity market endanger the operation of the distribution networks due to its excessive fluctuating nature. Consequently, in a real-world microgrid situation, it is important that energy aggregators address the issues arising from uncertainty. However, energy aggregators require powerful models to deal with the growing variety of energy resources and their uncertainty. When essential decisions are to be taken a day in advance to maximize income by minimizing operating expenses, day-to-day energy planning is a major problem in the management of energy resources. However, due to the large number of energy resources and their natural uncertainties, the problem of energy planning becomes very difficult.

The difficulty of DERs management considered in this paper is a massive integrative problem aimed at maximizing aggregator revenue by minimizing the total operating cost of DERs by taking into account the uncertainties related to solar generation, load demand, electric vehicle travel scheduling and market price variations. The integration of the uncertainties transforms the ERM problem into a Mix-integer non-linear problem (MINLP) [1]. This type of problem is very difficult to solve using a deterministic technique, because it may take several hours to determine the optimal scheduling for these huge dimensions and complex problems. In evolutionary computing [2], uncertainties can be classified into four groups, namely fitness estimation, noise, time-varying fitness functions and robustness. In this paper, the ERM problem relates to the robustness group in which the control variables and parameters are subject to change after each optimal solution has been determined. Therefore, in solving an ERM problem with uncertainties, the energy aggregator aims to find solutions that are near optimal in terms of operating costs and as low as sensitive to parameter variations. In other words, the solution obtained should be close to the optimum and robust for parameter variations. In view of the above-mentioned uncertainty, the ERM problem has become very difficult and complex. Recently, many metaheuristic algorithms have been widely used to solve real-world optimization problems with uncertainty [3].

Some of the most popular metaheuristic algorithms such as Particle Swarm Optimization (PSO), Evolutionary Particle Swarm Optimization (EPSO), Cuckoo Search (CS), Flower Pollination (FP), Simulated Annealing (SA), Differential Evolution (DE), Tabu Search (TS), and Genetic Algorithm (GA) have been extensively used to solve power system optimization problems and they give better results than deterministic methods like MILP and MINLP. Due to the economic environment of microgrid operation, the ERM problem of the power network has gain much popularity in recent decades. To solve this problem, many modified and hybrid versions of metaheuristic algorithms have been implemented in many literatures. Ref. [4] presents the Hybrid Differential Search Algorithm (HDSA) and Quantum Particle Swarm Optimization (QPSO) to solve the ERM problem, this is the hybrid version of Differential Search (DS) and PSO, respectively. The results showed that HDSA performs better than QPSO, DS and PSO in terms of profit and execution time. The Multi- Objective Particle Swarm Optimization (MOPSO) is used to address the ERM problem with the aim of maximizing the profit of the aggregator and minimizing CO2 emissions from conventional DG units [5]. In [6] the hybrid version of Ant Colony Optimization (ACO) and Simulated Annealing (SA) called Hybrid Simulated Annealing (HSA) approach was used to handle ERM by considering the excess use of EVs. The solution given by HSA was better than the SA and faster than the MINLP. Signaled Particle Swarm Optimization (SiPSO) was proposed in [7] to handle shortterm energy resource planning and found a very good solution in terms of low operating costs compared to PSO and its variant called NPSO, but higher than MINLP. The performance of all of these metaheuristic methods could be improved by tuning the different parameters of each method and hybridizing two or more good algorithms to find the near-optimal solution and reduce the convergence time of the optimization methods [8].

Thus, the literature review of latest papers reveals the fact that even though excellent advancements have been carried out in the performance of the aforementioned algorithms, finding of ‘‘Sub-optimum’’ solutions are still a great challenge in optimization field. So to tackle this challenge a novel, robust and efficient hybrid optimization algorithm entitled ‘‘Enhanced Velocity Differential Evolutionary Particle Swarm Optimization’’ (EVDEPSO) is proposed and its superiority over the latest state of art optimization algorithms are established for getting better sub-optimum solutions.

The EVDEPSO algorithm is the modified version of the Differential Evolutionary Particle Swarm Optimization (DEEPSO) [9]. The main purpose of this paper is to assess the usefulness and effectiveness of the EVDEPSO algorithm for the day ahead ERM problem with sourcerelated uncertainties. For this purpose, EVDEPSO and the recently developed metaheuristic techniques such as Variable Neighborhood Search(VNS) [10], DEEPSO and techniques presented in the CEC 2018 competition [11] 5 such as the Chaotic Evolutionary Particle Swarm Optimization Algorithm (CEPSO), Particle Swarm Optimization with Global Best Perturbation(PSO- GBP), Improved Chaotic Differential Evolutionary Particle Swarm Optimization (IC-DEEPSO), Unified PSO (UPSO), Improved Differential Evolution (IDE) and Firefly algorithms are applied to solve such complex and non-linear optimization problem. These algorithms are applied to a case study of a 25-bus microgrid system with 100 different scenarios generated by Monte Carlo Simulation (MCS) techniques with high penetration of photovoltaic generation, DR program for 90 residential loads, 36 electric vehicles, 2 energy storage systems and 2 electricity markets (wholesale market, local market). Figure 1 shows the Overview of Aggregator Energy Resource Management.

This paper contains the following sections after introductory part: Part II, Day-ahead Energy Resource Management (ERM) With Uncertain Environments. Part III. EVDEPSO algorithm. Part IV. Case study and results Part V. Conclusion and Future Work.

II. DAY-AHEAD ENERGY RESOURCE MANAGEMENT (ERM) WITH UNCERTAIN ENVIRONMENTS

This section is divided into four following parts: A) Problem formulation, B) Network constraints C) Unpredictability modeling and D) Fitness function and solution representation.

A. PROBLEM FORMULATION

The proposed problem is classified as a problem of mix-integer non-linear programming (MINLP) because of the existence of consistent, distinct and binary variables. The aim of the energy aggregator is to reduce operating costs and maximize the revenue. Operating costs (O.C) are associated with the generation costs of all types of DG units managed by the

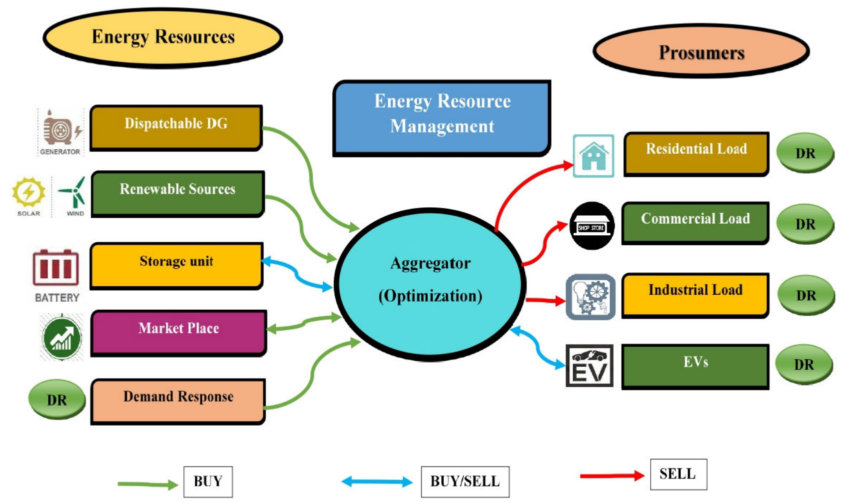

FIGURE 1. Overview of aggregator energy resource management.

aggregator and represented by equation (1) consider the costs of conventional DGs, external suppliers, non-dispatchable DGs (i.e. Solar), ESS, EV discharge, penalization of excess generation of DG units, penalization of non-supplied demand and DR through direct load control programs (load curtailment) [4].

Equation (2) represents the income obtained from market transactions [11], where bids and offers are permitted in two markets with unique features, namely local and wholesale markets. The aim of the aggregator is to reduce operating costs (O.C) while maximizing the income [21]. So objective function becomes minimization to get the maximum profit [4] as shown in equation (3).

$$
\begin{aligned}
\mathrm{O.C} &= \sum_{t=1}^{T}\sum_{DiG=1}^{N_{DiG}} \mathrm{C}_{\mathrm{DiG}(\mathrm{DiG},t)} \times \mathrm{P}_{\mathrm{DiG}(\mathrm{DiG},t)} \\
&\quad + \sum_{t=1}^{T}\sum_{Sup=1}^{N_{Sup}} \mathrm{C}_{\mathrm{Sup}(\mathrm{Sup},t)} \times P_{\mathrm{Sup}(\mathrm{Sup},t)} + \sum_{SE=1}^{N_{SE}}\sum_{t=1}^{T} \\
&\quad \times \left[\left(\begin{array}{l}
\sum_{Solar=1}^{N_{Solar}} \mathrm{C}_{\mathrm{Solar}(\mathrm{Solar},t)} \times P_{\mathrm{Solar}(\mathrm{Solar},t,\mathrm{SE})} \\
+ \sum_{ST=1}^{N_{ST}} \mathrm{C}_{\mathrm{Dis}(\mathrm{ST},t)} \times P_{\mathrm{Dis}(\mathrm{ST},t,\mathrm{SE})} \\
+ \sum_{Ev=1}^{N_{Ev}} \mathrm{C}_{\mathrm{Dis}(\mathrm{Ev},t)} \times P_{\mathrm{Dis}(\mathrm{Ev},t,\mathrm{SE})} \\
+ \sum_{DiG=1}^{N_{DiG}} \mathrm{C}_{\mathrm{GC}(\mathrm{DiG},t)} \times P_{\mathrm{GC}(\mathrm{DiG},t,\mathrm{SE})} \\
+ \sum_{LD=1}^{N_{LD}} \mathrm{C}_{\mathrm{NSLoad}(\mathrm{LD},t)} \times P_{\mathrm{NSLoad}(\mathrm{LD},t,\mathrm{SE})} \\
+ \sum_{LD=1}^{N_{LD}} \mathrm{C}_{\mathrm{CutDR}(\mathrm{LD},t)} \times P_{\mathrm{CutDR}(\mathrm{LD},t,\mathrm{SE})}
\end{array}\right) \bullet \pi(\mathrm{SE})\right]
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
\mathrm{Income} &= \sum_{SE=1}^{N_{SE}}\sum_{t=1}^{T}\left(\sum_{Ms=1}^{N_{Ms}} (P_{\mathrm{Buy}(\mathrm{Ms},t)} - P_{\mathrm{Sell}(\mathrm{Ms},t)}).\mathrm{MP}_{(\mathrm{Ms},t,\mathrm{SE})}\right) \\
&\quad \bullet \pi\ (\mathrm{SE})
\end{aligned} \tag{2}
$$

$$
Minimize\_f = \mathrm{O.C}^{d+1}_{total} - \mathrm{Income}^{d+1}_{total} \tag{3}
$$

B. NETWORK CONSTRAINTS

Objective function given by equation (3) has the following network constraints from equations (4-29) taken from [1].

Power balance of network active and reactive power, with power loss at bus i in period t for the SE scenario are given by equations (4) and (5):

$$
\begin{aligned}
\mathrm{P}_{\mathrm{gi}(t,\mathrm{SE})} - \mathrm{P}_{\mathrm{di}(t,\mathrm{SE})} &= \mathrm{G}_{\mathrm{ii}} \times \mathrm{U}^2_{\mathrm{i}(t,\mathrm{SE})} \\
&\quad + \mathrm{U}_{\mathrm{i}(t,\mathrm{SE})} \times \sum_{j\in L^i} \mathrm{U}_{\mathrm{j}(t,\mathrm{SE})}(\mathrm{G}_{\mathrm{ij}}\cos(\theta_{\mathrm{ij}(t,\mathrm{SE})}) \\
&\quad + \mathrm{B}_{\mathrm{ij}}\sin(\theta_{\mathrm{ij}(t,\mathrm{SE})}))
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{P}_{\mathrm{gi}(t,\mathrm{SE})} &= \sum_{DiG=1}^{N^i_{DiG}} (\mathrm{P}^i_{\mathrm{DiG}(\mathrm{DiG},t)} - \mathrm{P}^i_{\mathrm{GC}(\mathrm{DiG},t)}) \\
&\quad + \sum_{Solar=1}^{N^i_{Solar}} \mathrm{P}^i_{\mathrm{Solar}(\mathrm{Solar},t,SE)} + \sum_{Sup=1}^{N^i_{Sup}} \mathrm{P}^i_{\mathrm{Sup}(\mathrm{Sup},t)} \\
&\quad + \sum_{Ev=1}^{N^i_{Ev}} \mathrm{P}^i_{\mathrm{Dis}(\mathrm{Ev},t,\mathrm{SE})} + \sum_{ST=1}^{N^i_{ST}} (\mathrm{P}^i_{\mathrm{Dis}(\mathrm{ST},t,\mathrm{SE})} \\
&\quad + \sum_{Ms=1}^{N^i_{Ms}} \mathrm{P}^i_{\mathrm{Buy}(\mathrm{Ms},t,\mathrm{SE})})
\end{aligned}
$$

$$
\mathrm{P}_{\mathrm{di}(t,\mathrm{SE})} = \sum_{LD=1}^{N^i_{LD}} (\mathrm{P}^i_{\mathrm{Load}(\mathrm{LD},t,\mathrm{SE})} - \mathrm{P}^i_{\mathrm{NSLoad}(\mathrm{LD},t,\mathrm{SE})} - \mathrm{P}^i_{\mathrm{CutDR}(\mathrm{LD},t,\mathrm{SE})})
$$

$$+\sum_{Ev=1}^{N^i_{Ev}} P^i_{Cha(Ev,t,SE)} + \sum_{ST=1}^{N^i_{ST}} P^i_{Cha(ST,t,SE)} + \sum_{Ms=1}^{N^i_{Ms}} P^i_{Sell(Ms,t,SE)}) \tag{4}$$

$$Q_{gi(t,SE)} - Q_{di(t,SE)} = U_{i(t,SE)} \times \sum_{j\in LD^i} U_{j(t,SE)}(G_{ij}\sin(\theta_{ij(t,SE)}) - B_{ij}\cos(\theta_{ij(t,SE)})) - B_{ii} \times U^2_{i(t,SE)}$$

$$Q_{gi(t,SE)} = \sum_{DiG=1}^{N^i_{DiG}} Q^i_{DiG(DiG,t)} + \sum_{Sup=1}^{N^i_{Sup}} Q^i_{Sup(Sup,t)}$$

$$Q_{di(t,SE)} = \sum_{LD=1}^{N^i_{LD}} Q^i_{Load(LD,t,SE)} - Q^i_{NSLoad(LD,t,SE)} \tag{5}$$

Here, $\theta_{ij(t,SE)} = \theta_{i(t,SE)} - \theta_{j(t,SE)}$.

Voltage and angle limit at bus i in time slot t are given by equations (6) and (7):

$$U_i^{min} \le U_{i(t,SE)} \le U_i^{max} \tag{6}$$

$$\theta_i^{min} \le \theta_{i(t)} \le \theta_i^{max}; \tag{7}$$

Thermal limit of line k in period t is given by equation (8)

$$\begin{aligned}
&\left|\overline{U_{i(t,SE)}} \times [\overline{Ad_{ij}} \times (\overline{U_{i(t,SE)}} - \overline{U_{j(t,SE)}}) + \overline{Ad_{sh_i}} \times \overline{U_{i(t,SE)}}]^*\right| \le Ap^{max}_{Lk}\\
&\left|\overline{U_{j(t,SE)}} \times [\overline{Ad_{ij}} \times (\overline{U_{j(t,SE)}} - \overline{U_{i(t,SE)}}) + \overline{Ad_{sh_j}} \times \overline{U_{j(t,SE)}}]^*\right| \le Ap^{max}_{Lk}\\
&\forall t \in \{1,\ldots,T\};\ i \ne j;\quad \forall SE \in \{1,\ldots,N_{SE}\}\\
&\forall i,j \in \{1,\ldots,N_B\}
\end{aligned} \tag{8}$$

Conventional types of distributed generation the active and reactive generation limit in time slot t for the DiG unit are formulated by equations (9) and (10):

$$P_{DiGMin(DiG,t)} \times X_{DiG(DiG,t)} \le P_{DiG(DiG,t)} \le P_{DiGMax(DiG,t)} \times X_{DiG(DiG,t,SE)} \tag{9}$$

$$\begin{aligned}
&Q_{DiGMin(DiG,t)} \times X_{DiG(DiG,t)} \le Q_{DiG(DiG,t)} \le Q_{DiGMax(DiG,t)} \times X_{DiG(DiG,t,SE)}\\
&\forall t \in \{1,\ldots,T\};\quad \forall DiG \in \{1,\ldots,N_{DiG}\}
\end{aligned} \tag{10}$$

Maximum active and reactive power generation limit of external supplier Sup in time slot t are given by equations (11) and (12):

$$P_{Sup(Sup,t)} \le P_{Sup\_MaxLimit(Sup,t)}$$

$$Q_{Sup(Sup,t)} \le Q_{Sup\_MaxLimit(Sup,t)} \tag{11}$$

$$\forall t \in \{1,\ldots,T\};\quad \forall Sup \in \{1,\ldots,N_{Sup}\} \tag{12}$$

1) ELECTRIC VEHICLES CONSTRAINTS

In the proposed model, Ev are regarded as a virtual battery bank. Battery balance for each Ev for scenario SE in time slot t is given by equation (13):

$$E_{Stored(Ev,t,SE)} = E_{Stored(V,t\text{-}1,SE)} - E_{Trip(Ev,t,SE)} + (\eta_{Cha(Ev)} \times P_{Cha(Ev,t,SE)} - \frac{1}{\eta_{Dis(Ev)}} \times P_{Dis(Ev,t,SE)}) \times \Delta t \tag{13}$$

Maximum and minimum energy stored in the Ev for the scenario SE in time slot t is given by equation (14):

$$E_{MinCha(Ev,t,SE)} \le E_{Stored(Ev,t,SE)} \le E_{BatCap(Ev)} \tag{14}$$

Equation (15) states that, charging and discharging processes in Ev cannot be simultaneous in time slot t:

$$X_{Cha\_Ev(Ev,t,SE)} + X_{Dis\_Ev(Ev,t,SE)} \le 1 \tag{15}$$

Charge and Discharge limit of Ev in time slot t for scenario SE is represented by equations (16) and (17):

$$\begin{aligned}
&P_{Cha(Ev,t,SE)} \le P_{ChaLimit(Ev,t,SE)} \times X_{Cha_Ev(Ev,t,SE)}\\
&\eta_{Cha(Ev)} \times P_{Cha(Ev,t,SE)} \times \Delta t \le E_{BatCap(Ev)} - E_{Stored(Ev,t\text{-}1,SE)}
\end{aligned} \tag{16}$$

$$\begin{aligned}
&P_{Dis(Ev,t,SE)} \le P_{DisLimit(Ev,t,SE)} \times X_{Dis_Ev(Ev,t,SE)}\\
&\frac{1}{\eta_{Dis(Ev)}} \times P_{Dis(Ev,t,SE)} \times \Delta t \le E_{Stored(Ev,t,SE)}
\end{aligned} \tag{17}$$

$$\forall t \in \{1,\ldots,T\};\ \forall Ev \in \{1,\ldots,N_{Ev}\};\ \forall SE \in \{1,\ldots,N_{SE}\}$$

$$X_{Cha\_Ev(Ev,t,SE)}, X_{Dis\_Ev(Ev,t,SE)} \in \{0,1\};\ \Delta t = 1;$$

2) ENERGY STORAGE CONSTRAINTS

Battery balance equation (18) of Energy storage unit ST in time slot t for scenario SE is:

$$\begin{aligned}
&E_{Stored(ST,t,SE)} = E_{Stored(ST,t\text{-}1,SE)} + (\eta_{Cha(ST)} \times P_{Cha(ST,t,SE)} - \frac{1}{\eta_{Dis(ST)}} \times P_{Dis(ST,t,SE)}) \times \Delta t\\
&t = 1 \rightarrow E_{Stored(ST,t\text{-}1,SE)} = E_{Initial(ST)}
\end{aligned} \tag{18}$$

Maximum and minimum energy storage limit in Energy storage unit ST in time slot t is given by equation (19):

$$E_{MinCha(ST,t,SE)} \le E_{Stored(ST,t,SE)} \le E_{BatCap(ST)} \tag{19}$$

Equation (20) states that, charge and discharge processes in energy storage unit ST cannot be simultaneous in time slot t:

$$X_{Cha\_ST(ST,t,SE)} + X_{Dis\_ST(ST,t,SE)} \le 1 \tag{20}$$

Charge and Discharge limit of Energy Storage unit ST in time slot t is given by equations (21) and (22):

$$\begin{aligned} & P_{Cha(ST,t,SE)} \\ & \quad \leq P_{ChaLimit(ST,t,SE)} \times X_{Cha\_ST(ST,t,SE)} \\ & \eta_{Cha(ST)} \times P_{Cha(ST,t,SE)} \times \Delta t \\ & \quad \leq E_{BatCap(ST)} - E_{Stored(ST,t\text{-}1,SE)} \end{aligned} \tag{21}$$

$$\begin{aligned} & P_{Dis(ST,t,SE)} \\ & \quad \leq P_{DisLimit(ST,t,SE)} \times X_{Dis\_ST(ST,t,SE)} \\ & \frac{1}{\eta_{Dis(ST)}} \times P_{Dis(ST,t,SE)} \times \Delta t \\ & \quad \leq E_{Stored(ST,t,SE)} \end{aligned} \tag{22}$$

$$\forall t \in \{1, \ldots, T\};\ \forall ST \in \{1, \ldots, N_{ST}\}; \forall SE \in \{1, \ldots, N_{SE}\}$$
$$X_{Cha\_ST(ST,t,SE)},\ X_{Dis\_ST(ST,t,SE)} \in \{0, 1\};\ \Delta t = 1;$$

3) DEMAND RESPONSE CONSTRAINTS

Equation (23) formulates a Demand response load model. The maximum amount of load that can be curtailed by each load LD in each time slot t in the scenario SE is formulated as:

$$\begin{aligned} & P_{CutDR(LD,t,SE)} \leq P_{MaxCutDR(LD,t)} \times X_{CutDR(LD,t,SE)} \\ & t \in \{1, \ldots, T\}; \quad \forall LD \in \{1, \ldots, N_{LD}\} \\ & \forall SE \in \{1, \ldots, N_{SE}\}; \quad X_{CutDR(LD,t,SE)} \in \{0, 1\} \end{aligned} \tag{23}$$

Equation (24) states that, the non-supplied load cannot be more than the difference between forecasted load and demand response curtailed load in scenario SE in each time slot t:

$$\begin{aligned} & P^{i}_{NSLoad(LD,t,SE)} \leq P^{i}_{Load(LD,t,SE)} - P^{i}_{CutDR(LD,t,SE)} \\ & \forall t \in \{1, \ldots, T\}; \quad \forall i \in \{1, \ldots, N_B\};\ \forall SE \in \{1, \ldots, N_{SE}\} \\ & \forall LD \in \{1, \ldots, N_{LD}\} \end{aligned} \tag{24}$$

4) RESTRICTIONS OF THE ELECTRICITY MARKET

Equations (25) and (26) state that, the market offers for selling and buying the electricity respectively are constrained by maximum and minimum market offer:

$$\begin{aligned} & P_{MktOfferMin(Ms,t)} \times X_{MktSell(Ms,t,SE)} \\ & \quad \leq P_{Sell(Ms,t)} \leq P_{MktOfferMax(Ms,t)} \times X_{MktSell(Ms,t,SE)} \end{aligned} \tag{25}$$

$$\begin{aligned} & P_{MktBuyMin(Ms,t)} \times X_{MktBuy(Ms,t,SE)} \\ & \quad \leq P_{Buy(Ms,t)} \leq P_{MktBuyMax(Ms,t)} \times X_{MktBuy(Ms,t,SE)} \\ & \quad \forall t \in \{1, \ldots, T\}; \quad \forall Ms \in \{1, \ldots, N_{Ms}\}; \\ & \quad \forall SE \in \{1, \ldots, N_{SE}\} \end{aligned} \tag{26}$$

Equation (27) represents that, at each time slot t of the market, either buying or selling bids are allowed:

$$X_{MktBuy(M,t,SE)} + X_{MktSell(M,t,SE)} \leq 1 \tag{27}$$

5) PV CURTAILMENT POWER LIMITATION

In some scenarios, generation is more than the load demand. At that time, we must curtail the generation of non-dispatchable DG units such as solar to strike a balance between generation and load. In this case, the solar generation curtailment must be lower than the predicted solar generation value as per equation (28):

$$P_{GC(DiG,t,SE)} \leq P_{SolarScenario(Solar,t,\ SE)} \tag{28}$$

In each time t, upstream solar power limits can be articulated as equations (29):

$$\begin{aligned} & P_{Solar(Solar,t)} \\ & \quad \leq P_{SolarMAX(Solar,t)} \times X_{Solar(Solar,t,SE)} \\ & \quad \forall t \in \{1, \ldots, T\}; \quad \forall Solar \in \{1, \ldots, N_{Solar}\}; \\ & \quad \forall SE \in \{1, \ldots, N_{SE}\} \end{aligned} \tag{29}$$

C. UNPREDICTABILITY MODELING

The energy aggregator relies on forecast load demand, weather conditions (to forecast solar generation), electricity market prices and electric vehicle trips to perform the day ahead ERM. The assumption of a perfect prediction could have a disastrous corollary for the grid operation if the results do not meet the expected forecast.

To deal with this problem, we presume that a correct set of scenarios that imitate actual conditions can be produced based on trends or past experiences with forecasts and associated errors. The uncertainties considered in this work are: (I) solar power generation, (ii) EV scheduling, (iii) load demand profiles and (iv) local and wholesale market prices [11].

The Monte Carlo Simulation (MCS) technique is applied to scenario generations and reduction [12]. In MCS, the probability distribution function (PDF) is used to produce scenarios from historical data. Equation (30) is used to generate scenarios.

$$y_{SE}(t) = y^{predict}(t) + y^{error,SE}(t) \tag{30}$$

where, $y^{error,SE}(t)$ is a normal distribution function with average zero and standard deviation σ, $y^{predict}(t)$ is predicted value of y variable at t time and $y_{SE}(t)$ is final value of y variable for scenario SE at t time. In addition, the scenario reduction method is used to exempt low probability scenarios and merge with the high probability scenario in terms of static metrics. Detailed information about this technique is available in [12].

In this problem, 5000 scenarios are generated for solar power generation, market price deviations and load demand. Errors of 15%, 20% and 10% are considered for solar power generation, market price deviations and load demand respectively. The scenarios are also reduced by 100 using the MCS reduction method. In MCS technique, all forecast errors of the uncertain inputs are signified by the normal distribution functions. To produce uncertainty related to electric vehicle trips, the tools described in ref. [13] is used to randomly generate 100 different scenarios.

D. FITNESS FUNCTION AND SOLUTION REPRESENTATION

The fitness function F presented by equation (31) is the sum of objective function f and the summation of the penalties [11]. Penalties due to the constrains violation found during assessment of the solutions:

$$F(X) = f + \rho \sum_{i=1}^{N_{co}} \max[0, g_i] \tag{31}$$

where x is the solution of problem, it is presented in vector form. Here, g_i indicate the value of the i$^{\text{th}}$ constraint and ρ is the penalty coefficient, N_{co} is number of constraints.

In this case, we consider uncertainty in some solution parameters of X, which changes the fitness function value according to the different scenarios generated by MCS. The fitness function [11] value is modified by equation (32):

$$F_{SE}(X) = f(X + \delta_{SE}) \tag{32}$$

where, δ_{SE} is the deviation of parameters and variable in scenario SE, $F_{SE}(X)$ is the fitness value for the scenario SE. The mean value and the standard deviation [11] of fitness function for considered scenarios SE can be evaluated by equations (33) and (34) respectively:

$$Mean\_F_{SE}(X) = \frac{1}{N_{SE}} \sum_{SE}^{N_{SE}} f(X + \delta_{SE}) \tag{33}$$

$$Std\_F_{SE}(X) = \sqrt{\frac{1}{N_{SE}} \sum_{SE=1}^{N_{SE}} [f(X+\delta_{SE}) - Mean\_F_{SE}(X)]^2} \tag{34}$$

The mean and standard deviation values of fitness function obtained from equations (33) and (34) rely on considered scenarios in the fitness function evaluation. Therefore, the number of function evaluations during the execution of the metaheuristic algorithms are based on the size of the population and the number of scenarios considered.

Figure 2 shows a schematic representation of the Internal functioning of fitness function. Here, the fitness function receives the input arguments as an array with the solutions, the information of the case study, some additional parameters, and the number of scenarios to evaluate (a maximum of 100 scenarios is considered). The internal operation of the fitness function, which randomly selects the number of scenarios $N_{SE} = 100$ from the total number of available scenarios.

The number of functions evaluations are calculated by the equation (35) as follows:

$$NFEs = N_P{}^* N_{SE}{}^* N_{iteration} \tag{35}$$

The solution structure is an important part of metaheuristics to represent a solution. In this work, the solution demonstration follows the vector representation shown in Figure 3. Each solution is encoded as a vector with six group of variables contains total 142 different variables in each period t of 1 hour, which are repeated sequentially for 24 hours. Therefore, dimension of solution vector in 24 hours period is 1*3408. Detail information about the solution structure is given in [11].

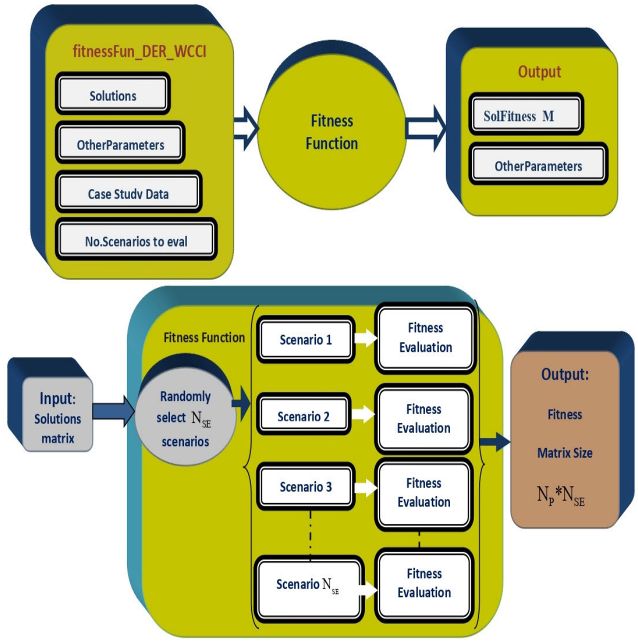

FIGURE 2. Internal functioning of fitness function.

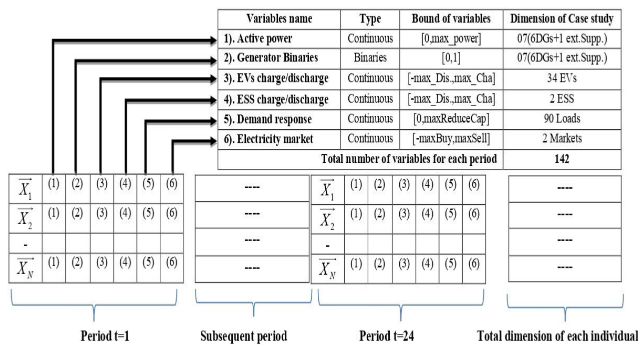

FIGURE 3. Solution representation [11].

III. ENHANCED VELOCITY DIFFERENTIAL EVOLUTIONARY PARTICLE SWARM OPTIMIZATION (EVDEPSO) ALGORITHM

Enhanced Velocity Differential Evolutionary Particle Swarm Optimization (EVDEPSO) algorithm, which is an improved version of Differential Evolutionary Particle Swarm Optimization (DEEPSO). Where DEEPSO is the hybrid version of PSO, EA and DE. Please refer ref. [9] for more details on the DEEPSO algorithm.

In the EVDEPSO algorithm, the first step is to set the strategic parameters and then initialize the position and velocity of the population by equations (36) and (37) respectively:

$$X_{p,d} = X_d^{\min} + (X_d^{\max} - X_d^{\min}) \tag{36}$$
$$V_{p,d} = V_d^{\min} + (V_d^{\max} - V_d^{\min}) \tag{37}$$

Initialize the position and velocity of the population by the minimum and maximum limit of each particle variable and ensure that the solution vector is within the maximum and minimum possible bound.

Where, $X_{p,d}$ and $V_{p,d}$ is the initial position and velocity of the particle 'p' for dimension 'd'. Here, p=1, 2...,N$_P$ and d=1, 2..., D. Where, 'N$_P$ ' is the size of population and 'D' is the dimension of the solution vector, After initialization of the populations, evaluate the fitness of each particle by using the equation (31) and find the global best particle G_{best}.

$$W^*_{(I,C,G)} = W_{(I,C,G)} + \tau N(0,1) \quad (38)$$
$$G^*_{best} = G_{best}(1 + W^*_G) \quad (39)$$
$$V_p^{new} = X_p + V_p(1 + W_I^* N[0,1]) + PW_C^*(G^*_{best} - X_p) + 2[1 + rand(0,1) + U(0,1)] \quad (40)$$

Equation (40) presents the new velocity V_p^{new} of pth particle, which is the vector sum of current particle position, X_p Enhanced Velocity, Cooperation and Stochastic Uni-random Distribution (SUD). The detailed explanation about the equation (40) is give below.

A. CURRENT POSITION

By adding the current particle position X_p to the new velocity V_p^{new}, it boosts up the search process to find the nearly optimal solution in a reasonable computational time. This term thus helps to achieve the best results in a short period of time, which is good for the day ahead ERM problem.

B. ENHANCED VELOCITY

This term called enhanced velocity V_p or mutated current velocity due to the mutation of current velocity by mutated inertia weight and normal distribution function N [0,1]. W_I Enhanced velocity term helps in searching the local search space to find the nearest optimal solution. Where, is the inertia weight obtain from the random value between [0,1], W_I is the mutation of inertia weight obtained by using equation (38), Mutation rate (or learning parameter) τ, which must be fixed externally.

C. COOPERATION

In this term, the current particle position X_p follows the mutated current global best particle, G^*_{best} which is obtained from equation (39), where, G_{best} is the current global best particle among all particles, W_G is the global weight obtain from the random value between [0,1], W^*_G is the mutation of global weight by using equation (38). The term 'P' called Communication factor, which creates the communication topology among the current particles to controls the passage of information within the population. This will helpful for the global exploration of search space to find the nearest optimal solution. The tuned value of 'P' for this problem is set to 0.5.

D. STOCHASTIC UNI-RANDOM DISTRIBUTION (SUD)

It is generated by a uniform distribution function and a random number between [0,1]. This term stochastically enlarges the step length and changes the search direction towards the near optimal solution.

New velocity V_p^{new} found by equation (40) is the particle step length to reach the optimal solution. The value of the step length is neither too small nor large; otherwise, the solution may stuck into local minima. Therefore, the metaheuristic algorithm is designed in such a way that it gives the optimal value and direction of the step length to achieve the near optimal solution in short period of time. If the new velocity obtained by equation (40) violates the boundary limit, then it is modified using equation (41).

$$V_p^{new} = \begin{cases} V_p^{Min} + L.F(V_p^{Max} - V_p^{Min}) \ldots if..V_p^{new} > V_p^{Max} \\ V_p^{Min} + L.F(V_p^{Max} - V_p^{Min}) \ldots if..V_p^{new} < V_p^{Min} \end{cases} \quad (41)$$

where, the limit factor $(L.F)$ keeps the new velocity V_p^{new} away from the boundary limit.

$$X_p^{new} = D.F * \left(X_p + V_p^{new}\right) \quad (42)$$

After finding the optimal value of the new velocity, V_p^{new} the new position X_p^{new} of each particle 'p' is found using equation (42). This equation is the modified version of the conventional new position equation described in all population-based algorithms. In this equation, the vector sum of the current particle position X_p and new velocity multiplied by Deceleration Factor (D.F), which decelerates the movement of particles and save them from trapping into the local minima. Figure 4 illustrates the concept of EVDEPSO movement rule.

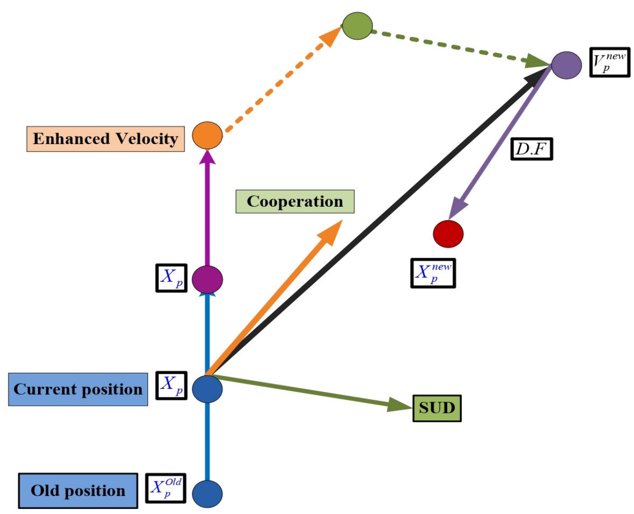

FIGURE 4. Illustration of the EVDEPSO movement rule.

Figure 5 illustrates the concept of the EVDEPSO algorithm in terms of flowchart for the optimal scheduling of the distributed energy resources with consideration of uncertainties. The EVDEPSO algorithm considers the following steps:

Step 1: Set the strategic parameter of EVDEPSO and then initialize the velocity and position of each particle using equations (36) and (37).

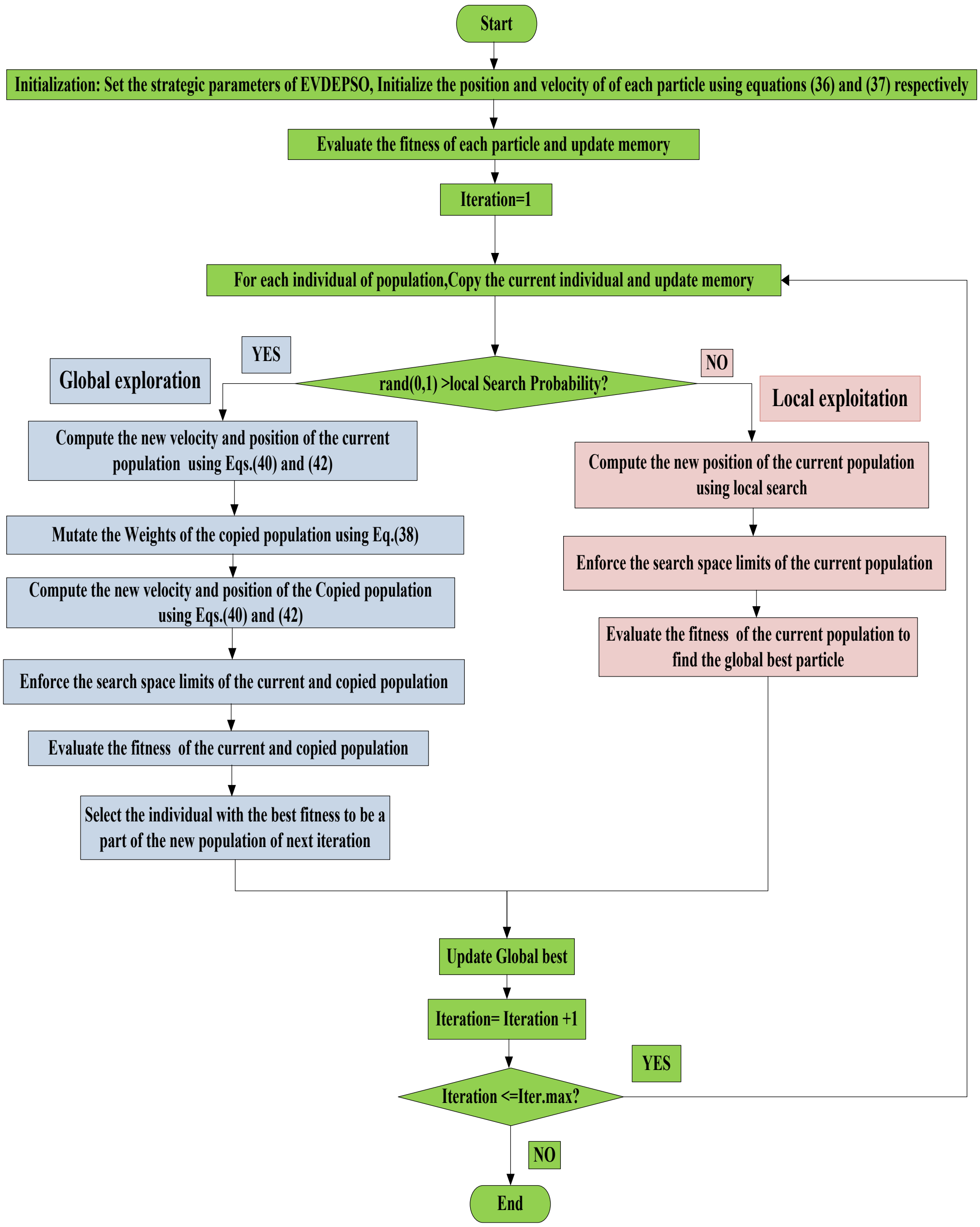

FIGURE 5. Flowchart of the EVDEPSO algorithm.

Step 2: Evaluate the fitness of each initialized particle using the fitness function given by equation (31) to find the global best particle, and then update the EVDEPSO memory with the global best particle.

Step 3: Start the iterations. Copy the current position and velocity of each particle and update memory by copied population and current global best particle.

Step 4: Randomly generate the number between [0, 1], if its value is higher than the local search probability then go to step 5 for global exploration of search space, otherwise go to step 9 for local exploitation of search space.

Step 5: **Global exploration-** Compute the new velocity and position of each particle using equations (40) and (42).

Step 6: Mutate the weights of the copied population using equation (38) to alter it and then calculate the new velocity and position of the copied population using equations (40) and (42).

Step 7: Enforce the search space limits of the current and copied population, if it violates the search space boundary.

Step 8: Evaluate the fitness of each current and copied population to find the best particles and then generate a new population for the next iteration. Then follow the step 12.

Step 9: **Local exploitation**- Compute the new position of the current population using local search.

Step 10: Enforce the search space limits of the current population if it violates the search space boundary.

Step 11: Evaluate the fitness of each current population to find the global best particle.

Step 12: Update the EVDEPSO memory by the global best particle.

Step 13: Increase the iteration by one and then check the threshold limit of the maximum number iterations.

Step 14: Terminate the EVDEPSO, if the threshold limit is reached otherwise go to step 3.

IV. CASE STUDY AND RESULTS

The distribution network used in this case study is a real network of a residential area in Portugal. The network comprises 24 underground lines connected to the main grid via a MV / LV transformer at bus 1. The case study of 25-bus microgrid comprises of 22 DGs (5 dispatchable units and 17 PV generators), 1 external supplier, 2 ESSs, 34 EVs and 90 loads with demand response capacities. In addition to this, two markets (wholesale and local) are available for the purchase and sale of energy. Figure 6 represents the single line diagram of the 25-bus microgrid. Table 1 presents the energy resources available in the considered network.

TABLE 1. Energy resources available in case study [15].

Energy resources		Prices (m.u./kWh)	Capacity (kW)	Units
Dispatchable DGs		0.07-0.11	10-100	5
External suppliers		0.074-0.16	0-150	1
ESS	Charge	-	0-16.6	2
	Discharge	0.03	0-16-6	
EV	Charge	-	0-111	34
	Discharge	0.06	0-111	
DR Curtailable loads		0.0375	4.06-8.95	90
		Forecast (kW)		
Photovoltaic		-	0-106.81	1 (17 agg)
Load		-	35.82-83.39	90
		Limits (kW)		
Market 1 (WS)		0.021-0.039	0-85	1
Market 2 (LM)		0.021-0.039	0-40	1

The proposed EVDEPSO algorithm had participated in the IEEE Computational Intelligence Society sponsored competition. The title of the competition was "Evolutionary Computation in Uncertain Environments: A Smart Grid Application" which was held at IEEE World Congress on Computational Intelligence conference 2018 (WCCI 2018), at Rio de Janeiro, Brazil [11]. In this competition, EVDEPSO had secured the second rank.

In this competition, the aim of the aggregator was to optimally manage the available distributed energy resources of the above described 25-bus microgrid in a day ahead context.

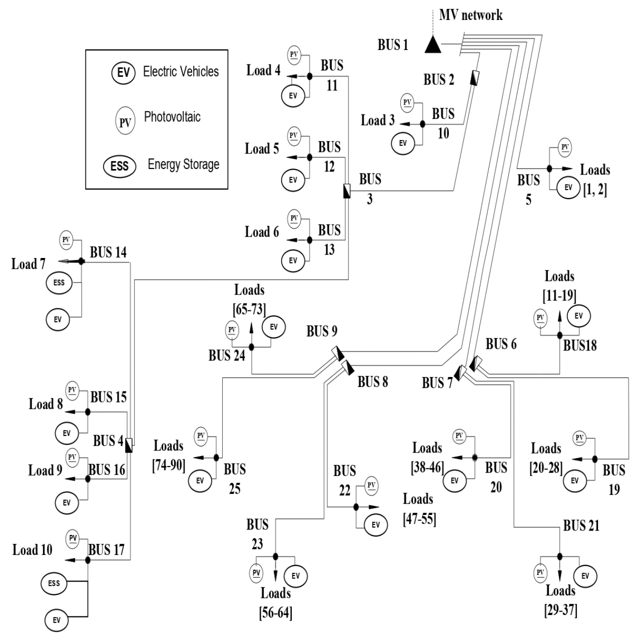

FIGURE 6. 25-Bus Microgrid system [14].

For that, EVDEPSO algorithm was tested for solving the case study with 100 different scenarios for different behaviors of the PVs, load profiles, EVs trip profiles and the market price. According to competition rule, to check the effectiveness and robustness of the algorithms, all algorithms were executed for 20 runs (trials) to solve the problem and in each run a maximum of 50,000 function evaluations were permitted.

In order to confirm the competence of EVDEPSO solution to the problem, the obtained results were compared with the results of CEPSO, PSO-GBP, IC-DEEPSO, UPSO, IDE and Firefly algorithms, which were submitted by the participants of the competition at WCCI 2018. The results of all the above-mentioned participated algorithms were extracted from the database of competition [11]. It is also compared with the Differential Evolutionary Particle Swarm Optimization (DEEPSO) and Variable neighborhood search (VNS), which were participated in IEEE PES WGMHO,2014 [16] and 2017 [17] competitions respectively.

These approaches were tested on a computer with an Intel Core(TM) i7- 2600 processor and 8 GB of RAM running on Windows 7 Professional 64-bit operating system. MATLAB R2016a was used to solve the EVDEPSO algorithm.

A. TUNING OF EVDEPSO PARAMETERS

The tuning of the optimization parameters is one of the most important aspects when designing any metaheuristic techniques. In EVDEPSO technique, experiments for the tuning of the parameters to find the optimal values of all strategic parameters were carried out. In this experiments we fix the population size $N_P = 10$ and No. of Iteration (I_itermax) = 285 and changed the other strategic parameters like local search probability, Learning parameter (τ), Deceleration Factor (D.F), Communication probability (P) and Limit Factor (L.F) in their optimal ranges to find out the A.R.I as shown in Table 2. For each change of any strategic parameter, we set the optimal value for the remaining parameters as per the given in Table 3. For example, for Local Search Probability of 0.4, we set the other strategic parameters like Learning parameter (τ) = 0.7, Deceleration Factor (D.F) = 0.33, Communication probability (P) = 0.5 and Limit Factor (L.F) = 0.25. From the results of these experiments given in Table 2, we concluded that, the strategic parameters of the EVDEPSO given in Table 3 gave the best results in terms of A.R.I.

TABLE 2. **Tuning the strategic parameters of EVDEPSO.**

Parameters	Value	A.R.I
Local Search Probability	0.3	19.573
	0.4	19.575
	0.5	19.623
Learning parameter (τ)	0.6	19.593
	0.7	19.573
	0.8	19.582
Deceleration Factor (D.F)	0.25	19.908
	0.33	19.573
	0.5	21.048
Communication probability (P)	0.4	19.590
	0.5	19.573
	0.6	19.581
Limit Factor (L.F)	0.2	19.800
	0.25	19.573
	0.33	19.705

TABLE 3. **The strategic parameters of the EVDEPSO.**

Parameters	Value
Populations size (N_P)	10
No. of Iteration ($N_{iteration}$)	285
Local Search Probablity	0.3
Learning parameter (τ)	0.7
Deceleration Factor (D.F)	0.33
Communication probability (P)	0.5
Limit Factor (L.F)	0.25

After the sensitivity analysis (tuning) of the parameters, the EVDEPSO algorithm is used to solve the optimal scheduling of the DERs. The comparison of obtained results of all tested algorithms in terms of average fitness and standard deviation over 50,000 function evaluation in each run are presented in Table 4. Figure 7 shows the graphical representation of average fitness of all tested algorithms over 20 runs, which are given in Table 4.

Table 5 shows the Ranking Index (R.I) of all tested algorithms, which is the sum of the average fitness function and standard deviation of each run presented in Table 4 as per the equation (43). Table 5 clearly shows that, compared to all tested algorithms, R.I of EVDEPSO is the best in all 20 runs. Figure 8 shows the graphical representation of R.I, which are given in Table 5 for all tested algorithms over 20 runs. Table 5. Shows that, the third run gives the best ranking index of 18.79 out of 20 runs. It means that, for this run EVDEPSO gives the best solution for the optimal scheduling of the energy management problem in 20 runs. Solution of the third run is presented in Appendix.

$$R.I = Mean\_F_{SE}(X) + Std\_F_{SE}(X) \tag{43}$$

$$A.R.I = \frac{1}{N_{Runs}} \sum_{i=1}^{N_{Runs}} (Mean\_F_{SE}(X) + Std\_F_{SE}(X)) \tag{44}$$

where, N_{Runs} is the number of runs (trials) consider for the calculation of A.R.I.

Table 6 presents the Average Ranking Index (A.R.I) of the all tested algorithms and the deterministic approach, i.e Mixed-Integer Non-linear Programming (MINLP) over 20 runs as per the equation (44). Table 6 also shows the best and worst fitness function values as well as the mean execution time over 20 runs for all tested methods.

Day ahead calculated total operating cost is the sum of the fitness function calculated in each hour for 24-hour period. As per Table 6, EVDEPSO algorithm achieved the lowest A.R.I of 19.57 m.u., which is the sum of average fitness of 17.67 m.u. and standard deviation of 1.90 m.u. Where, MINLP, VNS and DEEPSO achieved the second, third and fourth ranks with A.R.I of 20.74, 20.78 and 20.85 m.u respectively.

It is clear from the comparison that, EVDEPSO gives the best results among all tested eight metaheuristic techniques and MINLP in terms of A.R.I. The best and worst value of operation cost given by EVDEPSO is 13.20 and 22.99 m.u. respectively. Best value of the operation cost attained by EVDEPSO is also the lowest among all the tested algorithms. However, the execution time is also an important aspect to check the robustness of any algorithm. As per Table 6 EVDEPSO, gets the sixth rank among all compared algorithms in terms of mean execution time. The algorithms UPSO, IC_DEEPO, IDE, and CEPSO get the first, second, third, and fourth ranks respectively in terms of mean execution time but having very high value of A.R.I as compared to EVDEPSO. VNS get the fifth rank with mean execution time of 51.84 s, which is very nearer to the time taken by EVDEPSO of 53.56 s. Mostly, the metaheuristic approaches, as expected, present lower mean execution times than the MINLP approach of 627 s, confirming their advantage in tackling large-scale problems that require a decision in a short time. Therefore, over all the EVDEPSO has found the best solution in a competitive mean execution time, which shows the computational efficiency and robustness of the proposed technique.

The standard deviation presented in Table 6 shows the deviation of the fitness function in 20 trials for 100 scenarios. Here, high value of standard deviation indicates a high variability of fitness function over the number of function evaluation in each run.

Table 7 demonstrates the comparison of all tested methods in terms of no of iterations and mean execution

TABLE 4. Comparison of algorithms in terms of average fitness and standard deviation for each run.

Run	EVDEPSO		VNS		DEEPSO		PSO_GBP		CEPSO		IC_DEEPSO		UPSO		IDE		FIREFLY	
	Avg. Fit.	Std. Dev.	Avg. Fit.	Std. Dev.	Avg. Fit.	Std. Dev.	Avg. Fit.	Std. Dev.	Avg. Fit.	Std. Dev.	Avg. Fit.	Std. Dev.	Avg. Fit.	Std. Dev.	Avg. Fit.	Std. Dev.	Avg. Fit.	Std. Dev.
1	17.75	1.85	17.56	2.48	18.52	1.70	22.93	2.19	22.63	2.23	30.02	1.95	29.42	1.80	35.44	1.83	36.27	1.46
2	17.22	1.94	18.85	2.44	18.33	1.73	22.62	2.23	22.67	2.24	26.54	1.71	32.19	1.75	34.16	1.55	34.73	1.78
3	17.04	1.75	17.15	2.46	18.81	1.75	22.64	2.17	22.71	2.13	27.56	1.61	32.77	2.08	34.77	1.67	36.37	1.57
4	17.85	1.95	18.59	2.45	18.82	1.71	22.71	2.21	22.62	2.24	28.62	1.71	29.87	1.78	38.32	1.65	34.86	1.89
5	17.33	1.74	17.97	2.47	18.84	1.70	22.76	2.29	22.60	2.25	30.02	1.92	31.03	1.86	34.80	1.66	35.28	1.47
6	17.71	1.98	18.49	2.48	19.61	1.71	22.70	2.19	22.72	2.00	31.61	1.66	33.49	1.79	30.94	1.56	36.29	1.62
7	18.14	1.89	18.94	2.43	18.84	1.72	22.63	2.21	22.88	2.09	28.51	1.75	35.64	1.73	36.14	1.70	34.48	1.59
8	18.33	1.87	18.81	2.45	19.86	1.71	22.67	2.17	22.88	2.22	27.76	1.61	33.14	1.87	31.82	1.57	34.93	1.57
9	17.28	1.84	18.85	2.44	19.32	1.71	22.69	2.24	22.61	2.26	28.09	1.94	32.96	1.65	38.05	1.65	35.34	1.51
10	18.03	1.94	18.62	2.45	19.59	1.68	22.78	2.21	22.59	2.19	28.97	1.71	31.41	1.86	37.61	1.63	35.30	1.56
11	17.20	2.01	18.07	2.44	19.00	1.76	22.64	2.28	22.61	2.18	28.28	1.78	33.51	1.88	32.80	1.62	36.11	1.51
12	17.67	1.91	18.16	2.46	18.77	1.67	22.63	2.19	22.76	2.25	31.06	1.69	32.34	1.92	36.84	1.61	33.56	1.51
13	17.64	1.84	18.32	2.47	19.13	1.69	22.63	2.20	22.62	2.25	29.91	1.68	32.31	1.75	32.62	1.61	36.41	1.59
14	17.16	1.81	18.42	2.46	19.20	1.79	22.68	2.15	22.62	2.17	29.18	1.70	33.04	1.71	36.06	1.61	37.72	1.67
15	18.02	1.98	18.32	2.45	20.08	1.69	22.60	2.21	22.58	2.21	32.02	1.94	35.61	1.70	34.38	1.70	35.95	1.48
16	17.87	1.95	18.59	2.44	18.78	1.69	22.68	2.32	22.59	2.26	33.39	1.80	30.49	1.85	32.79	1.66	33.33	1.63
17	17.58	1.84	18.27	2.47	19.49	1.73	22.65	2.12	22.60	2.25	28.64	1.72	33.69	1.73	33.24	1.77	35.45	1.50
18	18.06	2.02	18.11	2.45	19.86	1.72	22.68	2.14	23.37	2.16	31.13	1.62	34.15	1.77	34.66	1.75	35.41	1.60
19	18.13	1.93	18.10	2.45	18.83	1.72	22.61	2.28	22.60	2.25	28.24	1.80	33.25	1.72	33.42	1.79	31.72	1.63
20	17.57	1.90	18.37	2.45	19.15	1.70	22.77	2.19	22.64	2.23	25.78	1.76	34.25	1.69	33.44	1.68	35.51	1.59

TABLE 5. Comparison of algorithm in terms of Ranking Index (R.I) in each run.

Run	EVDEPSO	VNS	DEEPSO	PSO_GBP	CEPSO	IC_DEEPSO	UPSO	IDE	FIREFLY
	RANKING INDEX								
1	19.60	20.04	20.22	25.12	24.86	31.97	31.22	37.27	37.73
2	19.16	21.29	20.06	24.85	24.91	28.25	33.94	35.71	36.51
3	18.79	19.61	20.56	24.81	24.84	29.17	34.85	36.44	37.94
4	19.80	21.04	20.53	24.92	24.86	30.33	31.65	39.97	36.76
5	19.07	20.44	20.54	25.05	24.85	31.94	32.89	36.46	36.75
6	19.69	20.97	21.32	24.89	24.72	33.27	35.28	32.50	37.91
7	20.03	21.37	20.56	24.84	24.97	30.26	37.37	37.84	36.06
8	20.20	21.26	21.57	24.84	25.10	29.37	35.01	33.39	36.50
9	19.12	21.29	21.03	24.93	24.87	30.03	34.61	39.70	36.85
10	19.97	21.07	21.27	24.99	24.78	30.68	33.27	39.24	36.86
11	19.21	20.51	20.76	24.92	24.79	30.06	35.39	34.42	37.61
12	19.58	20.62	20.44	24.82	25.01	32.75	34.26	38.45	35.07
13	19.48	20.79	20.82	24.83	24.87	31.59	34.06	34.23	38.01
14	18.97	20.88	20.99	24.83	24.79	30.88	34.75	37.67	39.40
15	20.00	20.77	21.77	24.81	24.79	33.96	37.31	36.08	37.43
16	19.82	21.03	20.47	25.00	24.85	35.19	32.34	34.45	34.97
17	19.42	20.74	21.22	24.77	24.85	30.36	35.42	35.01	36.94
18	20.08	20.56	21.58	24.82	25.53	32.75	35.92	36.41	37.02
19	20.06	20.55	20.55	24.89	24.85	30.04	34.97	35.21	33.35
20	19.47	20.82	20.85	24.96	24.87	27.54	35.94	35.12	37.09

time. In competition, for effective comparison of algorithms, the convergence criteria was set to 50,000 no of function evaluation and scenario was set at 100 for all tested methods. Different algorithms in this competition have chosen the different number of population. Therefore, they have different iterations according to the equation (35).

Nevertheless, a comparison based only on the ranking index signifies a poor approach to compare the results. Aside

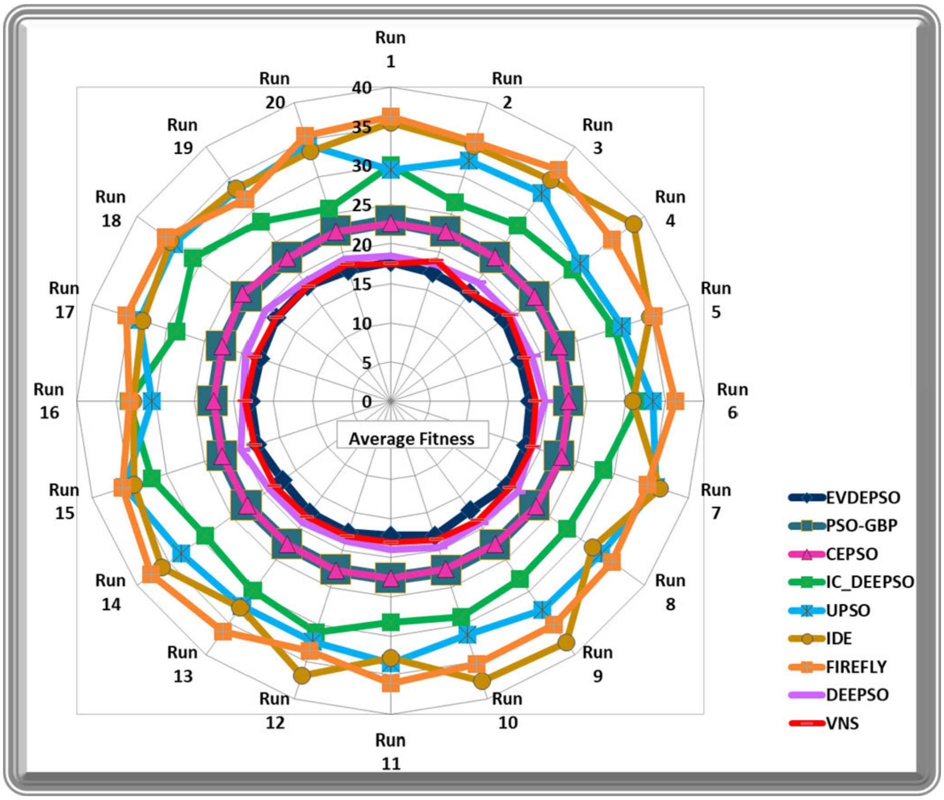

FIGURE 7. Average fitness of all tested algorithms for each run.

TABLE 6. Comparison of algorithms over 20 runs.

Method	Operation Cost (m.u)					Mean Exe. Time(s)
	Avg. Ranking Index	Avg. Fit.	Std. Dev.	Best	Worst	
EVDEPSO	19.57	17.67	1.90	13.20	22.99	53.56
VNS	20.78	18.33	2.45	14.34	22.97	51.84
DEEPSO	20.85	19.14	1.71	15.14	23.66	54.53
PSO-GBP	24.89	22.68	2.21	16.55	28.62	54.25
CEPSO	24.89	22.69	2.20	17.08	28.69	47.04
IC_DEEPO	31.02	29.27	1.75	24.75	34.23	42.11
UPSO	34.52	32.73	1.79	28.55	38.31	19.82
IDE	36.28	34.62	1.66	30.58	39.44	45.65
Firefly	36.84	35.25	1.59	31.54	39.66	483.65
MINLP	20.74	20.74	0	20.74	-	627

TABLE 7. Comparison in terms of Iterations and Mean execution time.

Method	No. of Iterations	Mean Execution Time (s)
EVDEPSO	285	53.56
VNS	492	51.84
DEEPSO	249	54.33
PSO_GBP	500	54.25
CEPSO	104	47.04
IC_DEEPSO	280	42.11
UPSO	240	19.22
IDE	499	45.65
FIREFLY	500	483.65
MINLP	500	627

from the fact that EVDEPSO's ranking index value is lower than the all tested methods, it is not possible to determine whether this discrepancy is statistically significant.

B. STATISTICAL ANALYSIS

One-way ANOVA [18] is a statistical method used to check whether the R.I of all tested algorithms for each run shows any significant differences. In the context of this experiment, a hypothesis experiment was used to validate the R.I equality.

$$\begin{cases} h_0 : m_i = m_j, & \forall i, j; \\ h_1 : m_i \neq m_j, & for\_any\_i \end{cases}$$

The null hypothesis h_1, which assumes the ranking index equality and the another hypothesis h_1, suggests that there is at least one ranking index that is not equal to the others. If one-way ANOVA shows a significant result, it means that at least one algorithm is distinct from another. The degree of significance is set to 1% to check any statistical differences between all tested methods. When the value of P in the one-way ANOVA is below 0.01, then it can be said that there is ample statistical proof to exclude null hypothesis, implying that either one or more algorithms are significantly different from other in terms of R.I, else, it is not possible to exclude the null hypothesis. Although One-way ANOVA can only decide whether the ranking index of all algorithms have significant differences, it has no hint of which particular algorithm is

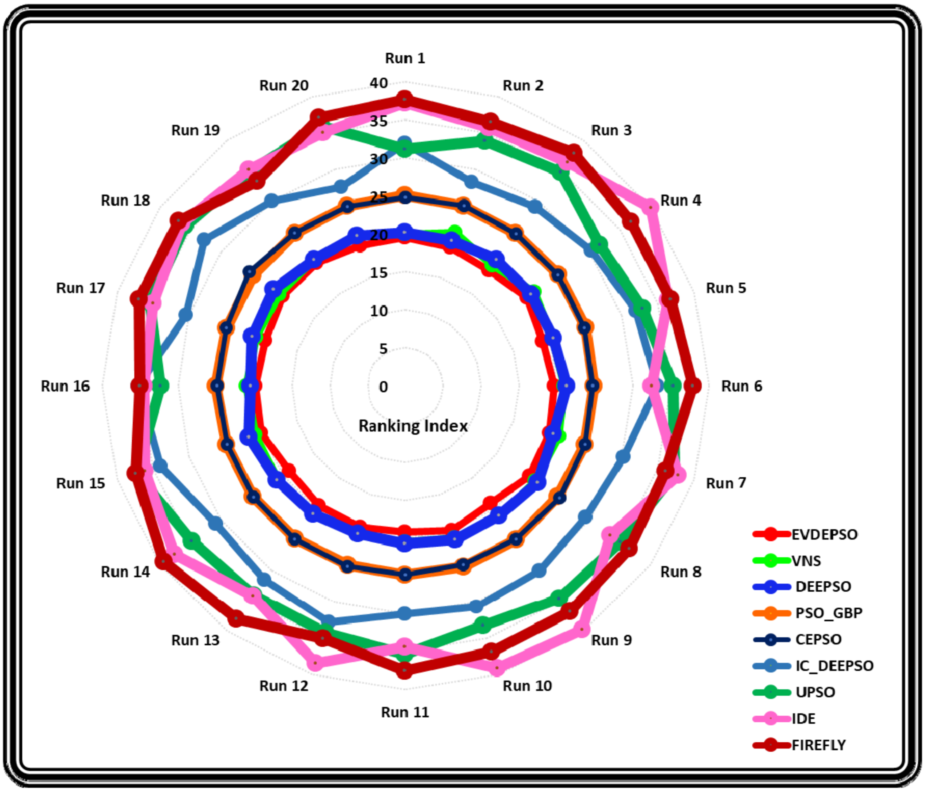

FIGURE 8. Ranking Index of all tested algorithms for each run.

TABLE 8. One-way ANOVA for ranking index.

Source of Variation	Sum of Squares	DF	MS	F	P-value
Between Algorithms	7821.30	8	977.66	676.96	3.52E-125
Within Algorithms	246.96	171	1.44		
Total	8068.25	179			

TABLE 9. Tukey HSD Q statistic results.

Pairwise Treatments	Tukey HSD Q statistic
EVDEPSO to VNS	4.489
EVDEPSO to DEEPSO	4.761
EVDEPSO to PSO_GBP	19.792
EVDEPSO to CEPSO	19.805
EVDEPSO to IC_DEEPSO	42.585
EVDEPSO to UPSO	55.621
EVDEPSO to IDE	62.155
EVDEPSO to FIREFLY	64.238

distinct from other. A pairwise comparison test, known as Tukey's HSD (honestly significant difference) test [19] was used to classify which of the algorithms were significantly distinct from EVDEPSO.

Table 8 shows the results of the one-way ANOVA test for the R.I of all tested algorithms given in Table 5 for each run. The P-value in one-way ANOVA is smaller than 0.01, indicates a significant difference in one or more algorithms.

In Tukey HSD test, the critical value of the studentized range statistic based on the k=9 treatments (algorithms) and degrees of freedom DF=171 for within algorithms term given in Table 8, for significance level P= 0.01 were selected. The critical value $Q_{critical} = 4.44$ was obtained from the table of studentized range distribution [20]. Then, the Tukey HSD Q-statistic as per the equation (45) were calculated for all the pairwise comparisons with EVDEPSO. The values of $Q_{i,j}$ are given in Table 9.

$$Q_{i,j} = \frac{\left|\overline{x_i} - \overline{x_j}\right|}{\sqrt{\frac{(MS)}{N_{Runs}}}} \tag{45}$$

where, i, j = 1, ... k, i ≠ j. $\overline{x_i} - \overline{x_j}$ is the difference between the Average Ranking Index (A.R.I) of the comparison pair algorithms. MS =1.44 is the Mean Square for within algorithms term from the Table 8.

Table 9 shows that, for all the pairwise treatments, Tukey HSD Q statistic value $Q_{i,j} > Q_{critical}$. It reveals that Ranking Index of EVDEPSO is significantly different from all tested eight algorithms in each run. So, it is cleared that, EVDEPSO gives the best R.I and A.R.I as compared to all tested algorithms and provides the competitive result for the

TABLE 10. Optimal solution by EVDEPSO.

	Hours																							
Energy Sources	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
PV	0	0	0	0	0	0	0.50	6.70	32.13	55.53	78.58	99.10	126.23	107.83	87.44	116.39	96.92	88.44	61.65	37.24	12.53	1.79	0.14	0
Dispatchable DGs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49	9.49
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32	21.32
External supply	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10	57.10
Electrical vehicles	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	0	0	0	0	0	-0.09314	0	0	0	0	0	0	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314
	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	0	0	0	0	-0.09314	0	0	0	0	0	0	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314
	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314	0	0	0	-0.09314	0	0	0	0	0	0	0	-0.09314	-0.09314	-0.09314	-0.09314	-0.09314
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0.00127	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0.00127	0	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0.00127	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0.00127	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0.00127	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0.00127	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0.00127	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
	0.00127	0.00127	0.00127	0.00127	0.00127	0.00127	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00127	0.00127	0.00127	0.00127	0.00127
Energy storage	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94	-8.94
	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87	-0.87
Electricity market	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24	-70.24
	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72	-31.72

day ahead energy resource scheduling in a highly uncertain environment.

V. CONCLUSION AND FUTURE WORK

In the Microgrid environment, the intensive use of uncertain energy sources for different scenarios of PVs, ESSs, DR programs, V2G or G2V and Electricity Markets has significantly increased the uncertainty and dimension of the day ahead energy resource planning problem. This makes it extremely important for the aggregator to use the appropriate approach to achieve maximum profit.

This paper has introduced a new metaheuristic algorithm called Enhanced Velocity Differential Evolutionary Particle Swarm Optimization to solve this problem. To check the robustness and effectiveness of the EVDEPSO, it is compared with other latest state of art algorithms, namely VNS, DEEPSO, CEPSO, PSO-GBP, IC-DEEPSO, UPSO, IDE, Firefly and MINLP. Comparative analysis shows that, EVDEPSO gives low R.I and A.R.I as compared to the aforementioned algorithms. It concludes that, with EVDEPSO, aggregator gets more profits. Statistical analysis using one-way ANOVA and Tukey HSD test also proves its effectiveness by showing that EVDEPSO's R.I is statistically significantly different from the aforementioned algorithms. The optimum results obtained by the proposed method shows that, it is capable to handle the realistic problems involving large number of variables.

In the future, EVDEPSO will be applied to solve the highly complex microgrid system with high penetration of uncertain energy sources and large number of scenarios.

APPENDIX

See Table 10.

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