

A Decentralized Control Strategy for Voltage Regulators and Energy Storage Devices in Active Unbalanced Distribution Systems

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Abstract—This paper studies a multi-objective optimization problem that optimizes unbalanced distribution networks with high penetration of photovoltaic power generation whereby the aim is to find the optimal tap positions of voltage regulators (VRs) and locally optimized charging and discharging power profiles for energy storage devices (ESDs) based on a decentralized coordination process. The corresponding objective function is based on the voltage profile of the network and the lifetime improvement of the VRs and ESDs. The Advanced Arithmetic Optimizer (AAO) algorithm combined with the profile steering approach is used to find a near-optimal solution for the problem. The decentralized process is compared to a centralized approach for the IEEE 13 and 123 bus systems. Results show that the proposed decentralized method is able to resolve all voltage problems and find good quality solutions in lower computational time compared to the centralized approach and other optimization algorithms.

Index Terms—Distributed generation, Voltage control, Regulators, Optimal control, Profile steering, Heuristic algorithm

I. INTRODUCTION

A. Background

In the last years, distribution system operators have faced new challenges due to the integration of new elements into the distribution systems, such as renewable energy resources, energy storage devices (ESDs), and electric vehicles. Approximately 178 gigawatts (GW) of distributed generators (DGs) were installed up to 2017 worldwide of which around 55% were solar photovoltaic (PV) panels [1]. This increase in penetration of DGs affect the operation of the system and results in a higher degree of phase imbalance and a wide range of voltage fluctuations.

The increase of in the PV penetration changes the characteristics of distribution networks (DNs) from a passive system to active DNs. A heavy penetration of PV units in the medium and low voltage networks can create problems such as voltage violations, voltage fluctuations, and voltage imbalance [2]. Therefore, the system operators may use ESDs and corresponding charging and discharging powers or dynamically adjust the tap position of voltage regulator (VR) devices. An improved control strategy for ESDs and VRs while aiming for maximizing the lifetime of the devices can mitigate the impact of the mentioned problems from a techno-economical perspective.

Classic control techniques for VR devices, such as on-load tap changers (OLTCs), step voltage regulators (SVRs), and switchable capacitors (SCs), are developed based on

the unidirectionally power flow scheme in passive DNs. However, the multi-directional power flow in DNs caused by the injected power generated by PV and ESD units can mislead such classic control strategies and create voltage violations and tap oscillations of VR devices [1].

B. Relevant Literature

Recently, various research has been performed to find optimal voltage control strategies to control devices in DNs. A Local coordination technique for PVs and ESDs [3], various single and multi-objective optimization techniques [4], [5], neural network applications [6], and decentralized and curtailment control strategy techniques [7] are studied by researchers. Hereby, the voltage control methods can be classified into centralized and distributed methods.

Centralized control methods aim to find the optimal control parameters of VRs and/or ESDs by optimizing towards a predefined goal. The goal of the optimization process can be to minimize the voltage deviations, lifetime improvement, and peak shaving in DNs. Coordinating DGs, OLTCs, and SCs using a centralized control method for day-ahead coordination is investigated in [8]. The same method is used for managing the active and reactive power of DGs [4], and for voltage rise mitigation by controlling the charge and discharge powers of ESDs [9]. Centralized control strategies may be able to find optimal control strategies. However, the performance and optimality of the solutions are based on often costly communication systems and the reliability of the solutions maybe poor.

On the other hand, decentralized control strategies rely on various individual objectives and controllers' decisions. Decentralized methods coordinate the parameters of distributed controllers and multi-agent systems on local levels and allow communication between local areas. There have been various works to enhance the implementation of the decentralized methods in DNs, such as the charge/discharge of ESDs [10], reactive power-sharing and curtailment of the output of DG units [7], and coordination among VRs, and PV output [11]. In general, a decentralized approach is more reliable than a centralized methods, and system operators can consider both local and global objective functions for the optimization process.

C. Contributions and Organization

This study proposes a decentralized optimization model and a strategy to simultaneously minimize the voltage deviation and maximize the lifetime of VRs and ESDs

in three-phase unbalanced electricity systems. The optimal control strategy for the ESDs (state of charge (SOC) based on charge and discharge powers) is determined locally at each bus using the *Profile Steering* (PS) method [12], hereby considering the local load and generation in the network. The near-optimal tap position of VRs is determined using the proposed advanced arithmetic optimizer (AAO) algorithm. Besides the optimal control strategy for the VRs and ESDs, the AAO algorithm is proposed based on the improvement of the convergence speed of the arithmetic optimization algorithm (AOA) [13] and adapting the algorithm to solve the specific problem of DNs' voltage control strategy. Compared to the cited references, the proposed algorithm enhances the search capability of the AOA and improves its suitability for dealing with mixed-integer nonlinear programming (MINLP) problems. The proposed optimization algorithm for solving the problem of unbalanced networks is tested on the IEEE 13-bus and the IEEE 123-bus systems with a high integration of PV units. The optimization result found by the presented AAO method are compared to the AOA [14] method, grey wolf optimization (GWO) [15], and particle swarm optimization (PSO) [13] in terms of convergence speed and the quality of the solutions.

The main contributions of the paper are as follows:

- A new objective function for solving the voltage violations while maximizing the lifetime of the used assets.
- Investigation of the potential benefits of the PS method in finding optimal charging and discharging strategies of the ESDs and extention of the control strategy by the use of VRs to eliminate voltage magnitude deviations.
- Investigation of the potential benefits of the decentralized method over a centralized approach.
- Development of the AAO algorithm based on the AOA formulation that also solves MINLP problems using an additional stopping criteria that improves its convergence characteristics and allows finding better solutions compared to other metaheuristic algorithms.

The rest of the paper is organized as follows. The proposed methods are discussed in Section II. Section III briefly describes the AAO algorithm and focuses on the optimization problem framework. Simulation results are presented in Section IV. Final remarks and conclusions are given in Section V.

II. OPTIMIZATION FRAMEWORK

A. Centralized approach

The centralized method is taking the network's perspective as its base. Consider a network with N_{br} buses, during a planning horizon with N_T periods, where each bus has its own energy assets (PV, ESD, load) with controllable variables $\vec{X}_{SOC} = (P_{j,t}^{ESD}, \forall j \in N_b, t \in N_T)$. Furthermore, the DN has a set of VRs with controllable tap positions (\vec{X}_{TAP}). The objective of the operator is to mitigate voltage deviations from the nominal value in the network and to maximize the expected lifetime of VRs and ESDs considering power flow equations and operational limits. Hence, the control variables are given by $\vec{X} = (\vec{X}_{TAP}, \vec{X}_{SOC})$ and the centralized problem is formulated as follows:

$$\min_{w.r.t \quad \vec{X}} \quad F(\vec{X}_{TAP}, \vec{X}_{SOC}) \quad (1)$$

s.t.

$$h(\vec{X}_{TAP}, \vec{X}_{SOC}) = 0 \quad (2)$$

$$P_{j,ph,t} = P_{j,ph,t}^{PV} + P_{j,ph,t}^{ESD} - P_{j,ph,t}^{Load}, \quad \forall j \in N_b, t \in N_T, ph \in N_p \quad (3)$$

$$SOC_{j,t}^{ESD} = SOC_{j,t-1}^{ESD} - \frac{\Delta t}{E_j^{ESD}} \sum_{ph} P_{j,ph,t}^{ESD}, \quad \forall j \in N_b, t \in N_T \quad (4)$$

$$\underline{\lambda}_j E_j^{ESD} \leq SOC_{j,t}^{ESD} \leq \bar{\lambda}_j E_j^{ESD}, \quad \forall j \in N_b, t \in N_T \quad (5)$$

$$-\beta_j \leq \sum_{ph} P_{j,ph,t}^{ESD} \leq \beta_j, \quad \forall j \in N_b, t \in N_T \quad (6)$$

where (2) represents the power flow equations, (3) the power balance at node j , (4) the state of charge of the ESD unit at node j , while (5) and (6) are the operational limits of the ESD. Notice that $SOC_{j,t}^{ESD}$ is the energy stored in ESD unit j at time t , while E_j^{ESD} stands for its energy capacity. The lower and upper limits for the state of charge are represented by $\underline{\lambda}_j$ and $\bar{\lambda}_j$ and the upper limit for charge and discharge power of each ESD unit is represented by β_j . Finally, Δt is the length of time intervals in the simulation.

The objective function (F) represents voltage deviations from the nominal value, $V_{ref} = 1 p.u$ by (7a) and the expected lifetime of VRs and ESDs by (7b) as follows:

$$F(\vec{X}) = \frac{f_1(\vec{X})}{f_1(\vec{X}_{bc})} + \frac{f_2(\vec{X})}{f_2(\vec{X}_{bc})} \quad (7)$$

where,

$$f_1(\vec{X}) = \sum_{t=1}^{N_T} \sum_{j=1}^{N_{BUS}} \sum_{ph} (V_{t,j,ph}(\vec{X}) - V_{ref})^2 \quad (7a)$$

$$f_2(\vec{X}) = \sum_{i=1}^{N_{VR}} LT_{VR_i}(\vec{X}) + \sum_{l=1}^{N_{ESD}} LT_{ESD_l}(\vec{X}) \quad (7b)$$

$$LT_{VR}(\vec{X}_{TAP}) = \sum_{t=1}^{N_T} (X_{TAP_t})^2 \quad (7c)$$

$$LT_{ESD}(\vec{X}_{SOC}) = \sum_{t=1}^{N_T} (X_{SOC_t} - 0.5E^{ESD})^2 \quad (7d)$$

$$f_{3,j} = \sqrt{\sum_{t=1}^{N_T} (P_{j,t})^2}, \quad \forall j \in N_b \quad (8)$$

Hereby the term \vec{X}_{bc} denotes the control variables of the base case scenario, i.e., where no control strategy is used in the network. The voltage magnitude of the phases is denoted by $V_{t,j,ph}$ at bus j , time t , and phase ph . LT is the expected lifetime of a VRs and ESDs. Finally, N_{VR} and N_{ESD} denote the number of VRs and ESDs in the DN. It is worth mentioning that (8) is used only as an assessment measure of the consumption profile at each bus j ; hence, it is not minimized in the centralized method.

The proposed objective minimizes the voltage deviation of the nodes from a reference voltage and as a result minimizes the unbalanced voltage profile. The objective functions in (7c) and (7d) are used to maximize the lifetime of the VR and ESD units. The functions aim to minimize the charge and discharge power usage of ESDs and the change in the taps of the VR.

B. Decentralized approach

The decentralized method decouples the coordination of the ESDs into local subproblems. Each local subproblem is represented by a node in the system, and PS is used to peak shave its energy profile using ESDs to minimize the impact on the DN. The decentralized problem is formulated as follows:

$$\begin{aligned} \min_{w.r.t. \vec{X}} \quad & F(\vec{X}_{\text{TAP}}, \vec{X}_{\text{SOC}}^*) \\ \text{s.t.} \quad & (2), (7a) - (7d) \end{aligned} \quad (9)$$

$$\begin{aligned} \vec{X}_{\text{SOC}}^* = \arg\min_{w.r.t. \vec{X}_{\text{SOC}}} \quad & f_{3,j}(\vec{X}_{\text{SOC}}) \quad \forall j \in N_b \\ \text{s.t.} \quad & (3) - (6) \end{aligned} \quad (10)$$

where \vec{X}_{SOC}^* is the optimal control strategy of the ESDs for the subproblems optimized by the PS method. The PS methodology aims to minimize (8) for the local problems.

The optimal solution of the local subproblems is denoted by \vec{X}_{SOC}^* . Thus, the task of the DN is to react to these actions by modifying $\vec{X} = \vec{X}_{\text{TAP}}$ given \vec{X}_{SOC}^* to improve the system's characteristics.

III. PROPOSED OPTIMIZATION ALGORITHM

AAO is a modified version of the Arithmetic optimization algorithm (AOA) [13] and it aims to enhance the search capability of the AOA at finding good approximations of the global minimum solution. The main arithmetic operators (addition, subtraction, multiplication, and division) are the primary motivation of the AAO algorithm formulation.

The AAO algorithm is composed of the following steps. At first, a set of solutions ($\vec{X} = X_{m,n} : m = 1, 2, \dots, N$ and $n = 1, 2, \dots, D$) is generated randomly with the variables within the boundaries. Hereby N represents the number of solutions in the set and D is the number of control parameters in each solution vector. Each solution is evaluated using a power flow formulation [16], and a subset of best solutions is selected $F^* = F(X_{m,n}^*) : X_{m,n}^* \in \vec{X}$.

The algorithm comprises two phases in the main loop of the optimization process: an exploitation phase and an exploration phase. Both phases update the solutions to improve the objective function value in search for the optimal solution. The exploration phase focuses on searching the entire solution space and identifying potential candidates to avoid being trapped in locally optimal solutions. In contrast, the exploitation phase focuses on local areas of the solution space around the identified candidates in the exploration phase. The algorithm enters the exploitation or exploration phase based on a decision factor DF :

$$\left\{ \begin{array}{ll} \text{exploration phase,} & DF(k) > r_1 \\ \text{exploitation phase,} & \text{otherwise} \end{array} \right. \quad (11)$$

$$DF(k) = a^{(1 - \frac{k}{k_{Max}})} - 1$$

where k and k_{Max} show the current and maximum number of iterations of the process, r_1 is a random number between zero and one, and a is a constant number which based on experimental results is set to 2 to maximize the efficiency of the exploration and exploitation search. The minimum and maximum values of the DF function change from

one to zero. The values of DF determine the selection of exploitation or exploration evaluation for the solutions. By introducing the iteration number in the DF function, in the early iterations the probability of choosing the exploration phase is much greater than exploitation phase, and also in the final iteration, the chance of exploitation phase is higher.

In the next step, if the value of DF is exceeds r_1 or in other words, exploration phase is selected. For the exploration phase, AAO uses the multiplication, and division from the arithmetic operators to update the solutions. The new solutions is determined according to (12):

$$X_{m,n}^{k+1} = \begin{cases} X_n^* \div r_3 \cos(2\pi r_4)x, & r_2 > 0.5 \\ X_n^* \times r_3 \cos(2\pi r_4)x, & \text{otherwise} \end{cases} \quad (12)$$

$$x = ((UB_n - LB_n)r_5 + LB_n) \quad (13)$$

where $X_{m,n}^{k+1}$ denotes the m_{th} solution in the next iteration and n shows the n_{th} position of the solution. r_2 , r_3 , and r_5 are a random numbers in between 0 to 1. The allowed ranges of the variables are shown with UB for the upper limits and LB for the lower limits, and r_4 is a random number with in [-1,1] range.

If DF is less than r_1 (exploitation phase) the subtraction and addition operators are used.

$$X_{m,n}^{k+1} = \begin{cases} X_n^* + r_3 \cos(2\pi r_4)X_{m,n}^k, & r_2 > 0.5 \\ X_n^* - r_3 \cos(2\pi r_4)X_{m,n}^k, & \text{otherwise} \end{cases} \quad (14)$$

As the optimization algorithms based on heuristic methods, having a robust strategy that determines the evaluation of the positions through the exploitation phase or exploration phase can improve the searchability of the algorithm [14]. Compared to the AOA formulations, both exploitation and a exploration phases methodology were modified to improve the global search capability in the first iterations and improve the exploitation in the last iterations. Besides the improvements in the exploitation and a exploration behavior, AAO used a new boundary check method called mirroring correction [13] for checking the variables constraints and also a dynamic stopping criterion for stooping optimization process [4].

The flowchart in Fig. 1 shows the proposed methodologies (centralized and decentralized) to solve the proposed optimization model. It is worth mentioning that the steps defined as *optimization algorithm* (OA) can be solved with different techniques. Specifically, the formulation for the AAO has been introduced in this section, while the formulations of the AOA, GWO, and PSO algorithms can be found in [14], [15], [17]. Note that X^{k^*} and F^{k^*} represent the best solution found by the OA and the best objective value corresponding to the solution in the current iteration.

IV. TEST SYSTEMS AND SIMULATIONS RESULTS

A. Test systems, load, and PV characteristics

The IEEE 13 and 123 bus distribution systems [18] are used in the simulations. Within these models, the main modifications are the addition of PV systems and ESDs at several busses of the systems. Real data concerning the sun irradiation and load curve behavior are used to model the PV yield and load characteristic [19]. For both test systems, the locations and sizes of the PVs and ESDs that are added

TABLE I
PROPOSED PV AND ESDS LOCATIONS AND SIZES FOR IEEE 13-BUS SYSTEM.

PV		ESD	
Location	Size [kW]	Location	Capacity [kWh]
671 (3ph)	100	671 (3ph)	100
675 (3ph)	100	675 (3ph)	100

TABLE II
PROPOSED PV AND ESDS LOCATIONS AND SIZES FOR IEEE 123-BUS SYSTEM.

PV		ESD	
Location	Size [kW]	Location	Capacity [kWh]
47 (3ph)	60	47 (3ph)	40
48, 49, 65 (3ph)	110	48, 49, 65 (3ph)	100
76 (3ph)	160	76 (3ph)	100
16, 33 (1ph)	50	16, 33 (1ph)	40
104, 113 (1ph)	60	104, 113 (1ph)	40

to the systems are presented in Table I and Table II. Note that these locations are the same as in [20].

The optimal \vec{X}_{SOC} control parameters for the ESDs are to be found based on the local consumption at each ESD's installation location. The tap positions (\vec{X}_{TAP}) of the VRs are the control parameters to be found using OAs (AAO, AOA, GWO, and PSO). The VRs are connected to the three phases of the system at the installation place located inbetween nodes of the systems as presented in Table III. Note that for the base case scenario the tap positions of VRs are set according to the parameters found in [18] without ESD units. The Laurent power flow analysis methods [16] is used for evaluating the impact of the VRs and ESDs on voltage levels.

B. Simulation Results

The results of finding the near-optimal values of the objective functions in the IEEE 13 and 123 bus system based on optimizing the problem using the decentralized approach are provided in Table IV. The performance of the different methods in terms of the average (mean), standard deviation (Std.), and best objective function (best) values of 20 independent runs are compared in this table. Besides

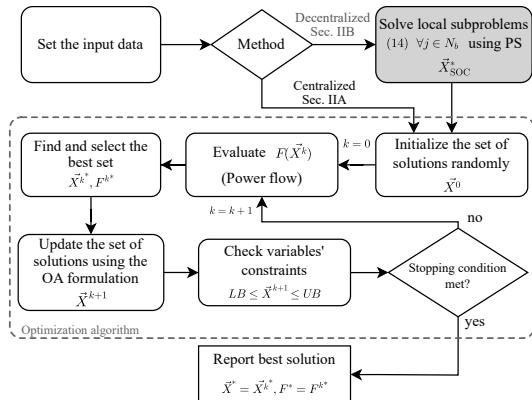


Fig. 1. Flowchart of the proposed methodology.

TABLE III
THE VR LOCATIONS IN BOTH SYSTEM.

	IEEE 13-bus	IEEE 123-bus		
From	RG60	149	9	25
To	630	150	14	26

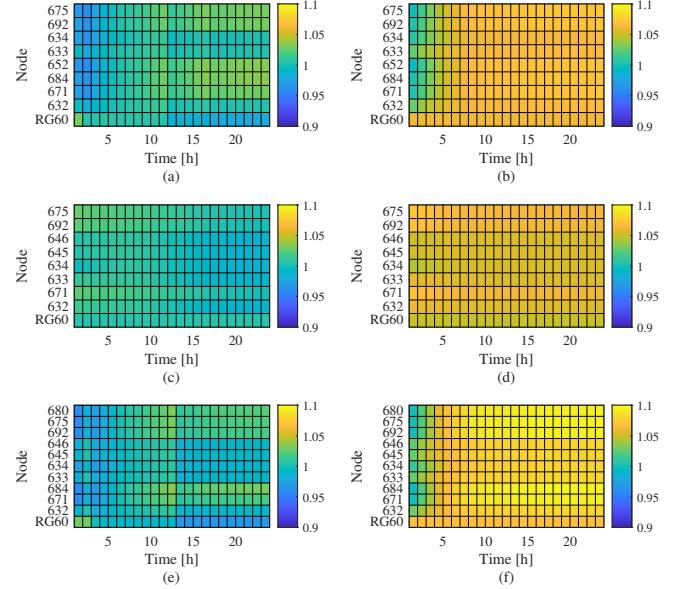


Fig. 2. Voltage profile of the IEEE 13-bus system for the best solution per phase (a, c, and e) and base case solutions per phase (b, d, and f). Note that the color bar values for the three phases are in p.u.

the performance of the methods in finding the near-optimal solutions, the convergence speeds of the different OAs are compared based on computational time.

The discussion around the near-optimal solutions, OAs performance, convergence behavior of the OAs, and comparison of the decentralized method with centralized method results are summarized in the following subsections.

1) Near-optimal solutions: The near-optimal solutions for both test systems were found by the AAO method with an F value of 0.2487 for IEEE 13-bus and 1.4188 for IEEE 123-bus systems. Fig. 2 and Fig. 3 visualize the voltage profile of the system for the near-optimal solution case and the base case, the near-optimal solutions for control of ESDs and VRs show that all the voltage violations created by the integration of PV units were eliminated. Note that the voltage violation problem is defined as the voltage magnitude that exceeds the $\pm 5\%$ of the V_{ref} defined for the system [9].

2) Optimization algorithms performance and Convergence behavior: The results show that the proposed AAO algorithm finds a better mean value and the best solution for both test system problems in 20 independent optimization process runs. Based on the IEEE 13-bus system results, both AOA and AAO found better results than the other algorithms. On the other hand, the AOA method could not find a better mean value and solution than the GWO method, and it shows that AAO modifications can cover the disadvantages of the AOA method while dealing with a large number of the optimization variables number (high dimensions). The simulation results show that the AAO method finds a better solution in the least amount of time for both test systems.

The performance analysis of the OAs in finding the near-optimal solution and also better strategy for exploitation and exploration phases compared based on convergence behavior of the OAs. Fig. 4 and Fig. 5 show the convergence curves of the optimization process for finding best solutions.

TABLE IV
COMPARISON OF THE METHODS IN SOLVING THE DISTRIBUTION SYSTEM PROBLEM.

	F	AAO			AOA			GWO			PSO		
		mean	std.	best	mean	std.	best	mean	std.	best	mean	std.	best
IEEE 13-bus	execution time (s)	0.2495	0.0005	0.2487	0.2498	0.0004	0.2488	0.2503	7.3E-18	0.2503	3.2861	3.6745	0.2583
IEEE 123-bus	execution time (s)	1.6100	0.0371	1.4188	1.9215	1.1264	6.1359	4.1726	2.7877	1.5272	11.0283	0.6490	8.2710
		38	1.5	37	41	1.1	40	39	1.4	37	43	1.1	42
		661	62.5	648	690	51.2	663	964	63.2	947	779	55.0	777

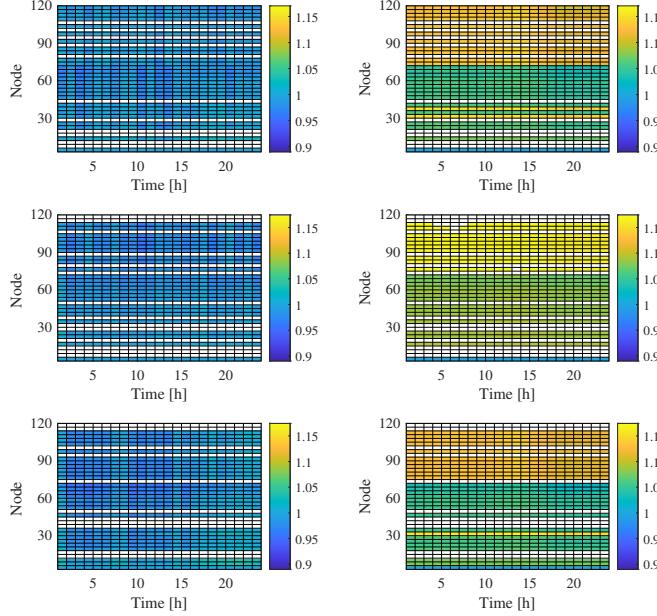


Fig. 3. Voltage profile of the IEEE 123-bus system for the best solution per phase (a, c, and e) and base case solutions per phase (b, d, and f). Note that the color bar values for the three phases are in p.u.

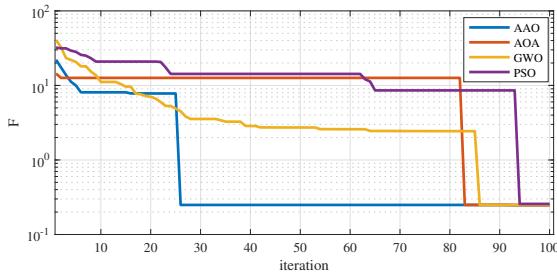


Fig. 4. Convergence behavior of the methods for IEEE 13-bus simulation.

The convergence curves show enhancement in exploitation and exploration phases developed for the AAO method and better behavior compared to the other algorithms. More exploration search behavior in the early iterations shows the better quality in exploring the search space in AAO, while other OAs get stuck in local minima and try to search for better solutions around that solution. In the final iteration, instead of searching the whole search space, unlike the other OAs, AAO focused on the local search around the best solution found so far.

3) *Advantages of the decentralized method:* The advantages and disadvantages of the proposed decentralized method are compared to a centralized coordination method in this section. Dynamic stopping criteria are added to the AAO algorithm to stop the optimization process while the algorithm converges to the near-optimal result. The results of 20 independent runs of the algorithms are compared based on the quality of the results and the convergence

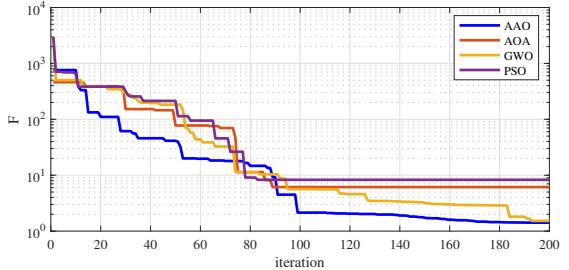


Fig. 5. Convergence behavior of the methods for IEEE 123-bus optimization problem.

speed. Table V shows that the average values of the F function found by the centralized method are lower than the decentralized method. Compared to the decentralized method, the centralized method could not find the best solution for the IEEE 123-bus (the high dimension problem compared to the IEEE 13-bus problem). The dimension of the problem in the centralized method (\vec{X}) is higher than the problem solved by AAO in the decentralized method (\vec{X}_{VR}), and as a result finding the optimal solution is more complicated. By splitting up the problem into decentralized problem, the subproblems are less complex and hence solving is easier as shown as follow.

The convergence curve of each individual run of the method is shown in Fig. 6 and Fig. 7 for IEEE 13-bus and 123-bus systems. As shown in the figures and Table V, the optimization process in the centralized method took more time. The AAO algorithm in the decentralized method needs fewer iterations (80% less for IEEE 13-bus and 78% less for IEEE 123-bus less iterations). The minimum number of the iterations required for the centralized method to converge to a near-optimal solution was 545 iterations and 893 iterations for the problem of IEEE 13 and 123 bus systems, respectively. Similar solutions were found after 78 and 190 iterations using the decentralized method.

The different parts of the objective functions in the best solutions found for centralized and decentralized methods are compared in Table V. In the optimization problems, the centralized method found a better solution w.r.t. voltage profile, while the lifetime of the ESDs and VRs and coordination of the EDSs considering the local area problems was improved most by the decentralized method. The minimum and maximum voltage magnitudes for the three phases of the system are presented in Table VI. The results show that both methods eliminate the voltage violations existing in the base case.

V. CONCLUSION

The simulation results for the IEEE 13 and 123 bus systems show the helpfulness of the proposed objective functions formulated to eliminate the voltage violation and maximize the expected lifetime of devices like VRs and

TABLE V
DETAIL OF THE SOLUTION FOUND BY CENTRALIZED AND DECENTRALIZED METHODS.

		F			execution time (s)			F^*		
		mean	std	best	mean	std	best	f_1	f_2	f_3
IEEE 13-bus	Centralized	0.2467	0.0004	0.2466	211	8.4	201	0.0451	252	741
	Decentralized	0.2501	0.0011	0.2487	30	1.2	29	0.0482	264	675
IEEE 123-bus	Centralized	1.5122	0.0564	1.4242	2993	41	2958	0.1811	1189	3063
	Decentralized	1.6007	0.0741	1.4188	663	10	651	0.1883	1261	2839

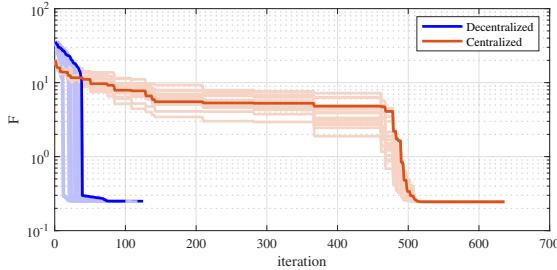


Fig. 6. Convergence behavior of the AAO for IEEE 13-bus optimization problem in both centralized and decentralized methods.

ESDs based on decentralized local and global coordinators. The study shows that the AAO method finds better solutions in the least amount of time for the given problem. The algorithm achieved a better exploitation and exploration phases and better convergence behavior. The results also show that the proposed formulation for the decentralized optimization of the ESDs in the local area of the system and global coordination of the VRs are save up to 80% computation time compared to the centralized formulation in our evaluation study. Future work covers the impact of multi-objective versions of the OAs based on decentralized coordination of multi-carrier energy networks.

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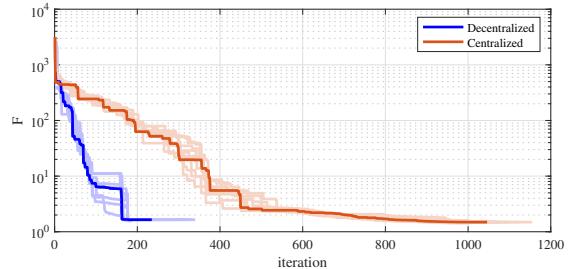


Fig. 7. Convergence behavior of the AAO for IEEE 123-bus optimization problem in both centralized and decentralized methods.

TABLE VI
MINIMUM AND MAXIMUM VOLTAGE MAGNITUDE (P.U) FOUND BY THE CENTRALIZED AND DECENTRALIZED METHODS.

		ph 1		ph 2		ph 3	
		min	max	min	max	min	max
IEEE 13-bus	Centralized	0.9561	1.0375	0.9847	1.0303	0.9566	1.0411
	Decentralized	0.9603	1.0360	0.9881	1.0275	0.9592	1.0408
IEEE 123-bus	Centralized	0.9578	1.0482	0.9608	1.0216	0.9525	1.0391
	Decentralized	0.9629	1.0480	0.9588	1.0218	0.9508	1.0387