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An Optimization Framework for Distributed Energy Resource Planning and Energy Management Strategy of Storage Devices and Electric Vehicles

Bahman Ahmadi[1], Oguzhan Ceylan[2], and Aydogan Ozdemir[3]

[1]Department of EEMCS, University of Twente, Enschede, Netherlands
Email: b.ahmadi@utwente.nl

[2]Department of Electrical and Electronics Engineering, Marmara University, Istanbul, Turkey
Email: oguzhan.ceylan@marmara.edu.tr

[3]Department of Electrical Engineering, Istanbul Technical University, Istanbul, Turkey
Email: ozdemiraydo@itu.edu.tr

***Abstract*—This paper proposes an optimal coordination strategy for electric vehicles and energy storage devices in distribution grids besides the optimal allocation problem of renewable distributed generation (RDGs) and energy storage devices (ESDs). By finding the optimal number, size, and site of the RDGs and ESDs, together with the operation strategy of the ESDs and smart charging of a large number of EVs, the performance of the distribution grids will be improved. An advanced grey wolf optimization (AGWO) algorithm is used to minimize energy losses and voltage violations simultaneously in the test systems. Simulations are tested on IEEE 33 and 69 bus networks to find near-optimal solutions for the optimization problem. Based on the simulation results, the proposed optimization framework reduced the systems' losses while minimizing the voltage violations by finding the optimal control parameters of the devices.**

***Index Terms*—Distributed generation, storage systems, Heuristics, electric vehicle charging management, Real power losses**

I. INTRODUCTION

Renewable energy sources and electric vehicles (EVs) are the leading network modernization factors to decrease transportation and power generation carbon emissions [1]. The high penetration of renewable distributed generation (RDGs), energy storage devices (ESDs), and electric vehicles (EVs) in distribution networks (DNs) can cause technical and operational problems. Discontinuous energy generation in renewable energy sources such as wind turbine (WT) and photovoltaic (PV) units and extra loads raised by the EV charging may result in voltage deviations and increased losses in the DNs. Coordination is required between EVs charging strategy and RDGs and ESDs operation to guarantee the secure and reliable operation of the DNs.

While EVs may account for a small percentage of cars on the market today, growth in the number of EVs is being accelerated. Already, the total number of EVs will reach 35 million worldwide [2]. The prediction for 2024 is the increase in the number of EV sales by 2.4 million in the United States [3], and the total number of EVs will reach approximately 130 million worldwide in 2030 [4]. Having more EVs on the roads needs a vast electrical energy requirement and has inverse impacts on the energy sector. An uncoordinated EV charging strategy can create higher demand during peak hours and a severe issue for utility services [5].

Some recent publications have studied the integration of EVs and ESDs for demand-side management in smart grids to enhance the system load profile and exchange the energy between off and on peak load hours [6]–[8]. Authors in [9] evaluated electric vehicle coordination impacts on a grid using a scenario-based methodology. The authors also suggested optimal smart coordination for EVs to minimize load variance and operating costs of the grid. In [10], the significant effects of plug-in EVs on the low voltage DNs without considering the electric vehicle uncertainties in the state of charge and different technological charging powers. A probabilistic smart charging strategy for charging schedule of EVs was proposed based on Monte-Carlo simulation in [11] to optimize the effect of slow or fast charging of EVs on the load profile of the system.

Besides the optimal smart charging strategies for the EVs in the DNs, the optimal sizing of the RDGs and ESDs and optimal coordination for the charging and discharging powers of the ESDs have been studied previously. The effect of optimal control for ESDs to maximize the energy exchange generated by EDGs to the high peak load hours was studied in [12]. Smart grid management using ESDs was formulated and optimized by convex optimization problem and it sought the solution through different methods such as Lagrange–Newton [13], Interior Point Technique [14], Lagrangian Algorithm [15], and Lyapunov Method [16]. Adding the smart control strategy for ESDs to the smart charging problem of the EVs creates a complex mixed integer nonlinear programming (MINLP) problem. Solving the problem using the aforementioned classical optimization algorithms is affected by scalability and convergence issues due to the non-convex nature of the problem. Therefore, the computational burden and the complexity of solving ESD and EV allocation problems and coordinating their charging and discharging process increases with the increasing penetration rate of those devices and the size of the system. For this purpose, heuristic techniques are more convenient than analytical methods, especially for optimal utilization of EVs and ESDs under different scenarios using real data while considering the different goals for the optimization process.

This paper proposes a new approach to optimizing allocation problem of RDGs and ESDs, the smart charging of the EVs, and control strategy for the ESDs in DNs. For this purpose, the optimal charging strategy for the EVs, optimal control strategy of ESDs, and also number, location, size, capacity, and powers of the RDGs and ESDs are determined simultaneously using an advanced Grey Wolf optimizer algorithm (AGWO) [17]. The goal for the optimization problem is to minimize the impact of additional EV loads on the DNs' energy losses and voltage violations. The algorithm is developed to find optimal control parameters of the problem for IEEE 33 and 69 bus systems. The optimality of the solution and convergence speed of the AGWO [17] method are tested by comparing the results obtained with the other well-known algorithms, including particle swarm algorithm (PSO) [18], Grey Wolf optimizer (GWO) [19], and advanced arithmetic optimization (AAO) algorithm [20].

The main contributions of the paper are as follow:

- Extension of the traditional RDG and ESD allocation and sizing problem with optimal charging scheduling of the EVs.
- Investigation of near-optimal allocation and sizing of RDG and ESD supports to the system performance for increasing EV penetration rates.
- Finding the maximum limit of the EV penetration for the system while minimizing the energy losses and voltage violations.
- Investigation on the quality of the solution found by AGWO method.

The rest of the paper is organized as follows. The objective function formulations are discussed in Section II. Section III briefly describes the optimization algorithms and focuses on the implementation of the optimization problem. Simulation results of test systems applications are presented in Section IV. Final remarks and conclusions are summarized in Section V.

II. Problem Formulation

The single objective optimization model for the problem can be given as follows.

$$\underset{w.r.t\ \mathbf{X}}{\text{minimize}}\ \ f(\mathbf{X}), \tag{1}$$

$$\mathbf{X} = [\overrightarrow{N}_{RDG}, \overrightarrow{L}_{RDG}, \overrightarrow{S}_{RDG}, \overrightarrow{T}_{RDG}, \overrightarrow{N}_{ESD}, \overrightarrow{L}_{ESD}, \overrightarrow{E}_{ESD}, \overrightarrow{P}_{ESD}, \overrightarrow{O}_{ESD}, \overrightarrow{C}_{EV}],$$

$$\text{subject to}: \begin{cases} g_i(\mathbf{X}) \geq 0, & i = 1, 2, ..., m \\ h_i(\mathbf{X}) = 0, & i = 1, 2, ..., p \end{cases}$$

where the vectors $\overrightarrow{N}$, $\overrightarrow{L}$, $\overrightarrow{L}$, $\overrightarrow{E}$, $\overrightarrow{P}$ and $\overrightarrow{O}$ represent the number, size, locations, capacity, maximum charge and discharge power and operation strategy of the RDGs and ESDs. The term $\overrightarrow{T}_{RDG}$ represents the type of RDGs, $\overrightarrow{C}_{EV}$ denotes to the charging strategy of the EVs. The terms $g_i(\mathbf{X})$ and $h_i(\mathbf{X})$ represent the i^{th} inequality and equality constraints. In Eq. (1), the terms of m and p denote the numbers of inequality and the equality constraints. The objective function is the extension of the energy losses of the system with a penalty function that aims to minimize voltage violations. The resulting augmented objective function is as follows:

$$f(\mathbf{X}) = \sum_{t=1}^{N_T} \sum_{k=1}^{N_{br}} R_k I_{tk}^2 + \zeta P(\mathbf{X}) \tag{2}$$

$$P(\mathbf{X}) = \sum_{t=1}^{N_T} \sum_{j=1}^{N_bus} \begin{cases} (v_{tj} - 0.95)^2, & \text{if } v_{tj} < 0.95 \\ 0, & \text{if } 0.95 < v_{tj} < 1.05 \\ (v_{tj} - 1.05)^2, & \text{if } v_{tj} > 1.05 \end{cases} \tag{3}$$

where k stands for the line number between two busses, N_T refers to simulation period of the study and R represent the line resistance, respectively. I_{tk} denotes the current passing through the k_{th} line at time t. v_{tj} shows the voltage magnitude of the j_{th} bus in the system and ζ is a coefficient that forces the optimization algorithm initially minimize the voltage violation in the system.

A. Constraints

The details the network inequality and equality constraints, including voltage magnitude limitations, nodal power balance equations, constraints of PV units constraints, and ESDs are given in [8] and [12].

The boundaries for different variables of the $\mathbf{X}$ vector are proposed as follows. The installation locations of the RDGs and ESDs set to all the nodes in the system except the first bus. The upper boundary for a RDG's size and ESD's capacity and charge/discharge power is defined as 1000 kW, 1000 kWh and 1000 kW. The optimization problem for charging of EVs considers a smart charging scheduling for time intervals of the optimization process that EV owners coming home from work (6 PM) until a time interval that they want to go to work the next day (6 AM).

III. Optimization method

To determine the optimal solution for the problem presented in (1), the framework uses different optimization algorithms based on heuristic methods. The main focus of the study is to optimize the frame work to find a better quality solution using AGWO method.

A. Advanced grey wolf optimizer

The AGWO algorithm proposed in 2022 [17] aims to improve the disadvantages of GWO [19] using the following ideas:

- Applying a dynamic method to evaluate the search agent either in the exploitation or in the exploration phases.
- Adding a new formulation for evaluating the search agents in the exploitation phase.
- Checking the boundaries of the evaluated search agent and bringing the variables back to allowed ranges using a new method.
- Using new stopping criteria to be sure to find the near-global optimum.

The algorithm shows a better performance in finding a good quality solution for various type of optimization problems compared to other well-known methods. The algorithm shows that it can deal with MINLP problems in smart grids and it is the main reason for choosing this method for solving the problem presented in (1). Note that the optimization problem presented in this work is a MINLP problem.

In (1), considering a random $\mathbf{X}$, we can find an objective value for the problem. The best three objective values for $\mathbf{X}_\alpha$, $\mathbf{X}_\beta$, and $\mathbf{X}_\delta$ at each iteration of the AGWO's optimization process will be used to update the other solutions. The evaluation of each position of solutions based on the exploration phase or exploitation phase is mathematically formulated as:

$$r_d : \text{a random number within } [0\ 1], \quad \forall\, d \in 1, 2, ..., 7 \tag{4}$$

$$A_d = 2.a.r_1 - a, \quad \forall\, d \in 1, 2, 3 \tag{5}$$

$$B_d = sin(2\pi r_2), \quad \forall\, d \in 1, 2, 3 \tag{6}$$

$$a = 2 - 2 \times \frac{t}{\text{Max}_t} \tag{7}$$

$$C_d = 2.r_3, \quad \forall\, d \in 1, 2, 3 \tag{8}$$

$$ER = 1 - 0.8 \times \frac{t}{\text{Max}_t} \tag{9}$$

$$X_1 = \mathbf{X}_\alpha - A_1.B_1.|C_1.\mathbf{X}_\alpha - X| \tag{10}$$

$$X_2 = \mathbf{X}_\beta - A_2.B_2.|C_2.\mathbf{X}_\beta - X| \tag{11}$$

$$X_3 = \mathbf{X}_\delta - A_3.B_3.|C_3.\mathbf{X}_\delta - X| \tag{12}$$

$$X_4 = X + A_4 \times sin(2\pi r_4).|C_4.\mathbf{X}_\alpha - X| \tag{13}$$

$$X_5 = X + A_5 \times cos(2\pi r_5).|C_5.\mathbf{X}_\alpha - X| \tag{14}$$

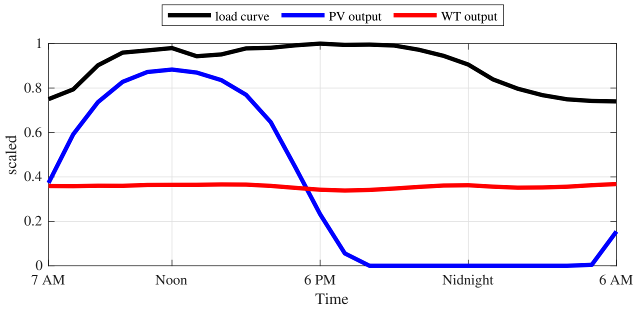

Fig. 1. Estimated scaled RDG output and load characteristic.

$$X_{t+1} = \begin{cases} \frac{X_1+X_2+X_3}{3} & r_6 \geq ER \\ \begin{cases} X_4 & r_7 < 0.5 \\ X_5 & r_7 \geq 0.5 \end{cases} & r_6 < ER \end{cases} \tag{15}$$

where t and Max_t are the current iteration number and maximum number of iterations required in the process.

B. Optimization framework for the problem

The implementation of the proposed AGWO and the other methods (GWO, AAO, and PSO) to solve the optimization model comprises of the following steps:

1) Provide optimization algorithm parameters and the problems inputs.
2) Initialize the first solutions randomly within the boundaries of the variables.
3) Check if the variables are within the predefined boundaries
4) Calculate the Forward Backward Sweep power flow analysis based on each solution ($\mathbf{X}$).
5) Calculate the $f(\mathbf{X})$ value and save the best f values and corresponding $\mathbf{X}$ parameters for the best solution(s).
6) Update the solutions using the solution evaluation equations of the optimization algorithms.
7) Stop the optimization cycle if the tolerance condition is satisfied or the maximum number of iterations is reached. Otherwise, go to step 3.

IV. Simulation Result and Discussion

A. Load characteristics and the systems data

The mentioned formulations are applied to IEEE 33 and 69 bus radial DNs. The details of the line data, peak load data, load behavior and the daily load curve taken from the Turkish medium voltage distribution feeder can be found in [8]. Note that the given load data does not include the EV charging . The output of RDG units (WT and PV) and the load characteristic for the simulations are shown in Fig. 1.

B. EV modeling

The assumption for the state of charge (SOC) of the EVs at beginning of the work day is 100%, means that it is fully charged. EVs can charge with 11 kW chargers. The

TABLE I
THE COMPARISON BETWEEN THE NEAR-OPTIMAL SOLUTIONS AND THE BASE CASE SOLUTIONS.

	$f(\mathbf{X})$	EL MWh	RDG size MW	ESD capacity MWh
BC-33bus	439.011	5.012		
NGS-33bus	1.628	1.628	7.04	3.82
BC-69bus	342.794	5.794		
NGS-69bus	1.523	1.523	9.93	4.24

EV charging models used in the simulations are developed with respect to the average EV battery capacity taken from [21], [22]. We modeled an EV with various battery capacities with a fixed charging rate of 11 kW in the simulations. We assumed that each bus has five EVs in the test systems under some consideration for initial SOC. The aim is to find optimal charging scheduling for the EVs for the time that arrive at their homes after the work (6 PM) until they depart to work the next day (6 AM).

C. Test system results

The first simulations' goal is to find the near-optimal solution of (1) for a critical condition of charging the empty (SoC=0%) batteries of EVs, where the battery size of an EV is taken as 65.5 kWh. Simulation results including objective function values, and the sizes of RDG units and ESDs are tabulated in Table I for the two test systems, where BC represents for base case operating condition without and RDGs and ESDs and NGS stands for near global solution. Note that the objective function values for both systems are quite high for BC operating solutions, as there are so many voltage violations in the system. Moreover, operation without any RDGs and ESDs (uncontrollable charging of EVs from 6 PM to approximately midnight) gives quite high energy losses.

The optimal sizes of RDGs were found to be 7.04 MW (PV: 2.17 MW and WT: 4.87 MW) and 9.93 MW (WT: 9.93 MW) for NGS-33bus and NGS-69 bus optimal solutions, respectively. The optimal sizes of ESDs were found to be 3.82 MWh and 4.24 MWh for the two test systems. Those optimal RDG and ESD sizing and allocation was found to reduce the energy losses by 68% and 73% for the 33-bus and 69-bus test systems, respectively. Besides, the results also show that all the voltage violations that existed in BC operating conditions were eliminated.

The improvements in the system losses for the test systems are shown in Fig. 2 and Fig. 3. Based on the optimal charging scheduling of the EVs in the NGS-33bus and NSG-69bus solutions, the system's energy consumption become flatter over time compared to the BC operating conditions. The differences between system loads for the near optimal solutions and base case operating conditions are shown in Fig. 4 and Fig. 5. The minimum and maximum voltage magnitudes for the IEEE 33-bus system are found as 0.951 p.u and 1.016 p.u., respectively. Similarly, the minimum and maximum voltage magnitudes for the 69-bus system are calculated as 0.953 and 1.006 p.u., respectively.

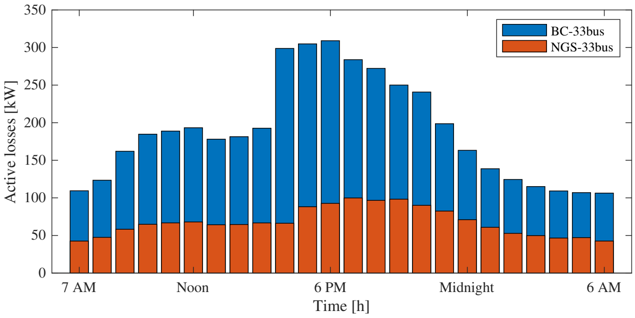

Fig. 2. Comparison of the losses for NGS-33bus and BC-33bus solutions.

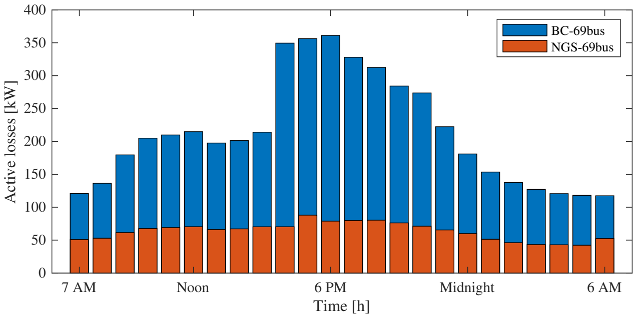

Fig. 3. Comparison of the losses for NGS-69bus and BC-69bus solutions.

The second simulation's aim is to find optimal $\overrightarrow{O}_{ESD}$ and $\overrightarrow{C}_{EV}$ control parameters for more EV (parameters are given in [22]) penetration at each bus. Moreover, the travel distance of the users during the day and so does the initial SOC values of the EVs at 6 p.m. [23] are considered in the simulations. Based on the energy consumption of the EVs [22] and the travel distance of the users [23] the extra charging load is added to the system during the simulation period from 6 pm to 6 am. The optimization process tries to find the optimal charging scheduling for the EVs and optimal operation of the ESDs based on the size and location of the RDGs and ESDs found for (1) in the first simulations.

The simulation results for the IEEE 33-bus system show that up to 8.4 times more EV can penetrate into the system without giving any voltage violations, for the optimal siting and sizing parameters of the first simulations. The energy losses for the simulation were found as 1.91 MW and the minimum voltage magnitude was calculated as 0.95 p.u. for the 33-bus system.

When compared with the first simulations, optimal charging of the EVs and operation strategy of ESDs can provide 14 times more EV penetration to the IEEE 69-bus tests system without voltage violations. Moreover, total energy losses are reduced to 1.94 MWh (66% improvement over the BC-69bus). The voltage profile of the systems are shown in Fig. 6 and Fig. 7. Note that each color in the figures represent a time step of the simulation and the dashed curves correspond to the voltage profiles of base case scenarios. Based on the formulation for the penalty function in (2), the optimization process tries to keep the voltage magnitude of the busses in between 0.95 and 1.05

TABLE III
COMPARISON OF THE OBJECTIVE FUNCTION VALUES AND CONVERGENCE SPEED FOR DIFFERENT ALGORITHM.

			AGWO			AAO			GWO			PSO		
			mean	std.	best	mean	std.	best	mean	std.	best	mean	std.	best
IEEE 33-bus	first simulations	$f(\mathbf{X})$	1.80	1.2E-1	1.62	7.25	1.4E+3	1.62	2.89	6.5E0	1.63	2.42	4.8E0	1.62
		execution time [s]	1820	214	1668	1831	125	1668	1949	170	1701	1963	131	1743
	second simulations	$f(\mathbf{X})$	1.92	1.4E-5	1.91	1.92	3.1E-5	1.91	1.92	2.0E-5	1.91	1.93	6.6E-3	1.91
		execution time [s]	571	18.9	563	602	23.7	564	596	28.9	581	606	22.5	564
IEEE 69-bus	first simulations	$f(\mathbf{X})$	1.56	2.6E-2	1.52	1.83	2.3E-1	1.52	1.82	1.9E-1	1.53	2.01	3.2E-1	1.52
		execution time [s]	4370	36	4345	4381	16	4352	4374	22	4341	4413	40	4351
	second simulations	$f(\mathbf{X})$	2.01	4.8E-2	1.93	2.19	1.1E-1	1.94	2.11	1.1E-1	1.93	2.41	2.9E-1	1.97
		execution time [s]	1189	66.1	1179	1237	32.5	1182	1210	20.2	1179	1274	44.3	1183

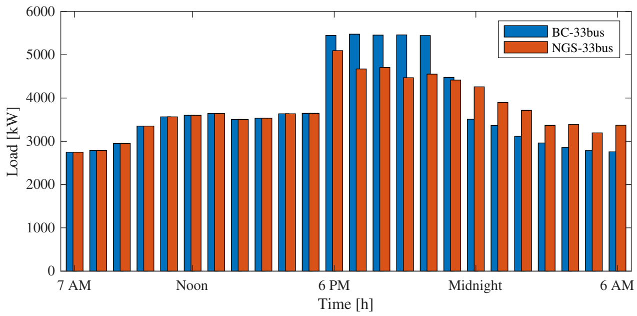

Fig. 4. Comparison of the system loads for NGS-33bus and BC-33bus solutions.

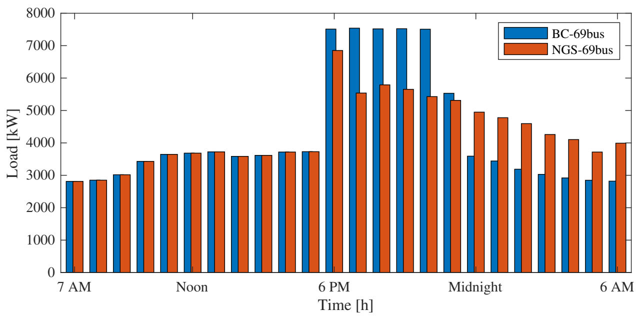

Fig. 5. Comparison of the system loads for NGS-69bus and BC-69bus solutions.

p.u.

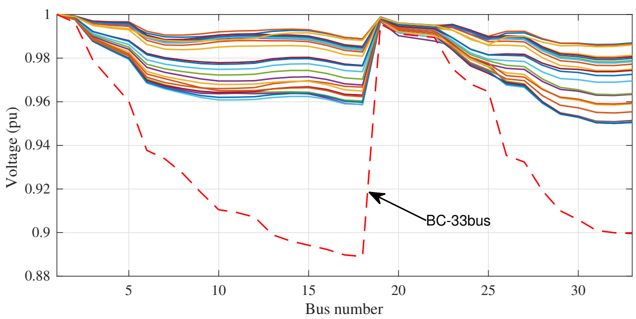

Fig. 6. The voltage profiles of IEEE 33-bus test system.

D. Quality of the near-optimal solutions

To check the quality of the near-optimal solutions determined by the AGWO method, the objective function values of the solutions are compared to the solutions found by the PSO, AOA, and GWO methods with the same condition of the optimization process. Therefore, PSO parameters are first optimized based on the grid search of the parameters

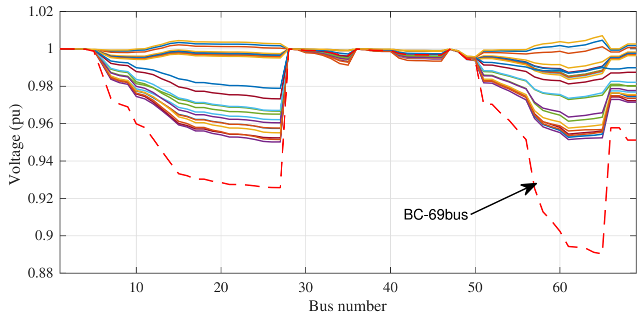

Fig. 7. The voltage profile of the IEEE 69-bus system.

and are illustrated in Table II. On the other hand, AGWO, AAO, and GWO methods do not require any parameter optimization.

TABLE II
PARAMETERS OF PSO.

Parameter	Value
Personal Learning Coefficient (c1)	1.0
Global Learning Coefficient (c2)	1.0
Damping ratio	0.95

The statistics of 50 independent near-optimal solutions for each simulation of the two tests systems are illustrated in Table III. The performance of the heuristic methods are compared with respect to corresponding average values (mean), standard deviations (Std.), and the best objective functions (best). Besides, the performance of the methods are evaluated with respect to their computation speeds.

The results show that the best objective function values for the first simulations are almost the same in all methods, AGWO method gives the best mean values and the less standard deviations. It means that the AGWO method provides the most reliable solutions for the first simulations. However, its high performance in providing better mean values and standard deviations is less remarkable for the second simulation. That is, all four heuristic methods can be assumed to show similar performances for the second simulations. On the other hand, AGWO shows better performance in terms of providing less mean computation times for both simulations.

V. CONCLUSION

This study has presented a framework for finding optimal parameters of RDGs, ESDs, and EVs in DNs. Optimal size, site, type, and number of the RDGs are the main parameters for RDG units for minimizing the energy losses of the systems. Besides, the aim is to find the optimal locations, capacity, maximum charge/discharge power, and operation strategy for the ESDs for maximizing the impact of the generated power by RDGs by maximizing the exchange energy between different hours of the simulation. The optimal charging coordination of the EVs in the system is investigated for the system to minimize the voltage violation problems.

The framework used different optimization algorithms but the main focus of the study is to use AGWO method to find a better solutions for the problems. Based on the results, the optimal control parameters suggested by the framework, reduces the energy losses of the system by 68% and 73% for IEEE 33-bus and 69-bus systems, respectively. Also the solutions eliminated all the voltage violations of the systems for the critical condition of the initial state of charge for the EVs where the SOC was set as zero. Based on the simulation results for the near-optimal solutions and while increasing the EV penetration in the system, still the solutions can decrease the energy losses up to 66%. In addition, near-optimal solutions can solve the voltage violation problem for up to 8.4 times more EVs in 33-bus system and 14 times more EVs in 69-bus system.

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