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Multi-Objective ORPD Considering Different Load Models for Active Distribution Networks

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ABSTRACT

Secure and economical operation of distribution networks needs the management of reactive power resources. Optimal Reactive Power Dispatch (ORPD) optimally manages the reactive power scheduling of generators and distribution generations, as well as the Reactive Power Compensation (RPC) devices. This paper investigates the effect of load models on the multi-objective ORPD problem in active distribution networks. Moreover, a modified Grey Wolf Optimizer (GWO), called Civilized GWO (CGWO), is introduced in this paper to solve the ORPD problem. The proposed strategy, including multi-objective function, various load models, DG's reactive power, RPCs, and the introduced CGWO, is tested on standard IEEE 33- and 69-bus distribution systems. The results indicate that the load models have a significant impact on the cost function amount. Moreover, the performance of the proposed algorithm is evaluated using ten standard benchmark functions. The optimization results demonstrate the robustness of the introduced optimization algorithm and its capability in finding better solutions than the Particle Swarm Optimization (PSO), Exchange Market Algorithm (EMA), and the original GWO.

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ABBREVIATION

ABC	Artificial Bee Colony
ACOPF	AC Optimal Power Flow
ALC	Aging Leader and Challengers
ALO	Ant Lion Optimizer
BSO	Backtracking Search Optimizer
CBA	Chaotic Bat Algorithm
CGWO	Civilized Grey Wolf Optimizer
CKHA	Chaotic Krill Herd Algorithm
CLPSO	Comprehensive Learning Particle Swarm Optimization
COM	Commercial
CPSMOEA	Classification and Pareto domination based Multi-Objective Evolutionary Algorithm
CP	Constant Power
DAMOPSO	Dynamically Adaptive Multi-Objective Particle Swarm Optimization
DE	Differential Evolution
DG	Distributed Generation
DMSDE	Dynamic Multi-group Self-adaptive Differential Evolution
DS	Distribution System
DSA	Differential Search Algorithm
EMA	Exchange Market Algorithm
FAHCLPSO	Fuzzy Adaptive Heterogeneous Comprehensive-Learning Particle Swarm Optimization
FF	Firefly
GBTLBO	Gaussian Barebones Teaching-Learning Based Optimization
GWO	Grey Wolf Optimizer
GSA	Gravitational Search Algorithm
HSA	Harmony Search Algorithm
HTSSA	Hybrid Tabu Search-Simulated Annealing
ICA	Imperialist Competitive Algorithm
IND	Industrial
IPM	Interior Point Method
ISFSOA	Improved Stochastic Fractal Search Optimization Algorithm
IWO	Invasive Weed Optimization

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MO	Multi-Objective
MOEA	Multiple Evolutionary Algorithms
MTLA-DDE	Modified Teaching Learning Algorithm and Double Differential Evolution
NA	Not Available
NLP	Nonlinear Programing
OGSA	Opposition-based Gravitational Search Algorithm
OGWO	Opposition-based Grey Wolf Optimizer
OPF	Optimal Power Flow
ORPD	Optimal Reactive Power Dispatch
PLoss	Power Loss
PSO	Particle Swarm Optimization
QP	Quadratic Programing
RES	Residential
RPC	Reactive Power Compensation
SARGA	Self-Adaptive Real Coded Genetic Algorithm
SDP	Semidefinite Programming
SDR2	Semidefinite Programming Relaxation
SO	Single-Objective
SOA	Seeker Optimization Algorithm
SPMGSO	Strength Pareto Multigroup Search Optimizer
Std.	Standard Deviation
TS	Transmission System
TVD	Total Voltage Deviation
VSI	Voltage Stability Index
WOA	Whale Optimization Algorithm

NOMENCLATURE

f_{loss}	Active power losses
G_k	Conductance of kth branch which connects bus i and bus j
V_i	Voltage magnitude of ith bus
θ_{ij}	Voltage phase between bus i and bus j
N_{bra}	Number of branches
$f_{\Delta V}$	Total voltage deviation
V_i^*	Desired voltage magnitude at bus i
f_{RPC}	Cost of RPC devices
C_{CAP}	Cost coefficient of RPC
Q_{Cs}	Actual capacity of sth RPC
N_Q	Number of RPC devices
P_{Gi}	Active power output of generator i
Q_{Gi}	Reactive power output of generator i
P_{DGi}	Active power output of DG at bus i
Q_{DGi}	Reactive power output of DG at bus i
P_{Li}	Active power demand at bus i
Q_{Li}	Reactive power demand at bus i
Q_{Ci}	Reactive power of RPC at bus i
B_k	Susceptance of the kth branch
N_{bus}	Number of buses
N_G	Number of generators
N_{DG}	Number of DG sources
N_T	Number of tap setting transformer branches
T	Tap setting
S_l	Branch loading of lth line
P_{Li0}	Active power demand at bus i for a specified operating point
Q_{Li0}	Reactive power demand at bus i for a specified operating point
α	A parameter of load model related to active power
β	A parameter of load model related to reactive power
$ObjFunc$	Objective function
$\vec{X}$	Position vector of a wolf
$\vec{A}$	Random value in a specified interval
$\vec{C}$	Random value in a specified interval
rand	Random value in a specified interval
max	Maximum
max	Minimum
$\text{Iteration}_{\max}$	Maximum iteration
N	Number of grey wolves
N_s	Number of societies
D_{is}	Distance between ith wolf and sth beta
C_α	Importance coefficient related to alpha wolf
C_β	Importance coefficient related to beta wolf
C_δ	Importance coefficient related to delta wolf
t	Iteration

I. INTRODUCTION

The expansion of power systems in large geographic areas to supply the loads has led to an unreasonable increase in electrical losses. Although these losses cannot completely be eliminated, they can be limited to an acceptable value. This affects the whole system operation, decreases the voltage drops, and yields different economic and environmental benefits [1–3].

ORPD is a sub-problem of the OPF that aims to minimize the total power losses through finding an optimal setting of the control variables and satisfying operational constraints. The independent variables are generator voltage, transformer tap setting, and reactive power output of RPC devices (such as capacitor banks [4]).

Furthermore, DGs have drawn special attention all over the world [5]. Generally, these devices are installed in distribution networks [6]. However, a high DG's penetration may lead to an overvoltage due to reverse power flow [7]. So, ORPD can be applied to optimize the active power losses and prevent voltage violations by managing reactive power resources.

Different optimization algorithms have been applied to the ORPD problem. Conventional approaches such as the gradient method, NLP, QP, IPM [8,9], and the Lagrangian method [10] have been proposed to optimize RPD in the power grids. Since this problem is non-differential, nonlinear, multi-modal, and non-convex, most algorithms find local optimums and need excessive numerical iterations [11].

The advent of heuristic optimization algorithms has provided alternative powerful approaches for solving the ORPD problem. In [2], WOA-based ORPD has been proposed to reduce electrical losses. Reference [12] has

presented an ABC algorithm to optimize the power losses in which the penalty method is used to satisfy the inequality constraints. A similar work considering three objectives including voltage deviation and stability in addition to power loss is proposed in [13]. Reference [14] separately optimized the same objectives for TSs using CBA. In [15], GSA has been introduced to find the best settings of independent variables of ORPD through the Newtonian laws. An OGSA has been introduced in [11] to improve the voltage stability of the power system in addition to minimizing transmission loss. GBTLBO algorithm and its modified version have been presented in [16]. GWO algorithm has been suggested in [17] to handle the ORPD problem. Reference [18] has applied the OGWO to the mentioned issue. The work presented in [19] has reported CKHA that is based on the concept of chaos theory to enhance the computational speed and improve the convergence profile of ORPD. Improved versions of DE, namely quasi-oppositional DE and multi-objective DE have respectively been used in [20,21] to solve both the single- and multi-objective ORPD problems. Reference [22] solved the problem based on the EMA by modeling the behavior of the stock market under diverse market conditions. In [23], the ORPD and some single- and multi-objective problems have been solved by DSA. Another paper reported the application of HSA in optimizing some objectives such as power losses, bus voltages, and voltage stability [24]. Zhou et al. in [25] introduced SPMGSO for a multi-objective ORPD problem. In [26], an optimal setting of the problem's control variables has been found by BSO to minimize the total line losses. Reference [27] proposed ALO, which is based on the antlion's hunting behavior in nature to escape the local minima. Reference [28] introduced conic relaxation (a tight SDP and SDR2) of the ORPD based on the convex relaxations of the ACOPF problem. A similar relaxation has been proposed in [29]. In [30] the ISFSOA has been used to optimize three objectives separately. The reviewed studies are some examples of heuristic optimization algorithms used for this challenging problem.

A new category of methods known as hybrid optimization algorithms has widely been applied to ORPD problems. A combination of ABC and DE techniques as a hybrid optimization algorithm has been reported in [31] to overcome the disadvantage of requiring a large population size of DE and strengthen the global search ability of ABC. Reference [32] has offered a hybrid modified TLBO and double DE algorithm to handle ORPD. Other hybrid approaches, such as HTSSA [33] and ABC-FF algorithm [34], have been addressed to find the optimal solution to the ORPD problem. Reference [35] reported a candidate pool of different algorithms such as genetic algorithm, PSO, DE, and adaptive metropolis search to form adaptive MOEA for multi-objective ORPD problems. A combination of PSO and ALC has been introduced by Singh in [36] for solving ORPD. Reference [37] proposed CPSMOEA, which has two steps including optimization and decision stages for solving multi-objective ORPD problems.

Due to the integration of reactive power generation of DGs as control variables, a multi-objective ORPD problem has been established. This problem aims to decrease the total power loss, reduce voltage deviation, and minimize the total capacity of RPC devices. In [6], the DAMOPSO technique has been introduced for the ORPD problem in distribution systems. Reference [38] has proposed an organizational multi-agent system based on Holonic structure for optimal dispatch of reactive power in smart grids.

A taxonomy of the reviewed approaches in terms of objectives, optimization frameworks, case studies, considered DGs, penalty terms, etc. is shown in Table I. According to this table, four objectives including the total PLoss, TVD, VSI, and RPCs were optimized with/without DGs so that in all of these researches, PLoss is considered as the main objective function. Some approaches consider the penalty function to satisfy the violated constraints such as PQ buses voltage. Also, the listed papers are classified based on SO and MO, different analyzed case studies, publication year, and publisher. As can be seen, the main differences of these papers are in the solving algorithms, considered objective functions, and kind of the case study systems (transmission or distribution). For instance, in [36] PLoss and TVD have been considered separately as objective functions for solving the ORPD problem by the ALC-PSO approach on IEEE 30, 57, and 118-bus transmission test systems without considering DG. As another example, in [39] ADMM algorithm has been proposed for the ORPD problem in distribution systems (69, 123, and 1066-bus) in which DG units are considered.

As one can see in Table I, most of the studies have just analyzed the ORPD for transmission systems. However, due to the importance of integration of distribution systems and DGs, some research, like [6,38,39,46–48], has focused on the ORPD in distribution networks. Nevertheless, among the reviewed papers for distribution grids, [6,38,39] have only considered the reactive power of DGs as the main control variable. Moreover, [6,38,39,46–48] have not considered different load models such as IND, RES, or COM.

This work responds to the following needs of the ORPD problems:

- Proposing a powerful optimization algorithm: In this paper, a modified GWO, called CGWO, is proposed to solve the ORPD problem in active distribution networks. The suggested algorithm is based on a population of wolves, so it has greater exploration than mathematical approaches that are based on a single solution. Thus, there are multiple candidates that can share their information to suddenly jump and search the promised parts of the solution space according to behavior and social life of grey wolves more extensively; moreover,

they help other candidate wolves avoid local minima. The proposed CGWO is a swarm intelligence method, which means that it can memorize the search space information at each course of iteration while evolutionary methods such as GA and DE discard the obtained data of the former generations. Also, compared to the mentioned techniques, the CGWO has fewer operators and can easily be implemented. The entire hunting process with all of the existing wolves (solutions) reflects a random search one without derivative operations. The proposed CGWO is more robust than other analyzed algorithms. Its robustness is evaluated based on mean and standard deviation. Moreover, it can always search for global or near-global solutions.

- Considering real models of distribution network loads: Different load types have significant effects on the power system studies including the ORPD problem. Their impacts are usually applied by the mathematical representation of approximate relationships between active/reactive power and voltage magnitude. Our work covers the effects of different load types (such as CP, IND, RES, and COM loads) on the multi-objective ORPD problem.
- Considering impact of the outputs of DGs and RPCs on the ORPD: This paper aims to simultaneously consider DG and RPC outputs and various load models to make a new version of the ORPD problem according to the real-world active distribution networks that has not been considered so far.
- Considering various objectives: In this paper, a single-objective function is suggested that simultaneously handles different objectives including total power losses, voltage deviation, and RPC costs. In fact, using an efficient method, three described objectives are converted into a single objective function.

The main contributions of this paper can be highlighted as:

- Introducing a new and powerful CGWO algorithm for ORPD problems in active distribution networks.
- Introducing a multi-objective function to simultaneously optimize line losses, voltage deviation, and RPC cost.
- Proposing a new definition of ORPD in active distribution networks.
- Integrating various load models to the ORPD problem and analyzing their effects on this kind of problem.
- Considering DG's reactive power output as a control variable.

The rest of the paper is organized as follows: Section II presents the ORPD formulation. In Section III, the CGWO structure is addressed. Simulation results on two distribution case studies are discussed in Section IV. The conclusion is presented in Section V.

TABLE I
TAXONOMY OF THE PROPOSED APPROACHES FOR ORPD PROBLEM

Ref	Approach	Objective Functions				Optimization	Case Study	Year & Publisher	Main Findings/Advantages/Disadvantages
		PLoss	TVD	VSI	RPC				
[49]	DE	●				SO	14-30-118 (TS)	2008-Elsevier	The penalty method has been applied for all inequality constraints. It fails to provide a meaningful solution with lower power losses for large scale transmission networks.
[24]	HSA	●	●	●		SO	30-57 (TS)	2011-Elsevier	It optimized three objectives separately and changing some constraints lead to bad solutions.
[12]	ABC	●				SO	30-118 (TS)	2012-Elsevier	This paper is based on the penalty method and in comparison to DE, PSO, and IPM, it can find solutions with better power losses.
[15]	GSA	●	●			MO	30-57-118 (TS)	2012-IET	This work uses of a constant term to convert a multi-objective problem into a single-objective one.
[31]	DE-ABC	●				SO	14-30-57 (TS)	2013-Elsevier	The findings confirm that this method is slightly better than DE and ABC.
[25]	SPMGSO	●	●	●		SO	30-162 (TS)	2014-IEEE	The optimization algorithm has many parameters and all objectives have separately been optimized.
[6]	DAMOPSO	●	●		●	MO	33 (DS)	2014-Elsevier	This paper could not provide an operating point optimizing all objectives considering DGs of distribution grid.
[11]	OGSA	●	●	●		SO	30-57-118 (TS)	2014-Elsevier	The reported approach is competitive in small bi-objective problems and greatly superior in high dimensional ones.
[35]	MOEA	●	●			MO	30 (TS)	2014-Wiley	The proposed method is a penalty based-bi-objective optimization algorithm which is based on evolutionary method.
[16]	GBTLBO	●				SO	14-30 (TS)	2015-Elsevier	This work only optimized the power losses applying the penalty factors for voltage and reactive power constraints. It covers insufficiencies of TLBO.
[17]	GWO	●				SO	30-118 (TS)	2015-Elsevier	It only optimized the transmission losses and outperforms six techniques.

Table .1 Continued

[19]	CKHA	•	•	•	SO	30-57 (TS)	2015-IET	This method needs two additional adjustable parameters to outperform 12 other algorithms and shows fast convergence behaviour than original KHA.
[36]	ALC-PSO	•	•		SO	30-57-118 (TS)	2015-Elsevier	Due to the single-objective characteristic of the reported algorithm, it can only optimize two objectives separately.
[39]	ADMM	•			SO	69-123-1066 (DS)	2016-IEEE	This work converts the nonconvex ORPD problem applying DG's output to a convex one. The reported method has not been validated by comparing with other new techniques.
[26]	BSO	•			SO	14-30-57 (TS)	2016-IEEE	All inequality constraints have been met by the penalty method. The introduced algorithm needs two operators. The simulation results do not show significant improvement in objective function.
[33]	HTSSA	•	•		SO	30 (TS)	2016-Elsevier	It combines the main search strategies of TS and SA algorithms. The results indicate that considering penalty terms can increase the run time.
[20]	QODE	•	•	•	MO	30-57-118 (TS)	2016-Elsevier	It applies a constant term to convert the multi-objective problem into a single-objective one. Compare to DE, it needs more time to find the solution.
[23]	DSA	•	•	•	SO	30-57 (TS)	2016-Springer	This method slowly convergences and most of the reported solutions is same as those searched by other techniques.
[22]	EMA	•	•	•	SO	30-118 (TS)	2016-Elsevier	This technique needs two market risk factors with four parameters which should always be adjusted to find the best solution. This method is a penalty based-single-objective optimization
[2]	WOA	•			SO	14-30 (TS)	2017-Elsevier	It is a penalty based method and the simulation results show that the WOA outperforms other algorithms such as ABC, GSA, and PSO.
[27]	ALO	•		•	SO	30-118-300 (TS)	2017-Elsevier	Convergence behaviour of the reported algorithm is very similar to ABC. This paper optimized different objectives separately considering penalty function.
[34]	ABC-FF	•	•		SO	14-39 (TS)	2018-Elsevier	The reported solutions confirm that combination of two algorithms with many parameters does not form a powerful optimization technique.
[18]	OGWO	•			SO	14-30-57 (TS)	2018-Wiley	It only minimized the power losses and outperforms seven techniques and quickly convergence to optimal solution.
[28]	SDR2	•			SO	3375 (TS)	2019-IEEE	It applied a tight semidefinite programming relaxation to the ORPD problem and used convex relaxations of AC power flow.
[29]	-	•			SO	30-118(TS)	2019-IEEE	It only optimized the transmission losses and outperforms some techniques.
[30]	ISFSOA	•	•	•	SO	30 (TS)	2019-UAD	It considered three objectives. But, it separately optimized them.
[13]	ABC	•	•	•	SO	30-57 (TS)	2020-Elsevier	It is not so fast for large systems and used of the penalty function to satisfy inequality constraints.
[37]	CPSMOEA	•	•		MO	30-118 (TS)	2020-IEEE	It applied a two-stage algorithm to solve the multi-objective ORPD problem.
[14]	CBA	•	•	•	SO	14-39-57-118-300 (TS)	2020-IEEE	Three objectives were optimized separately. It used of the penalty function to satisfy inequality constraints.

II. ORPD PROBLEM FORMULATION

This paper considers three objective functions, including active power losses, the sum of the voltage deviations, and the total capacity of RPC devices. These objective functions are optimized for different load models and considering the operational constraints.

A. Objectives

1) Minimization of Active Power Losses

Minimizing the active power losses f_{loss} in the network is one of the main objectives of the ORPD and can be defined as:

$$f_{loss} = \sum_{k=1}^{N_{bra}} G_k \left[V_i^2 + V_j^2 - V_i V_j \cos\theta_{ij}\right] \quad (1)$$

2) Minimization of Total Voltage Deviation

Minimization of total voltage deviation as (2) can improve the voltage profile and enhance the security level

of the network.

$$f_{\Delta V} = \sum_{i=1}^{N_{bus}} (V_i - V_i^*)^2 \quad (2)$$

where V_i^* is usually set to 1.00 pu.

3) Minimization of RPC Cost

In addition to optimizing the power losses and voltage deviation, the ORPD problem aims to reduce the cost of RPC devices [6]. This cost (f_{RPC}) depends on the total capacity of RPC devices so that a lower cost means a lower capacity of them. Cost minimization of RPC devices can be presented as follows:

$$f_{RPC} = \sum_{s=1}^{N_Q} C_{CAPs} |Q_{Cs}| \quad (3)$$

If C_{CAP}=1, (3) becomes a function of the total capacity of RPC devices.

B. Constraints

1) Equality Constraints

The power balance equations represent a set of equality constraints considering DG and RPC outputs as follows:

$$P_{Gi} + P_{DGi} - P_{Li} - V_i \sum_{j=1}^{N_{bus}} V_j \left(G_k \cos\theta_{ij} + B_k \sin\theta_{ij}\right) = 0 \quad (4)$$

$$Q_{Gi} + Q_{DGi} + Q_{Ci} - Q_{Li} - V_i \sum_{j=1}^{N_{bus}} V_j \left(G_k \sin\theta_{ij} + B_k \cos\theta_{ij}\right) = 0 \quad (5)$$

2) Inequality Constraints

Inequality constraints for control and state variables can be listed as below:

- Inequality constraints on control variables: Generally, these constraints consist of limitations on the terminal voltage of generators (6), the reactive power output of the RPC devices (7), and DGs (8), and tap setting of transformers (9).

$$V_{gi}^{min} \le V_{gi} \le V_{gi}^{max}, \quad i = 1,2,\dots,N_G \quad (6)$$

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, \quad i = 1,2,\dots,N_G \quad (7)$$

$$Q_{DGi}^{min} \le Q_{DGi} \le Q_{DGi}^{max}, \quad i = 1,2,\dots,N_{DG} \quad (8)$$

$$T_i^{min} \le T_i \le T_i^{max}, \quad i = 1,2,\dots,N_T \quad (9)$$

- Inequality constraints on dependent variables: The voltage level at each bus should be limited as follows:

$$V_i^{min} \le V_i \le V_i^{max}, \quad i = 1,2,\dots,N_{bus} \quad (10)$$

Other inequality constraints are the line thermal capacity and reactive power output of the generators, which can be expressed by:

$$S_l^{min} \le S_l \le S_l^{max}, \quad l = 1,2,\dots,N_{bra} \quad (11)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, \quad i = 1,2,\dots,N_G \quad (12)$$

C. Load Modeling

Voltage-dependent load models can be stated as below:

$$P_{Li} = P_{Li0} V_i^{\alpha} \quad (13)$$

$$Q_{Li} = Q_{Li0} V_i^{\beta} \quad (14)$$

In this work, practical voltage-dependent load models (i.e., industrial, residential, and commercial loads) are considered in addition to the constant power model. According to [50], the values of α and β for different load types are illustrated in Table II.

TABLE II
DIFFERENT LOAD MODELS [50]

Load model	α	β
CP	0.00	0.00
IND	0.18	6.00
RES	0.92	4.04
COM	1.51	3.40

D. ORPD as an Optimization Problem

The ORPD problem provides optimum values of control variables by minimizing a pre-specified objective function with respect to the operational constraints of the system. The ORPD problem can mathematically be formulated as follows:

$$\begin{cases} \min\ ObjFunc \\ \text{subject to } (4) - (12) \text{ considering } (13) \text{ and } (14) \end{cases} \quad (15)$$

In this paper, using the method presented in [51], three objectives described as (1)-(3) are converted into a single objective function as follows:

$$ObjFunc = f_{loss}\left(1 + s_{\Delta V} \times \frac{f_{\Delta V}}{\sum_{i=1}^{N_{bus}} P_{Li}} + s_{RPC} \times \frac{f_{RPC}}{\sum_{i=1}^{N_{bus}} P_{Li}}\right) \quad (16)$$

Where $s_{\Delta V}$ and s_{RPC} are equal to 0 or 1. If $s_{\Delta V} = 1$, then $f_{\Delta V}$ is considered as a part of the objective function; otherwise, $f_{\Delta V}$ is not one of the objectives. The same statement is valid for RPC devices.

III. PROPOSED OPTIMIZATION ALGORITHM

A. Brief GWO Formulation

Social Hierarchy: GWO algorithm was first proposed in [52]. There are four types of wolves affected by a social hierarchy as shown in Fig. 1. The leader wolf is called

alpha or dominant wolf. He/he decides about all things (hunting, sleeping, etc.) and his/her decisions are mostly dictated to the group. At the next level, beta or subordinate wolf helps alpha type make a better decision or do other activities related to the pack. He/she commands the other lower-type wolves but only respects the alpha type and plays the advisor role to the dominant wolf. The lowest level in the wolf hierarchy is omegas. They are non-dominant wolves and always have to surrender to all the other dominant ones. Since omegas are at the bottom of the social chain, they are allowed to eat as the last wolves. The third level is delta. In fact, if a wolf is not an alpha, beta, or omega, he/she is a delta wolf. He/she has to respect the alpha and beta types while commanding the omegas.

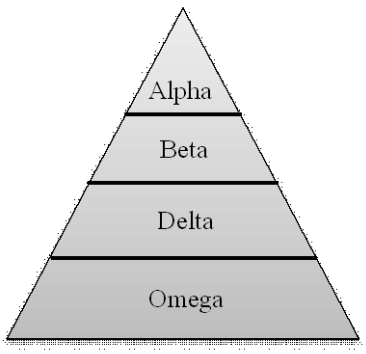


Fig. 1. Grey wolves hierarchy [52]

Designation of Superior Wolves: Among N solutions, the first three best ones are selected as alpha, beta, and delta wolves. Other solutions are omega wolves. The optimization process (procedure of hunting) is guided by alpha, beta, and delta because they have better knowledge about the potential position of prey.

Encircling Prey and Hunting: During hunting, wolves encircle the prey. The model of the encircling behavior of grey wolves is [52]:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{17}$$

where

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha; \qquad \vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|;$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta; \qquad \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|;$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta; \qquad \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right|;$$

$$\vec{A}_1 = 2\vec{a} \cdot \mathrm{rand}_{\alpha 1} - \vec{a}; \qquad \vec{C}_1 = 2 \cdot \mathrm{rand}_{\alpha 2};$$

$$\vec{A}_2 = 2\vec{a} \cdot \mathrm{rand}_{\beta 1} - \vec{a}; \qquad \vec{C}_2 = 2 \cdot \mathrm{rand}_{\beta 2};$$

$$\vec{A}_3 = 2\vec{a} \cdot \mathrm{rand}_{\delta 1} - \vec{a}; \qquad \vec{C}_3 = 2 \cdot \mathrm{rand}_{\delta 2};$$

and where $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ denote the position of alpha, beta, and delta, respectively, $\vec{A}$ contains random values in interval $[-2\vec{a},\ 2\vec{a}]$ to mathematically model approaching the prey and attacking it, where attacking the prey is modeled by $\vec{a}$; $\vec{C}$ is a random value in interval [0, 2] and models the effects of barriers for approaching the prey in nature, and rand represents a random number in interval [0, 1].

Searching prey (Exploration): As mathematically described, the position of the alpha, beta, and delta wolves affects the other grey wolves. They firstly diverge from the hunt and each other to find the prey and then converge to attack it. $\vec{A}$ Mathematically indicates the divergence so that $|\vec{A}| > 1$ forces the search agents to diverge from the hunt and hopefully explore a better solution and also emphasizes the exploration power of GWO to globally search.

Attacking Prey (Exploitation): Hunting is terminated by attacking the prey. Approaching the target is mathematically modeled by linearly decreasing the value of $\vec{a}$ from 2 to 0 as below:

$$\vec{a} = 2 - \frac{2t}{\mathrm{Iteration}_{\max}} \tag{18}$$

As another part of exploitation, $|\vec{A}| < 1$ means that the next position of a grey wolf is between its current position and the prey position. In other words, it obliges the grey wolves to attack the prey. It is worth to mention that $\vec{a}$ can also affect exploration power by forcing $|\vec{A}| > 1$ as already described.

B. Formulation of the Introduced CGWO

1) CGWO Concept

Suppose that there are N grey wolves as N potential solutions. The best solution among all wolves is considered as the alpha wolf. He/she is the leader. In order to form different societies, N_s groups of wolves are considered as N_s societies. Each society has its own leader; in other words, the next best N_s solutions (among $(N-1)$ ones) are considered as N_s beta wolves (leader of each society). Betas respect the leader (i.e., alpha) and help him/her make a better decision; moreover, they can only command the other lower-level wolves in their society. In addition to betas, there are N_s delta wolves; but they are not necessarily the next best N_s solutions among the remaining $(N-N_s-1)$ ones. Accordingly, the distance between each remaining wolf and N_s betas should be determined. A wolf belongs to the society s if the distance between him/her and sth beta is minimum. The best solution (except its beta) is selected as delta wolf. Therefore, each society has its own delta and each delta only follows his/her beta and commands the other wolves in the beta's society. The rest of the wolves (i.e., $(N-2N_s-1)$ solutions) are members of societies. The concept of CGWO is illustrated in Fig. 2.

The main steps are:

Step 1. Determine the number of societies, N_s.

Step 2. Calculate $ObjFunc$ for all wolves and sort them from the best to the worst solutions.

Step 3. Select the best wolf as alpha.

Step 4. Select the next best N_s solutions as betas.

Step 5. Calculate the distance between the rest of the wolves and all betas as follows:

$$D_{is} = \|X_i(t), X_s(t)\|_2, \quad i \in \{(N - N_s - 1)\text{remained wolves}\}, \quad s \in \{N_s \text{ beta wolves}\} \tag{19}$$

Since D_{is} represents the distance between ith wolf and sth beta, so the ith wolf belongs to the sth society if D_{is} is minimum.

Step 6. Select the next best wolf in each society as the delta.

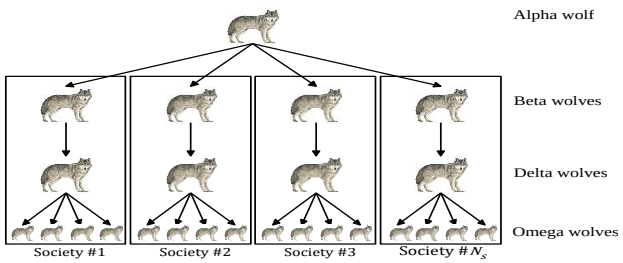


Fig. 2. Concept of CGWO

2) Modification of Hunting Model

In the original GWO, as presented in (17), there is a constant weighting factor (equal to ≈0.33) to model the effect of alpha, beta, and delta for X_1, X_2, and X_3, respectively. In order to give CGWO more random behavior throughout optimization and increase the effect of betas in societies, the following equation is proposed to modify (17) as (20).

$$\vec{X}(t+1) = C_\alpha \times \text{rand} \times \vec{X}_1 + C_\beta \times \text{rand} \times \vec{X}_2 + C_\delta \times \text{rand} \times \vec{X}_3 \tag{20}$$

where C_α, C_β, and C_δ show the importance of alpha, beta, and delta wolves in societies. Based on our experiments, choosing $C_\beta > C_\alpha$ provides a better solution because, in each society, beta is the leader, not alpha. Additionally, because, in each society, beta represents a better wolf than delta, so $C_\beta > C_\delta$.

C. CGWO Algorithm

The main steps of the introduced CGWO algorithm are presented in Fig. 3 and can be stated as follows:

Initialization Step. Initialize the number of grey wolves, societies, a, A, C, C_α, C_β, C_δ, and $\text{Iteration}_{\max}$. Then, set $t = 0$.

Iteration Step. Set $t = t + 1$.

Load Flow Step. Get the results of (4) and (5) considering different load models (applying (13) and (14)). These represent the load flow equations considering DG and RPC outputs as well as various demand types. These equations as the main equality constraints are satisfied by the power flow program.

Civilization Step. Run six steps presented in subsection III.B.1 (i.e., Step 1-6) to set/update societies and determine alpha, beta, delta, and then omega wolves. It is important to note that due to the evaluation of $ObjFunc$ in each iteration, the designation of wolves (i.e., alpha, beta, and delta wolves) may be changed.

Update Position Step. Use (20) to update the positions of grey wolves.

Boundaries Step. Check that the variables are within their pre-specified limits. Apply boundaries (Eq. (6)-(12)) if limits are violated; This can be investigated for X_i as:

$$X_i = X_i * F(ubt + lbt) + X_i^{max} * ubt + X_i^{min} * lbt \tag{21}$$

where ubt, lbt and F are defined as below:

$$ubt = \begin{cases} 1 & if\ X_i > X_i^{max} \\ 0 & if\ X_i \le X_i^{max} \end{cases} \tag{22}$$

$$lbt = \begin{cases} 1 & if\ X_i < X_i^{min} \\ 0 & if\ X_i \ge X_i^{min} \end{cases} \tag{23}$$

$$F(ul) = \begin{cases} 1 & if\ ul \ge 1 \\ 0 & if\ ul < 1 \end{cases} \tag{24}$$

Otherwise, go to **Criterion Step**.

Criterion Step. If $t = \text{Iteration}_{\max}$, then go to the **Results Step**; otherwise, go to the **Iteration Step**.

Results Step. Print the results of alpha.

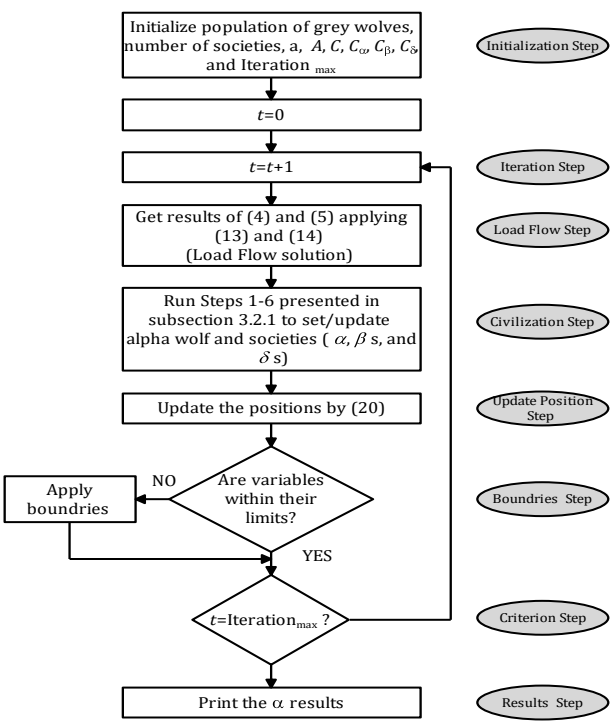


Fig. 3. CGWO algorithm

IV. SIMULATION RESULTS

The proposed strategy is investigated on two distribution systems including the IEEE 33-bus and 69-bus networks and also ten benchmark functions in Appendix A. The suggested strategy has been developed in MATLAB software and the best obtained results, as well as the mean and standard deviation over 20 runs, are compared with other programmed algorithms such as GWO, PSO, and EMA [53]. To aim this purpose, different case studies based on the objectives presented in (1)-(3) investigating (15) and (16) are considered as:

Case 1– Optimization of three objectives including f_{loss}, $f_{\Delta V}$, and f_{RPC} ($s_{\Delta V} = 1$ and $s_{RPC} = 1$).

Case 2– Optimization of two objectives including f_{loss} and $f_{\Delta V}$ ($s_{\Delta V} = 1$ and $s_{RPC} = 0$).

Case 3– Optimization of two objectives including f_{loss} and f_{RPC} ($s_{\Delta V} = 0$ and $s_{RPC} = 1$).

In this paper, in addition to the above cases, four different load models, according to Table II, are also considered. The parameters of CGWO are illustrated in Table III. It should be noted that regarding the radial structure and high R/X ratios of test systems, the power flow method is backward-forward power flow. By using this method, power losses for each branch and voltage magnitudes for each bus node are determined. The forward/backward sweep for the solution of distribution network load flow is utilized to investigate the power loss, line current, and voltage at each bus. This paper uses the power flow results of MATPOWER [54].

TABLE III
CGWO PARAMETERS

Parameter	value
Number of grey wolves (N)	20
Number of societies (N_s)	4
Maximum iteration ($\text{Iteration}_{\max}$)	50
Importance coefficient of alpha wolf (C_α)	0.3
Importance coefficient of beta wolves (C_β)	0.6
Importance coefficient of delta wolves (C_δ)	0.1

A. IEEE 33-bus Distribution System

The first test network is IEEE 33-bus radial system with a total load of $3.72 + j2.30$ MVA. Data of 32 branches and 32 loads are given in [55]. Based on [6], as depicted in Fig. 4, two DGs and two capacitors as RPC devices are installed in this system according to Table IV.

1) Total power losses and voltage deviation before optimization

Before optimization, the total power losses and voltage deviation for three operation conditions under different load types are as Table V. In the first operation condition (denoted with I in Table V), the test network is considered without DGs and capacitors. In the second operation condition (denoted with II in Table V), it is supposed that the capacitors are connected to the test network and the DGs are not exploited. Finally, in the third operation condition (denoted with III in Table V), it is assumed that the DGs are connected to the test network and the capacitors are disconnected.

TABLE VI
DATA OF DGS AND RPC DEVICES [6] – IEEE 33-BUS SYSTEM

RPC/DG	Installed at node	Parameter	value
C_1	6	$Q_{C1,\min}$ (kVAR)	0
		$Q_{C1,\max}$ (kVAR)	600
C_2	31	$Q_{C2,\min}$ (kVAR)	0
		$Q_{C2,\max}$ (kVAR)	1050
DG_1	2	P_{DG1} (kW)	1000
		$Q_{DG1,\min}$ (kVAR)	-100
		$Q_{DG1,\max}$ (kVAR)	500
DG_2	13	P_{DG2} (kW)	1000
		$Q_{DG2,\min}$ (kVAR)	-100
		$Q_{DG2,\max}$ (kVAR)	500

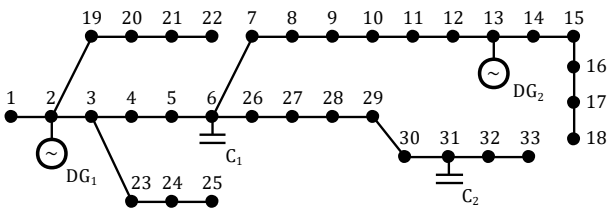


Fig. 4. Modified IEEE 33-bus distribution network

TABLE V
SYSTEM CONDITION UNDER DIFFERENT LOAD MODELS BEFORE OPTIMIZATION – IEEE 33-BUS SYSTEM

Parameter	Condition	Load model			
		CP	IND	COM	RES
Total real power loss (f_{loss} in MW)	I	0.2027	0.1617	0.1550	0.1594
	II	0.1425	0.1409	0.1264	0.1323
	III	0.1348	0.1037	0.1073	0.1072
Total voltage deviation ($f_{\Delta V}$ in pu)	I	0.1171	0.0914	0.0883	0.0909
	II	0.0614	0.0494	0.0476	0.0490
	III	0.0485	0.0369	0.0364	0.0373

I: Without DGs and RPCs; II: Without DGs; III: Without RPCs.

2) Optimization results for CP load model

The optimization results are presented in Table VI for the CP model considering different objectives as Cases 1-3. This table shows that the CGWO proposes a better and more robust solution than GWO, PSO, EMA, and DAMOPSO algorithms for all cases. In Case 1, three objective functions, f_{loss}, $f_{\Delta V}$ and f_{RPC}, are considered as a multi-objective function. In Case 2 and Case 3, f_{RPC} and $f_{\Delta V}$ are not considered in the multi-objective function, respectively.

a) Case 1

Based on Table VI, in Case 1, the proposed CGWO finds an operating point with $f_{loss} = 0.0689$ MW, $f_{\Delta V} =$

0.0148 pu, and $f_{RPC} = 0.7646$ MVAR. In this condition, the objective function is 0.0833 MW. It is clear that the total power losses searched by CGWO are improved by about 3%–33% compared to other presented algorithms. Moreover, the voltage deviation is reduced at least by 1% up to 58% in comparison with other optimization techniques and the base case. In this case, it is important to note that DAMOPSO shows different solutions (Pareto ones) in which minimum values of f_{loss}, $f_{\Delta V}$ and f_{RPC} are not simultaneously searched, while our proposed CGWO and $ObjFunc$ (as (16)) are powerful enough to find the best operating point simultaneously. Results of Case 1 in Table VI show that the best operating point found by EMA is close to that searched by GWO. But, the robust results indicate that GWO has a better mean and standard deviation than EMA.

b) Case 2

In Case 2, the suggested technique outperforms other algorithms and improves f_{loss} and $f_{\Delta V}$ (main objectives) by 2%–16% and 18%–22%, respectively compared to the other methods due to finding $f_{loss} = 0.0675$ MW and $f_{\Delta V} = 0.0141$ pu. Although, in this case, f_{RPC} is not taken as a part of $ObjFunc$, and CGWO reduces it by 14% (average-in comparison with other algorithms). In this case, the value of the objective function is 0.0677 MW. Like Case 1, the results of EMA and GWO are approximately the same in power losses, voltage deviation, and objective function. But, PSO and DAMOPSO propose two quite far operating points. The robust results in terms of mean and standard deviation indicate that the introduced algorithm can provide better solutions than the other presented techniques.

c) Case 3

In the final case, CGWO introduces the best solution ($ObjFunc$ is 0.0830 MW) in terms of the minimum line losses (0.0699 MW) and RPC capacity (0.6931 MVAR). In Case 3, although it is not necessary to optimize $f_{\Delta V}$, the proposed method shows a lower $f_{\Delta V}$ (on average, 12% better than GWO, EMA, PSO, and DAMOPSO). The best, mean, and standard deviation of CGWO clearly demonstrate that it can always converge to a better operating point than the other analyzed algorithms. Moreover, EMA and GWO find similar solutions. In comparison with CGWO, PSO and DAMOPSO converge to bad operating points due to their higher power loss, bigger voltage deviation, and the use of more reactive power.

The optimal settings of control variables for Cases 1-3 are depicted in Figs. 5(a)-(c), respectively. It can be seen that all variables are within their limits and CGWO proposes the full usage of DGs in Cases 1 and 3 and almost does not offer the use of C_1 in the same cases. The position of operating points in the objective space found by CGWO is compared with GWO (as better solution among GWO, EMA, and PSO) and Pareto solutions obtained by DAMOPSO in Fig. 6.

TABLE VI
OPTIMIZATION RESULTS OF IEEE 33-BUS SYSTEM – CP MODEL

Cases	Technique	f_{loss} (MW)	$f_{\Delta V}$ (pu)	f_{RPC} (MVAR)	$ObjFunc$ (MW)		
					Best	Mean	Std.
Without optimization (with only DGs)		0.1348	0.0485	0.0000	-	-	-
1	DAMOPSO[a] [6]	0.0799	0.0162	1.6500	NA	NA	NA
		0.0806	0.0149	1.6500	NA	NA	NA
		0.1016	0.0345	0.3000	NA	NA	NA
	PSO	0.0709	0.0172	0.7758	0.0860	8.61E-2	4.08E-5
	EMA	0.0708	0.0171	0.7750	0.0859	8.61E-1	3.66E-6
	GWO	0.0708	0.0171	0.7800	0.0857	8.58E-2	3.56E-6
	CGWO	0.0689	0.0148	0.7646	0.0833	8.33E-2	3.43E-6
2	DAMOPSO [6]	0.0800	0.0180	1.5000	NA	NA	NA
	PSO	0.0691	0.0181	1.0086	0.0694	6.97E-3	4.16E-6
	EMA	0.0687	0.0172	0.9897	0.0690	6.92E-2	2.79E-5
	GWO	0.0686	0.0170	0.9996	0.0689	6.90E-3	3.05E-6
	CGWO	0.0675	0.0141	0.9455	0.0677	6.77E-2	2.90E-6
3	DAMOPSO [6]	0.0795	0.0182	1.5000	NA	NA	NA
	PSO	0.0713	0.0183	0.8204	0.0871	8.73 E-2	4.20 E-7
	EMA	0.0709	0.0177	0.7420	0.0851	8.52 E-3	2.98 E-6
	GWO	0.0708	0.0175	0.7500	0.0850	8.50 E-2	2.88 E-5
	CGWO	0.0699	0.0159	0.6931	0.0830	8.30 E-2	1.43 E-6

a For Case 1, [6] has proposed different solutions and three of them (based on minimum f_{loss}, $f_{\Delta V}$, and f_{RPC}) are presented here.

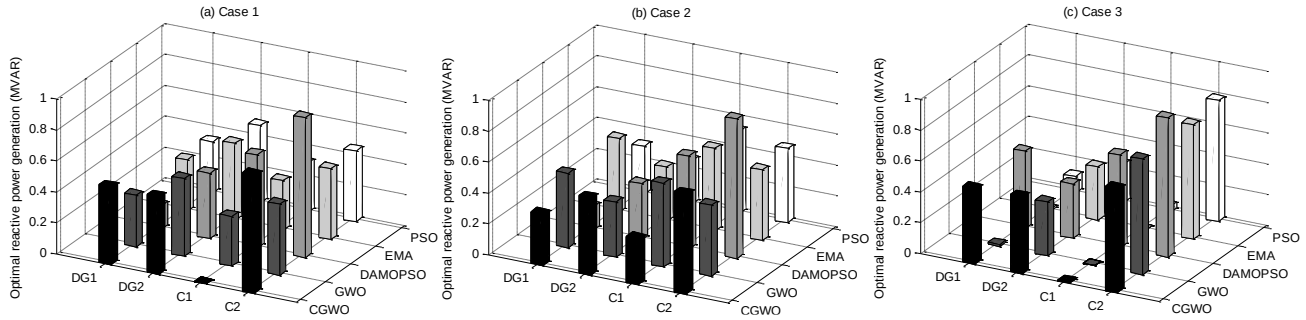


Fig. 5. OPTIMAL OUTPUTS OF DGS AND RPC DEVICES IN IEEE 33-BUS SYSTEM – CP MODEL

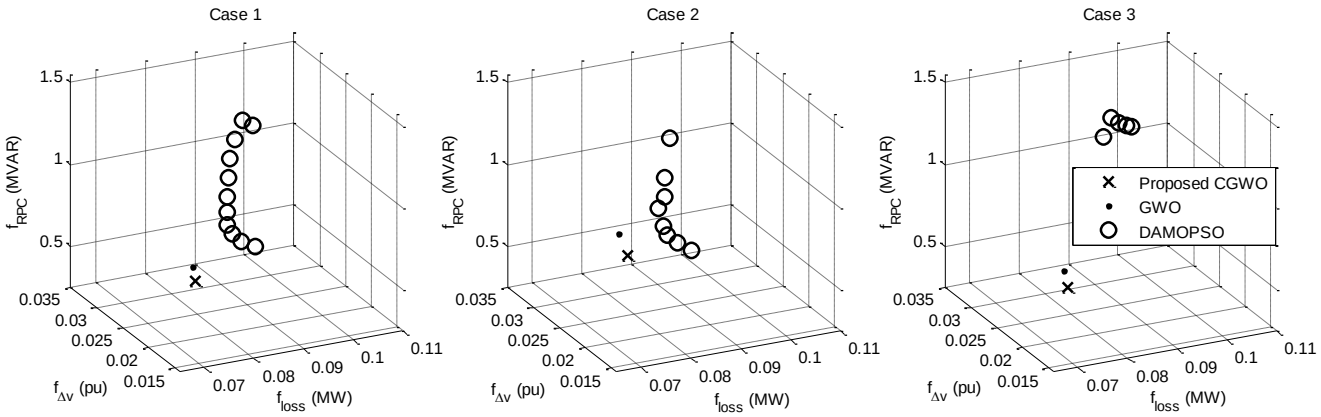


Fig. 6. COMPARISON OF DIFFERENT METHODS BASED ON THE FOUND OPERATING POINTS – IEEE 33-BUS SYSTEM – CP MODEL

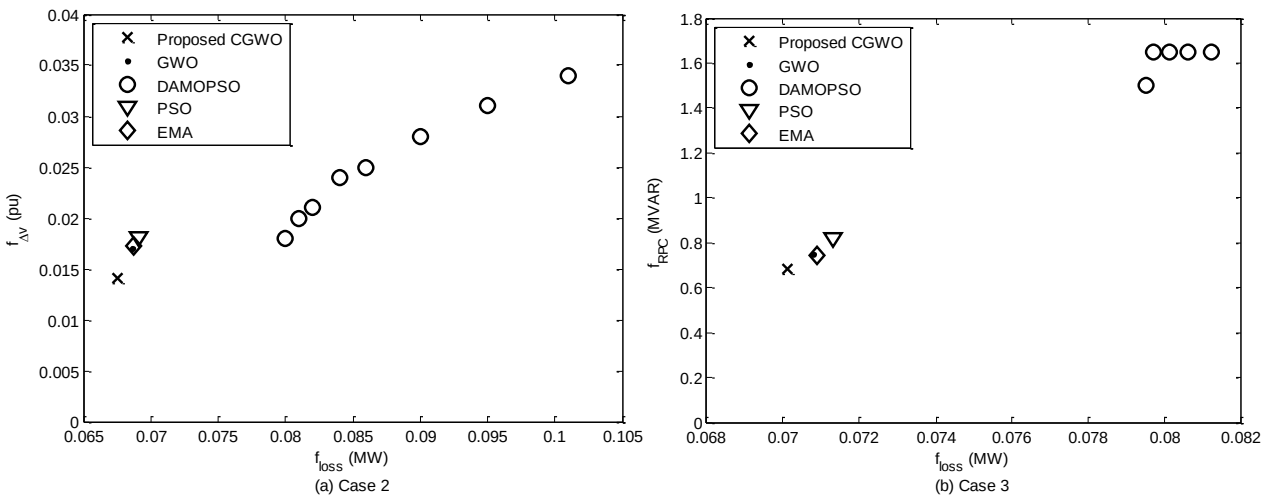


Fig. 7. COMPARISON OF DIFFERENT METHODS BASED ON THE FOUND OPERATING POINTS FOR CASES 2 AND 3 – IEEE 33-BUS SYSTEM – CP MODEL

The results of CGWO demonstrate the best operating point to optimize the distribution system based on the ORPD. This implies that there is a solution that can satisfy all objectives to be minimum simultaneously (less than [6]).

Figs. 7(a) and (b) compare the objectives in the objective space for Cases 2 and 3, respectively. Although the total RPC capacity is in conflict with the line loss, the CGWO can find a better solution than other algorithms. The voltage profiles of different cases based on the CGWO results are shown in Fig. 8. This figure demonstrates that the voltage magnitude of all nodes is improved. Accordingly, the proposed technique offers the best voltage profiles, but the relationship between the power losses and voltage deviation is complex (according to (2) and Fig. 7(a)).

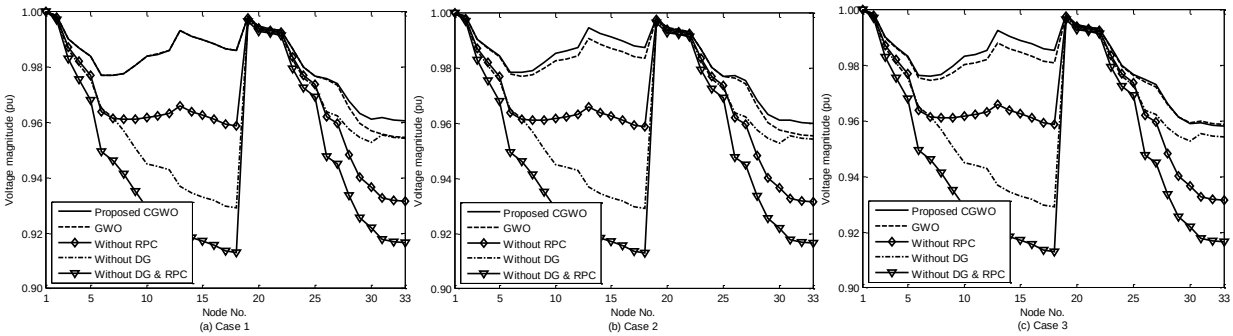


Fig. 8. VOLTAGE PROFILE OF IEEE 33-BUS SYSTEM BASED ON THE CGWO RESULTS

3) Optimization results for IND, COM, and RES load model

Here, only Case 3 is applied to the ORPD problem because investigating $f_{\Delta V}$ as a part of the $ObjFun$ leads to $V_i \to 1$ for $i = 1, 2, \dots, N_{bus}$. Based on (13) and (14), IND, COM, and RES demands (both actively and reactively) converging to the CP model. This means that α and β are not so important in optimization.

The best, mean, and standard deviation of results are presented in Table VII. From this table, it can be seen that the proposed CGWO is robust and can search a better operating point. The $ObjFun$s for IND, RES, and COM types are 0.0759, 0.0748, and 0.0732 MW, respectively. The results obtained by the CGWO algorithm clearly demonstrate that, compared to the best solution of the other reported algorithms, the total power losses are leastwise improved by 6%, 4%, and 4% for IND, RES, and COM loads, respectively. The total RPC capacity as the second part of the $ObjFun$ is also reduced at least by 11% for all load types. As Case 3 for CP load, the proposed approach shows an about 17% reduction in $f_{\Delta V}$ compared to GWO as a better solution among the other techniques. In accordance to Table VIII, it is interesting to note that if the results of the CP model, i.e., its optimal reactive power injections by DGs and RPCs, are considered for other load types, they lead to an increase in the objective functions of IND, RES, and COM by 2.5%, 1.5%, and 1.4%, respectively (in comparison with optimal results of these models). The control variables obtained in optimization by the proposed CGWO are reported in Table IX. The optimal reactive power generation by all DGs and RPC devices are illustrated in Fig. 9.

Fig. 10 shows the relationship between different objectives and various load types. In fact, it illustrates the interesting effect of different load types on the total power losses and RPC capacities (two main objectives) as well as the total voltage deviation. In other words, this shows the relationships between $\{f_{loss}, f_{RPC}, \text{ and } f_{\Delta V}\}$ and $\{\alpha \text{ and } \beta\}$. According to Fig. 10(a), the total active power losses, as per the main objective, are reduced by increasing the factor α. Fig. 10(b) indicates that the COM and CP models lead to the lowest and highest voltage deviation, respectively. In fact, COMs' bus voltages are closer to the desired magnitude, $V^* = 1$ pu and therefore the minimum value of $f_{\Delta V}$ occurs at this load condition. Finally, Fig. 10(c) shows that the lowest reactive power injection by RPC devices is obtained for the IND model, which has the highest value of β. Among different load types, CP reflects the worst condition in terms of the total power losses, RPCs, and the voltage deviation.

TABLE VII
OPTIMIZATION RESULTS OF IEEE 33-BUS SYSTEM – CASE 3 – DIFFERENT LOAD MODELS

Load model	Technique	f_{loss} (MW)	$f_{\Delta V}$ (pu)	f_{RPC} (MVAR)	$ObjFunc$ (MW)		
					Best	Mean	Std.
IND	PSO	0.0715	0.0213	0.5152	0.0816	8.18E-3	3.89E-5
	EMA	0.0710	0.0206	0.5350	0.0813	8.15E-2	4.11E-6
	GWO	0.0704	0.0201	0.5308	0.0805	8.07E-1	3.98E-6
	CGWO	0.0673	0.0158	0.4771	0.0759	7.59E-5	4.61E-8
RES	PSO	0.0680	0.0188	0.6146	0.0796	7.97E-2	3.02E-5
	EMA	0.0675	0.0189	0.6077	0.0788	7.90E-3	2.36E-3
	GWO	0.0663	0.0171	0.5950	0.0772	7.73E-2	4.11E-5
	CGWO	0.0648	0.0147	0.5677	0.0748	7.48E-2	2.67E-6
COM	PSO	0.0662	0.0181	0.6794	0.0787	7.81E-1	3.79E-4
	EMA	0.0651	0.0176	0.5965	0.0760	7.61E-3	3.31E-5
	GWO	0.0650	0.0175	0.6059	0.0759	7.61E-2	3.15E-7
	CGWO	0.0636	0.0146	0.5491	0.0732	7.33E-2	2.97E-6

TABLE VIII
OBJECTIVE FUNCTION EVALUATION FOR IND, RES, AND COM LOADS USING THE OPTIMAL RESULTS OF CP COMPARED TO THE OBTAINED RESULTS FOR EACH TYPE RESPECTIVELY – IEEE 33-BUS SYSTEM

Load model	$ObjFunc$ (MW) using X_{CP}	$ObjFunc$ (MW) using $X_{Load\ types}$
IND	0.0778	0.0759
RES	0.0759	0.0748
COM	0.0742	0.0732

TABLE IX
CONTROL VARIABLES OF IEEE 33-BUS SYSTEM BY CGWO– DIFFERENT LOAD MODELS

Load Model	Q_{DG1} (pu)	Q_{DG2} (pu)	Q_{C1} (pu)	Q_{C2} (pu)	$ObjFunc$ (MW)
CP (Case 1)	0.50000	0.50000	0.00031	0.76429	0.0833
CP (Case 2)	0.33313	0.50000	0.29752	0.64793	0.0677
CP (Case 3)	0.49173	0.50000	0.00819	0.67649	0.0831
IND	0.50000	0.46607	0.00053	0.47658	0.0759
RES	0.46887	0.47505	0.01174	0.55592	0.0748
COM	0.50000	0.47550	0.00000	0.54910	0.0733

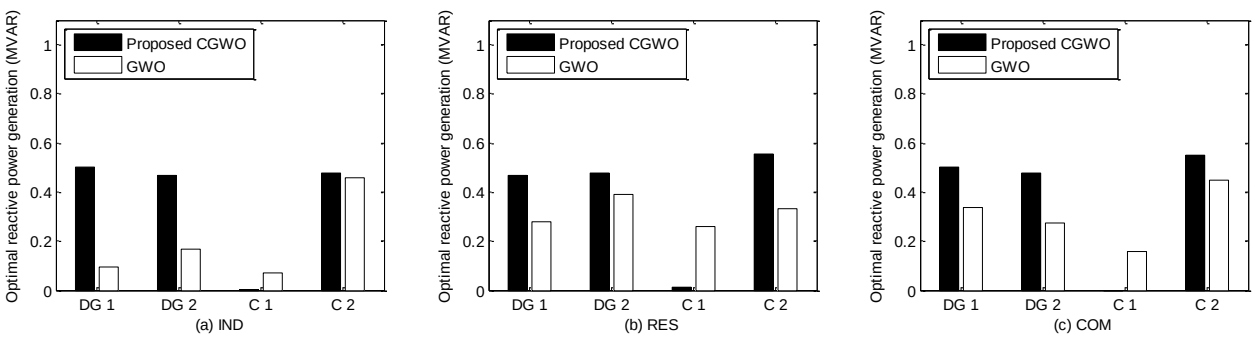


Fig. 9. Optimal outputs of DGs and RPC devices in IEEE 33-bus system – Case 3 – Different load models

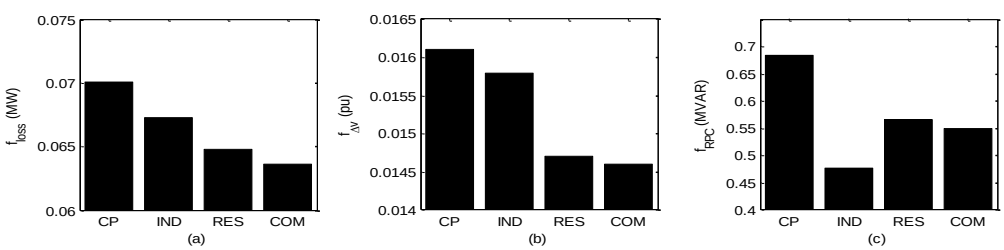


Fig. 10. Relationships between $\{f_{loss},\ f_{RPC}$, and $f_{\Delta V}\}$ and {CP, IND, RES, and COM} in IEEE 33-bus system by CGWO – Case 3

B. IEEE 69-bus Distribution System

The IEEE 69-bus distribution network is a larger-scale system, which was used as the second case study to verify the wide application of the proposed method. Its detailed data are taken from [55] and its single line diagram is shown in Fig. 11. In this network, there are two DGs and three RPC devices (based on [6]) and their capacities and sits are presented in Table X.

1) Total power losses and voltage deviation before optimization

Similar to the previous network, the total power loss and the total voltage deviation in base conditions (without ORPD) of the 69-bus network under different load models are listed in Table XI. In condition I, the studied network is considered without the presence of the DGs and capacitors. In condition II, three capacitors are considered to be connected to candidate buses. In this condition, it is supposed that the DG units are disconnected. In the final operation condition, the test system is analyzed with two DG units connected to buses 17 and 63, but all capacitors are overlooked according to condition III.

2) Optimization Results

The results of ORPD based on the GWO, PSO, EMA, and the proposed CGWO for optimizing Case 3 (as the previous network) are tabulated in Table XII. As can be seen, the suggested optimization strategy is robust and shows high performance in improving total power losses and total RPC capacity. This table clearly shows that the total power losses obtained by CGWO are improved by 4%, 4%, 5%, and 5% compared to the best solution of other

methods for CP, IND, RES, and COM models, respectively. This means that in comparison with the base case (without optimization-only with DGs), CGWO can significantly reduce f_{loss} by 41% (on average) for all load types. Moreover, the RPC capacity as the second part of the objective function is reduced by 3%, 5%, 4%, and 5% versus the best reported solution of the other methods for the mentioned models, respectively. The values of the objective function obtained by CGWO are 0.0880, 0.0799, 0.0765, and 0.0720 MW, which show a 5% improvement versus the traditional GWO. From the obtained results in Table XIII, it can be found that if the optimal reactive power injections by DGs and RPCs related to CP type are considered for IND, RES, and COM load models, their objective functions are increased by 2.16% (in comparison with optimal results of these models).

Fig. 12 compares the operating points for various load models obtained by CGWO (solid shapes) and GWO as the best method among the other analyzed algorithm (hollow shapes). It is clear that the proposed CGWO results outperform the GWO ones.

The optimal outputs related to DGs and RPCs searched by all the analyzed algorithms for various load models are depicted in Fig. 13. This figure shows that in all load models except for the RES one, CGWO sets DG_1 output to its maximum value. Additionally, the reactive generation of C_2 is negligible, while, for example, GWO uses about 5% (on average) of its capacity. However, CGWO for CP, RES, and COM demands utilizes 35% of C_3, while GWO uses less than 29% (unlike C_2). As can be seen in Fig. 13 and Table X, the newly introduced algorithm has a high capability to find more suitable control variables than other techniques for all load models; this leads to lower power losses and RPC cost, better voltage deviation, and considerably lower objective function. Finally, Table XIV demonstrates the optimal control variables obtained by the CGWO approach for this network. This table clearly shows that all independent variables related to reactive power injections by DGs and RPCs are within their pre-specified limits.

Fig. 14 illustrates the relationships between $\{f_{loss}, f_{RPC}, \text{and } f_{\Delta V}\}$ and {CP, IND, RES, and COM}. The total power losses show exponential decay behavior by increasing α in Fig. 14(a). As it can be seen in Fig. 14(c), the RPC cost has a similar behavior (unlike the 33-bus system). Injecting more reactive power by RPCs in IND load than RES load leads to a lower $f_{\Delta V}$ (Fig. 14(b)). In addition, in this network, the COM type makes the studied network to have lower power losses, RPC cost, and better voltage deviation. This condition leads to a minimum bus voltage better than the other models as shown in Fig. 15. It is observed that the highest f_{loss}, f_{RPC}, $f_{\Delta V}$, and minimum voltage magnitude are obtained from the CP load model.

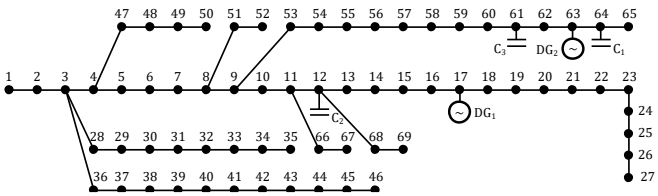


Fig. 11. Modified IEEE 69-bus distribution network

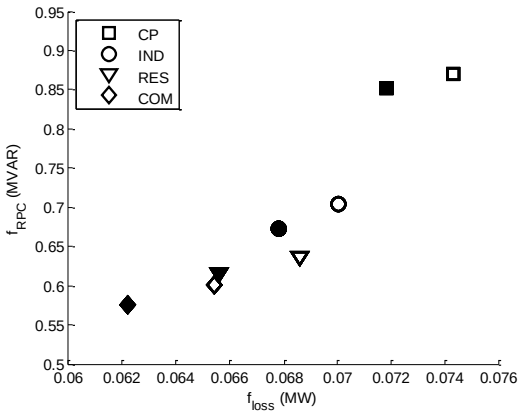


Fig. 12. Comparing the found operating points by different methods – IEEE 69-bus system – Solid and hollow shapes are respectively for CGWO and GWO – Case 3

TABLE X
DATA OF DGS AND RPC DEVICES [6] – IEEE 69-BUS SYSTEM

RPC/DG	Installed at node	Parameter	value
C_1	64	$Q_{C1,\min}$ (kVAR)	0
		$Q_{C1,\max}$ (kVAR)	900
C_2	12	$Q_{C2,\min}$ (kVAR)	0
		$Q_{C2,\max}$ (kVAR)	1500
C_3	61	$Q_{C3,\min}$ (kVAR)	0
		$Q_{C3,\max}$ (kVAR)	1500
DG_1	17	P_{DG1} (kW)	296
		$Q_{DG1,\min}$ (kVAR)	0
		$Q_{DG1,\max}$ (kVAR)	250
DG_2	63	P_{DG2} (kW)	500
		$Q_{DG2,\min}$ (kVAR)	0
			156

TABLE XI
SYSTEM CONDITION UNDER DIFFERENT LOAD MODELS BEFORE OPTIMIZATION – IEEE 69-BUS SYSTEM

Parameter	Condition	Load model			
		CP	IND	RES	COM
Total real power loss (f_{loss} in MW)	I	0.2250	0.1750	0.1708	0.1650
	II	0.2276	0.2568	0.2383	0.2289
	III	0.1413	0.1043	0.1060	0.1045
Total voltage deviation ($f_{\Delta V}$ in pu)	I	0.0993	0.0813	0.0788	0.0756
	II	0.0286	0.0243	0.0235	0.0225
	III	0.0523	0.0423	0.0413	0.0397

I: Without DGs and RPCs; II: Without DGs; III Without RPCs.

TABLE XII
OPTIMIZATION RESULTS OF IEEE 69-BUS SYSTEM – CASE 3 – DIFFERENT LOAD MODELS

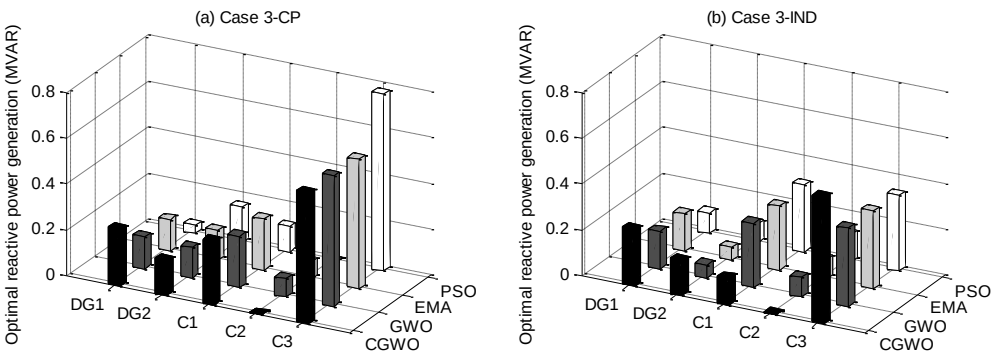
Load model	Technique	f_{loss} (MW)	$f_{\Delta V}$ (pu)	f_{RPC} (MVAR)	$ObjFunc$ (MW)		
					Best	Mean	Std.
CP	PSO	0.0756	0.0315	0.8807	0.0932	9.34E-2	3.45E-6
	EMA	0.0746	0.0311	0.8623	0.0915	9.17E-2	4.32E-5
	GWO	0.0743	0.0310	0.8702	0.0914	9.14E-3	2.93E-7
	CGWO	0.0718	0.0289	0.8521	0.0880	8.80E-2	2.89E-6
IND	PSO	0.0702	0.0285	0.7427	0.0840	8.41E-3	4.02E-6
	EMA	0.0701	0.0284	0.7010	0.0831	8.32E-2	3.51E-8
	GWO	0.0700	0.0283	0.7047	0.0831	8.32E-2	3.10E-3
	CGWO	0.0678	0.0261	0.6733	0.0799	7.99E-3	2.73E-6
RES	PSO	0.0694	0.0294	0.6631	0.0819	8.20E-2	2.97E-9
	EMA	0.0683	0.0286	0.6448	0.0803	8.05E-2	4.81E-6
	GWO	0.0686	0.0287	0.6367	0.0804	8.05E-1	2.93E-5
	CGWO	0.0656	0.0272	0.6153	0.0765	7.66E-2	2.80E-6
COM	PSO	0.0675	0.0279	0.6498	0.0794	7.96E-3	3.89E-7
	EMA	0.0652	0.0268	0.6240	0.0762	7.63E-2	2.56E-4
	GWO	0.0654	0.0268	0.6010	0.0760	7.61E-3	3.38E-6
	CGWO	0.0622	0.0256	0.5750	0.0720	7.21E-2	3.09E-6

TABLE XIII
OBJECTIVE FUNCTION EVALUATION FOR IND, RES, AND COM LOADS USING THE OPTIMAL RESULTS OF CP COMPARED TO THE OBTAINED RESULTS FOR EACH TYPE RESPECTIVELY – IEEE 69-BUS SYSTEM

Load model	$ObjFunc$ (MW) using X_{CP}	$ObjFunc$ (MW) using $X_{Load\ types}$
IND	0.0826	0.0799
RES	0.0786	0.0765
COM	0.0724	0.0720

TABLE XIV
CONTROL VARIABLES OF IEEE 69-BUS SYSTEM BY CGWO– DIFFERENT LOAD MODELS-CASE 3

Load Model	Q_{DG1} (pu)	Q_{DG2} (pu)	Q_{C1} (pu)	Q_{C2} (pu)	Q_{C3} (pu)	$ObjFunc$ (MW)
CP	0.25000	0.15600	0.27901	0.00046	0.57265	0.0880
IND	0.25000	0.15600	0.11830	0.00150	0.55352	0.0799
RES	0.16570	0.15600	0.04782	0.00097	0.56653	0.0765
COM	0.25000	0.15600	0.15440	0.00067	0.41993	0.0720



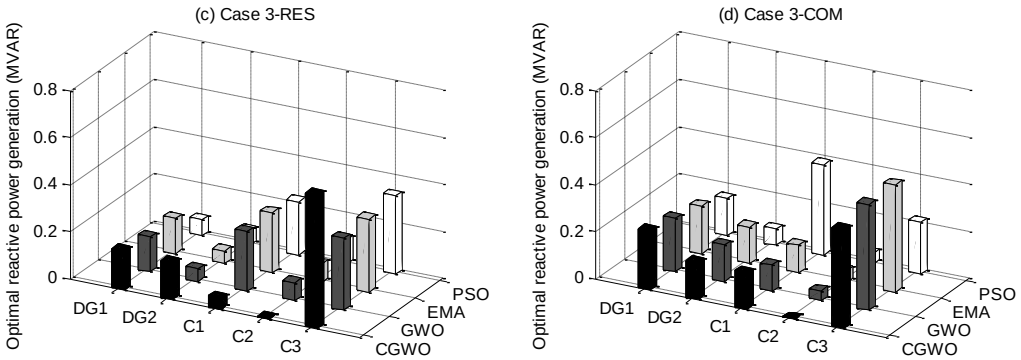


Fig. 13. Optimal outputs of DGs and RPC devices in IEEE 69-bus system – Case 3

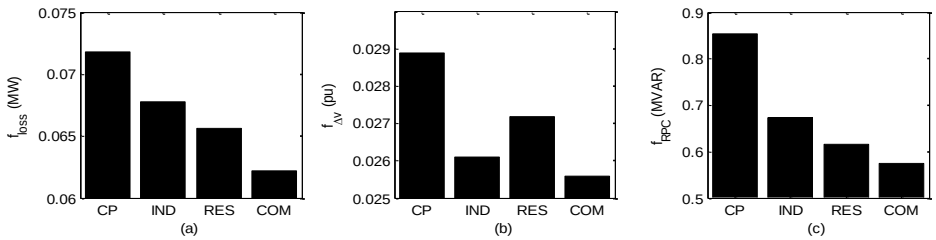


Fig. 14. Relationships between $\{f_{loss},\ f_{RPC}$, and $f_{\Delta V}\}$ and {CP, IND, RES, and COM} in IEEE 69-bus system by CGWO – Case 3

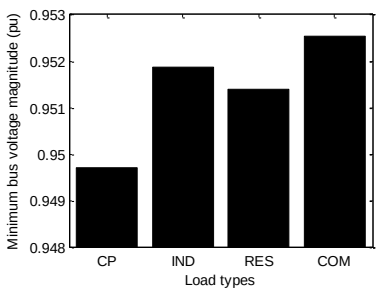


Fig. 15. Minimum bus voltages of different load models by CGWO – IEEE 69-bus system

V. CONCLUSION

This paper proposed a CGWO as a powerful optimization technique for solving the ORPD problem. In the CGWO, the best wolf is selected as alpha and each society has its own beta and gamma. Based on the social hierarchy of grey wolves, beta wolves respect and help alpha and can only command the other lower-level wolves (gamma and omega) in their society. In addition, a new version of the ORPD was introduced for distribution networks considering different load models, including CP, IND, COM, and RES types. Furthermore, for this optimization problem, a novel objective function was suggested that investigates different objectives such as total power losses, voltage deviation, and RPC cost. The proposed technique was tested on two standard distribution systems including IEEE 33- and 69-bus distribution grids considering DGs and RPC devices. The results indicated that:

- The proposed CGWO can solve high-complex ORPD problems in distribution systems considering different load models.
- The CGWO can search a better operating point (in terms of line losses, RPC capacity, and voltage deviation) than other presented methods for all load types.
- It is robust, meaning that it can always find a better $ObjFunc$ for different distribution systems (in comparison with different analyzed techniques) while meeting all constraints.
- The performance of the proposed $ObjFunc$ is more efficient than the Pareto solution. In fact, it properly converts a multi-objective ORPD problem into a single-objective one.
- The lowest power losses are related to the COM load, while the CP leads to the highest line losses.
- The CP and COM types lead to the lowest and highest minimum bus voltages, respectively. This means that COM reflects a better voltage profile than the other types.
- The worst voltage deviations are related to the COM model.
- The behavior of IND and RES load models is between CP and COM load models.

APPENDIX A

The effectiveness of the proposed CGWO in solving standard optimization problems is verified by ten benchmark functions as Table AI. The optimum value of all listed functions is 0. The proposed CGWO was run over 20 times on each standard function and its parameters are =

30, $N_s = 4$, $\text{Iteration}_{\max} = 1000$, $C_\alpha = 0.3$, $C_\beta = 0.6$, and $C_\delta = 0.1$. The optimization results of CGWO, GWO [52], EMA, and PSO [52] in terms of average and standard deviation are presented in Table AII. As it is obvious, the CGWO outperforms the other methods and results in high local minima avoidance. This shows the superior ability of the proposed hunting model and civilization and also emphasizes the balance between exploitation and exploration power.

TABLE AI
BENCHMARK FUNCTIONS

No.	Name	Formulation	Dimension	Range	$f_{\min}$
1	Sphere	$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-100, 100]	0
2	Step function	$f_2(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	[-100, 100]	0
3	Quartic	$f_3(x) = \sum_{i=1}^{n} i x_i^4 + \text{rand}[0,1)$	30	[-1.28, 1.28]	0
4	Schwefel's 1.2	$f_4(x) = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j \right)^2$	30	[-100, 100]	0
5	Schwefel's 2.21	$f_5(x) = \max_i \{\lvert x_i \rvert, 1 \le i \le n\}$	30	[-100, 100]	0
6	Schwefel's 2.22	$f_6(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	30	[-10, 10]	0
7	Ackley	$f_7(x) = -20 \exp\left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \right) - \exp\left(\frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i) \right) + 20 + e$	30	[-32, 32]	0
8	Griewank	$f_8(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}} \right) + 1$	30	[-600, 600]	0
9	Penalized function 1	$f_9(x) = \frac{\pi}{n} \left\{ 10 \sin(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 [1 + 10 \sin^2(\pi y_{i+1})] + (y_n - 1)^2 \right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$, $y_i = 1 + \frac{x_i + 1}{4}$, $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	30	[-50, 50]	0
10	Penalized function 2	$f_{10}(x) = 0.1 \left\{ \sin^2(3\pi x_i) + \sum_{i=1}^{n} (x_i - 1)^2 [1 + \sin^2(3\pi x_{i+1})] + (x_n - 1)^2 [1 + \sin^2(3\pi x_n)] \right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	30	[-50, 50]	0

TABLE AII
OPTIMIZATION RESULTS OF BENCHMARK FUNCTIONS

Method		Function									
		f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}
PSO [52]	Avg	1.360E-04	1.02E-04	1.228E-01	7.012E+1	1.086E+1	4.214E-02	2.76E-01	6.917E-03	6.917E-03	6.675E-03
	Std	2.020E-04	8.28E-05	4.495E-02	2.211E+1	3.170E-01	4.542E-02	5.09E-01	2.63E-02	2.630E-02	8.907E-03
EMA	Avg	6.382E-25	0	3.717E-02	5.716	1.017E-02	2.335E-13	1.180E-01	1.079E-02	1.077	5.943E-03
	Std	1.433E-24	0	1.036E-02	2.904	7.401E-03	3.854E-13	3.682E-01	1.493E-02	1.466	4.213E-03
GWO [52]	Avg	6.59E-28	8.165E-01	2.213E-03	3.29E-06	5.61E-07	7.18E-17	1.06E-13	4.485E-03	5.343E-02	6.544E-01
	Std	6.34E-05	1.26E-04	1.002E-01	7.914E+1	1.315	2.901E-02	7.783E-02	6.659E-03	2.073E-02	4.474E-03
CGWO	Avg	6.544E-36	0	1.517E-03	2.565E-09	7.365E-08	2.677E-21	5.524E-14	1.395E-03	2.490E-06	3.971E-05
	Std	6.177E-36	0	7.264E-04	5.957E-09	7.177E-08	1.990E-21	7.207E-15	3.411E-03	1.017E-06	1.060E-05

APPENDIX B

In this section, the values of some parameters of the CGWO algorithm including the number of grey wolves, societies, and maximum iteration are experimented and their influence on the performance of the proposed technique is analyzed to determine their optimal settings. To evaluate the effect of these parameters on the final solution, only the results of Case 1 of IEEE 33-bus distribution network considering the CP model are presented here. So, several runs with different parameter values were carried out. The results depicted in Fig. B indicated that:

Number of society: According to Fig. B(a), this parameter varied in the range of 1–7 to study the effect of N_s on the $ObjFunc$. It is clear that the optimum choice for this parameter is $N_s = 4$. Increasing the number of society ($N_s \geq 5$) can slightly improve the final solution.

Number of grey wolves: Based on Fig. B(b), the best choice is $N = 20$ and more wolves can reduce the objective function by less than 0.1%.

Number of iteration: Fig. B(c) indicates that $\text{Iteration}_{\max} > 50$ cannot help the algorithm find better $ObjFunc$.

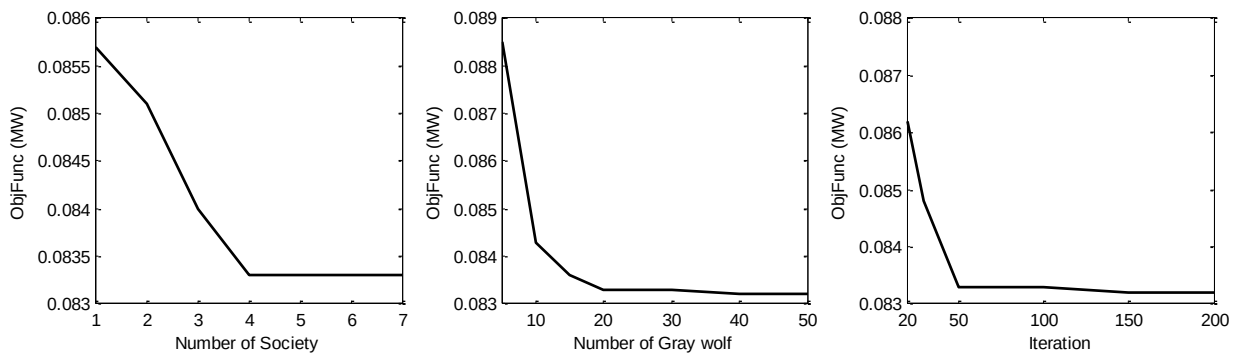


Fig. B. Effect of the CGWO parameters on the objective function – IEEE 33-bus – Case 1 – CP model

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