Analyzing the Load Modelling Impacts on Uncertain Optimal Reactive Power Dispatch Problem by Using Grey Wolf Optimization

Hamdi Abdi, Mansour Moradi, and Shahram Karimi

Abstract— **Optimal Reactive Power Dispatch (ORPD) is an essential subject in the economic operation of power systems. This issue is generally an optimization constrained problem satisfying the dominant control parameters. Due to the non-linear nature of the ORPD problem, solutions include several optima, and deterministic methods may lead to poor performance. On the other hand, the diversity and stochastic nature of electrical loads, arising from renewable energy penetration in the power system create significant challenges in solving this problem. Therefore, stochastic methods are required to find the appropriate solutions. In this paper, the Monte Carlo Simulation (MCS) is used to model the uncertainty of loads. Static modeling methods implement the type of load modeling. The polynomial ZIP method is applied to solve the ORPD problem for the first time. Optimizing the control parameters by applying the Grey Wolf Optimization (GWO) and based on the IEEE 30-bus standard as a general model is performed. Due to this, in the proposed method, the minimum voltage level will be 0.4 per unit less than the other methods. Also, the rate of system losses is improved by 7.61% compared to the base-case network, but compared to the other methods, regardless of the load model, it has a 10.76% higher loss rate. The simulation results show that the load models have a significant effect on the ORPD problem, and this concept is completely and directly transferred to the operation of the power system, and power system stability, accordingly.**

Index Terms— **Optimal Reactive Power Dispatch (ORPD), Uncertainty, Load Model, Monte Carlo Simulation (MCS), Grey Wolf Optimization (GWO), Power Losses.**

I. INTRODUCTION

Nowadays, by developing different trends in power systems, shifting and reconstruction of market mechanisms in the power industry, the importance of auxiliary services such as reactive power service is increasing more and more. The power system operator should optimally provide the reactive power service to establish the system's security. This is mainly due to the fact that the reactive power is an essential auxiliary service that makes possible the scheduled generation of electrical power. Generally, the appropriate distribution of reactive power among its supplier can significantly impact the security and efficiency of the power network [1-5].

The ORPD problem affects the optimal operation of the power system, and it is an essential issue in power system studies [2, 3]. The precise solution of this problem leads to optimal usage of reactive power compensation problem in order to achieve the problem objectives such as loss reduction, minimizing the investment cost (costs of purchase, installing, and maintenance of new sources of reactive power), voltage profile smoothing, and maximizing the voltage stability margin in the normal operating state or after being exposed to an un-normal condition [1-6]. The most important constraints and parameters requiring control and regulation in this problem are: load constraints: includes active and reactive power distribution equations also known as load distribution equations; and operational constraints: including the reactive output power of generators and synchronous compensators, transformer on-load tap changers, and the capacity of parallel capacitors.

This problem has a non-linear mixed-integer optimization structure [4-8]. Any form of variations in relevant variables might affect the network voltage level, the reactive power of generators, and electrical losses. Hence, it is required that variables be limited to minimize the power losses [4-8]. Based on the no convexity nature of the ORPD problem, deterministic and traditional algorithms cannot be applied to solve it.

In power system studies, applying a precise model of the loads, to find realistic results is essential. The precision and complexity of the load model are determined by considering the horizon of system studies and the relevant technical constraints. Generally, the simplified constant power model is used to fully model the load. Linearization methods to consider the non-linear variations of load are not acceptable. For this reason, and to model the diversity and span of loads due to uncertainty, presenting a comprehensive model is difficult. Hence, multiple methods, including static and dynamic modeling [9, 10] are suggested. Also, several CIGRE reports have addressed the load remodeling in [11]. One of this research team's main challenges was determining the desirable load model for the diverse static and dynamic studies. A questionnaire was made for this purpose and was sent to 160 operating units in more than 50 countries of five continents. According to the presented reports, considering the importance of load modeling, the ZIP model is used as the static, and the motor load is used as the dynamic load in most locations of the world. Presenting an inappropriate model for load, causes the difference between the simulation results and the measured results. Considering the addition of electronic and

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non-linear loads into the modern power systems, revealed the importance of accurate load modeling.

The load modeling is an essential concept in power systems planning, and as the literature review shows, enough attention is not paid to it in the ORPD problem. The current paper investigates the effect of static voltage-dependent load models, including constant impedance, current, and power, on the ORPD problem. The ZIP model is also used to consider different load modes and their impacts, to determine the best control parameters in solving the ORPD problem. Also, due to the variety of loads in power systems, different load categories, namely constant impedance, current, and power, considering their uncertainty, have been used. In this study, the frequency-dependent load model is neglected due to the complexity of the problem. Different load models have been investigated using the MCS method to clarify the effectiveness of different control variables more accurately.

II. Problem Formulation

A. The ORPD problem formulation

Considering that minimizing the real power loss in the distribution system is a crucial objective, the objective function of ORPD problem is expressed as equation (1) [1-5].

$$Minimize\ P_{Loss} = \sum_{k=1}^{Nl} G_k\left(V_i^2 + V_j^2 - 2V_iV_j cos\delta_{ij}\right) \quad (1)$$

G_k is the conductance of line k between i and j buses. Nl is the number of distribution lines, V_i is the voltage at the i bus, and δ_{ij} is the angle difference between the i and j buses. Minimizing the objective function (1) depends on the satisfaction of constraints (equality and inequality constraints). The equality constraints are the active and reactive power equalities (2) and (3):

$$P_{G_i} - P_{D_i} - V_i\sum_{j=1}^{NB} V_j\left(G_{ij}cos\delta_{ij} + B_{ij}sin\delta_{ij}\right) = 0 \quad (2)$$

$$Q_{G_i} - Q_{D_i} - V_i\sum_{j=1}^{NB} V_j\left(G_{ij}sin\delta_{ij} - B_{ij}cos\delta_{ij}\right) = 0 \quad (3)$$

These two constraints are the equality of the reactive and active powers in load modeling as ZIP polynomial in equations (4) and (5).

$$P_{G_i} - P_{D_i}\left(Z_p\left(\frac{V}{V_0}\right)^2 + I_p\left(\frac{V}{V_0}\right) + P_p\right) - V_i\sum_{j=1}^{NB} V_j\left(G_{ij}cos\delta_{ij} + B_{ij}sin\delta_{ij}\right) = 0 \quad (4)$$

$$Q_{G_i} - Q_{D_i}\left(Z_q\left(\frac{V}{V_0}\right)^2 + I_q\left(\frac{V}{V_0}\right) + P_q\right) - V_i\sum_{j=1}^{NB} V_j\left(G_{ij}sin\delta_{ij} - B_{ij}cos\delta_{ij}\right) = 0 \quad (5)$$

In the above-mentioned equations, NB is the number of system buses, P_{G_i} and Q_{G_i} are the active and reactive powers generated in bus i, P_{D_i} and Q_{D_i} are the active and reactive powers consumed in bus i, G_{ij} and B_{ij} are the real and imaginary parts of the admittance matrix of buses i and j, respectively.

Inequality constraints are included the limitations expressed in equation (6) to (12):

$$P_{G_{slack}}^{min} \le P_{G_{slack}} \le P_{G_{slack}}^{max} \quad (6)$$

$$Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max}, \forall i \in NG \quad (7)$$

$$V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max}, \forall i \in NG \quad (8)$$

$$T_i^{min} \le T_i \le T_i^{max}, \forall i \in NT \quad (9)$$

$$Q_{C_i}^{min} \le Q_{C_i} \le Q_{C_i}^{max}, \forall i \in NC \quad (10)$$

$$V_{L_i}^{min} \le V_{L_i} \le V_{L_i}^{max}, \forall i \in NQ \quad (11)$$

$$\left|S_{l_i}\right| \le S_{l_i}^{max}, \forall i \in Nl \quad (12)$$

NG, NT, NC, and NQ represent the number of generators, transformers, reactive power compensation sources and load buses, respectively. $P_{G_{slack}}$, $P_{G_{slack}}^{max}$, and $P_{G_{slack}}^{min}$ define the active power, the maximum and minimum active powers of the slack generator, Q_{G_i}, $Q_{G_i}^{max}$ and $Q_{G_i}^{min}$ respectively represent the amount of reactive power, the maximum and minimum reactive powers of the generator, V_{G_i}، $V_{G_i}^{max}$ and $V_{G_i}^{min}$ describe the amount of generator voltage, maximum and minimum generator voltages, T_i, T_i^{max} and T_i^{min} present the amount of transformer tap-changer, the maximum and minimum transformer tap settings, Q_{C_i}، $Q_{C_i}^{max}$ *and* $Q_{C_i}^{min}$ define the capacitance, the maximum and minimum capacity of the capacitor, V_{L_i}, $V_{L_i}^{max}$ and $V_{L_i}^{min}$ describe the load voltage, maximum and minimum load magnitude voltages, S_{l_i} and $S_{l_i}^{max}$ are also indicate the capacity of the transmission line and its maximum transmission capacity.

B. Optimization algorithm

In this paper, the GWO is used as the optimization algorithm, which is a nature-inspired algorithm based on the hierarchical modeling and social behavior of wolves when hunting [16]. This algorithm is also based on the initial population. In implementing this algorithm, four types of grey wolves including α, β, δ, and ω are used to simulate the leadership hierarchy in which three main steps of hunting (the food search, surrounding it, and attack) is applied. In this hierarchy:

- ✓ The leading wolves of the pack are known as α;
- ✓ The β wolves help α ones in decision making and are also likely to replace them;
- ✓ The δ wolves are inferior to β ones and have a lower contribution in the decision-making process;
- ✓ Finally, the ω wolves are the lowest in the hierarchy with the lowest rights compared to the other members and have no contribution to decision-making.

The optimization process is performed based on the moves of α, β, δ wolves. An α wolf is assumed as the main leader of the algorithm. A β and a δ wolf also contribute, and the other wolves are considered as their followers.

Modeling the hunting and surrounding trend is as equations (13) and (14):

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \tag{13}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{14}$$

In which C and A are vectors of the coefficients, X_p is the location vector of the hunt, X is the location vector of every wolf, and t is the number of iterations. Vectors A and C are calculated as:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{15}$$

$$\vec{C} = 2\vec{r}_2 \tag{16}$$

Components of a reduce from 2 to 0 linearly during consecutive iterations. r and 2_r are stochastic vectors in the space of [0,1].

The α and β wolves estimate the prey location and the other wolves update their location stochastically around the prey.

When the wolves surround the prey, the attack commences with the leadership of the α wolf. Modeling this process is done by reducing the a vector. Since A is a stochastic vector within$[-2a, 2a]$, a coefficient vector reduces as the a does. If $|A| < 1$, the α wolf approaches the prey and so do the others. If $|A| > 1$, the α wolf gets away from the prey and the other wolves. The GWO algorithm requires all wolves to update their location based on the population of α, β, and δ wolves.

C. Load modeling

C.1. modeling the load uncertainty with the MCS method

As the loads in power systems are uncertain, their accurate modeling for different operational conditions is very difficult and somewhat impossible. Using the probability distribution function can be considered as one of the most common methods for uncertainty modeling [4, 17]. But only using this method can not provide a suitable model of load. Therefore, using different techniques based on pdf, such as MCS seems necessary. MCS obtains more accurate results by relying on repeated sampling (for example, 10000 iterations). In this method, a sample of the expected model will be created in each iteration that represents a possible quantity for it in the future. With the mentioned purpose, in this study, to increase the accuracy in load modeling, the uncertainty of electric charges has been modeled using Gaussian and MCS normal distribution functions together.

The probability function of this distribution has two parameters, one of which is the mean value (μ) and the other is the standard deviation (σ) of the load as shown in figure (1).

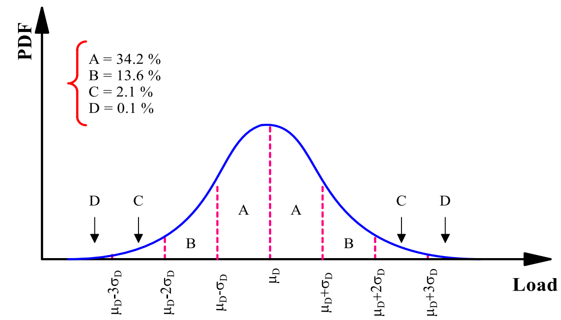

Fig. 1. The normal Gaussian distribution probability function.

These parameters are calculated with equations (17) and (18). Assuming the average and standard deviation of the Probability Density Function (PDF) as μ_D and σ_D, and by using equation (19), the probability of the load is obtained from at least 1000 iterations in the MCS method.

$$\mu_D = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{17}$$

$$\sigma_D = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_D)^2} \tag{18}$$

$$P_D = f(x|\mu_D, \sigma_D) = \frac{1}{\sigma_D\sqrt{2\pi}} e^{\frac{-(x-\mu_D)^2}{2\sigma_D^2}} \tag{19}$$

C.2. Load model

In power system analysis, the system load is usually assumed as a mixture of domestic and industrial loads, as follows [4]: Induction motors form 55% to 77% of the entire load; Synchronous motors form 5% to 15% of the entire load; and Lighting and heating form 20% to 30% of the entire load.

Constant current, impedance, and power and considering the dependence of power on voltage [6, 12]. In the case of a constant impedance load, the dependence of power on voltage is as of a grade 2 function; in case of a constant current, it is linear; and in case of constant power, there is no dependence on voltage. The ZIP model (equations (20) and (21)) is a polynomial model:

Hence, the static features of the load can be classified into

$$P = P_0\left(Z_p\left(\frac{V}{V_0}\right)^2 + I_p\left(\frac{V}{V_0}\right) + P_p\right) \tag{20}$$

$$Q = Q_0\left(Z_q\left(\frac{V}{V_0}\right)^2 + I_q\left(\frac{V}{V_0}\right) + P_q\right) \tag{21}$$

In which P_0, Q_0, and V_0 are the initial values of the studied system (rated conditions) and Z_p, I_p, P_p, Z_q, I_q, and P_q coefficients are the parameters of the model. But to separately express each constant current, voltage, or power load model, we use (22) and (23) equations that demonstrate the dependence of power on voltage in the form of an exponential function [6, 7].

$$P = P_0\left(\frac{V}{V_0}\right)^{\alpha} \quad (22)$$

$$Q = Q_0\left(\frac{V}{V_0}\right)^{\beta} \quad (23)$$

α and β, are equal to the sensitivity coefficients of the active and reactive loads to voltage fluctuations in the operating point of the system (P_0, Q_0, and V_0), and they are equal to 0, 1, or 2, in different load models.

III. The Proposed Algorithm

In figure (2), the flowchart of the proposed algorithm is given. In the optimization process, the program is done in 10000 iterations both in the external loop and for load modeling in order to calculate the active power loss. In each iteration of the external loop (each MCS iteration), simulation and optimization of parameters of the ORPD problem are performed by creating a different load model by the MCS of the internal loop of the algorithm (the left side part). Eventually, estimation of the optimized parameters in the entire iterations of MCS is calculated and presented as the final parameters.

Figure (2) presents the flowchart of the proposed method, in which, at first, the minimum and maximum values of each parameter in the ZIP model are obtained for Z_p ،I_p ،P_p ،Z_q ،I_q, *and* P_q from the values presented in TABLE VI [13]. To calculate the coefficients of α and β in the static model, taking into account $V = \left({}^{V}/_{V_0}\right)$, and removing the common factors of P_0 and Q_0 in relations (20), and (21) for each combined load coefficient obtained in the reference [15], 13 values for α and β used in formulas (22) and (23) concerning relations (24) and (25) result. These values are obtained for 10-step changes in voltage with 0.01 steps, from 0.95 to 1.05 per unit. The minimum and maximum values for α and β will be obtained by considering their average.

$$\alpha = \frac{log\left(Z_p(V)^2 + I_p(V) + P_p\right)}{log(V)} \quad (24)$$

$$\beta = \frac{log\left(Z_q(V)^2 + I_q(V) + P_q\right)}{log(V)} \quad (25)$$

Then, in each iteration of the MCS method, some probabilistic load models for the static and the ZIP models are placed in the obtained intervals to consider different load modes. In all probabilistic models, the constraints of $Z_q + I_q + P_q = 1$ and $Z_p + I_p + P_p = 1$ should be fully observed.

A. The studied standard network

The studied network is an IEEE 30-bus standard test system [10, 13 and 14]. This system consists of 6 power plants, 4 transformers, 41 transmission lines, and 3 capacitive banks. The active and reactive power generated in this system are respectively 298.23 MW and 139.1 MVAR; the active and reactive power consumption are respectively 238.4 MW and 126.2 MVAR; and the active power loss is 5.832 MW. Limitations of the control parameters of this system are introduced in TABLE I [4, 12].

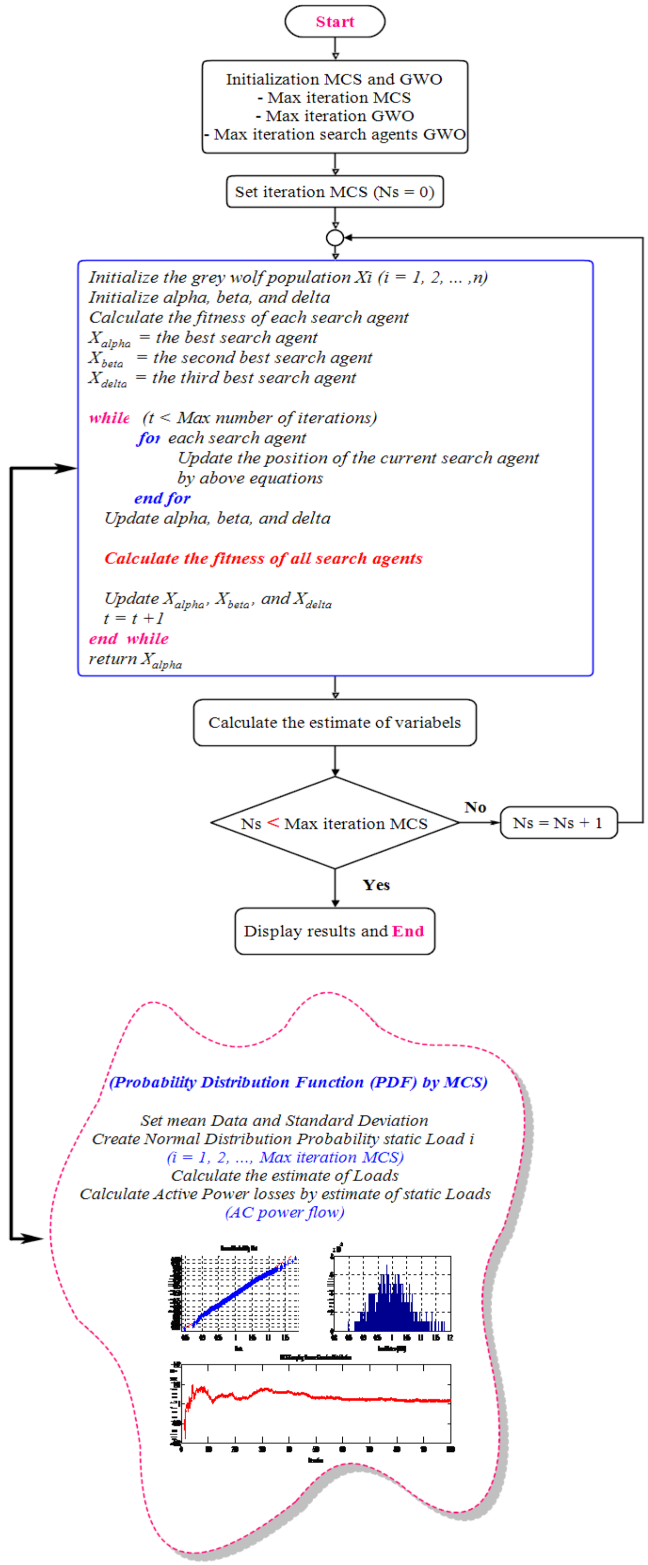

Fig. 2. Flowchart of the proposed method

TABLE I

Control Limitation of the Control Parameters of the System [8-10].

V_G^{max} (pu)	V_G^{min} (pu)	V_{PQ}^{max} (pu)	V_{PQ}^{min} (pu)	T_k^{max} (pu)	T_k^{min} (pu)	Q_C^{max} (Mvar)	Q_C^{min} (Mvar)
1.10	0.95	1.10	0.95	1.10	0.90	36	0

IV. Simulation and Numerical Results

B. Numerical results

As mentioned previously, the mission of ORPD in power systems is to detect control variables in order to minimize the objective function (25) (active power loss) considering the constraints mentioned in equations (30) to (36) of the system. In TABLE II, the optimum values of control parameters of different algorithms mentioned in references for constant power load are addressed. In TABLE III, the proposed algorithms' optimum values of control parameters are presented. In this table, the impact of three types of loads (constant impedance, current, and power) and combined using MCS-GWO (considering the uncertainty of load) and GWO (without considering the uncertainty of load) on the results of solving the reactive power optimum distribution is presented. The presented values for coefficients of the load model in TABLE III are expressed by averaging of load coefficients presented in [15].

C. Analysis of results

Considering the results, it can be concluded that:

- ✓ **The voltage of generators:** re-modeling the load of the power system greatly affects the precision of results of load dispatch. Inaccuracy in modeling will bring unauthentic and unreliable results. In case the load models used in the power system are not of enough precision, the results of the simulation will be different from the real response of the network. This will affect the analysis of the power system. Using the static model of ZIP and increasing the precision in load modeling causes the voltage magnitude generated in each generator to reduce by 0.05 pu on average. This issue is demonstrated in figure (3).
- ✓ **The size of capacitors:** more precise modeling of load to constant power load ratio in the previous studies has caused the reactive power received by the initial capacitors of the system (close to the generators) to drop; a matter which is demonstrated in figure (4). This is because the voltage of busses in the presence of these capacitors is in the acceptable range which is shown in figure (5).
- ✓ **Tap-changers of the transformers:** in this regard, according to figure (6) it can be concluded that unlike the two latter cases mentioned, tap-changers of the transformers have increased when compared to the constant power model. This is due to the low cost of operation and using the system's capacity, which imposes fewer challenges.
- ✓ **Loss:** considering the results depicted in TABLE III and figure (7), it can be concluded that almost in both mentioned methods the loss fluctuation trend has been uniform in comparison to the load model; meaning that the constant power model and the constant current one have the maximum losses. Since a more precise load model is considered, the system loss is slightly increased.

TABLE II
Best Results of Control Variables and Power Loss of the IEEE 30-Bus Standard Test System for the Constant Power Model (α and β=0)

Variable	**C-PSO [9]**	**CL-PSO [9]**	**LDI-PSO [9]**	**B-DE [9]**	**R-DE [9]**	**SFLA [9]**	**NMSFLA [9]**	**ICA [4]**	**IWO [4]**	**MICA-IWO [4]**
V_{G1} (pu)	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000
V_{G2} (pu)	1.1000	1.0947	1.0946	1.0946	1.0949	1.0945	1.0945	1.0928	1.0931	1.0927
V_{G5} (pu)	1.0747	1.0755	1.0753	1.0754	1.0707	1.0751	1.0753	1.0754	1.0741	1.0756
V_{G8} (pu)	1.0867	1.0774	1.0773	1.0774	1.0730	1.0770	1.0773	1.0780	1.0779	1.0772
V_{G11} (pu)	1.1000	1.1000	1.1000	1.0999	1.0650	1.0949	1.1000	1.0915	1.0913	1.1000
V_{G13} (pu)	1.1000	1.1000	1.1000	1.1.000	1.0961	1.1000	1.1000	1.0994	1.0998	1.1000
T_{6-9} (pu)	0.99	1.08	1.08	1.08	1.05	0.98	1.06	1.03	1.03	1.10
T_{6-10} (pu)	1.05	0.90	0.90	0.90	0.90	1.03	0.92	1.01	1.01	0.90
T_{4-12} (pu)	0.99	0.96	0.96	0.96	1.00	0.96	0.95	0.99	1.01	0.96
T_{28-27} (pu)	0.96	0.96	0.96	0.96	0.97	0.96	0.96	0.98	0.97	0.96
Q_{C3} (MVar)	9.00	7.00	7.00	7.00	1.00	8.00	8.00	8.00	8.00	10.00
Q_{C10} (MVar)	30.00	25.00	25.00	25.00	26.00	31.00	26.00	34.00	26.00	35.00
Q_{C24} (MVar)	8.00	10.00	10.00	10.00	12.00	10.00	10.00	12.00	11.00	12.00
***Ploss* (MW)**	**4.9135**	**4.8394**	**4.8394**	**4.8396**	**4.8215**	**4.8995**	**4.8672**	**4.8937**	**4.8701**	**4.8646**

** The reason for incompatibility of the final result (loss) of this table with the main references is the probable incompatibility of the studied network in terms of load dispatch. For match the network and the final result, the optimum parameters presented in this table should be set as the network data to present the loss results.*

TABLE III
Best Results of Controlling Variables and IEEE 30-Bus Standard Test System Losses in Proposed Methods

Variables	**GWO**			**MCS-GWO**			**Zp=0.98 Ip=-1.19 Pp=1.21 Zq=6.32 Iq=-10.43 Pq=5.11**	
α and β	**0**	**1**	**2**	**0**	**1**	**2**	**GWO (ZIP)**	**MCS-GWO (ZIP)**
V_{G1} (pu)	1.1000	1.0989	1.0133	1.0997	1.0877	0.9963	1.0483	1.0471
V_{G2} (pu)	1.0560	1.0482	0.9676	1.0766	1.0562	0.9687	1.0199	1.0255
V_{G5} (pu)	1.0728	1.0683	0.9910	1.0775	1.0564	0.9659	1.0166	1.0216
V_{G8} (pu)	1.1000	1.0988	1.0053	1.0900	1.0773	0.9728	1.0418	1.0406
V_{G11} (pu)	1.1000	0.9674	0.9550	1.0762	0.9878	0.9682	0.9937	1.0142
V_{G13} (pu)	1.1000	0.9501	0.9500	1.0875	0.9650	0.9517	1.0333	1.0247
T_{6-9} (pu)	1.02	1.06	1.10	1.00	1.08	1.06	0.93	0.98
T_{6-10} (pu)	0.90	1.09	1.05	0.98	1.05	1.05	0.98	0.97
T_{4-12} (pu)	1.04	1.10	1.10	1.05	1.09	1.09	1.05	1.02
T_{28-27} (pu)	0.98	1.08	1.05	0.99	1.08	1.08	0.97	0.95
Q_{C3} (MVar)	33.54	16.81	7.33	16.11	16.75	16.54	9.16	17.17
Q_{C10} (MVar)	25.58	13.13	2.45	15.80	16.21	16.53	22.57	17.18
Q_{C24} (MVar)	5.65	10.75	11.70	16.15	16.75	16.25	24.22	17.33
***Ploss* (MW)**	**4.7573**	**4.6305**	**4.0697**	**4.8000**	**4.7233**	**4.0543**	**5.2648**	**5.3880**

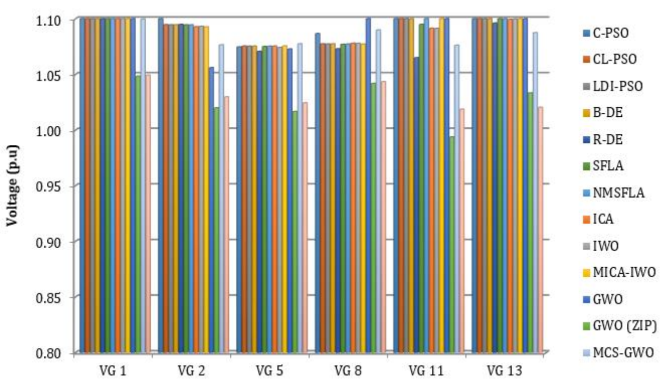

Fig. 3. Voltage's magnitude of the generators in different algorithms

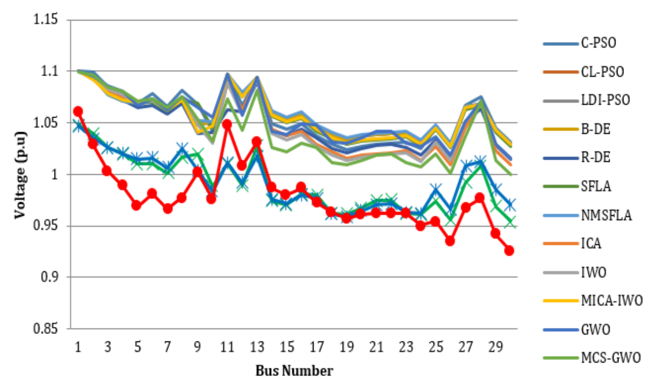

Fig. 5. Voltages buses of the IEEE 30-bus standard test system

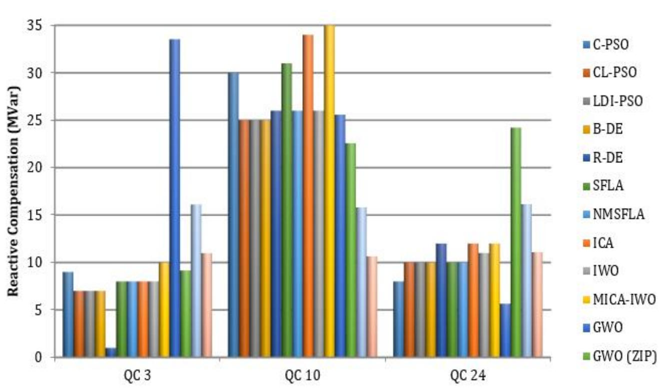

Fig. 4. Scales of the capacitors in different algorithms

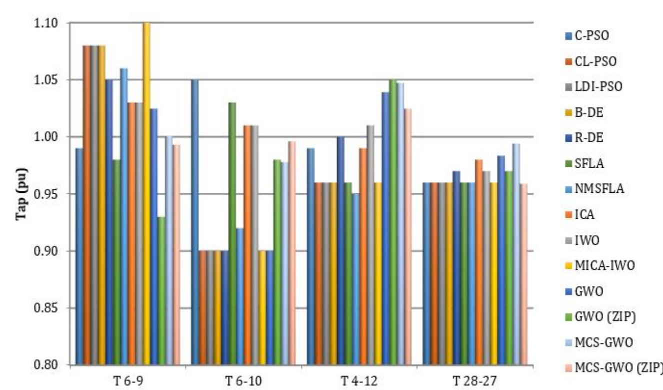

Fig. 6. Position of tap changers of transformers in different algorithms

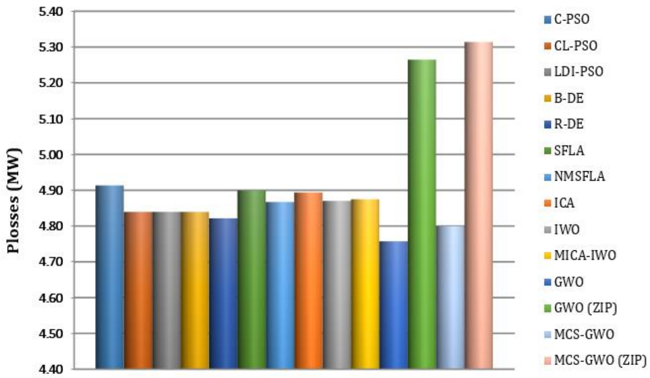

Fig.7. Power losses in different algorithms

V. Conclusion

Generally, with ever-increasing non-linear and complex loads, accurate load modeling in power system analysis is becoming more and more crucial in terms of the precision of the load dispatch results. Any inaccuracy in load modeling leads to unauthentic and unreliable results. Whenever the applied load models in the power system are not of enough precision, the simulation results will be different from the realistic response of the network. Most of the power system operation studies are based on applying the static load model, but in this paper, unlike the researches in the field of ORPD problem, the load model is considered as the alternative to the constant power model. Because the mission of ORPD in the power system is to specify the control variables to minimize the objective function (mainly active power losses) considering the limitations of the power system. In this paper, the ORPD problem in the power systems is studied to achieve the minimum generated active power losses considering the impact of the load model. Furthermore, to model the load type, the static modeling method (constant impedance, current, and power); and to model the uncertainties of loads to study the impressibility of control variables in every state and investigate the impacts of these models on the objective function, for the first time, the MCS method is implemented. The simulation results performed with the MCS-GWO optimization algorithm suggest that the load model has a crucial role in results. As observed, control parameters fluctuate with the load model. The results also suggest that precise load recognition and modeling, affect specifying the control parameters of the ORPD problem greatly.

VI. References

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