IJE TRANSACTIONS A: Basics Vol. 37 No. 01, (January 2024) 37-47

International Journal of Engineering

Journal Homepage: www.ije.ir

Probabilistic Reactive Power Flow Optimization of Distribution System in Presence of Distributed Units Uncertainty Using Combination of Improved Taguchi Method and Dandelion Algorithm

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PAPER INFO

Paper history:
Received 31 July 2023
Received in revised form 28 September 2023
Accepted 30 September 2023

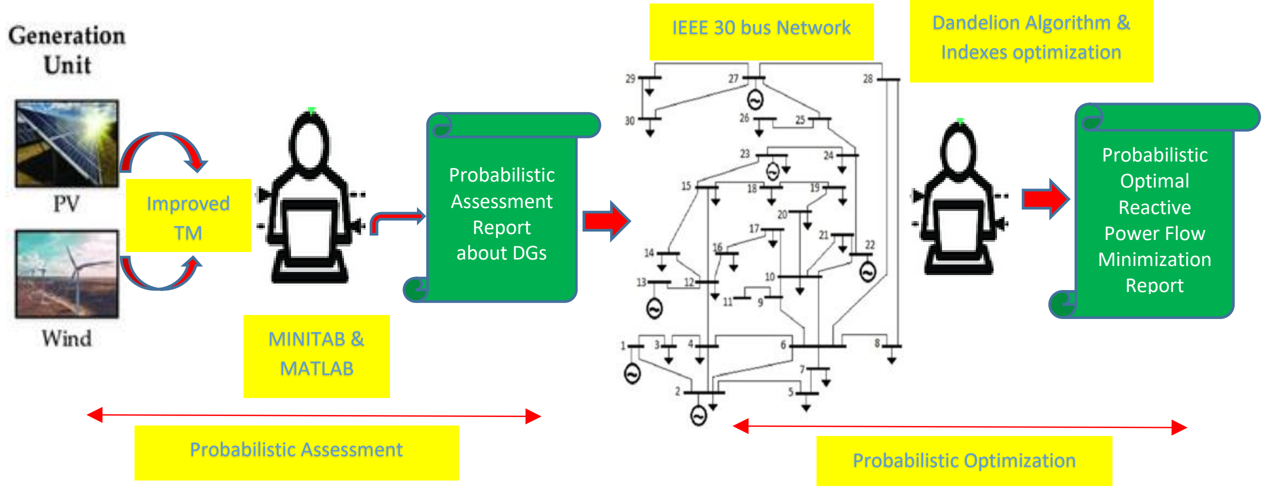
Keywords:
Renewable Energy
Improved Taguchi Method
Orthogonal Arrays
Optimal Reactive Power Distribution
Dandelion Optimizer
Uncertainty

ABSTRACT

Nowadays, due to the growing population, rising global warming, environmental pollution, and the reduction of fuel sources, the use of Distributed Generation Sources (DGs) has grown, and because of their random nature, the conventional performance of power systems is being changed. Reactive power has a considerable role in power systems management and control indexes such as loss, stability, reliability, and security, among which the loss index usually can be easily minimized and controlled. Thus the modeling and optimizing of reactive power must be done accurately and correctly. This paper uses a novel metaheuristic algorithm which is called Dandelion, to solve the constrained non-linear optimal reactive power dispatch problem, and the Improved Taguchi method based on orthogonal arrays has been applied in order to the uncertainty of DG units modeling. The applied optimal reactive power dispatch algorithm is tested and validated using standard IEEE 30-bus test power systems. These results show that the Computational time of the applied algorithm in comparison with other used algorithms is the least value and reduces the reactive power from 22.244 to 2.366 Mvar; also, the losses of the power system significantly will be decreased with the tested and introduced algorithm. Genetic Algorithm(GA), Particle swarm optimization algorithm (PSO), and Prairie dog optimization algorithm (PDO) have been utilized to solve the problem.

***doi**: 10.5829/ije.2024.37.01a.04*

Graphical Abstract



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Please cite this article as: Najjarpour M, Tous B. Probabilistic Reactive Power Flow Optimization of Distribution System in Presence of Distributed Units Uncertainty Using Combination of Improved Taguchi Method and Dandelion Algorithm. International Journal of Engineering, Transactions A: Basics, 2024;37(01):37-47.

NOMECLATURE

V_i^{min} , V_i^{max}	The minimum and maximum voltage in the bus i, respectively.	N_{exp}, n_g, N_C, N_T, N, N_B, N_L	Number of experiments, generator, compensators, transformers,modules, buses, and lines, respectively.
P_i^{min} , P_i^{max}	The minimum and maximum active power in the bus i, respectively.	GA, nb-1	Genetic algorithm, All basses except Slack bus, respectively.
Q_i^{min} , Q_i^{max}	The minimum and maximum reactive power in the bus i, respectively.	OA, FF, WT, PV	Orthogonal Arrays, Full factor, Wind turbine, and Photovoltaics, respectively.
s_{ij}^{max}	Maximum apparent transmission power.	${V_{out}}^{cut}$, ${V_{in}}^{cut}$, V_{rated}	The minimum, maximum, and nominal speed of the turbine.
${T_i}^{max}$, ${T_i}^{min}$	The maximum, and minimum taps number of transformers, respectively.	Voc, I_{SC}	Module open circuit/ short circuit voltage/ current , respectively.
$f_{j\psi}$, f^*_{ψ}	The power and the nominal power passing through the ψ transmission line and experiment j and , respectively.	T_C ,T_a, N_{OT}	Photovoltaics, Ambiance, and Nominal operating temperatures, respectively.
σ , μ, Y_j	Standard deviation, Mean, and Test performance index, respectively.	Kv ,K_I	Voltage and current temperature coefficient $(\frac{A}{°C})$ $(\frac{V}{°C})$, respectively.
$\overline{A}_j$, P_d	Average effects levels factor, Active demand power, respectively.	V_{MPP} , I_{MPP}	Maximum power point voltage and current flow, respectively.
Level	The value of a random variable is based on an orthogonal array.	$V_{i,j}$	The voltage of bus i, and j respectively.
Delta	The main effect of random variables on performance indicators.	$G_{i,j}$, B_{ij}	Line i – j conductance, and suspension respectively.
Rank, TM	Random variable class, and Taguchi method, respectively.	$Q_{ci,min}$, $Q_{ci,max}$	The minimum and maximum allowable reactive power generation, respectively.

1. INTRODUCTION

Optimal reactive power dispatch (ORPD) is a major condition for the secure and economic operation of power systems, which will be reachable by suitable coordination of the system equipment used to manage the reactive power flow in order to reduce the active power losses.

The active power losses have been set as an objective in the ORPD problem. In order to achieve the desired objective, the generator bus voltages, and settings of passive devices such as transformers and shunt VAR compensators are adjusted to reduce the active power losses (1). The issue of reactive power control is vital in the distribution networks because if the consumption of reactive power in the distribution part has increased the power plants will not be able to produce more reactive power due to their technical limitations, so the losses will increase and thus the stability of distribution networks will change (2). Due to the reactive power consumption by the loads, the power factor of the distribution network will change, which will affect the network losses; according to technical concepts, the power factor must be near to one; of course, the unit power factor is an ideal state that will not be reachable (3). In distribution networks, capacitors have been used in order to loss reduction and also power factor correction, when the power factor has been decreased the reactive power will be injected into the network (4, 5). According to the above-mentioned statements explains, due to many consumed loads and transformers and generators, and other equipment, it is required to apply the optimal power flow (OPF) to control the reactive power because (6). Similar to OPF, the OPRD includes some continuous and discrete variables every one of them at least has one limitation, to solve the nonlinear problem, and optimization of reactive power, using classic mathematics methods such as Gradient (7), Newton-Raphson (8), the interior point (9), linear programming (LP) (10), non-linear programming (11), and Quadratic programming (QP) (12). Enormous mathematical calculations and operations, getting stuck in local answers, are disadvantages of the mentioned classical methods (13). Using the metaheuristic method in order to solve the ORPD problem is strongly recommended because the mentioned disadvantages of the classical method will be eliminated. These algorithms are such as Whale Optimization Algorithm (WOA) (14), Particle Swarm Optimization (PSO) (15), Ant Lion Optimizer (ALO) (16), Improved Social Spider Optimization Algorithm (ISSO) (17), Improved Antlion Optimization Algorithm (IALO) (18), Genetic Algorithm (GA) (19), Ant Colony Optimizer (ACO) (20), Opposition-Based Gravitational Search Algorithm (OGSA) (21), Wind Driven Optimization Algorithm (WDO) (22), modified differential evolution algorithm (MDEA) (23), Specialized Genetic Algorithm (SGA) (24), evolutionary programming (19), comprehensive learning particle swarm optimization (25), fuzzy adaptive PSO (FAPSO) (26), seeker optimization algorithm (SOA) (27), cuckoo search algorithm (CA) (28), Hybrid Evolutionary Programming (HEP) (29), harmony search algorithm (30), Teaching Learning-Based Optimization (31), biogeography-based optimization (32), modified sine cosine algorithm (1), water cycle algorithm (33), hybrid Fuzzy- Jaya optimizer (34). With population and global warming increasing, the sources of fossil fuels are being decreased, so traditional power plants will have a problem in order to produce electrical power. These traditional power plants pollute the air and cause other environmental problems and have low efficiency (35). In recent years the use of DGs has increased. The produced electrical power of DGs depends on the intensity of sunlight, the angle of sunlight, wind speed, and the altitude of the turbine tower respectively in photovoltaic cells and wind turbines (36). These DG units, due to their random and probabilistic natures thus in OPF or OPRD should be used in probabilistic modeling methods. These DGs do not have the traditional power plants problems, even having high efficiency (37-39). According to the random nature of DG units, in order to convert uncertainties of their inputs the probabilistic modeling methods such as the Latin hypercube [26], point estimate method [27], scenario-based method [28] , and Monte Carlo method, the Monte Carlo method is the basic method for any probabilistic assessment method [29] , must be used. An optimization algorithm which is named improved social spider optimization algorithm (ISSO) has been used for optimizing the active and active power distribution, which is compared to the standard SSO, passes each process with two equations, using only one modified equation of the first and the second generations, creates the solution and has good and fast performance, less computation, less simulation time, and higher quality results in the ORPD problem than the standard SSO [31]. In order to solve the problem of ORPD, the water wave optimization algorithm (WWO) was used by Bhattacharya and Chattopadhyay [32]. The improved antlion optimization algorithm (IALO) has been used to solve OPRD and OPF for different constrained IEEE distribution networks, the good and accurate results in networks with bus voltage limitations and limitations of all capacitor banks prove that this algorithm is a powerful and accurate algorithm [33]. A new adaptive multi-objective optimization artificial safety algorithm has been used for OPRD, which is based on the Pareto coefficient, a method that is provided by Gafar et al. [34] for the classification of antibodies. Using the integration of three algorithms, particle swarm optimization (PSO), genetic algorithm (GA), and search for symbiotic organisms (SOS) (HGPSOS) to OPRD, which (SOS) has been based on the interactions between two various organisms which in the ecosystem - mutualism, hybridism, and parasitism are used. The HGPSOS algorithm has high computational speed and accuracy due to the presence of three precise and powerful algorithms, and it also has a high convergence rate, because it is combined with the GA, it shows that it is a stable and accurate algorithm [30]. Combining the heat transfer optimization algorithm (HTO) and the simulated coronary circulation system optimization algorithm (SCCS) was used by Zhang et al. [36] to reduce the losses and OPRD, each factor in the HTO algorithm is considered such as a cooling entity that is surrounded by other factors, like heat transfer, the thermodynamic law is used in the HTO algorithm. A candidate solution algorithm, which has been built and has been designed from the mechanisms of the human body and capillaries, and is being used to optimize the OPRD and loss reduction, in this algorithm, the Coronary Development Factor (CDF) is responsible for the evaluation, and the initial population space has been selected freely, then in the whole population, the best solution is considered as the stem and the minimum value of the coronary will be expansion coefficient, then the crown production of the stem has been called the divergence phase, and the growth of other capillaries has been called the clip phase. According to the coronary artery growth factor (CDF), there will be superior capillary growth (BCL), With and without the L index (voltage stability). The (ORPD) problem, as a sub-problem of OPF, has significant effects on providing reliability and economical performance [37]. A new optimization algorithm which has been named Turbulent Flow Water Based Optimization Algorithm (CTFWO) is used to solve the OPRD which is a complex mixed integer nonlinear optimization problem that includes discrete and continuous control variables (40). The Benchmark table was utilized by Kumar et al. (41), which could be an enormous table with awfully expansive numbers that need much time and calculations to run for OPRD while the improved TM, employs OAs that have lower numbers and need lower time and calculations to run for the ORPD problem. The TM is a statistical and quality-control-based strategy (42) that is utilized to show the vulnerabilities of DGs, and OPF calculations using the relationship and correlation concepts of RVs while the improved TM is being utilized in the MINITAB and MATLAB computer software that the relationship and correlation concepts of RVs run automatically in the computer programs. The improved TM is accurate and has lower computational levels than TM, the time, and speed of converge are quick. to assess the capability of the Dandelion calculations and improved TM to solve the ORPD, the simulation results of the Dandelion algorithm calculation are compared with varied algorithms, including PSO, GA, HGPSOS, HTO, PDO, ISSO, WWO, and IALO. The calculations and the results of PSO, PDO, DO, and GA are compared and discussed in thr presentation of results. Furthermore, the results of the improved TM are compared with the results of the assessed execution of different POPF methods in Tables 3 and 4. The results show that the Dandelion algorithm calculation has the finest response, and is excellent in comparison to other algorithms in terms of arrangement precision, joining rate, and solidness. The improved TM is accurate in comparison to the TM and employs data amid the optimization process in other words, utilizing the POPF results amid optimization and the correlation of RVs, the discharge variable is required for more examination and optimization with more precision afterward in arrange to assess the productivity of the displayed strategy.

The notable contributions of this study can be categorized as follows:
1) Solving ORPD problem considering uncertainties of DG units and Time-varying load.
2) Applying the Improved Taguchi method for modeling load, solar irradiance, and wind speed uncertainties.
3) Using a new optimizing algorithm for solving the ORPD problem with and without DGs presence.
4) Comparing the performance of the Dandelion algorithm with the GA, PSO, and PDO for solving the ORPD problem.

2. FORMULATION OF THE PROBLEM

In this section, the objective function of the OPRD problem is equal to loss minimization of the distribution network using reactive power optimization which has been expressed as Equation (1).

$$P_{Loss} = \sum_{l=1}^{nl} G_{ij}({V_i}^2 + {V_j}^2 - 2V_iV_j \cos \delta_{ij}) \quad (1)$$

The minimization of the objective function is being limited by various constraints, such as Equations 2 and 3 which show equal limits in the network,indexes G, and D have been applied to represent generation, and demand respectively. Equations 4 and 5 express unequal constraints which include the voltage constraints of generators, tap transformers, and the reactive power of compensating equipment. The taps of the transformers are also limited in their minimum and maximum range according to Equtaion 6. The constraints of parallel compensators are also according to Equtaion 7. In addition to these restrictions, according to Equtaion 8. The three main parameters in this function are: V_{rated}, V_{in}, and V_{out}. When the wind speed reaches V_{in}, the WTs start generating power; when the wind speed reaches V_{rated}, the output power reaches the nominal P_{rated}. If the wind speed exceeds V_{out}, power generation will be stopped [25]. From a probabilistic aspect, the outputs can no longer be called definitive. In other words, all the outputs of the problem will be presented as mathematical expected values. This means that in this case, the outputs of losses and voltages are the mathematical expected values of voltages and losses.

$$PG_i - PD_i = V_i \sum_{j=1}^{nb} V_j \left(G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}\right) \quad (2)$$

$$QG_i - QD_i = -V_i \sum_{j=1}^{nb} V_j \left(G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}\right) \quad (3)$$

$$QG_i^{min} \le QG_i \le QG_i^{max} \quad (4)$$

$$VG_i^{min} \le VG_i \le VG_i^{max} \quad (5)$$

$$T_i^{min} \le T_i \le T_i^{max} \quad (6)$$

$$QC_i^{min} \le QC_i \le QC_i^{max} \quad (7)$$

$$V_i^{min} \le V_i \le V_i^{max} \quad (8)$$

2. 1. Uncertainties Modelling In probabilistic planning, it is important to state an appropriate statistical model for RnVr s, and it is being used in some models of uncertainty sources such as PV, WT, and electrical vehicle (EV) which the EV can charge at parking in smart distribution networks and can control the network indexes such as losses, voltage drop (43, 44).

2. 2. Load Modelling Using normal distribution, the density function of the corresponding probability distribution has been expressed in Equtaion 9:

$$f(P_d) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(P_d-\mu)^2}{2\sigma^2}\right) \quad (9)$$

2. 3. Wind Turbine Modeling The modeling of wind has consisted includes two steps, as follows:
I) **Wind speed modeling:** Due to the wind speed having random behavior, the wind speed must be modelled using a proper statistical distribution, and usually, to do so the continuous Weibull probability distribution is utilized according to Equtaion 10.

$$f(v) = \frac{h}{c}\left(\frac{v}{c}\right)^{h-1} \exp\left(-\left(\frac{v}{c}\right)^h\right) \quad (10)$$

in the above-mentioned equation, v, c, and h represent the wind speed, the shape factor, and the scale factor respectively.
II) **Turbine output power modeling:** depends on the wind speed and other parameters of the wind turbine, which has been explained in Equtaion 11.

$$p = \begin{cases} 0 & {V_{out}}^{cut} \le V \ or\ V \le {V_{in}}^{cut} \\ K_1V + K_2 & 0 \le V \le {V_{in}}^{cut} \\ P_{rated} & V_{rated} \le V \le {V_{out}}^{cut} \end{cases} \quad (11)$$

$K_1 = \frac{P_{rated}}{V_{rated} - {V_{in}}^{cut}}$, $K_2 = -K_1{V_{in}}^{cut}$, V is the wind speed.

The details of power generation using wind turbines are shown in Figure 1.

2. 4. Photovoltaics Modelling Due to the sunlight radiation having random behavior, the radiation should be modeled using an appropriate statistical distribution, and usually, to do so the continuous Beta probability distribution is used according to Equtaion 12-a, using Equtaions 12-16 the active power can be calculated.

$$F(G) = \frac{1}{G\sigma\sqrt{2\pi}} exp\left[-\frac{\ln{(G-\mu)^2}}{2\sigma^2}\right] \quad (12\text{-a})$$

$$P_{pv}(s) = N * FF * V(s) * I(s) \quad (12)$$

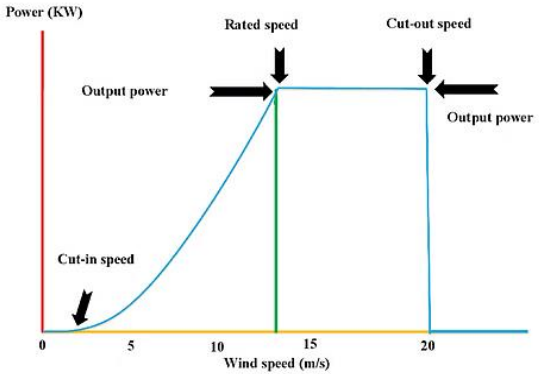

Figure 1. Wind turbine production capacity

$$V(s) = V_{oc} - K_V * T_C \tag{13}$$

$$I(s) = s * (I_{SC} + K_I * (T_C - 25)) \tag{14}$$

$$T_C = T_a + s * (\frac{N_{OT} - 20}{0.8}) \tag{15}$$

$$\text{FF}=\frac{V_{MPP}*I_{MPP}}{V_{OC}*I_{OC}} \tag{16}$$

3. ORTHOGONAL ARRAYS

An OA is a fractional factorial matrix whose rows represent factor levels in each run and its columns represent a specific factor whose levels change in each experiment. All traditional factorial designs and fraction arrays are orthogonal. In the past, OA was known as magic squares. Perhaps the effect of OA in experiments has led to such naming. Because a fraction of the experiments is chosen in it, each combination is repeated in equal numbers, the reason they are named orthogonal is that all the columns are examined independently. The OAs are denoted by the letter L, which comes from the Latin word because the use of OA in experimental designs is related to Latin square designs. An OA is basically a table whose rows are used for experiments and whose columns are used for an RnVr (Table 1). Each of the numbers in the table describes the modes of a RnVr. OAs are sorted with the symbol $OA_{N_{exp}}\ (N_L)^{N}$.

For example, Table 2 is used for a problem with seven random variables and eight experiments; each random variable has two levels. Generally, must be done 128 processes, but by using the OA just eight experiments are needed. So, the calculation steps will be decreased to 6.25% of the total steps; this shows the ability and Advantage of OA (45, 46).

4. IMPROVED TAGUCHI METHOD

The improved Taguchi method is to increase the accuracy of the Taguchi method and the flowchart of this method is discussed as illustrated in this section. In this method, steps 1 to 5 of the Taguchi method, and the Improved Taguchi method are exactly repeated, but in the following, other steps are also performed. By comparing sets 1 and 2, probably some of the same variables will have the same levels. These variables are called certain variables and other variables are called uncertain variables. The reason for this naming is that are being obtained the same levels for these variables from two different paths, one of the experiments and the other of averaging the values obtained from the experiments. Certain variables are excluded from the optimization process. In the next section, the sixth step, the placement process is explained.

TABLE 1. Orthogonal array $\boldsymbol{OA_{N_{exp}}}\ (\boldsymbol{N_L})^{\boldsymbol{N}}$

Experiment number	Levels			
	RnVr1	**RnVr 2**	**…**	**RnVr N**
1	L_{11}	L_{12}	…	L_{1N}
2	L_{21}	L_{22}	…	L_{2N}
….	….	….	…	….
N_{exp}	LN_{exp1}	LN_{exp2}	…	LN_{expN}

TABLE 2. Orthogonal array $OA_8 2^7$

Experiment	Level of each variable						
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	2	2
6	2	1	2	2	1	1	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

4. 1. Placement of Uncertain Variables in the Experiment with the Best Value

The experiment that has the best result among the experiments performed is one of the possible experiments to examine all combinations of different variables. Therefore, there may be another combination of variables that has a better outcome compared to the current best available test. One of these more suitable combinations may be the combination corresponding to the best experiment, while its uncertain variables are placed according to set 2. Because the averaging of the obtained results was the basis for choosing set 2, the statistical nature of this process increases the probability of choosing the optimal values for the variables. The certain variables determined by the task are removed from the process and only the uncertain variables are re-examined. In order to prevent the interaction of variables, the process of placing uncertain variables from the second set in the best experiment is done individually. If the inserted variable causes a better result than the previous variable, we call this variable definite and fix it in the best test. Other uncertain variables will be placed in the same way.

4. 2. Choosing the Orthogonal Array for the Remaining Uncertain Variables In this stage, uncertain variables are optimized by using another Taguchi table that is selected for them. If the number of remaining variables is small, we test all possible combinations. The optimization process continues until the optimization completion condition is met.

4. 3. The Differences between the TM and the Improved TM In the TM, finally, the levels of the RVs in sets 1 and 2 are placed in the best experiment, and each of the two sets that bring a better result is considered as the set containing the optimal values. In the improved TM, the RVs are divided into two groups of certain and uncertain variables. Certain variables are determined and removed from the optimization process. While the uncertain variables are checked more carefully, this is the difference between the improved TM and the TM. Since the presented method uses the TM, there is no need to prove the convergence towards the optimal point. To prevent the interaction of variables, the improved TM suggests the placement of individual variables. In this paper, the aim is to show the effect of the high precision of the simulation results of the Improved TM utilizing the Dandelion algorithm.

5.DANDELION ALGORITHM

A new swarm intelligence bioinspired optimization algorithm that has low computational time and high convergence speed has been called the Dandelion algorithm (DA) which has been introduced recently (47). Dandelion algorithm flowchart is shown in Figure 2. It includes three stages,

1. Growth stage: In this stage, the seeds spiral down from a high height due to eddies, or they are driven locally due to different climatic conditions.
2. Descending stage: In this stage, the flying seeds decrease their height by continuously adjusting their direction.
3. Landing or sitting stage: In this stage, the seeds descend to grow and grow in places they have chosen randomly. Using Brownian motions and Levy's random walk, the movement path of grains is determined in the stages of decline and settlement, respectively.

6.OPRD USING IMPROVED TM

In Improved TM every uncertainty is named as a random variable (RnVr). In general, the relationship between input and output RnVr s in a distribution network is expressed according to Equation 18:

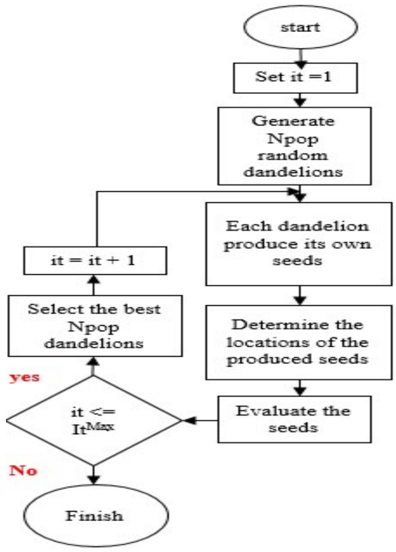

Figure 2. Dandelion algorithm flowchart

$$Y_{in} = f\ (X_{out}) \tag{18}$$

The f is a nonlinear relation that establishes the relationship between Xout and Yin. In OPRD, the factors are the same as RnVr s. In OPRD, the number of factors is expressed in m and the number of levels in n, and then the next mn test must be performed. In this paper, an OPRD of a distribution system that includes PV and WT DGs is investigated and analyzed using Improved TM based on OA.

In order to solve the OPRD problem:

(i) The structure and information of the power system equipment are important and practical.

(ii) The input RnVrs are shown by the vector Y_{in} according to Equation 18.

(iii) "Level" means the value below the curve is a function of the probability density of incoming RnVr s.

(iv) Every experiment refers to a load flow, if there are several RnVr s, thus the number of load flows will be increased, thus the final answer will be obtained after a long computational time and several mathematics operations. As the above- mentioned advantage of OA, thus should be used. The first step in deploying Improved TM is to determine the levels of each RnVr. Selecting two levels and three levels for each factor requires the least and most time and calculations, respectively. In Improved TM, levels 1 and 2 are being selected, respectively $\mu - \sigma$ and $\mu + \sigma$. In the TM, the final optimal answer is being reached using an optimal experiment based on the optimal levels of RnVr s instead of all experiments based on OAs. To use this optimal experiment, one must first express an index according to Equation 19.

$$Y_j = \sum_{\psi}^{NL} \left| f_{j\psi} - f^*{}_{\psi} \right| \quad j = 1،2،3، \ldots \tag{19}$$

The second step is to determine the average effect of the factors based on Equations 19 to 25.

The third step is to define the main effect of each factor on Y_j. These main effects of the factors are being calculated according to Equations 26 to 29:

$$\bar{A}_1 = (Y_1 - Y_2)/2 \tag{20}$$

$$\bar{A}_2 = (Y_3 - Y_4)/2 \tag{21}$$

$$\bar{B}_1 = (Y_1 - Y_3)/2 \tag{22}$$

$$\bar{B}_2 = (Y_2 - Y_4)/2 \tag{23}$$

$$\bar{C}_1 = (Y_1 - Y_4)/2 \tag{24}$$

$$\bar{C}_2 = (Y_2 - Y_3)/2 \tag{25}$$

$$\Delta A = (\bar{A}_2 - \bar{A}_1) \tag{26}$$

$$\Delta B = (\bar{B}_2 - \bar{B}_1) \tag{27}$$

$$\Delta C = (\bar{C}_2 - \bar{C}_1) \tag{28}$$

If the major effect is positive in RnVr or the same factor, the second level is considered otherwise.

It is now shown how to apply the OAs to the OPRD by performing the following main steps:

a) Determining the input RnVr s.
b) Determine the number and values of the levels of variables.
c) Determine the OA.
d) Execute OPRD.
e) Analysis of results.

$$\mu_j = \frac{1}{Nexp} \sum_{i=1}^{Nexp} x_{ji} \quad , \sigma_j = \left[\frac{(\sum_{i=1}^{Nexp} x_{ji} - \mu_i)^2}{Nexp} \right] \tag{29}$$

x_{ji} is the value of the jth output RV for the ith experiment.

7. SIMULATION RESULTS

In this study, the 30-bus IEEE standard system has been used in order to solve ORPD. This system includes 6 generators and 80 transmission lines, of which 17 lines have a tap changer. Also, three reactive power compensating equipment, which are installed in buses 15, 25, and 53, have been used for compensating. The initial active, and reactive power loss of the network without the presence of DGs are 22.244 Mvar and 17.59 MW respectively. The performance range of the variables is given in Table 3 and other network information has been obtained from (48). The Improved TM is tested in MATLAB and MINITAB software. In this study, there are two wind farms in bus 38, 39 and a PV cell in bus 16, which has a nominal capacity of 100 MW. To simulate this wind farm and PV cell, data has been received from the North Dekta site and the Watford area (49). Figure 3 shows IEEE 30-bus test system. The results are illustrated in Figures 4 and 5 show the converged plot of GA, PDO, DO, and PSO algorithms. Any of the optimizations have been run in 100 Iteration and more information about any optimization algorithms is explained below:

TABLE 3. Values of μ and σ using other methods

Entire losses	TM	Scenario	LHS	2PEM
μ [MW]	30.5	40.8	52.42	36.3
σ	11.15	26.1	36.22	12.2

7. 1. Genetic Algorithm

This optimization has been run in 26 populations and 100 iterations and in 44.076 (s). The number of the control variables is 13 and the percent of crossover is 0.1 and the best value for OPRD with GA is 3.891 MVar.

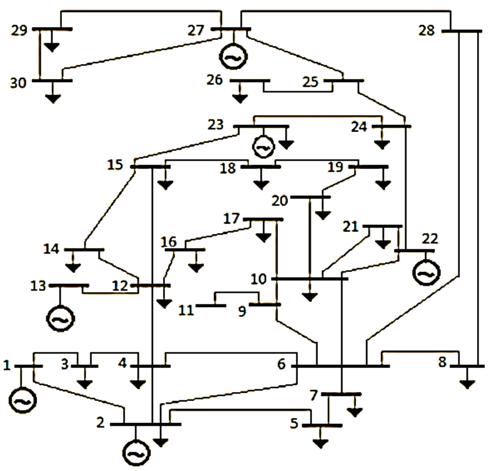

Figure 3. IEEE 30-bus Test system

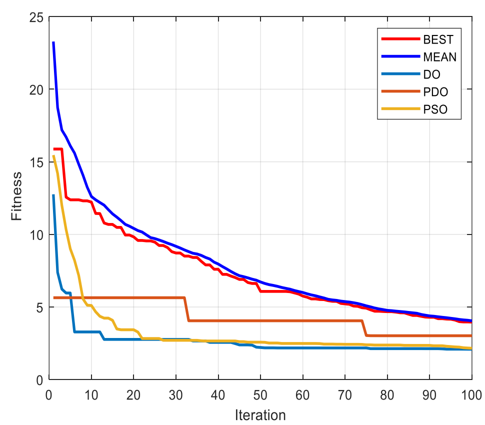

Figure 4. Reactive power optimization with algorithms

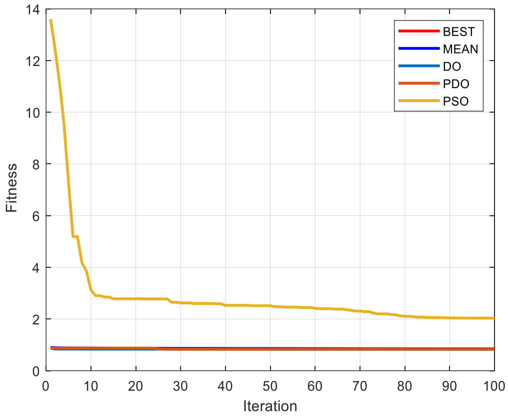

Figure 5. GA, DO, PDO, PSO Buses Voltage

7. 2. Particle Swarm Optimization Algorithm This optimization has been run in 26 populations and 100 iterations and in 21.940 (s). The number of the control variable is 13 and the inertia weight is 1 and inertia weight damping ratio is 0.99 and personal learning coefficient is 1.5 and global learning coefficient is 2 and the best value for OPRD with PSO is 2.038 Mvar.

7. 3. Prairie Dog Optimization Algorithm This optimization has been run in 26 populations and 100 iterations and in 82.830 (s). The number of the control variables is 13 and the best value for OPRD with PDO is 3.584 MVar.

7. 4. Dandelion Algorithm This optimization has been run in 26 populations and 100 iterations and in 19.996 (s), and the number of the control variables is 13 and the best value for OPRD with DA is 2.366 MVar according to Figure 6. Table 4 shows in terms of optimal value the PSO has a minimum value for OPRD and in terms of time the DA has a minimum value for OPRD so an algorithm that gives the best value in terms of time and optimal value for OPRD must be used and must be selected, according to Table 4 the PSO has a minimum value and maximum time even that time is equal to quadruple of DA time, but with pay attention to Table 4, the DA has closet value to PSO just with 0.3 MVar difference also has minimum time for solving of OPRD so the DA should be in OPRD problems. Before the use of the algorithms, the reactive power of 30 bus IEEE standard network was solved in 0.083(s) was equal to 22.244, and with paying attention to Table 4, it is concluded that the DA has closet time and much difference with the reactive power before using the optimization algorithms. using DA 20.2 MVar reductions will be had in reactive power which will be effective in terms of power losses and power transfer for power systems. Table 3 shows other probabilistic assessment methods such as point estimation, Taguchi, Scenario-based, and Latin hypercube sampling and their results.

Flowchart of improved Taguchi method is illustraed in Figure 6.

TABLE 4. Results of OPRD before and after using the algorithms

Algorithms	GA	PDO	DO	PSO	OPF
Time (s)	28.7	99.002	22.119	19.493	0.083
Reactive (MVar)	**3.9611**	**3.0206**	**2.0917**	**2.2106**	**22.244**
Buses Voltages (v)	**0.8429**	**0.8298**	**0.8301**	**2.0410**	
Time(sec)	**19.207**	**82.022**	**18.827**	**21.940**	

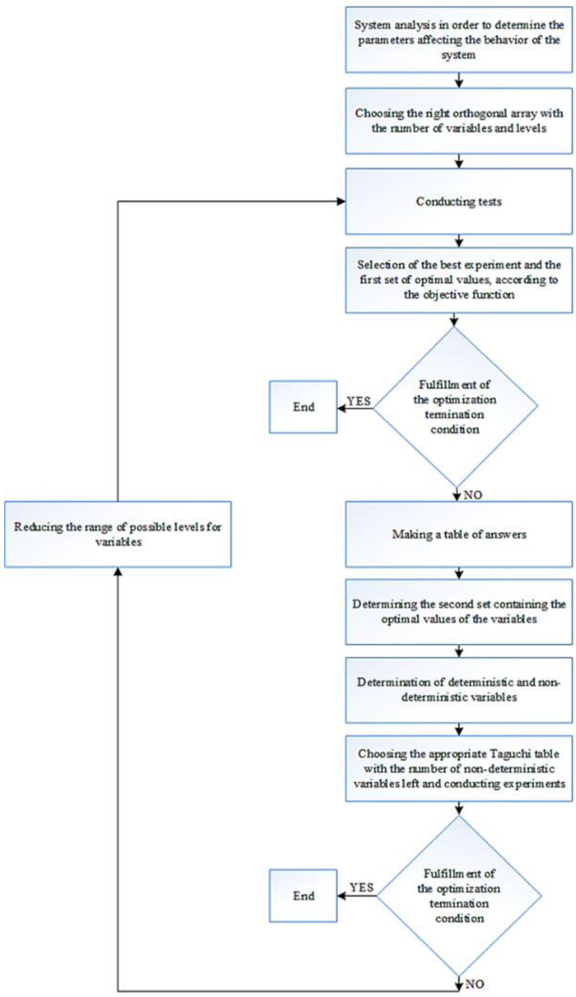

Figure 6. Flowchart of improved Taguchi method

8. CONCLUSIONS

The loss is an important index for power systems that can be controlled by reactive power, thus it is necessary to optimize the reactive power by increasing the DGs in power systems. In this paper, the dandelion optimization algorithm, and the improved Taguchi method which is based on orthogonal arrays have been utilized to solve complicated optimal reactive power dispatch problems and the modulation uncertainties of DG units, respectively. The use of portable systems such as wind turbines and photovoltaics as the most used technologies has been considered. Moreover, the load and uncertainties of wind turbines and photovoltaics have been investigated. The results show that the Dandelion algorithm has solved the OPRD in minimum time and has decreased the reactive power by about 20.2 Mvar which will be very good for the power system in terms of power losses and other aspects. Thus it is concluded that the Dandelion optimization algorithm and the Improved Taguchi method are effective, and accurate in solving the probabilistic ORPD problem compared with algorithms (GA, PDO, and PSO) applied for the ORPD problem.

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Persian Abstract

چکیده

امروزه با توجه به رشد روزافزون جمعیت، افزایش گرمایش زمین، آلودگی محیط زیست و کاهش منابع سوخت فسیلی، استفاده از DG ها رشد کرده و به دلیل ماهیت تصادفی آن ها، عملکرد متعارف سیستم های قدرت در حال تغییر است. توان راکتیو نقش قابل توجّهی در شاخص های مدیریت و کنترل سیستم های قدرت مانند تلفات، پایداری، قابلیت اطمینان و امنیت دارد که در این میان معمولاً شاخص تلفات را می توان به راحتی به حداقل رساند و کنترل کرد. بنابراین مدل سازی و بهینه سازی توان راکتیو باید به طور دقیق و صحیح انجام شود. در این مقاله از یک الگوریتم فراابتکاری جدید به نام قاصدک برای حل مسئله توزیع توان راکتیو بهینه غیرخطی محدود شده استفاده می‌شود و همچنین از روش تاگوچی بهبود یافته مبتنی بر آرایه‌های متعامد برای مدل‌سازی عدم قطعیت واحدهای DG استفاده شده است. الگوریتم توزیع توان راکتیو بهینه اعمال شده با استفاده از سیستم های قدرت تست استاندارد 30 باسه IEEE آزمایش و تایید می شود. این نتایج نشان می دهد که زمان محاسباتی الگوریتم اعمال شده در مقایسه با سایر الگوریتم های مورد استفاده کمترین مقدار را دارد و توان راکتیو را از ۲۲.۲۴۴ به ۲.۳٦٦ Mvar کاهش می دهد. همچنین تلفات سیستم قدرت با الگوریتم تست شده و معرفی شده به میزان قابل توجهی کاهش می یابد. الگوریتم ژنتیک (GA) ، الگوریتم بهینه‌سازی ازدحام ذرات (PSO) و الگوریتم بهینه‌سازی سگ دشتی (PDO) برای حل این مشکل استفاده شده‌اند.