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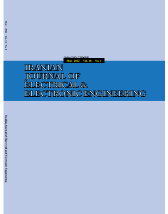
Research Paper



Loss Reduction in Distribution Networks With DG Units by Correlating Taguchi Method and Genetic Algorithm

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Abstract: Optimal power flow is an essential tool in the study of power systems. Distributed generation sources increase network uncertainties due to their random behavior, so the optimal power flow is no longer responsive and the probabilistic optimal power flow must be used. This paper presents a probabilistic optimal power flow algorithm using the Taguchi method based on orthogonal arrays and genetic algorithms. This method can apply correlations and is validated by simulation experiments in the IEEE 30-bus network. The test results of this method are compared with the Monte Carlo simulation results and the two-point estimation method. The purpose of this paper is to reduce the losses of the entire IEEE 30-bus network. The accuracy and efficiency of the proposed Taguchi correlation method and the genetic algorithm are confirmed by comparison with the Monte Carlo simulation and the two-point estimation method. Finally, with this method, we see a reduction of 5.5 MW of losses.

Keywords: Correlation, Distributed Generation, Distribution Networks, Orthogonal Arrays, Probabilistic Optimal Power Flow, Taguchi Method.

Nomenclature

V_i^{min}	Minimum voltage in the bus *i*.
V_i^{max}	Maximum voltage in the bus *i*.
P_i^{min}	Minimum active power in the bus *i*.
P_i^{max}	Maximum active power in the bus *i*.
Q_i^{min}	Minimum reactive power in the bus *i*.
Q_i^{max}	Maximum reactive power in the bus *i*.
s_{ij}^{max}	Maximum apparent transmission power.
θ_{ij}	Voltage angle between buses *i*, *j*.
N_B	Number of buses.
N_L	Number of transmission lines.
$f_{j\psi}$	The power passing through the ψ transmission line and experiment *j*.
f_ψ^*	The nominal power is the transmission line ψ.
σ	Standard deviation.
Y_j	Test performance index.
μ	Mean value.
P_d	Active demand power.
$\overline{A}_j$	Average effects levels factor.
Level	The value of a random variable based on an orthogonal array.
Delta	The main effect of random variable on performance indicator.
ρ	The correlation coefficient.
VMCS	Voltage by Monte Carlo simulation [p.u].
VTM	Voltage by Taguchi method [p.u].
MEMTC	Mean error of Monte Carlo simulation and Taguchi method correlated.
MEMT	Mean error of Monte Carlo simulation and Taguchi method [%].
VC	Voltage with correlation [%].
Rank	Random variable class.
PV	Photovoltaic.
WT	Wind turbine.
N_{exp}	Number of experiments.
GA	Genetic algorithm.
UT	Unscented transformation method.
PLF	Probabilistic load flow.
OA	Orthogonal arrays.
TM	Taguchi method.

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N	Number of modules.
FF	Full factor.
V_{oc}	Module open-circuit voltage.
K_v	Voltage temperature coefficient [V/°C].
T_c	Photovoltaic temperature.
T_a	Ambiance temperature.
K_I	Current temperature coefficient [A/°C].
N_{OT}	Nominal operating temperature.
I_{SC}	Module short circuit current.
V_{MPP}	Maximum power point voltage flow.
I_{MPP}	Maximum power point current flow.

1 Introduction

OPTIMAL Power Flow (OPF) problem was first formulated in 1962, but has proven to be a very difficult problem to solve. The OPF became a practical and powerful tool for systems in various fields. From the beginning, various methods have been proposed to solve the OPF problem. Over time, the formulation of OPF has become more accurate and new methods provide more accurate answers [1]. Classical methods of OPF including linear programming method [2], nonlinear programming [3], second-degree programming [4], gradient method [5], internal point method [6], Lagrange method [7], Newton-Raphson method [8] are precise methods used in objective functions that have the property of continuity and derivation. All of these optimization methods start from a starting point and reach by repetition and are suitable for a linear objective function [6, 8]. Due to the mathematical structure of the relationship between the problem of optimization, the classical and analytical methods cannot analyze and arrive at answers to these problems. To solve this problem, evolutionary algorithms are used in which nonlinearity and derivation do not slow down the problem analysis process. Intelligent methods have been created to overcome the obstacles and problems of classical optimization methods, which achieve the optimal response quickly with high accuracy [5-7]. These techniques using computers to solve power system optimization issues are; evolutionary programming [9], Genetic Algorithm (GA) [10], evolutionary differentiation [11], artificial neural network [12], ant colony [13] and particle aggregation algorithm [14]. These techniques can analyze optimization problems with uncertainty issues. Borkowska was first to propose the Probabilistic Load Flow (PLF) with uncertainties in 1970 [15]. The literature review is reviewed below: the Monte Carlo Simulation (MCS) is used for the problem of OPF in the presence of uncertainty in load modeling [16]. Using a new method in optimal load distribution problems bound to transient stability the method of path sensitivity rotor angle is discussed and shown it is time to simulate to check the transient stability of the system with this method greatly reduces. Also, the proposed method of accuracy has a system for detecting instability [17]. Correlated addressing based on Point Estimation Method (PEM) has been used to select the best value for entering random parameters into the optimal load flow problem [18]. An algorithm is proposed to solve the problem of Probabilistic Optimal Power Flow (POPF) by considering the network load changes. To solve the problem in this reference, the optimal nonlinear complementary problem method is used [19]. The combined Monte Carlo method and multi-line OPF are used to model uncertainties [20]. MCS is a method that provides accurate results, but its drawbacks include the need for a large memory to store information and a large number of steps to achieve the final convergent response reduction [2-4]. Two-Point Estimation Method (2PEM) is used to solve MCS problems, which has a low computational load and requires only the initial statistical torques of the Random Variables (RVs) to analyze the problems [13, 16]. A cumulant method is used for PLF study where the basis of this method is to generate new or unknown distributions of RVs using existing statistical information from predefined or known distributions. In this case, the information is mapped through a statistical measurement known as cumulative method. This method relies on the behavior of RVs when they are linearly combined [21]. In [22] a comparison between the cumulant and 2PEM methods is presented, which investigates the effect of uncertainty in the supply and distribution of loads on the market and the Local Margin Cost (LMP) index for solving the PLF. The second-order torque method is used to study the PLF, which uses the first-order Taylor series approximation to calculate the first-and second-order statistical information [23]. The Unscented Transformation (UT) method is used for the problem of OPF in the presence of uncertainties, which has less computational analysis than the MCS [24]. The improved 2PEM is used as a new evaluation method for modeling uncertainties by considering correlation [25]. Fuzzy sets are used to model uncertainties in [26]. It is proposed to consider the correlation between WT and PV in the distribution network using Taguchi Method (TM) [27]. In [27] the PLF problem has been studied using the TM for the IEEE standard 34-bus test system in which the three-phase voltages are unbalanced by considering the correlation between the input RVs and the results by 3PEM and the 2PEM and MCS are compared and it is concluded that the response of the TM for two levels and three levels of RVs are equal to the results of 2PEM and 3PEM, respectively, and that objective function is to reduce the total cost. In this paper, the objective function is to reduce the losses of distribution networks by using Orthogonal Array (OA)-based TM to analyze POPF by considering the correlation of uncertainties caused by input RVs. Also, according to the optimal values of the input RVs, which are calculated using the TM, the optimal values of the control variables of the POPF problem are obtained to reduce system losses. In this case, the answer is the lowest value because the values of RVs are adjusted to the optimal values based on OAs using the TM, and the control variables of the POPF problem are adjusted to optimal values based on the optimal values of RVs using GA. Optimization ensures that the amount of losses is not stuck in the local optimal domain and is located in the global optimal domain and the global optimal is absolute and also the optimal output response is more reliable, because the losses are the least amount. The test results on IEEE 30-bus network show the OA and TM have excellent accuracy, high speed, and simplicity in the OPF. And the use of GA increases processing speed and accuracy. Compared to other methods, the TM can apply the correlation between uncertainties. In the following sections, OPF, OA, and TM are presented first. The TM is then applied to the test system and the results are compared with MCS and 2PEM.

2 Problem Formulation

The goal of OPF is to assign a set of control variables to optimize the objective functions we have in mind. In power systems, the main part of the cost is related to the production of electrical power in power plants. Therefore, the share of each power plant in the production of electrical power to meet the system load demand is the main goal and should be determined so that the cost of the electricity production is minimum. The purpose of this paper is to optimally determine the share of the power output of each power plant by using the optimal load flow and also to reduce the excess power required for the system losses. Using the OPF, the control variables are set in their optimal states in order to optimize the objective function of the problem and satisfy the constraints at the same time. The objective function and the set of constraint equations (equalities and inequalities) are nonlinear functions of control variables and state variables. The OPF problem is then defined according to (1):

$$\min f\left(x,u\right) s.t \begin{cases} g_i\left(x,u\right)=0 & i=1,2,\ldots,N_{eq} \\ h_j\left(x,u\right)\le 0 & j=1,2,\ldots,N_{ineq} \end{cases} \tag{1}$$

In (1), x and u represent the state and the control variables, respectively. Also, $f(x, u)$ is the objective function, $g(x, u)$ are the constraints of equality, and $h(x, u)$ are the constraints of inequality of the problem. N_{eq} is the number of equality constraints and N_{ineq} is the number of unequal constraints. The control variables for OPF are as follows:

- ✓ P_g: Except for PV slack, the active power produced in the bus.
- ✓ V_g: Voltage amplitude in PV buses.
- ✓ T: Transformers tap settings.
- ✓ Q_c: Compensation of parallel structures.

In the case of OPF, the mode variables are as follows:

- ✓ P_{G1}: Active power generated in the reference bus.
- ✓ V_L: Voltage range in buses PQ.
- ✓ Q_G: Reactive power output of generators.
- ✓ S_l: Loading of electric power in transmission lines.

The main objective function is expressed as (2). The total loss of electrical power is equal to the sum of the electrical losses of the transmission lines, according to (3).

The purpose of optimization is to divide the system loads between the generators to generate electrical power so that each generator operates at the highest efficiency, and the objective function is to minimize system-wide losses. In addition, equal and unequal constraints must be satisfied. Equivalent load flow constraints reflect the technical condition of the system as expressed by load flow relationships and are defined according to (4) and (8).

The technical constraints of generators are expressed in (5) to (7).

$$P_{Loss}=\sum_{k=1}^{nl} g_k\left[V_i^2+V_j^{\,2}-2V_iV_j\cos\left(\theta\right)\right] \tag{2}$$

$$PLoss_T=\sum_{i=1}^{NL} PLoss_i \tag{3}$$

$$P_{G_i}-P_{D_i}=V_i\sum_{j=1}^{N_B}V_j\left[G_{ij}\cos\theta_{ij}+B_{ij}\sin\theta_{ij}\right] \tag{4}$$

$$Q_{G_i}-Q_{D_i}=-V_i\sum_{j=1}^{N_B}V_j\left[G_{ij}\sin\theta_{ij}-B_{ij}\cos\theta_{ij}\right] \tag{5}$$

$$V_{Gi}^{\min}\le V_{Gi}\le V_{Gi}^{\max},\quad i=1,\ldots,N_G \tag{6}$$

$$P_{Gi}^{\min}\le P_{Gi}\le P_{Gi}^{\max},\quad i=1,\ldots,N_G \tag{7}$$

$$Q_{Gi}^{\min}\le Q_{Gi}\le Q_{Gi}^{\max},\quad i=1,\ldots,N_G \tag{8}$$

2.1 Uncertainties Modeling

In probabilistic planning, it is important to state an appropriate statistical model for RVs.

2.1.1 Load Modeling

Using normal distribution the density function of the corresponding probability distribution is given in (9) [28, 29]:

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

In this paper, a μ equal to the bus consumption and a σ equal to 5% of μ are considered.

2.1.2 Wind Power Plant Modeling

To model a wind farm, first, the wind speed must be modeled. The wind speed has a random behavior. Proper modeling should be done to obtain the output power of the wind farm. The continuous Weibull probability distribution is the most suitable function for modeling the stochastic variable of wind speed according to (10) [30].

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

In this paper, h is considered equal to 8.78, and c is considered equal to 1.75. Also, v represents the wind speed, c represents the shape factor, and h represents the scale factor. In wind power plants, the output power of the turbine depends on the wind speed and other parameters of the wind turbine given by (11).

$$P=\begin{cases}0 & 0\le V\le V_{in}^{cut}\\ K_1V+K_2 & 0\le V\le V_{in}^{cut}\\ P_{rated} & V_{rated}\le V\le V_{out}^{cut}\\ 0 & V_{out}^{cut}\le V\end{cases} \tag{11}$$

where, $K_1 = P_{rated}/(V_{rated}–V_{in}^{cut})$, $K_2 = –K_1V_{in}^{cut}$, V is the wind speed in wind turbines in bus i, P_{rated} is the nominal power of wind turbine, V_{out}^{cut} and V_{in}^{cut} are the minimum and maximum value of wind speed, and V_{rated} is the nominal speed. Power generation in the wind turbine starts at V_{in}^{cut} speed. The output power of the turbine at nominal speed V_{rated} reaches the nominal power P_{rated}, then with increasing wind speed, the output power is constant. The power for the wind speed above the turbine V_{out}^{cut} is zero and the turbine stops operating and the electric power generated by the wind farm becomes zero, as shown in Fig. 1.

2.1.3 Photovoltaic Modeling

$$P_{pv}(s)=N\times FF\times V(s)\times I(s) \tag{12}$$

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

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

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

$$\mathrm{FF}=\frac{V_{MPP}\times I_{MPP}}{V_{OC}\times I_{OC}} \tag{16}$$

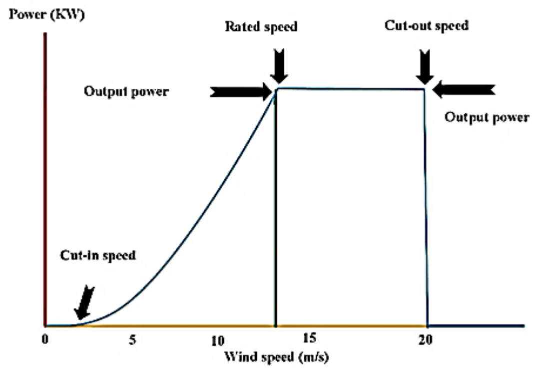

Fig. 1 Wind turbine production capacity.

2.2 Correlation in RVs

In power systems like other systems, the system RVs may be dependent on input uncertainties. If there is a dependency, this dependence may have a positive or negative effect from one variable to another. In general, the issue of correlation in RVs is expressed and determined by the covariance matrix or correlation coefficient matrix. Correlation coefficients are presented according to (17):

$$\rho_{x\cdot y}=\frac{\operatorname{cov}(x\cdot y)}{\sigma_x\sigma_y}=\frac{E\left[(x-\mu_x)(y-\mu_y)\right]}{\sigma_x\sigma_y} \tag{17}$$

The coefficient of correlation can be –1, +1, or between them, or zero. If it is +1, it is in relation to the perfect linear relation and if it is negative, it is in relation to the complete linear relation, and in other relations, the values between the interval [-1, 1] indicate the degree of correlation.

3 Orthogonal Arrays

An orthogonal array 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 selected in it, so that each combination is repeated in equal numbers. The reason they are called 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 composed of a matrix (Table 1) that consists of numbers that are arranged in rows and columns. Each row in the matrix is related to an experiment, and in the same way, each column corresponds to an RV; then, the dimension of the matrix is ($N_{exp}\times N$). Each element (i, j) of the matrix reports a

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

Experiment number	Level of each variable			
	RV_1	RV_2	⋯	RV_3
1	L_{11}	L_{12}	⋯	L_{1N}
2	L_{21}	L_{22}	⋯	L_{2N}
⋯	⋯	⋯	⋯	⋯
N_{exp}	LN_{exp1}	LN_{exp1}	⋯	LN_{exp1}

Table 2 Orthogonal array $OA_4 2^3$.

Experiment number	Level of each variable		
	RV_1	RV_2	RV_3
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

number. L_{ij} (frequently 1 and 2 or 1, 2, and 3 in case of two and three levels, respectively) that corresponds to the level to be appointed to the *i*-th variable in the *j*-th experiment. OAs are sorted with the symbol $OA_{N_{exp}}(N_L)^N$. For example, Table 2 indicates the array $OA_4 2^3$, i.e., an OA with four experiments, three variables, and two levels. The two levels allotted to each variable are denoted by the numbers 1 and 2. If we want to utilize the full factorial method, 2^3 experiments (N_{exp} = 8) are demanded, whereas the use of the OA in Table 2 lessens the required experiments to just four. for more clarification, in the array $OA_{16}2^{15}$, i.e., an OA with 16 experiments, 15 variables, and two levels, 2^{15} experiments (N_{exp} = 32,768) are demanded using the full factorial method, but only 16 experiments are required using the OA.

4 POPF With TM

In general, the relationship between input and output RVs in a distribution network according to (18):

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

The input and output RVs vectors are Y_{in} and X_{out}, respectively, and f is a nonlinear relation that establishes the relationship between X_{out} and Y_{in}. In POPF, the factors are the same as RVs. In POPF, the number of factors is expressed in m and the number of levels in n, and then the next m^n test must be performed. In this paper, a POPF of a distribution system including PV and WT distributed generations is investigated and analyzed by TM based on OA. In the POPF:

I. The structure and information of the power system equipment is important and practical.
II. The input RVs is the vector Y_{in} according to (18).
III. "Level" means the value below the curve is a function of the probability density of incoming RVs.
IV. Each experiment refers to a load flow, and on the other hand, because the distribution networks are three-phase, for each phase, if we have a number of RVs for a three-phase distribution network, their number will increase, so in this case the number of tests Also, the number of load flows will increase and as a result, the final answer will be obtained after a long time and many calculations. OAs can be used to dramatically reduce the number of experiments to get the answer instead of all the tests, so that these OAs get the same answer by performing a very small number of tests in less time and calculations than all experiments can be achieved. The first step in deploying TM is to determine the levels of each RV. Selecting two levels and three levels for each factor requires the least and most time and calculations, respectively. Relevant possible distributions should be provided to determine invoice levels. As in this paper, the normal distribution is used for load modeling because it is a symmetric continuous distribution and the Weibull continuous distribution is used to model wind speed. In this paper, levels 1 and 2 using the stated distributions are, respectively $\mu - \sigma$ and $\mu + \sigma$. In the TM, the final optimal answer was reached using an optimal experiment based on the optimal levels of RVs instead of all experiments based on OAs. To use this optimal experiment, one must first express an index according to (19):

$$Y_j = \sum_{\psi}^{NL} \left| f_{j\psi} - f_{\psi}^{*} \right|, \qquad j = 1, 2, \ldots \tag{19}$$

The second step is to determine the average effect of the factors based on (15) to (20).

The third step is to define the main effect of each factor on Y_j. These main effects of the factors are calculated according to (26) to (28):

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

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

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

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

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

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

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

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

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

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

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

a) Determining the input RVs.
b) Determine the number and values of the levels of variables.
c) Determine the OA.
d) Execute load flow.
e) Analysis of results.

All the details of the above-mentioned steps are provided:

a) RVs of the POPF input are active power and reactive power consumption, wind speed and intensity of sunlight, PV cell temperature.

b) By selecting the variables, the levels of each variable should be determined and it was stated that the number of levels depends on the RV. In this paper, the analysis is performed in two levels using TM and 2PEM and the results are reviewed and compared in terms of accuracy and computational time. By selecting two levels for each random variable, level 1 and level 2 are assumed to be $\mu - \sigma$ and $\mu + \sigma$, respectively.

c) After determining the number of random variables and the number of levels, it is necessary to select the appropriate OA that the types of OAs are available on the Internet. The number of variables was more or less than the standard OA, in which case we should choose the closest standard OA and not consider additional variables that are not related to our problem.

d) After determining the OA, the values determined by the OA are performed for the levels of random variables and load distribution operations, and this process is repeated in a number N_{exp} proportional to the OA values.

e) Once the load distribution output results are determined, statistical indicators such as mean and standard deviation are calculated using the following equations:

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

where x_{ji} is the value of the j-th output RV for the i-th experiment.

4.1 Correlation

Let be a $CR = [r_1, r_2, \ldots, r_M]^T$ matrix of M correlated vector variables characterized by a vector of mean value $\mu_{CR} = [\mu_1, \mu_2, \ldots, \mu_M]^T$ and a variance-covariance matrix, (C_{CR}). Applying the eigenvalue decomposition to C_{CR}:

$$C_{CR} = \varphi \Lambda \varphi^T \tag{30}$$

where φ is the matrix of the eigenvectors of C_{CR}, and Λ is a diagonal matrix with the corresponding eigenvalues on the diagonal. The matrix $D = \varphi^T$ constitutes an orthogonal transformation through which the set CR of correlated variables can be transformed into a set of uncorrelated variables $UR = [b_1, b_2, \ldots, b_M]^T$, such that:

$$UR = DCR \tag{31}$$

The UR has C_{CR}, which is equal to Λ.

In this paper, the correlation between two WTs at 29 and 30 bus is equal to 0.3, the correlation between load and WT 29 is -0.2, the correlation between load and WT 30 is -0.3, and the correlation It is 0.1 between loads with normal distribution according to (32).

$$\rho = \begin{bmatrix} 1.0 & 0.3 & -0.2 & -0.3 \\ 0.3 & 1.0 & 0.1 & 0.1 \\ -0.2 & -0.3 & 1.0 & 0.1 \\ -0.3 & -0.2 & 0.1 & 1.0 \end{bmatrix} \tag{32}$$

Eventually, the following procedure is used to solve the POPF problem of an active power system in the presence of correlated input RVs:

i. Given C_{CR}, of the input RVs, obtain the matrix $D = \varphi^T$ after (30).
ii. Transform CR, into UR, according to (31).
iii. Specify the number and values of the levels of the number of each UR.
iv. Determine an appropriate OA.
v. Formulate the experiments using the results of step (iii).
vi. Use the reverse CR input (31) to calculate the load flow of the steps of the previous experiment to the main space.
vii. Perform load flow for each experiment.
viii. Obtain the values of μ and σ using (29).

TM Constraints such as No OA table for any number of RVs that should be used in composite tables, the number of experiments increases with the number of RVs, and the computer must be used. TM is used in optimization and optimal placement, quality control, and cost reduction issues.

5 Simulation Results

This IEEE 30-bus test system has 30 buses, 41 transmission lines, 6 generators, and 24 load buses, and other information such as line impedance and generator cost function coefficients are mentioned in [31], and this test system is shown in Fig. 3. It can be seen from the

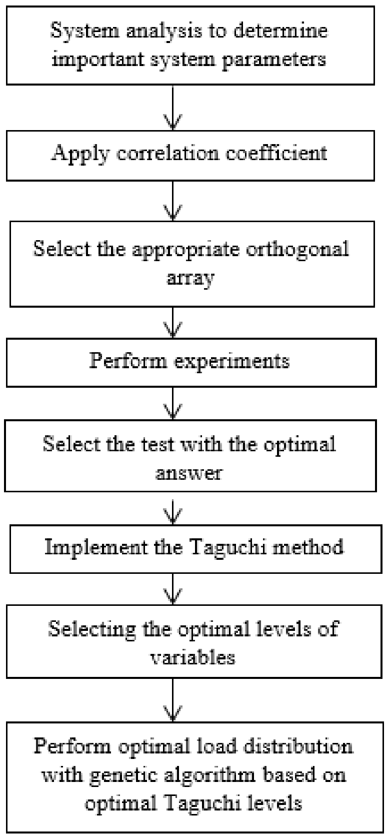

Fig. 2 Taguchi method flowchart.

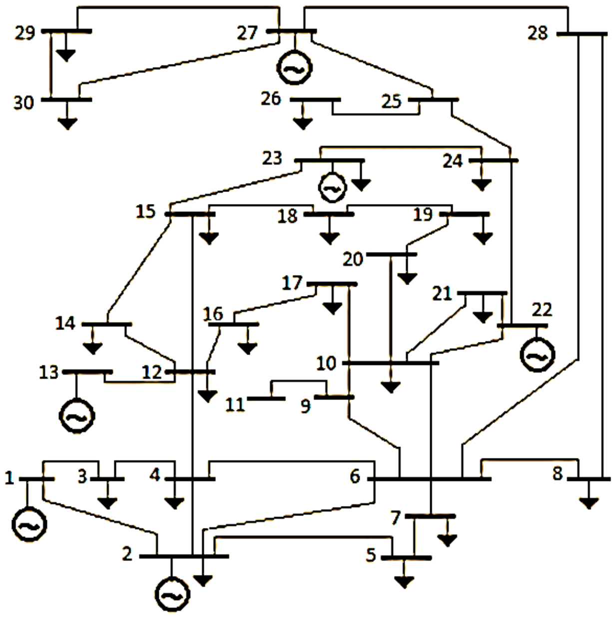

Fig. 3 IEEE 30-bus test system.

Table 3 Voltage size of TM and PEM methods and accuracy.

Bus	VMCS [p.u.]	VC [%]	VTM [p.u.]	MEMTC [%]	MEMT [%]
1	1.06	0.00	1.06	0.00	0.00
2	1.04	-5.13	1.04	-5.31	0.00
3	1.02	-7.13	1.02	-7.41	0.09
4	1.01	-8.78	1.013	-9.16	0.10
5	1.01	-13.7	1.01	-11.63	0.00
6	1.01	-10.5	1.01	-10.89	0.07
7	1.00	-12.4	1.01	-12.71	0.04
8	1.01	1.01	1.01	-11.63	0.00
9	1.01	1.04	1.05	-13.82	0.08
10	1.04	1.04	1.05	-14.62	0.11
11	1.06	1.06	1.10	-14.62	0.00
12	1.05	1.05	1.06	-15.51	0.07
13	1.06	1.06	1.07	-15.60	0.00
14	1.04	1.04	1.04	-15.18	0.08
15	1.03	1.04	1.04	-15.52	0.09
16	1.04	1.04	1.04	-16.21	0.11
17	1.03	1.04	1.03	-13.38	0.12
18	1.02	1.02	1.02	0.06	0.07
19	1.02	1.02	1.02	0.06	0.06
20	1.02	1.02	1.02	0.07	0.07
21	1.03	1.03	1.03	0.09	0.14
22	1.03	1.03	1.03	0.03	0.16
23	1.02	1.02	1.02	0.07	0.08
24	1.01	1.02	1.02	0.07	0.12
25	1.01	1.01	1.01	0.04	0.04
26	0.10	0.10	0.10	0.04	0.04
27	1.02	1.02	1.02	0.00	0.00
28	1.00	1.00	1.02	0.04	0.04
29	1.00	1.00	1.02	0.00	0.00
30	0.10	0.10	0.10	0.00	0.00

results that when we consider the correlation between the random variables, the voltage is improved, and the value obtained from the Taguchi method is very close to the results. It is the Monte Carlo method and also the error percentage in the Taguchi method is reduced. These are listed in Table 3.

Fig. 4 of the voltage profile using the TM shows the correlation between the input RVs. Because the main purpose of load flow is to determine the amplitude and angle of the bus voltage, to show the importance and benefits of considering correlation in TM, the amount of network bus voltage obtained by load flow is

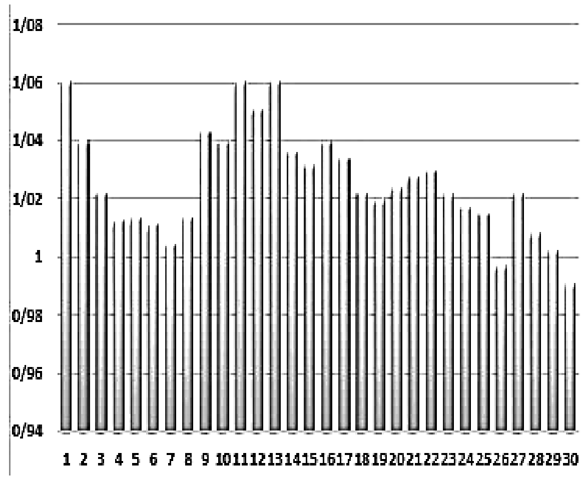

Fig. 4 Voltage profiles by TM considering correlation.

considered as a criterion.

Then, to calculate the objective function, the sweeping and similar load flow must be used for each of the generated random population patterns. That is, the amplitude and angle of the phase of the bus voltage, the transmission power of transmission lines, and the power of loads and generators are determined, and then the objective function, which is the losses of the whole system, is determined and calculated. And then the equal and unequal constraints are checked that if the constraints are met, the merit of the answers is calculated and used for the next generation. And the next steps of the algorithm are executed, otherwise, it goes to the random population generation stage. At each stage of the implementation, the number of control variables and the number of losses are obtained, and finally, the answer that satisfies all the constraints and is the least amount of losses will be the optimal answer of the optimization process. The TM has been studied. Now, according to the principles of the TM, there are 24 consumers in this standard network, and two wind power plants and a PV power plant, which have a total of 27 RVs in the system. Grid loads and wind farms and a PV power plant are all considered as RVs and using the MINITAB software because the OA is close to the sum of the number of RVs including grid loads and random power plants equal to 32. We have used the $OA_{32}(2)^{31}$ and the second level for load factors, which are the same RVs, we have considered 40 MW and the first level is equal to 0, and for distributed generation power plants, we have done the same, and the specific value We have assigned their own distribution, now in total for these 27 RVs we have to do 32 experiments and according to the principles of the TM presented in the previous chapter, the same test that has the lowest value of the standard test of the TM according to the method itself We select the resulting TM and assign the value of the RVs of that experiment to the RVs of the system, and then proceed to the optimization process using the GA. First, we perform 32 tests according to the table obtained from the MINITAB software based on the dual levels of factors, and then we implement the TM according to the principles of the TM and the objective function of reducing system losses. According to Table 4 below, where load1 to load24 are the same loads of the system as Wind1 and Wind2 are two wind power plants, and delta expresses the major effect of each factor on the function and the rank expression classify and number the variables based on the delta value. Now, according to the positive and negative signs of delta, we must select the levels of 1 or 2 factors. Looking at Table 4, the results of TM from MINITAB software, we see that except for variables 4, 5, 11, 13, 16, 18, 21, and 27, all of them have a negative delta value, and the mentioned factors are set to level 2, and then to the same stage as the main test. The specific levels for each factor were determined according to the TM.

Table 4 Results of TM from MINITAB software.

Load	Level 1	Level 2	Delta	Rank
1	538.0	508.3	-29.7	8
2	530.6	515.7	-14.9	13
3	560.8	485.5	-75.3	5
4	522.1	524.2	2.2	26
5	472.0	574.3	102.2	4
6	579.3	467.1	-112.2	3
7	530.4	515.9	-14.5	14
8	560.8	485.5	-75.3	6
9	527.3	519.0	-8.3	19
10	525.9	520.5	-5.4	24
11	371.8	675.5	302.7	2
12	531.7	514.6	-17.0	10
13	369.6	676.7	307.1	1
14	557.3	489.0	-68.4	7
15	530.1	516.2	-13.9	15
16	520.0	526.3	6.3	23
17	526.7	519.6	-7.1	21
18	510.0	536.3	26.3	9
19	529.8	516.5	-13.3	16
20	526.5	519.8	-6.6	22
21	521.0	525.3	4.4	25
22	530.9	515.4	-15.5	12
23	528.0	518.3	-9.7	18
24	528.8	517.6	-11.2	17
PV	531.1	515.2	-15.9	11
WT1	526.9	519.4	-7.4	20
WT2	522.8	523.5	0.6	27

In the following, we will first distribute 32 dual loads obtained from the TM tests in MATLAB software with the TM, and finally, the optimal load flow obtained from the TM test with GA will be equal to 27.5 MW, which is the number of system losses from the test. And the levels determined by the TM are obtained, but the answer that we obtain for the losses of the same system from the normal OPF by the Newton-Raphson load flow method is equal to 33 MW, and this indicates that TM adjusts the POPF of factor levels in such a way that the least number of losses occur in the system and reduces the difference between 33 and 27.5, which is equal to 5.5 MW, which is a large amount of losses. Also, in terms of operational speed, the work is faster and the result is faster too, because if it is argued that, like the MCS, at least 800 repetitions of OPF with GA should be

Table 5 Comparison of μ and σ for different methods.

Total losses	TM	Scenario	LHS	2PEM
μ [MW]	35.67	51.2	63.60	47.50
σ	18.77	38.32	48.64	24.35

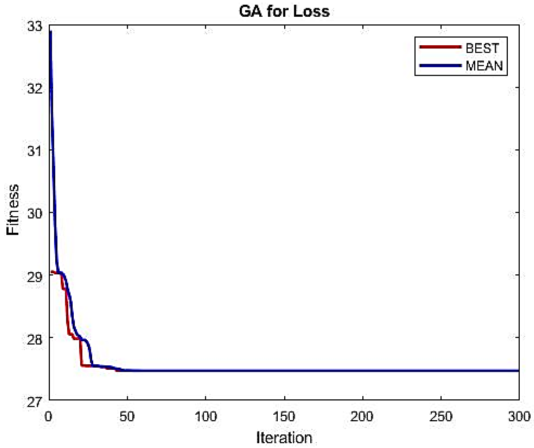

Fig. 5 Convergence of loss optimization by GA.

Table 6 Values of control variables by TM and 2PEM.

Control variables	TM	2PEM	Control variables	TM	2PEM	Control variables	TM	2PEM
P_{G2} [MW]	48.77	47.87	V_{G2} [p.u.]	1.03	1.03	$T_{6,10}$ [p.u.]	1.00	1.00
P_{G5} [MW]	21.98	21.84	V_{G5} [p.u.]	0.99	0.98	$T_{4,12}$ [p.u.]	1.01	0.98
P_{G8} [MW]	20.94	22.22	V_{G8} [p.u.]	1.01	1.03	$T_{28,27}$ [p.u.]	0.96	0.95
P_{G11} [MW]	12.74	12.94	V_{G11} [p.u.]	1.03	1.03	Q_{sh10} [MVAr]	31.30	35.40
P_{G13} [MW]	12.65	12.28	V_{G13} [p.u.]	1.04	1.05	Q_{sh24} [MVAr]	15.27	13.71
V_{G1} [p.u.]	1.05	1.04	$T_{6,9}$ [p.u.]	1.00	0.99			

repeated, then for 27 problem factors 800 times adjust the appropriate random number and repeat the relevant operation, which itself requires both a lot of time and a lot of memory to store information, but in the TM, first, the optimal levels of each factor are determined using the principles of the TM and then based on the same levels. The optimal load is done, and the optimal answer is obtained, and in this paper, instead of 32 tests that replaced the MCS, the same 32 tests are performed with a test in which all the factors are at their best according to the principles of TM. We replace it with much less time with a GA to get the desired answer. In Table 4, the values of the control variables are compared by 2PEM and TM. This optimization was performed by the GA and the TM in 52.21 seconds with 300 iterations for the GA, which converged in the 28 iterations of the answer as shown in Fig. 5.

By observing the results of Tables 5 and 6, it can be inferred that TM, considering the concept of correlation, has better results than the 2PEM, which shows the effect of correlation. In general, due to the fact that in the 2PEM we need the statistical torques of the input RVs and also we need to perform mathematical calculations of high-degree integrals to achieve the answer, which in itself increases the number of steps and at the same time the function of the PEM increases because in the TM these statistical moments are not required, and the answer can be achieved optimally with the simple formulation.

6 Conclusions

Optimal power flow is very important in the analysis and study of power distribution systems, especially in minimizing losses. In this paper, using the Taguchi method, the optimal power generation levels of wind turbine and photovoltaic cells and loads were selected as the uncertainty of the probabilistic optimal power flow problem by considering the correlation between random variables based on orthogonal arrays. And the genetic algorithm is used to minimize IEEE 30-bus distribution network losses and the losses were reduced from 33 MW to 27.5 MW. It was also shown that in addition to the optimal levels of uncertainty values can be selected by considering the correlation using the genetic algorithm, these optimal levels obtained the optimal values of the control variables of the optimal power flow problem and the minimum amount of losses. In this paper, Monte Carlo simulation plays the role of a reference method that is used to compare Taguchi method results with the two-point estimation method. Examining the results, it can be seen that the Taguchi method has closer results to Monte Carlo simulation results, the rate of losses with the Taguchi method is lower than Monte Carlo simulation and has higher accuracy, and in terms of operating time of this Taguchi method is very high. Better than the reference method for the number of two levels for each correlated factor. The number of tests required for a three-level Taguchi method for each random variable is equal to the number of two-point estimation method steps and is not comparable to a two-level Taguchi method in terms of computational load, computational time, and complexity. Taguchi method in large networks due to the increase of uncertain modes Monte Carlo simulation working time is greatly increased and in this type of network it is better to use Taguchi method, but in medium and small networks in terms of working time, etc. Monte Carlo simulation is recommended.

Intellectual Property

The authors confirm that they have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property.

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M. Najjarpour: Conceptualization, Methodology, Software, Formal analysis, Writing - Original draft. **B. Tousi:** Supervision. **S. Jamali**: Investigation.

Declaration of Competing Interest

The authors hereby confirm that the submitted manuscript is an original work and has not been published so far, is not under consideration for publication by any other journal and will not be submitted to any other journal until the decision will be made by this journal. All authors have approved the manuscript and agree with its submission to "Iranian Journal of Electrical and Electronic Engineering".

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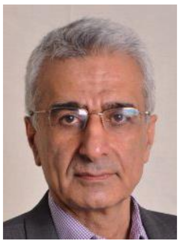

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