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Modified Taguchi-Based Approach for Optimal Distributed Generation Mix in Distribution Networks

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ABSTRACT In this paper, a new two-stage optimization framework is proposed to determine the optimal-mix integration of dispatchable Distributed Generation (DG), in power distribution networks, in order to maximize various techno-economic and social benefits simultaneously. The proposed framework incorporates some of the newly introduced regulatory policies to facilitate low carbon networks. A modified Taguchi Method (TM), in combination with a node priority list, is proposed to solve the problem in a minimum number of experiments. Nevertheless, the standard TM is computationally fast but has some inherent tendencies of local trapping and usually converges to suboptimal solutions. Therefore, two modifications are suggested. A roulette wheel selection criterion is applied on priority list to select the most promising DG nodes and then modified TM determines the optimal DG sizes at these nodes. The proposed approach is implemented on two standard test distribution systems of 33 and 118 buses. To validate the suggested improvements, various algorithm performance parameters such as convergence characteristic, best and worst fitness values, and standard deviation are compared with existing variants of TM, and improved genetic algorithm. The comparison shows that the suggested corrections significantly improve the robustness and global searching ability of TM, even compared to meta-heuristic methods.

INDEX TERMS Carbon tax, emission, power distribution, power generation planning, optimization, renewables, Taguchi method.

NOMENCLATURE

A. INDICES AND SETS

a_i	Integer.
i, j	Buses.
l	Load levels, e.g., light, nominal, and peak.
N	Set of buses in the system ($i, j \epsilon N$).
N_b	Set of feeders in the system ($u \epsilon N_b$).
N_L	Set of load levels ($l \epsilon N_L$).
N_{t_p}	Set of DG types ($t_p \epsilon N_{t_p}$).
u	Branch.
t_p	Type of DG, e.g. diesel, gas and biomass, etc.
T_d	DG life in years ($t \epsilon T_d$).

B. PARAMETERS

CF_{t_p}	Capacity factor of t_p type DG.
CO_2^{MaxS}	Maximum specified CO_2 intensity limit by regulator (kg/kWh)
$E_{DG_{t_p}}$	CO_2 emission intensity of t_p type DG (kg/kWh).
E_{Grid}	CO_2 emission intensity in grid energy (kg/kWh).
H_l	Number of hours in lth load level.
I_{lu}	Current in uth feeder in lth load level (Amp.).
I_u^{Max}	Ampacity of uth feeder (Amp.).
$K_{e,l}$	Grid energy price in lth load level (\$/kWh).
K_{em}	CO_2 tax (\$/kg).
$K_{t_p}^{Inst}$	Turnkey cost of t_p type DG (\$/kVA).
$K_{t_p}^{OM}$	Operation & Maintenance (O&M) cost of t_p type DG (\$/kWh).
$P_{a,l}, P_{b,l}$	Total real power losses of the system before and after DG integration, in lth load level (kW).

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$P_{D_{il}}$	Real power demand of bus i in lth load level (kW).
$P_{DG_{il}}$	Real power generation at bus i, in lth load level (kW).
$P_{DG_{t_p}}^{Max}$	Maximum power generation limit of t_p type DG (kW).
$P_{DG_{it_p}}$	Real power generation from t_p type DG at bus i.
pf_{l,it_p}	Power Factor (PF) of t_p type DG at bus i in lth load level.
$Q_{D_{il}}$	Reactive power demand at bus i in lth load level (kVAr).
$Q_{DG_{il}}$	Reactive power generation at bus i, in lth load level (kVAr).
R_{ij}	Line resistance between bus i & bus j.
R_{int}	Annual rate of interest (%).
$S_{DG_{it_p}}$	Installation capacity of t_p type DG, at bus i (kVA)
$S_{DG_{l,it_p}}$	Apparent power generation from t_p type DG, at bus i, in lth load level (kVA)
V_{il}	Voltage at bus i in lth load level (p.u.).
$V_{\max S}$	Maximum specified voltage limit at bus (p.u.).
$V_{\min S}$	Minimum specified voltage limit at bus (p.u.).
Y_{ij}	Element of Y-bus matrix
θ_{ij}	Impedance angle of line between nodes i and j.
σ_{it_p}	Binary decision variable for t_p type DG installation at bus i.
ρ_{l,it_p}	Binary decision variable for t_p type DG operation at bus i in lth load level.
δ_{il}	Voltages angles of bus i in lth load level.

I. INTRODUCTION

IN recent years, the Distributed Generation (DG) integration in Power Distribution Networks (PDNs) has received lot of attention from industry and academia due to its distinctive benefits. In addition to power generation support, the expected optimal DG integration benefits are power or energy loss reduction, voltage profile improvement, reactive power control, reliability improvement, hosting capacity enhancement, transformers MVA capacity and operational life enhancement, and emission reduction [1]. In order to maximize these benefits, the optimal number, site and size have to be determined by considering various constraints. Moreover, the impact of various DG technologies would be different in terms of system performance and economics. For example, solar and wind based DGs are non-dispatchable and cannot guarantee fixed power output due to uncertainties in power availability [2], and also involve high initial investment and space. The non-dispatchable DGs would need support of dispatchable DGs, e.g., Fuel Cell (FC), Micro-Turbine (MT), Diesel Engine (DE), Gas Engine (GE), Biomass (BM), energy storage etc., to participate in the competitive electricity market. Therefore, the selection of DG type should also be considered in Optimal DG Allocation (ODGA) problem formulations.

In literature, one part of ODGA research is focused on performance improvement of PDNs. Kanwar *et al.* [3] solved a simultaneous optimal allocation problem of distributed energy resources to minimize annual energy loss in PDNs. In [4]–[6], the ODGA problem is formulated to minimize the power loss in PDNs. In [7], [8], multiobjective ODGA problems are solved by considering power loss, node voltage deviation and voltage stability of distribution systems. A risk-based multiobjective ODGA model is also solved in [9]. The coordinated and simultaneous ODGA problems have been formulated and solved in [7], [10] by considering the effect of existing voltage regulators, i.e., on-load tap changer, already present in distribution systems. In [11], the optimal sites and sizes of DGs are determined to improve the reliability indices of large-scale PDNs. An optimal DG integration problem is solved in [12] to increase the voltage stability margin of distribution systems. Some of the distributed ancillary services, supported by DGs, have been considered in [13] while optimally integrating in PDNs. An ODGA problem is formulated in [14], by considering the probabilistic nature of load and generation, to reduce total harmonics distortion and power loss. In [15], power loss and voltage sag reduction based ODGA problem is formulated. The effect of voltage sag is measured in terms of the total load affected due to voltage sag.

The second part of the literature is focused on economic and market aspects of DG integration. In deregulated and restructured power systems, several economic based DG planning models are also investigated to maximize the profit of DG owner (DGO) and Distribution Network Operators (DNOs) along with performance improvement. In [16], the economic benefits, generated from life extension of distribution transformer, due to customer owned DGs has been investigated. In [17], [18], a method has been devised to encourage the DG investors to maximize the profit of DGOs and DNOs under power purchase agreements. A similar approach is presented in [19] by modeling the uncertainty of electric load, electricity price and wind by using the point estimation method. In [20], the retail energy market model of urban and remote community microgrids have been investigated to increase the third-party investment in local energy systems. An optimal reinforcement planning of PDNs is investigated in [21] by considering the cost of power loss, transformers and cables.

The increasing pressure of environment protection agencies aiming to reduce GHG emission has proliferated the concept of low carbon networks. The energy regulators are introducing new policies for system operators to reduce carbon emission caused by various energy related activities in PDNs. Some of the carbon policies, based on feed-in-tariffs, Carbon-dioxide (CO_2) tax and carbon cap-and-trade under multiple scenarios, are analyzed in [22] to encourage various DG investments. In [23], ODGA problem is solved to reduce the CO_2 emission however fixed DG sizes are assumed. The growing global concern on environmental issues has directed system planners to incorporate future environment

protection policies in active distribution planning, along with various techno-economic aspects of DG integration. However, the inclusion of multiple goals and aspects of different interest would increase the ODGA problem complexity due to their conflicting nature.

To solve such complex optimization problems of active distribution system planning, various analytical, numerical, statistical, and meta-heuristic optimization methods have been suggested in literature. It may be observed that analytical methods are based on some set of assumptions therefore sometimes fails to solve real-life engineering optimization problems. On the other hand, the numerical methods are computationally fast and efficient but their optimal solutions are also affected by accurate modeling and initialization of the problem [13]. Many population-based Artificial Intelligence (AI) techniques are also suggested to solve ODGA problems of distribution systems. Some of the well-known AI-techniques used to solve ODGA problem can include Particle Swarm Optimization (PSO) and Cat Swarm Optimization (CSO) [11], Hybrid Grey Wolf Optimizer (HGWO) [24], Teaching Learning-Based Optimization (TLBO) [3], Differential Evolution (DE) [17], dynamic Ant Colony Search (ACS) [21], Moth Search Optimization (MSO) [7], Harmony Search Algorithm (HSA) [4], Modified TLBO (MTLBO) [5], Multi-Objective PSO (MOPSO) [18], salp swarm optimization (SSO) [25], Hybrid Immune-Genetic Algorithm (HIGA) [19], Tribe-PSO (TPSO) [2], Hybrid Gradient PSO (HGPSO), and Bacterial Foraging Algorithm (BFA) [9], Genetic Algorithm (GA) [13], Dynamic Node Priority List based GA (DNPL-GA) [10], Non-dominated Sorting GA (NSGA) [23], etc. Most of the meta-heuristic techniques provide near-optimal solution for complex real-life ODGA problems but require significantly large computational time. Besides, the optimal solution of many of these methods are depending on algorithm parameters and initialization. A comparison of different optimization methods used to solve ODGA problems is presented in Fig. 1.

Taguchi Method (TM) is a statistical method developed by Dr. Genichi Taguchi. The method is less sensitive to initial values of parameters and capable of providing near optimal solution in a less number of experiments particularly, for large-scale problems [26], [27]. TM has been successfully applied to solve diversified power system optimization problems [26]–[28]. However, the effectiveness of this method depends on proper selection of factors and their corresponding levels, which requires brainstorming sessions. Moreover, the TM as such may not be a proper choice for the problems having factors varying in a continuous manner [29] thereby converges to suboptimal solutions. This paper is an extension of the work presented in [6], [8], in which a basic TM is introduced to solve the single objective, i.e., power loss minimization, and multiobjective ODGA (in combination with TOPSIS approach) problems of distribution systems respectively.

In this article, a modified Taguchi-based approach is proposed for optimal mixed-DG allocation and operational

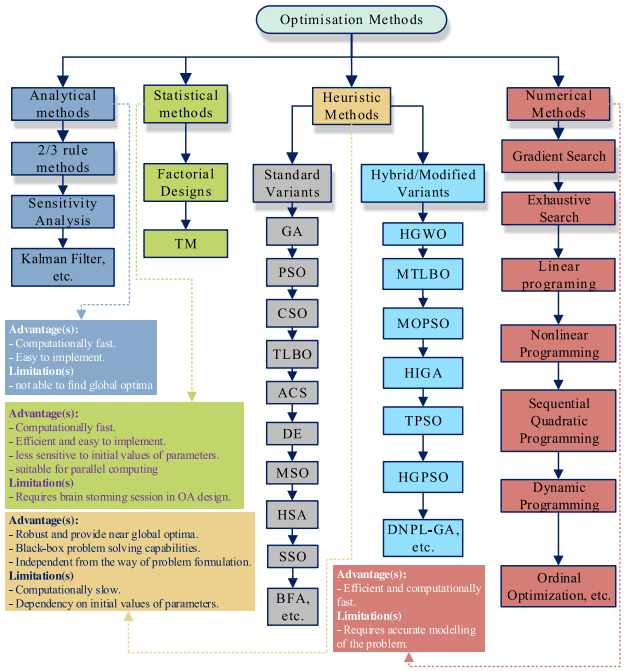

FIGURE 1. Different optimization methods used for ODGA.

management to facilitate low carbon PDNs by considering environment protection policies [30]–[33], recently imposed on DNOs. The modified Taguchi-based approach, in combination to a node priority list (NPL) based heuristic, is proposed to solve the problem. Modifications are mainly done in response analysis step of the method, in order to improve its local and global searching abilities. To demonstrate the effectiveness of suggested improvements, the proposed method is implemented on two standard test distribution systems of 33 and 118 buses. The performance of proposed approach is found to be promising when simulation results are compared with the same obtained by existing variants of TM [6], [8], [26] and an improved variant of genetic algorithm [34]. The proposed approach is found to be very effective and computationally fast to solve ODGA problems. On the other hand, various techno-economical aspects of proposed optimization framework are analyzed to proliferate low carbon networks which follow new emission policies imposed on DNOs.

II. PROBLEM FORMULATION

In this section, a new objective function is introduced for ODGA in low carbon distribution networks. It is composed of annual DG investment cost, operation and maintenance cost, grid power transaction cost and CO_2 taxes. A voltage penalty factor is also considered to maintain the specified bus voltage limits. In planning stage, it is difficult to consider all states of generation and load demand throughout the year therefore, the annual load is statistically divided into few load levels, as suggested in literature [4]. Usually, divided into three load levels, known as peak, nominal and light load demands. In order to generate DG integration benefits, at all load levels throughout the year, the most compromising solution of DG allocation has to be determined. Once compromising optimal

DG allocation is obtained, the optimal dispatch of these DGs are determined for each individual load level while maximizing operational benefits of DNO.

Based on above discussed requirements, the proposed ODGA problem is solved in two stages, i.e., optimal allocation followed by their optimal dispatch to optimize several techno-economic and social objectives.

A. OPTIMAL ALLOCATION OF DGS (STAGE–1)

It is a planning stage in which ODGA problem is solved to determined DG integration parameters such as number, size, site, and types. Different type and number of DGs are modeled by considering their investment cost, O&M cost, CO_2 emission intensity, capacity factor (CF) and PF. In the proposed DG integration model, following objective functions have been considered.

1) ANNUAL BENEFIT FROM ENERGY LOSS MINIMIZATION

The minimization of annual energy loss is one of the major concerns for DNOs as it affects the annual revenue. The cost of annual energy loss before DG integration over N_L load levels is expressed in (1), by using power loss expression presented in [35].

$$J_1^{before} = \sum_{l=1}^{N_L} K_{e,l} H_l \sum_{i=1}^{N}\sum_{j=1}^{N} \big[\alpha_{ij,l}\big(P_{il}P_{jl} + Q_{il}Q_{jl}\big) + \beta_{ij,l}\big(Q_{il}P_{jl} - P_{il}Q_{jl}\big)\big] \quad (1)$$

where, $\alpha_{ij,l} = R_{ij}\cos(\delta_{il} - \delta_{jl})/V_{il}V_{jl}$, $\beta_{ij,l} = R_{ij}\sin(\delta_{il} - \delta_{jl})/V_{il}V_{jl}$, $P_{il} = P_{DG_{il}} - P_{D_{il}}$, and $Q_{il} = Q_{DG_{il}} - Q_{D_{il}}$. For base system, $P_{DG_{il}}$ & $Q_{DG_{il}} = 0\ \forall\ i, l$ therefore, (1) can be modified as

$$J_1^{before} = \sum_{l=1}^{N_L} K_{e,l} H_l \sum_{i=1}^{N}\sum_{j=1}^{N} \big[\alpha_{ij,l}\big(P_{D_{il}}P_{D_{jl}} + Q_{D_{il}}Q_{D_{jl}}\big) + \beta_{ij,l}\big(Q_{D_{il}}P_{D_{jl}} - P_{D_{il}}Q_{D_{jl}}\big)\big] \quad (2)$$

The cost of annual energy loss after DG integration can be expressed as

$$\begin{aligned} J_1^{after} = \sum_{l=1}^{N_L} K_{e,l} H_l \sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_{ij,l}\big[&\big(P_{DG_{il}} - P_{D_{il}}\big) \times \big(P_{DG_{jl}} - P_{D_{jl}}\big) + \big(Q_{DG_{il}} - Q_{D_{il}}\big)\big(Q_{DG_{jl}} - Q_{D_{jl}}\big)\big] \\ &+\beta_{ij,l}\big[\big(Q_{DG_{il}} - Q_{D_{il}}\big)\big(P_{DG_{jl}} - P_{D_{jl}}\big) - \big(P_{DG_{il}} - P_{D_{il}}\big)\big(Q_{DG_{jl}} - Q_{D_{jl}}\big)\big] \end{aligned} \quad (3)$$

Further, to incorporate the effect of multi-type DGs in annual energy loss, the power generation of a DG is expressed in terms of its respective CF and PF as

$$P_{DG_{il}} = \sum_{t_p=1}^{N_{t_p}} \rho_{l,it_p} CF_{t_p} S_{DG_{l,it_p}} pf_{l,it_p}$$

$$Q_{DG_{il}} = \sum_{t_p=1}^{N_{t_p}} \rho_{l,it_p} CF_{t_p} S_{DG_{l,it_p}} \sqrt{1 - pf_{l,it_p}^2} \quad (4)$$

The annual profit from energy loss saving is expressed as

$$J_1 = J_1^{before} - J_1^{after} \quad (5)$$

2) ANNUALIZED DG INVESTMENT COST

The DG installation cost includes different initial costs known as turnkey cost of DG integration. For simplicity and without loss of generality, the annualized DG investment cost for various DGs is defined as

$$J_2 = \sum_{i=1}^{N}\sum_{t_p=1}^{N_{t_p}} \sigma_{it_p} K_{t_p}^{Inst} S_{DG_{it_p}} T_d^{-1}\big(1 + R_{int}\big)^{T_d} \quad (6)$$

3) ANNUAL BENEFIT BY OPTIMIZING THE ENERGY SUPPLIED TO CONSUMERS

After DG integration, annual energy purchase from the grid would reduce. Therefore, it would be beneficial to maximize the use of installed DGs economically. The cost of annual energy supplied to load before DG integration is expressed as

$$J_3^{before} = \sum_{l=1}^{N_L}\sum_{i=1}^{N} H_l K_{e,l} P_{D_{il}} \quad (7)$$

After DG integration, the load demand is supplied by DGs and grid both. The cost of annual energy supplied to load is expressed as

$$\begin{aligned} J_3^{after} = &\sum_{l=1}^{N_L}\sum_{i=1}^{N} K_{e,l} H_l \Big(P_{D_{il}} - \sum_{t_p=1}^{N_{t_p}} \rho_{l,it_p} CF_{t_p} S_{DG_{l,it_p}} \times pf_{l,it_p}\Big) \\ &+ \sum_{l=1}^{N_L}\sum_{i=1}^{N}\sum_{t_p=1}^{N_{t_p}} \rho_{l,it_p} K_{t_p}^{OM} H_l CF_{t_p} S_{DG_{l,it_p}} pf_{l,it_p} \end{aligned} \quad (8)$$

It is assumed that the energy selling price to consumer before and after DG integration would remain same. The annual benefit obtained by optimizing the energy sell to consumers from DGs and main grid is expressed as

$$J_3 = J_3^{before} - J_3^{after} \quad (9)$$

4) ANNUAL BENEFIT FROM MINIMIZATION OF CARBON TAX

Governments across the globe are trying to reduce the amount of emission by imposing penalties in terms of CO_2 taxes[1] or cap-and-trade mechanisms, etc. However, estimating the effect of CO_2 taxes would have on energy price would be difficult, and requires a model far beyond what has been done here. Instead, a rough approximation of this effect is used, as suggested in [22] and only CO_2 emission is considered in the proposed model due to its large sharing among greenhouse gases produced from power plants [31], [36]. The per ton tax is considered for carbon emission. The annual CO_2 tax, before DG integration, can be expressed as

$$J_4^{before} = \sum_{l=1}^{N_L} K_{em} E_{Grid} H_l \Big(\sum_{i=1}^{N} P_{D_{il}} + P_{b,l}\Big) \quad (10)$$

[1] In reality, taxes on carbon emission would apply not to DNOs but to the bulk generators supplying to DNOs.

After DG integration, the utility load will be supplied by DGs and grid simultaneously. Therefore, the annual carbon taxes on both grid and DGs are simultaneously expressed as

$$J_4^{after} = \sum_{l=1}^{N_L} K_{em} H_l \Big\{ E_{Grid} \Big(\sum_{i=1}^{N} P_{D_{il}} + P_{a,l} \Big) - \sum_{i=1}^{N} \sum_{t_p=1}^{N_{tp}} \rho_{l,it_p} CF_{t_p} S_{DG_{l,it_p}} pf_{l,it_p} \Big(E_{Grid} - E_{DG_{t_p}} \Big) \Big\} \quad (11)$$

The annual benefit from carbon emission reduction is expressed by using (10)-(11) as

$$J_4 = J_4^{before} - J_4^{after} \quad (12)$$

5) VOLTAGE PROFILE IMPROVEMENT

The proposed ODGA is a complex non-linear, mixed-integer optimization problem which creates some issues in initialization of the technique when hard voltage limits constraint. Therefore, a penalty is imposed to manage the node voltage profile in stage-1. A quadratic penalty factor is suggested in [35] but for more impact (as $\Delta V_i \leq 1, \ \forall i$), linear voltage penalty factor is proposed here, expressed as

$$J_5 = \sum_{l=1}^{N_L} \sum_{i=1}^{N} \Delta V_{il} \quad (13)$$

$$s.t. \ \Delta V_{il} = \begin{cases} |V_{\min S} - V_{il}|, & \text{if } V_{il} < V_{\min S} \\ 0, & \text{if } V_{\min S} \leq V_{il} \leq V_{\max S} \\ |V_{il} - V_{\max S}|, & \text{if } V_{il} > V_{\max S} \end{cases}$$

In order to maximize the annual profit of DG integration, a combined fitness function, J^{ODGA} is formulated in (14). A multiplicative penalty method is used [37], to combine all individual objectives such as profits, outflow, and voltage penalty expressed in (5), (6), (9), (12) and (13) respectively. The combined objective function is expressed as

$$\max \ J^{ODGA} = \big(J_1 + J_3 + J_4 - J_2\big).\big(1 + kJ_5\big)^{-1} \quad (14)$$

The objective function, J^{ODGA} is subjected to constraints expressed in (16)–(23), except node voltage constraint presented in (18). It has been analyzed that this hard voltage constraint in (18) can deteriorate the algorithm performance in planning stage and sometimes, algorithms are not initialized properly. In order to improve the node voltage profile of the system, a multiplicative penalty method is used to transform the voltage constrained problem into unconstrained one, as suggested in [3], [7], [35], [38].

As discussed, the objectives J_1 to J_4 are representing various annual monetary benefits and cost, associated to DG integration therefore, the objective function J_5 is introduced as a penalty to annual profit, with its controlling coefficient $k \epsilon [0, 1]$. The value of k depends on complexity of distribution system and can also select according to DNO requirements. For example, if optimization method is not converging then the voltage penalty factor 'kJ_5' would be relaxed by reducing the value of k.

B. OPTIMAL OPERATION OF DGs (STAGE–2)

In Stage–1, the compromising optimal mixing, siting and sizing of different DGs are determined by considering multiple load levels. In planning stage, the dispatch of these DGs is assumed to be fixed for all load levels which will not be optimal during system operations over variable load demand/levels. Therefore, various operational benefits of DNO are maximized in this stage, by determining the optimal dispatch of installed DGs at each load level. The objective function includes the running costs such as fuel cost, CO_2 taxes and grid energy transaction cost. The fitness/objective function of system operation J^{OPR} is expressed as

$$\max \ J^{OPR} = J_1 + J_3 + J_4 \quad (15)$$

here, J_2 is removed because investment is already done in Stage–1. Similarly, voltage penalty function J_5 is also removed instead a node voltage limits constraint is considered, expressed in (18). The objective function (15) is subjected to various constraints expressed in (16)–(23), except (20) and (21) as these are planning constraints.

C. CONSTRAINTS

1) POWER BALANCE CONSTRAINTS

$$P_{il} = V_{il} \sum_{j=1}^{N} V_{jl} Y_{ij} \cos(\theta_{ij} + \delta_{jl} - \delta_{il}) \quad \forall \ i, l \quad (16)$$

$$Q_{il} = -V_{il} \sum_{j=1}^{N} V_{jl} Y_{ij} \sin(\theta_{ij} + \delta_{jl} - \delta_{il}) \quad \forall \ i, l \quad (17)$$

2) VOLTAGES LIMIT CONSTRAINTS

$$V_{\min S} \leq V_{il} \leq V_{\max S} \quad \forall \ i, l \quad (18)$$

3) DG UNITS LIMIT CONSTRAINTS

$$P_{DG_{it_p}} \leq P_{DG_{t_p}}^{Max} \quad \forall \ i, t_p \quad (19)$$

4) DISCRETE DG SIZES CONSTRAINTS

$$P_{DG_{it_p}} = a_i \sigma_{it_p} \Delta P_{DG} \quad \forall \ i, t_p \quad (20)$$

5) DG PENETRATION LIMIT CONSTRAINT

Maximum DG penetration in the system must be limited to nameplate kVA rating (KVA_T) of the respective transformer [39] or peak demand of the system.

$$\sum_{i=1}^{N} \sum_{t_p=0}^{N_{tp}} \sigma_{it_p} P_{DG_{it_p}} \leq min(KVA_T, \text{peak demand}) \quad (21)$$

6) FEEDERS THERMAL LIMIT CONSTRAINTS

$$I_{lu} \leq I_u^{Max} \quad \forall \ l, u \quad (22)$$

TABLE 1. Orthogonal Array $L_8(2^5)$.

Test No.	Orthogonal array (A)					Fitness
	F_1	F_2	F_3	F_4	F_5	
1	1	1	1	1	1	Y_1
2	1	1	1	2	2	Y_2
3	1	2	2	1	1	Y_3
4	1	2	2	2	2	Y_4
5	2	1	2	1	2	Y_5
6	2	1	2	2	1	Y_6
7	2	2	1	1	2	Y_7
8	2	2	1	2	1	Y_8

7) CO_2 EMISSION CONSTRAINTS

From current trends, it may be observed that in future, the environmental policies would limit the CO_2 emission intensity (kg/kWh) in PDNs [30]–[33]. Therefore, the CO_2 emission constraint is also incorporated.

$$Avg.\ CO_2\ intensity \leq CO_2^{\mathrm{MaxS}} \tag{23}$$

III. STANDARD VARIANT OF TAGUCHI METHOD

The TM is developed by Dr. Genichi Taguchi to reduce the variation in manufacturing process through robust design of the experimentation. It is broadly divided into two essential steps, i.e., Orthogonal Array (OA) construction and response analysis. In this section, the basic TM is explained, followed by some of the limitations observed in its available variants.

A. ORTHOGONAL ARRAY

OA statistically organizes the possible levels of factors/parameters at which they can be varied and used in Design of Experiment (DOE) for determining the relationship between process input and process output. A sample case OA is given in Table 1, where each factor has two possible levels [6], [26], [29]. However, the user may choose more number of levels depending on the factors and design requirements. Some set of rules need to be followed when constructing Taguchi OAs.

For example, m and q are representing total number of factors & levels for each factor respectively then the maximum possible number of factorial DOE is expressed as q^m. However, maximum number of Taguchi experiments will be $M = m \times f + 1$; where, $f = (q - 1)$ is the degree of freedom for a factor. Here, $M \ll q^m$; therefore, very less number of experiments is required to obtain the near optimal solution using TM. Initially, user randomly assign the values of levels for each factor usually in ascending order, i.e. $Level_1 < Level_2 < Level_3 < \ldots < Level_q$.

B. RESPONSE ANALYSIS

In basic TM, the goal is to determine the optimal outcome $J = J(L_1, L_2, L_3 \ldots L_m)$ and respective optimal factor levels. After experimentations, i.e., J_1 to J_8 using OA in Table 1, fitness function recursively optimizes by using the analysis of means or variance, as suggested in [6], [27], [29]. In [8], [26], an effective approach is presented to update the factor levels. The levels of each factor are updated in such a way that the best level of that factor will be followed by its remaining levels. Additionally, gradient of fitness function J with respect to factor is used in [26] to determine the direction and amount to be adjusted.

C. LIMITATIONS OBSERVED IN AVAILABLE VARIANTS OF TM

From existing variants of TM [6], [8], [26], it may be observed that the levels of factors are updated, by following the mean response of corresponding factor, in the same cycle. However, the responses observed in previous cycles have been ignored. In the proposed work, the levels of factors are updated by tracing their behavior in the previous iterations. The suggested correction will improve the diversity and global searching ability of the method. In this paper, two basic improvements are suggested in response analysis of TM. These improvements along with systematic steps of modified Taguchi method are discussed in following sections.

IV. MODIFIED TAGUCHI-BASED APPROACHES

In this section, two modified Taguchi-based approaches are proposed. As an improvement-I, the levels of each factor will be updated by following the best mean response of their respective levels, observed in previous iterations/cycles. The correction will help the TM to keep track of best responses experienced by factors in previous iterations, unlike local response analysis in [6], [8], [26]. The suggested correction is expected to improve the global searching ability of the method.

It has been analyzed that the Taguchi-based optimization techniques suggested in [8], [26] show promising local searching ability. In these methods, the best level of a factor is followed by its remaining levels, in same cycle. To understand it better, three possible trends of mean responses over two levels are presented in Fig. 2. From this figure, the average minimum and maximum response values for factor-1 are observed at level-1 and 2 respectively. For fitness maximization problems, the level-1 will be updated towards or followed the level-2 [8], [26]. Similarly, the level-1 will be followed by the level-2 in case of factor-3. The levels of factor-2 are same in this case, therefore randomly updated.

In improvement-II, the suggested improvement-I is combined with the Taguchi-based approaches suggested in [8], [26] to also improve the local searching ability of the method. The proposed modified variants of TM are discussed in following sections.

A. PROPOSED TAGUCHI-BASED APPROACH–I

The essential steps of TM and suggested improvement-I, in response analysis, are systematically presented in this

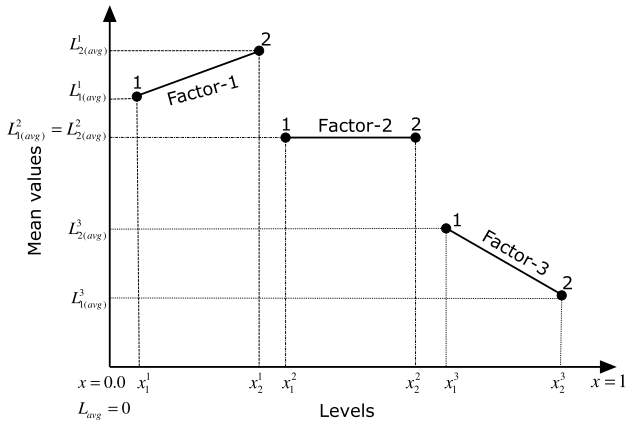

FIGURE 2. Three different trends of two levels factors.

section. For easy understanding, some examples are also adopted.

Step–1 (Parameter Initialization): All the considered m factors are initialized to their respective q $(x_1, x_2, x_3, ..., x_q)$ levels, defined by the user, generally in ascending order and can be presented as matrix $\boldsymbol{Q}^c(q \times m)$ in (24).

$$\boldsymbol{Q}^c = \begin{array}{c} \begin{array}{ccccc} \textbf{Factor}_1 & \textbf{Factor}_2 & \textbf{Factor}_3 & \dots & \textbf{Factor}_m \end{array} \\ \begin{bmatrix} x_1^1 & x_1^2 & x_1^3 & \dots & x_1^m \\ x_2^1 & x_2^2 & x_2^3 & \dots & x_2^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{q-1}^1 & x_{q-1}^2 & x_{q-1}^3 & \dots & x_{q-1}^m \\ x_q^1 & x_q^2 & x_q^3 & \dots & x_q^m \end{bmatrix} \end{array} \begin{array}{l} \\ Level_1 \\ Level_2 \\ \vdots \\ Level_{q-1} \\ Level_q \end{array} \tag{24}$$

For example, five factors shown in Table 1 can be initialized on two levels. Initially, the levels of all factors are equally assumed when these are of same nature, as shown in (25).

$$\boldsymbol{Q}^c = \begin{array}{c} \begin{array}{ccccc} F_1 & F_2 & F_3 & F_4 & F_5 \end{array} \\ \begin{bmatrix} 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \end{bmatrix} \end{array} \begin{array}{l} \\ Level_1 \\ Level_2 \end{array} \tag{25}$$

Similarly, the mean responses of factors on each level can be initialized as matrix $\mathbb{L}^c$. For maximization problems, all elements of $\mathbb{L}^c$ are initially set to zero or vice-versa.

$$\mathbb{L}^c = (Zeros)_{q \times m} \tag{26}$$

Step–2 (Updating the OA Elements): The OA$[\boldsymbol{L}_M(q^m)]$ is updated by replacing the respective levels of each factor by their defined levels in (24). The initialized OA will look like a matrix $\boldsymbol{A}^c$ $(M \times m)$ as

$$\boldsymbol{A}^c = \begin{pmatrix} x_1^1 & x_1^2 & x_1^3 & \dots & x_1^m \\ x_1^1 & x_2^2 & x_2^3 & \dots & x_2^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_q^1 & x_{q-1}^2 & x_1^3 & \dots & x_{q-2}^m \\ x_q^1 & x_q^2 & x_{q-1}^3 & \dots & x_1^m \end{pmatrix}_{M \times m} \tag{27}$$

For example, the OA shown in Table 1, can be updated by using the two levels of factors shown in (25) and can be presented as

$$\boldsymbol{A}^c = \begin{pmatrix} 0.5 & 0.5 & 0.5 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0.5 & 1.0 & 1.0 \\ 0.5 & 1.0 & 1.0 & 0.5 & 0.5 \\ 0.5 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 0.5 & 1.0 & 0.5 & 1.0 \\ 1.0 & 0.5 & 1.0 & 1.0 & 0.5 \\ 1.0 & 1.0 & 0.5 & 0.5 & 1.0 \\ 1.0 & 1.0 & 0.5 & 1.0 & 0.5 \end{pmatrix} \tag{28}$$

Step–3 (Fitness Calculations): In this step, fitness evaluation for each experiment is calculated by using $\boldsymbol{A}^c$ in (27). Each row of this matrix is representing one Taguchi experiment therefore, each row contains the values of factors at which the fitness would be evaluated. The fitness values of M Taguchi experiments can be summarized as

$$\boldsymbol{Fit}^c = (Y_1, Y_2, Y_3, \dots, Y_{M-1}, Y_M)_{1 \times M} \tag{29}$$

Step–4 (Mean Response Analysis): Then the mean responses of all factors at their respective levels are analysed. The mean response of factor z at level r can be expressed as

$$L^z_{r(avg)} = \frac{\sum_{g=1}^{\Re} \eta Y_g}{\Re} \tag{30}$$

$$\eta = \begin{cases} 1, & \text{if } A(g, z) = r \\ 0, & \text{else} \end{cases} \tag{31}$$

where, $\Re = M/q$; further, $\Re$, η, Y_g and $\boldsymbol{A}$ are representing the number of times a level appears in a factor out of M Taguchi experiments, binary decision variable, output/response value in gth Taguchi experiment and OA matrix as shown in Table 1 respectively.

For example, the mean responses for factor F_5 (see Table 1) on each level is expressed as

$$L^4_{1(avg)} = \frac{Y_1 + Y_3 + Y_6 + Y_8}{4}; \quad L^4_{2(avg)} = \frac{Y_2 + Y_4 + Y_5 + Y_7}{4} \tag{32}$$

Similarly, mean responses for other factors are also calculated and generalized for 'm' factors at their 'q' levels in

matrix $\mathbb{L}^c$ as shown below

$$\mathbb{L}^c = \begin{pmatrix} L^1_{1(avg)} & L^2_{1(avg)} & \cdots & L^m_{1(avg)} \\ \vdots & \vdots & \ddots & \vdots \\ L^1_{q-1(avg)} & L^2_{q-1(avg)} & \cdots & L^m_{q-1(avg)} \\ L^1_{q(avg)} & L^2_{q(avg)} & \cdots & L^m_{q(avg)} \end{pmatrix}_{q\times m} \tag{33}$$

Step–5 (Calculate the Direction of Movement): To obtain the direction of next optimal level in upcoming cycle, mean response of each factor on its all levels are compared with their respective best responses in previous cycles, unlike in [8], [26] where, the mean response of each level is compared with the best mean response of that factor in the same cycle. For maximization problem, the directional scaling matrix G^c, $\forall\, r\epsilon q$ and $z\epsilon m$ is defined as

$$G^c(r,z) = \begin{cases} +1, & \text{if } L^c_{avg}(r,z) - L^{best}_{avg}(r,z) > 0 \\ 0, & \text{if } L^c_{avg}(r,z) - L^{best}_{avg}(r,z) = 0 \\ -1, & \text{if } L^c_{avg}(r,z) - L^{best}_{avg}(r,z) < 0 \end{cases} \tag{34}$$

where, r and z are representing the indices of levels and factors of Taguchi design. Besides, $L^c_{avg}(r,z)$ and $L^{best}_{avg}(r,z)$ are representing the mean response of factor z at level r in current cycle and the best response observed in previous cycles respectively

Step–6 (Update the Levels): Using the direction matrix G^c of (34), levels of each factor or elements of matrix Q^c in (24) are updated as follows

$$x^z_r(c+1) = x^z_r(c) + G^c\Delta x, \quad \forall\, r \in q \;\&\; z \in m \tag{35}$$

where, Δx is a small amount of deviation in the levels.

Step–7 (Termination Criteria): Steps 2 to 6 are repeated until convergence is reached. The algorithm is terminated, if $D_P = max(\Delta D^c_z) \leq 10^{-2}$. The vector ΔD^c_z is defined as

$$\Delta D^c_z = \max\left[L^c_{avg}(r,z) - L^{c-1}_{avg}(r,z)\right];\ \forall\, r \in q \tag{36}$$

Steps 5 to 7 can be considered as the suggested corrections in existing variants of TM [6], [26].

B. PROPOSED TAGUCHI-BASED APPROACH–II

It may be observed that the proposed improved Taguchi based approach–I updates the factor levels by tracing their respective best mean performance in previous iterations. Whereas in [8], [26], the levels are updated by following the best level achieved in the same cycle. Therefore, the proposed approach–I is combined with the method of [8], [26] to further improve the local searching performance of TM. The contribution of [26] is inserted between steps 4 and 5 of section IV. Further, the levels are again updated according to steps 5 and 6. In this paper, the proposed approach–II is adopted to solve ODGA problems of distribution systems.

V. MODIFIED TAGUCHI-BASED APPROACHES FOR OPTIMAL DG-MIX INTEGRATION

In this section, the modified Taguchi-based approach proposed in previous section is introduced for ODGA in distribution systems. The aim is to determine optimal sites, sizes and types of DGs for a given distribution system. DG locations and their variable sizes are considered analogous to factors and levels in proposed Taguchi DOE respectively. In order to provide the promising DG nodes to TM as Taguchi factors, a NPL is adopted from [8].

A. TAGUCHI FACTOR SELECTION

The selection of factors have not been explored in available variants of TM. In existing literature [6], [26], [27], [29], the TM is adopted for the problems in which factors are already given or fixed. Therefore, a Roulette Wheel Selection (RWS) criteria based on a NPL is adopted from [8] to select the nodes as factors for Taguchi DOE. The adopted heuristic-based NPL is providing the engineering input to optimization technique to enhance its performance. Generally, node sensitivity list is prepared by penetrating small test size DG at all nodes one-by-one and top few nodes are selected as candidate nodes to reduce the search space [4]–[6]. The major drawback of such approaches is that they completely ignore other nodes which might be optimal. How many top nodes to be selected for the given system are also not specified. Moreover, by changing the test size of DG, the sensitivity order of nodes changes. To overcome these drawbacks, a modified heuristic-based approach is proposed in [8] to prepare the NPL. In this approach, at each node the test size of DG is varied from zero MW to peak demand of the system in small step size and based on best fitness values, expressed in (14), a NPL is prepared off-line, irrespective of DG test size.

In each iteration of modified TM, a RWS technique is applied on this NPL to select required number of DG nodes as Taguchi factors.

B. ODGA USING PROPOSED APPROACH

In this section, the proposed optimization problem for optimal DG integration in distribution systems is solved by using the modified TM combining to RWS-based heuristic NPL discussed in Section V-A. The objective is to determine the optimal sites and sizes of mixed DGs which maximizes the cost function (14) while satisfying various constraints defined in (16) to (23). Here, the number of Taguchi factors will be the number of DGs to be installed in a given system, i.e., m or N_{DG}. The basic steps of the proposed method for ODGA in distribution systems are summarized below. A flowchart is also presented in Fig. 3.

Step–I (Initialization): Set initial values of parameters such as number of factors, m; their levels, q; maximum iterations, Max_{iter}; maximum allowed capacity of single DG, $P^{Max}_{DG_{tp}}$, NPL list; system data, etc.

Step–II (OA selection and construction): Choose and construct an adequate OA design for $m = N_{DG}$ factors and q levels as per the requirements of the user and predefined rules in Section III-A. This is one time and offline exercise for system and objective.

Step–III: Spun the Roulette wheel for N_{DG} times to select N_{DG} nodes from NPL adopted in Section V-A. These selected nodes will be used as Taguchi factors in proposed DOE.

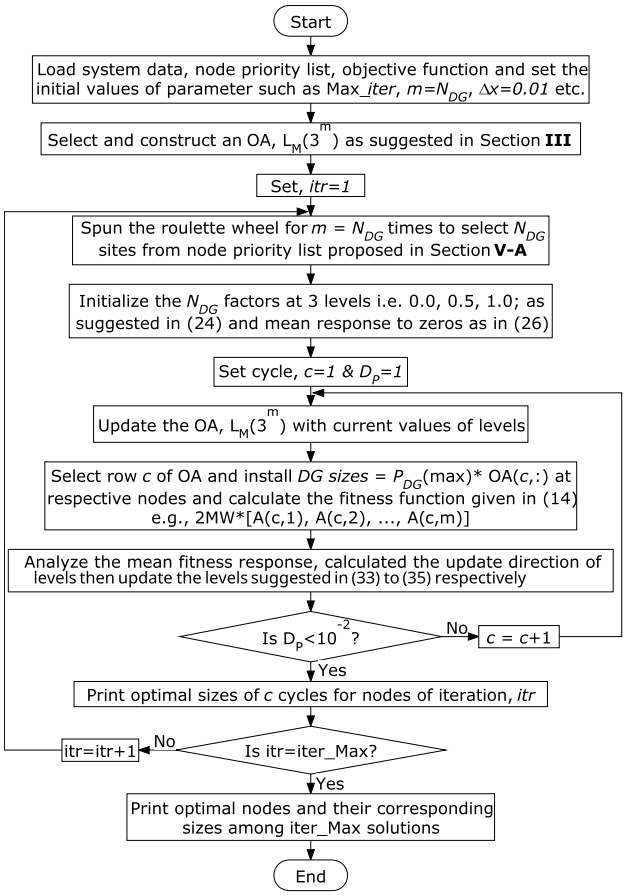

FIGURE 3. Flow chart of proposed improved Taguchi-based approach.

Step–IV: Apply the modified TM suggested in Section IV to determine optimal sizes at selected nodes in step–III. Retain the information of these DG sites and sizes of each iteration.

Step–V: Repeat steps III and IV till the end of prespecified number of iterations, Max_{iter}.

Step–VI: Print the best solution out of Max_{iter} solutions which contains the information of optimal nodes and their respective DG sizes.

VI. CASE STUDY

To demonstrate the effectiveness of the proposed modified Taguchi based approaches, and proposed optimization framework for mixed-DG integration in low carbon distribution systems, these are implemented on two benchmarked test distribution systems, i.e., 33-bus [40] and 118-bus [41] radial distribution systems (RDS), referred as system-1 and system-2 respectively. For better understanding, the case study is divided and presented in three sections namely, case study data and system information, proposed DG integration framework, and validation of suggested modifications in TM. In validation, the proposed DG integration problem is also solved by some of the existing variants of TM [6], [26] and an improve variant of GA [34]. The simulation results are compared to prove the promising searching ability and convergence performance of proposed method over existing variants of TM and meta-heuristic techniques.

TABLE 2. Load levels and energy pricing information for test systems.

Load level	Annual hours of load level, l	Load multiplying factor (%)	Energy Price (USD/MWh)
Light	2000	0.5	55
Nominal	5260	1.0	72
Peak	1500	1.6/1.2*	90

* – the load multiplying factors, in peak load level, used for system-1 and 2 are 1.6 and 1.2 respectively [38].

TABLE 3. Commercial information of DGs used in the proposed study.

Parameter	DE	GE	MT	BM	FC
Turnkey cost ($/kVA)	550	690	915	2293	1900
O&M cost ($/kWh)	0.09	0.009	0.011	0.012	0.005
CO_2 emission (kg/MWh)	650	560	360	003	430
Capacity factor (CF)	0.92	0.92	0.92	0.92	0.92
Power factor (PF)	0.85	0.85	0.85	0.85	1.00

A. TEST SYSTEMS AND DATA

In this section, the data and system information used in this study are presented. In order to reduce the computation burden in planning stage, the annual load is divided into three load levels ($N_L = 3$) namely light, nominal and peak load levels, as suggested in literature [4], [38]. The information of these load levels and energy pricing are presented in Table 2. The other simulation parameter considered in this study can include, life of DGs, $T_d = 20$ years; annual rate of interest, $R_{\text{int}} = 12.5\%$; CO_2 emission from grid energy, $E_{\text{Grid}} = 910$ kg/MWh, and CO_2 tax, $K_{\text{em}} = 10\$/\text{t}$ [19].

The minimum (V_{minS}) and maximum (V_{maxS}) permissible voltages limits are considered as 0.95 p.u. and 1.05 p.u. respectively. The maximum allowed average CO_2 emission intensity considered in this study is, $CO_2^{\text{MaxS}} = 459$g CO_2/kWh [31]. In base case condition (i.e., before DG integration), the minimum bus voltages and power loss of system-1 for light, nominal & peak loading are [0.96, 0.91, 0.85] p.u. and [47.07, 202.67, 575.31] kW respectively. For system-2, it is [0.94, 0.87, 0.77] p.u. and [297.14, 1298.0, 3797.8] kW respectively. The commercial information of various DG technologies is collected from [2], [17], [19], [22], [36] and summarized in Table 3.

In this work, five different types of dispatchable DG technologies have been considered with their CFs [22] as shown in Table 3. To examine the response of each DG type, at least one DG of each type is compulsorily installed in the system. The objective of optimization technique is to find the optimal site and size of different type of DGs. For system-1, optimization is done for five locations, one for each type of DG. For system-2, approximately 10% buses, i.e., 12 locations (2-DEs, 2-GEs,2-MTs, 3-BMs and 3-FCs) are considered for

TABLE 4. Optimal siting and sizing of mixed DG technologies along with technical and social benefits obtained after DG integration in distribution systems.

Systems	Parameters	After DG integration
33-bus RDS	DG type (sites)	DE(1), GE(30), MT(19), BM(12), FC(17)
	DG outputs (MVA)*	(0.252, 0.594, 1.116, 0.279, 0.114)[a]
		(0.576, 1.296, 1.944, 0.666, 0.228)[b]
		(0.900, 1.800, 3.600, 0.900, 0.300)[c]
	Power loss (kW)	(10.06[a], 34.76[b], 116.68[c])
	Min. bus voltages	(0.9867[a], 0.9790[b], 0.9508[c])
	Max. bus voltages	(1.0010[a], 1.0015[b], 1.0030[c])
	Total CO_2 intensity (kg/kWh)	0.410
118-bus RDS	DG type (sites)	DE(5, 36), GE(7, 107), MT(85, 70), BM(53, 34, 75), FC(9, 33, 3)
	DG outputs (MVA)*	(0.126, 0.132, 2.520, 3.840, 0.096, 1.080, 1.512, 0.048, 0.378, 2.400, 0.108, 1.560)[a]
		(0.300, 0.264, 6.000, 4.800, 2.400, 2.700, 0.504, 1.200, 0.900, 2.260, 2.700, 3.900)[b]
		(0.300, 3.300, 6.000, 4.800, 2.400, 2.700, 1.800, 1.200, 0.900, 3.000, 2.700, 3.900)[c]
	Power loss (kW)	(126.36[a], 368.58[b], 504.27[c])
	Min. bus voltages	(0.9789[a], 0.9614[b], 0.9529[c])
	Max. bus voltages	(1.0210[a], 1.0099[b], 1.0092[c])
	Total CO_2 intensity (kg/kWh)	0.435

a = light loading, b = nominal loading, c = peak loading, $*$ = the DG outputs shown are in the same order in which DG sites are presented

TABLE 5. The optimal values of individual objectives and annual profits, before and after DG integration in distribution systems.

Systems	Parameters/functions	Before DG integration, J^{before} (in M$)	After DG integration, J^{after} (in M$)	Individual profits, $J = J^{before} - J^{after}$ (in M$)
33-bus RDS	Objective function, J^{OPR}	26.044	0.486	25.558
	Costs of annual energy loss, J_1	1.596	00.300	01.296
	Annualized DG investment costs, J_2	0.000	04.041	-04.041
	Annual costs of grid energy purchase (excluding loss), J_3	24.137	0.052	24.085
	Annual CO_2 taxes, J_4	0.311	00.134	00.177
	Net annual profit, $J_1 + J_2 + J_3 + J_4$ (in M$)			**21.517**
118-bus RDS	Objective function, J^{OPR}	144.916	3.244	141.672
	Costs of annual energy loss, J_1	7.870	2.202	5.668
	Annualized DG investment costs, J_2	0.0	21.766	-21.766
	Annual costs of grid energy purchase (excluding loss), J_3	135.286	0.223	135.063
	Annual CO_2 taxes, J_4	1.760	0.819	0.941
	Net annual profit, $J_1 + J_2 + J_3 + J_4$ (in M$)			**119.906**

DG integration. It may be noted that the number of biomass based DGs is assumed more in order to restrict carbon emission within the specified limit.

B. SIMULATION RESULTS

In this section, the proposed optimization problem of optimal DG-mix in low-carbon energy networks is solved by using proposed Taguchi based approach. The simulation results of optimal DG-mix allocation are presented in Table 4. As discussed earlier, the optimal sites, sizes of mixed DG technologies are determined in Stage-1. The DG sizes during peak load hours are representing the original installation sizes of respective DG technologies. The maximum hosting capacity of dispatchable DGs (98.67% of peak demand) is achieved without violating the system constraints. In future, high DG penetration will allow DNOs to operate PDNs in islanding mode in case of emergency events. For system-1, the optimal mixing of various installed DGs such as DEs, GEs, MTs, BMs and FCs are about 12%, 24%, 48%, 12%, and 4% respectively. For system-2, it is about 10.90%, 32.73%, 15.45%, 11.82% and 29.09% respectively.

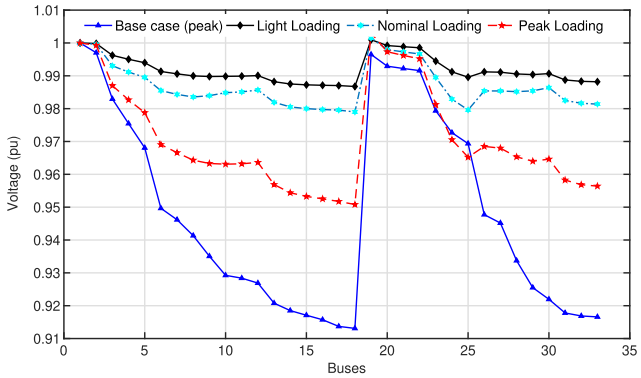

FIGURE 4. Node voltage profile of system–1, after DG allocation.

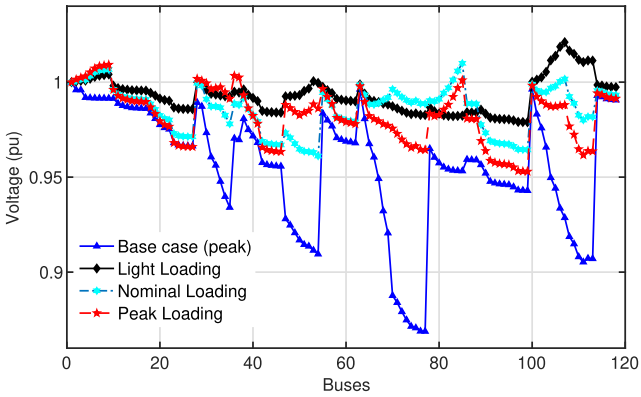

FIGURE 5. Node voltage profile of system–2, after DG allocation.

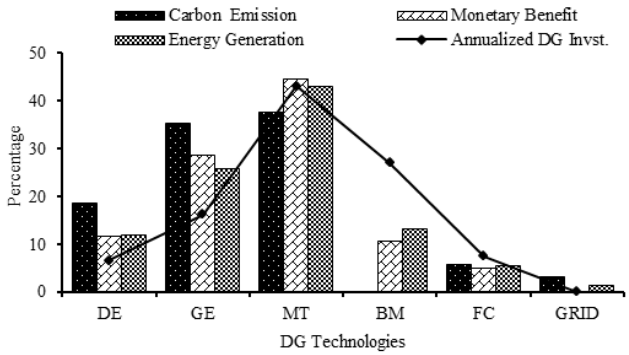

FIGURE 6. Share of different DG technologies in various objectives (system-1).

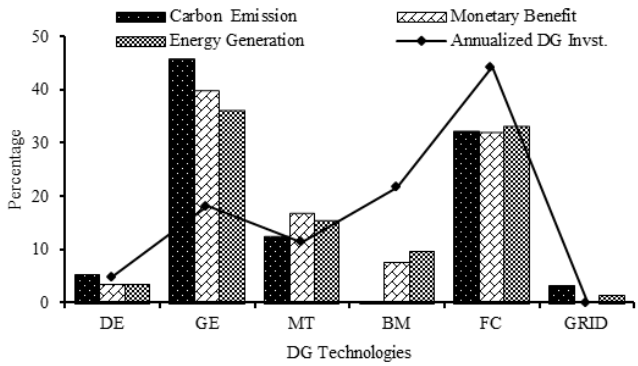

FIGURE 7. Share of different DG technologies in various objectives (system-2).

At present, the traditionally designed PDNs do not have technical abilities (e.g., protection system) to export power back to main grid however it could be possible in near future with enabling technologies. Therefore, the optimal dispatch of each installed DG, at each load level, is determined in Stage-2 to increase the operational benefit J^{OPR}. The simulation results of Stage-2 are shown in Table 4. It can be observed that significant amount of power loss reduction is achieved, at all load levels, for both the systems although the proposed problem deals with multiple objectives. In both test systems, all node voltages are found to be within specified limits which can be verified from Table 4. The node voltage profiles of system-1 & 2 are also shown in Figs. 4 & 5, over three load levels, respectively. Furthermore, the results show that no system is violating the annual average CO_2 emission intensity limit defined in (23). Table 5 shows various annual monetary benefits achieved from optimal DG mix approach. It shows that the maximum benefit is achieved by optimizing the annual energy purchase from DGs and main grid.

Figs. 6 and 7 show the annual percentage share of energy generation, carbon emission, monetary benefit and DG investment of various DG technologies for systems 1 & 2 respectively. For 33-bus system, it may be observed that the shares of MTs and GEs in all above mentioned factors are high due to their comparatively low installation and running costs. The investment cost of DE is also less but still its share is low due to high running and emission costs. Similarly, BM and FC also have less sharing due to high initial investment cost in-spite of less running cost and emission. For system-2, the number of renewable DGs (i.e., BMs and FCs) is more as compared to systems-1. The share of FCs is increased in system-2 due to less installation and running costs as compared to BM based DGs. The annual share of MTs is also reduced due to mutual advantages from BM and GE based DGs. The share of GEs is increased due to their less investment and running cost in-spite of high carbon emission, which have been compensated by BM based DGs. Therefore, the proposed DG-mix model and strategies, considering pros and cons of various DG technologies, maximize the total annual benefits of both DNO and DGO.

For system-1, Fig. 6 shows that the annualized DG investment line is below the maximum monetary benefit for all DGs (benefit-to-cost ratio is more than unity), except BMs and FCs. The same is also true for system-2 that can be observed from Fig. 7. The BM and FC based DGs are proved to be less economical due to their high investment costs. However, in future, the advancement in technologies may reduce various investment costs and increase the share of such DGs. As observed from Fig. 7, the benefit-to-cost ratio of DE investment in system-2 is also less than unity. The maximum power generation from DEs is found to be in peak load hours,

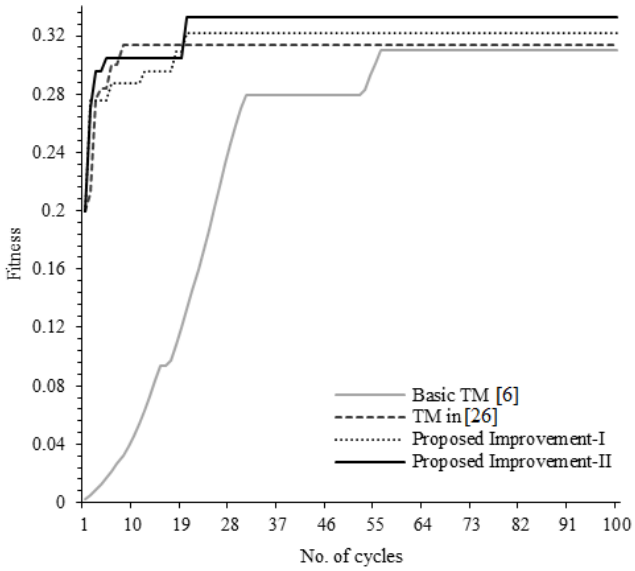

FIGURE 8. Convergence characteristics of different variants of TM.

as observed from Table 4. High running and emission costs are limiting the penetration of DEs thereby less preferred for large systems. The proposed optimization framework, aiming to integrate mixed-DGs in low carbon energy networks, is effectively optimized the mixing of energy fuels.

C. VALIDATION OF SUGGESTED IMPROVEMENTS IN TM

In order to validate the suggested improvements in standard TM, the performance of proposed approach is compared with basic TM and other available variants in existing literature. Fig. 8 shows the effect of suggested modifications on the convergence characteristic of TM. It may be observed that the standard TM [6] shows poor convergence and searching ability. Though, the method of [26] shows fast convergence in comparison to TM but unable to search the global optima. In proposed method, the suggested modifications have made significant improvement in the performance of TM as compared to its existing variants [6], [26]. Among these, the proposed approach-II shows promising global solution searching ability. To demonstrate the searching ability of proposed method over AI-techniques, the ODGA optimization problem of stage-I, i.e. planning, is also solved by an improved variant of GA [34].

It has been found that the GA requires high population size of 500 and 1000 for system-1 & 2 respectively to achieve the fitness close to that of proposed approach-II. Some of the performance parameters of these methods are summarized in Table 6 such as values of best fitness, worst fitness, mean fitness, standard deviation (STD) and average number of fitness evaluated (ANFE) to obtain the optimal solution. The ANFE may found to be a better measure than CPU time since it is not depending on system configuration or platform. The table shows that the proposed approach is capable to solve constrained ODGA problem in less ANFE as compared to GA. The approach takes only 9357 and 44066 ANFE

TABLE 6. The comparison of optimal values of objective function, J^{ODGA}, obtained by proposed approach and GA in 100 runs.

Parameters	33-bus RDS		118-bus RDS	
	GA	TM-II	GA	TM-II
Best fitness	0.3233	0.3327	1.5014	1.5050
Mean fitness	0.2125	0.3145	1.4479	1.4692
Worst fitness	0.1549	0.2890	1.2655	1.4324
STD	0.0544	0.0081	0.0411	0.0122
ANFE	26489	9357	72043	44066

whereas; the GA takes 26489 and 72043 ANFE for systems 1&2 respectively. Moreover, the proposed approach performs better as compared to improved GA in terms of best fitness, mean fitness, worst fitness and standard deviation. The optimal type-sites(sizes in MVA) obtained by GA for system-1 are as follows DE-9(0.34), GE-15(0.67), MT-28(2.54), BM-2(1.52), FC-19(2.13). Similarly for system-2, these are DE-90(2.97), DE-54(1.01), GE-108(4.27), GE-28(2.84), MT-31(3.96), MT-7(4.37), BM-56(0.67), BM-66(3.03), BM-52(1.37), FC-42(1.53), FC-75(2.46), FC-78(4.82).

VII. CONCLUSION

In this research work, a simple but powerful optimization method is proposed to solve the real-life engineering optimization problems. The method employs statistically designed Taguchi OA that recursively optimize the linear or nonlinear objective function in just a few number of experiments, as compared to meta-heuristic methods. The case study demonstrated that, the standard TM has some inherent limitations such as slow convergence and tendency to converge at suboptimal solutions. In order to overcome such limitations, some improvements are suggested in standard TM, without changing its internal mechanism, as summarized here.

1) Two response-analysis techniques have been suggested to update the levels of factors after each cycle of the method. The technique carefully modeled the behavioral dependencies of each level of factors on objective function and then suggested the new updates to enhance the global search ability of TM.
2) In proposed improvement-I, global reference is provided to each factor by considering their responses in previous iterations, unlike existing approaches. The global searching ability of the method has been improved.
3) In proposed improvement-II, the suggested improvement-I is effectively combined with one of the existing variant of TM in which factors are updated by following their own behavior in same cycle followed by an estimated gradient. The performance of TM is further improved.
4) To retain the fast computational ability of TM, the adopted heuristic node priority list based on RWS

criterion has effectively selected the most likely DG nodes, as Taguchi factors, in minimum time.

The performance of the proposed approach is also compared with one of the improved variants of GA. The comparison shows that the proposed approach determines near-global solution in less number of experiments as compared to meta-heuristic technique. The proposed method is parameter free and less dependent on initial values of variables. It can solve the complex optimization problems faster than population based AI-techniques e.g., GA.

On the other hand, a new optimization framework is developed for optimal planning of future low carbon distribution networks comprised of diversified dispatchable DG technologies. The proposed model considers some of the ongoing regulatory frameworks, aiming to minimize the carbon emission caused by DNO activities, especially, in United Kingdom (i.e. EU emission performance standard [31], [32] and Ofgem [30], [33]). The simulation results show that the proposed model is able to meet the EU emission reduction goals which limits the annual average carbon emission below 450g/kWh until 2044. It has been found that optimal DG-mix approach is better suited to solve technical, economic and environmental issues of deregulated power system.

In future, the proposed objective function may be extended to solve the ODGA problems considering uncertainties of solar, wind, load, fuel prices, etc. Furthermore, the improved Taguchi approach may be used for active network management of PDNs, as it requires less number of experiments to search the global optima.

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