Techno-Economic and Environmental Based Approach for Planning of SDG and DSTATCOM with Impact of Network Reconfiguration using APSO and TLBO

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Abstract

A Multi Objective based Fitness Function (MO_{FF}) is proposed for the optimum planning of multiple Solar Distributed Generation (SDG) and DSTATCOM with radial distribution network (RDN) reconfiguration impact for techno-economic and environmental benefit improvement. The Adaptive-Particle Swarm Optimization (APSO) and Teaching-Learning Based Optimization techniques (TLBO) are employed to accomplish this work. In the proposed MO_{FF}, the Active Power Loss (AP_{Loss}), Reactive Power Loss (RP_{Loss}), System Voltage Deviation (SV_D), Fault-Current

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Level-of-Line (FCL_{Line}), and System Service Reliability (SS_R) are considered. The economic-benefit measures along with Environmental Emissions Components (EEC) impact have also been considered in light of various system costs such as Fixed Capital Recovery Cost (FCR_{Cost}), Energy Loss Cost (EL_{Cost}) and Energy Not Supplied Cost (ENS_{Cost}). The novelty in the MO_{FF} is the simultaneous consideration of FCL_{Line} with AP_{Loss}, RP_{Loss}, SV_D, and SS_R along with EEC impact calculation. The IEEE 69 and 118 bus RDN is considered with three case studies to demonstrate the proposed methodology's usefulness. The result analysis reveals that better performances can be obtained based on the considered MO_{FF} in terms of environment-friendly techno-economic perspective, consistency, convergence, and computation time using TLBO rather than APSO.

Keywords: Solar-distributed generation, distribution STATic COMpensator, tie-switch, environmental emission components, adaptive-particle swarm optimization, teaching-learning based optimization.

List Abbreviations

SDG	Solar-Distributed Generation
DSTATCOM	Distribution STATic COMpensator
RDN	Radial Distribution Network
TS	Tie-Switch
APSO	Adaptive-Particle Swarm Optimization
TLBO	Teaching-Learning Based Optimization
AP_{Loss}	Active Power Loss
RP_{Loss}	Reactive Power Loss
SV_D	System Voltage Deviation
FCL_{Line}	Fault-Current Level-of-Line
SS_R	System Service Reliability
EEC	Environmental Emissions Components
FCR_{Cost}	Fixed Capital Recovery Cost
EL_{Cost}	Energy Loss Cost
ENS_{Cost}	Energy Not-Supplied Cost
IAP_{Loss}	Index of Active Power Loss
IRP_{Loss}	Index of Reactive Power Loss
ISV_D	Index of System Voltage Deviation
$IFCL_{Line}$	Index of Fault-Current Level-of-Line
ISS_R	Index of System Service Reliability

MO_{FF} Multiple Objective based Fitness Function
P_{SDG} Active Power generated from SDG
Q_{DSTAT} Reactive Power generated from DSTATCOM

1 Introduction

The distribution system is one of the vital parts of the power system. But nowadays, innovations in every area are rapidly increasing worldwide. These innovations and their mobilization in the society, increases the electricity demand for the distribution system. It causes severe techno-economic and environmental issues: power loss, poor voltage profile, lousy service reliability, economic loss and increased environmental emissions owing to many equipment failures. Hence, to meet the increased electricity demand, the different types of Distributed Generations (DGs) can be integrated by addressing the techno-economic and environmental issues.

The numerous DGs and their technology are discussed in [1]. The Backwards-Forward Sweep Load Flow Analysis (BFS-LFA) technique is explained in the literature [2] and [3]. In [4], Mixed Integer Non-Linear Programming (MINLP) was utilised in DG allocation for 33-bus and 69-bus IEEE RDN to reduce AP_{Loss} & SV_{D}. The APSO and TLBO are illustrated in [5] and [6], respectively. Researchers provided several methods for DG allocation-planning in the distribution system [7–9]. The many technologies that can be used in DGs to generate renewable energy close to the user side are listed in [10]. In [11–14], the authors have proposed optimal DG planning using the PSO, Bat Algorithm (BA) and Genetic Algorithm (GA) and their comparative analysis. The author of [15] introduces the minimization of loss and reliability indices as a goal via appropriate RDN reconfiguration. DGs are characterized in [16] according to how much power they inject. The different LFA techniques and IEEE test systems data are provided in [17]. The reconfiguration planning for 33-bus and 69-bus IEEE RDN has been completed in [18, 19] using GA and PSO. The many DG type concepts and how they are implemented utilising various ways to enhance system components are covered in [20–23]. The [24–27], provides an explanation of the planning of grid-connected and standalone hybrid renewable systems, including SDG and wind systems. In [28], a fuzzy-logic-based Non-dominant Sorting Genetic Algorithm NSGA-II (ENSGA-II) approach is used to maximise the network's economic, technological, reliable, and environmental features. In contrast, in [29], using the Immune Algorithm (IA), the best position and size for DSTATCOM are obtained with less power loss, lower installation costs for DSTATCOM, and better bus voltage and current profiles. The best possible strategic planning for solar, batteries, and FACTS devices has been provided in [30, 31]. To reduce losses and total harmonic-distortion in voltage, DG planning has been done using an Evolutionary Algorithm (EA) [32]. The literature [33] explains reconfiguration planning with DG of a 33-bus and 69-bus IEEE RDN using the Mixed Integer Linear Programming (MILP) considering ZIP load model. In [34], a $\mathrm{QP}_{\mathrm{Loss}}$ reduction planning approach for 69-bus IEEE RDN has been presented by optimally incorporating DGs and capacitors. In the 94-bus Portuguese practical RDN, the optimum sizing and placement of DGs have been implemented, where the noted results show that the $\mathrm{AP}_{\mathrm{Loss}}$ and SV_{D} decreased to 77.82%, and 9.68%, respectively [35]. In [36], by taking into account the seasonal-variation of load and DGs based on the objective to reduce the SV_{D}, SS_{R}, and economic benefit with reduction in $\mathrm{AP}_{\mathrm{Loss}}$ and greenhouse gas emission. The DGs have been implemented in an optimized reconfigured 33-bus and 69-bus IEEE RDN using hybrid PSO and Dragonfly Algorithm (DA). The [37] aims to enhance the 33-bus and 69-bus IEEE RDN planning via network reconfiguration and DG integration. This has been done to reduce the loss and improve the considered system quality of solution through data dispatch using Water Cycle Algorithm (WCA). The protective devices coordination planning with reconfiguration and DG integration has been carried out to reduce $\mathrm{AP}_{\mathrm{Loss}}$ and SV_{D}, using Firefly Algorithm (FA) and EA for 33-bus, 69-bus, and 118-bus IEEE RDN, respectively, in [38]. In [39], 33-bus and 69-bus IEEE RDN with a real 83 bus system have considered reducing the annual energy loss by decreasing SV_{D} and $\mathrm{AP}_{\mathrm{Loss}}$ using intelligent search-based TLBO (IS-TLBO) via reconfiguration with DG planning. The analysis for planning and operation of DGs, DSTATCOM, capacitor, and renewable resources has been carried out for various distribution networks using different optimization techniques [40–44]. In [45], the author has proposed a grid-connected hybrid micro-grid analysis with the impact of PE_{F}.

The above literature's state-of-the-art review reveals that the distribution system experiences significant techno-economic and environmental issues such as $\mathrm{AP}_{\mathrm{Loss}}$, $\mathrm{RP}_{\mathrm{Loss}}$, SV_{D}, lousy SS_{R} and poor fault current tolerance capability, i.e., high $\mathrm{FCL}_{\mathrm{Line}}$ with huge EEC and cost. It causes the distribution system suffers from deprived service quality. Therefore, to improve the service quality of the distribution system, the $\mathrm{AP}_{\mathrm{Loss}}$, $\mathrm{RP}_{\mathrm{Loss}}$, SV_{D}, EEC and cost parameters are needs to be minimized with enhanced SS_{R} and $\mathrm{FCL}_{\mathrm{Line}}$. It has also been noticed that none of the work in existing literatures had considered all these technical issues simultaneously as objectives for addressing the service quality of the distribution system. Hence, this is the motivation factor behind this proposed work with all these issues as novel MO_{FF}. Therefore, in this work, the optimum planning of multiple SDG and DSTATCOM with reconfiguration impact for techno-economic and environmental benefit improvement is carried out efficiently using the APSO and TLBO techniques based on the considered MO_{FF}.

Hence for the analysis, three case studies have been presented, (i) Proposed Study-0 (PS-0): Base case study, it is the case without any modification in the system, (ii) Proposed Study-1 (PS-1): optimum planning of multiple SDG & DSTATCOM, and (iii) Proposed Study-2 (PS-2): optimum planning of multiple SDG & DSTATCOM with RDN reconfiguration impact.

The proposed work of this paper is organized into following five sections: The Introduction and the Modelling of SDG and DSTATCOM are the first and second sections, respectively, of this five-section article. The Proposed Methodology and MO_{FF} is presented in the third part. The fourth and fifth sections are devoted to Results & Discussion, and Conclusion, respectively, which conclude the projected work based on the techno-economic parameter with EEC impact taken into consideration.

The following are the originality and noteworthy contributions reported in this paper:

(1) This paper proposes an innovative MO_{FF} which is comprised of five key technical problems such as AP_{Loss}, RP_{Loss}, SV_D, poor SS_R and high FCL_{Line}, i.e., poor fault current tolerance capability.
(2) In the MO_{FF}, an index for the improvement of tolerance level/capacity of fault (short circuit) current has been taken into account as an FCL_{Line}.
(3) The system's economic viewpoint has taken into account based on different costs: Fixed Capital Recovery Cost (FCR_{Cost}), Energy Loss Cost (EL_{Cost}), and Energy Not Supplied Cost (ENS_{Cost}).
(4) The impact of Environmental Emission Components (EEC): Carbon Dioxide (CO_2), Sulfur Dioxide (SO_2), & Nitrogen Oxide (NO_X) have also been considered as environmental performance parameters.
(5) By using the APSO and TLBO, the MO_{FF} is optimised for the optimum SDG and DSTATCOM allocation while taking into account the effect of network reconfiguration.
(6) The comparative result analysis using APSO and TLBO has been presented to verify the suggested work's techno-economic with environmental emission impact effectiveness for 69 and 118 bus IEEE RDN. The outcomes are also compared with more current published research.

2 Modelling of Solar Distributed Generation and DSTATCOM

Power generation from renewable SDG (P_{SDG}) can overcome power sector dependency on fossil-fuels [23, 24]. The formulas for calculating power output and efficiency are (1) and (2).

$$P_{SDG} = aH\eta^{SDG} \tag{1}$$

$$\eta^{SDG} = \eta^{STC}[1 + \zeta(T^{cell} - 25)] \tag{2}$$

Where P_{SDG} is SDG output power, a is the area of the panel in meter square (m^2), and H is the incident solar-radiation which is measured in watts per square metre (W/m^2). Efficiency is calculated by the η^{SDG} and η^{STC} in predetermined operating circumstances in established test scenarios (STC). The temperature of the cell is T^{cell} in degrees Celsius, and the coefficient ζ is shown as a percentage per degrees Celsius.

The DSTATCOM is considered as a reactive power DG (Q_{DSTAT}) for this work. In (3) and (4), an estimation of the equation for the correction of angle and voltage by DSTATCOM current injection is given [27–31]. After installing DSTATCOM on the $(y+1)^{th}$ bus, the current I_k and I_{DSTAT} flow over the line simultaneously. The DSTATCOM's reactive power injection for the $(y+1)^{th}$ bus voltage correction is shown in (5):

$$\angle I_{DSTAT} = \frac{\pi}{2} + \varepsilon'_{y+1} \tag{3}$$

$$V'_{y+1}\angle\theta'_{y+1} = V'_y\angle\theta'_y - (R_y + jX_y)\left\{I_y\angle\delta + I_{DSTAT}\angle\left(\frac{\pi}{2} + \varepsilon'_{y+1}\right)\right\} \tag{4}$$

$$Q_{DSTAT}^{Injection} = (V'_{y+1}\angle\theta'_{y+1})\left\{I_{DSTAT}\angle\left(\frac{\pi}{2} + \varepsilon'_{y+1}\right)\right\}^* \tag{5}$$

The injected current by DSTATCOM (I_{DSTAT}) and angle change (ε'_{y+1}) will become zero when the voltage is the same after and before installing DSTATCOM in the $(y+1)^{th}$ bus, that is when $V'_{(y+1)} = V_{(y+1)}$.

3 Proposed Methodology & Multi-Objective Fitness-Function

This section includes the formulation of novel MO_{FF} and optimization techniques. The MO_{FF} in (6) comprises significant core technical issues: indices for active power loss (IAP_{Loss}), reactive power loss (IRP_{Loss}), system voltage deviations (ISV_D), system service reliability (ISS_R) and Fault-Current Level-of-Line ($IFCL_{Line}$), respectively.

$$MO_{FF} = \beta_1 \times IAP_{Loss} + \beta_2 \times ISV_D + \beta_3 \times IRP_{Loss} + \beta_4 \times IFCL_{Line} + \beta_5 \times ISS_R \quad (6)$$

The modelling of indices for the formulation of the novel MO_{FF} are as follows:

$$IAP^{\delta}_{Loss} = \frac{AP^{\delta}_{Loss}}{AP^{\rho}_{Loss}} \quad (7)$$

$$IRP^{\delta}_{Loss} = \frac{RP^{\delta}_{Loss}}{RP^{\rho}_{Loss}} \quad (8)$$

$$ISV^{\delta}_{D} = max\left(\frac{\Delta V^{\delta}}{v_{ref}}\right) \quad (9)$$

$$IFCL^{\delta}_{Line} = \frac{FCL^{\delta}_{Line}}{FCL^{\rho}_{Line}} \quad (10)$$

$$ISS^{\delta}_{R} = \frac{Total\ MVA\ Intrupted\ Power^{\delta}}{Total\ MVA\ Intrupted\ Power^{\rho}} \quad (11)$$

The system cost parameters (FCR_{Cost}, EL_{Cost}, and ENS_{Cost}) are defined as [11]:

$$FCR_{Cost} = \mu \sum_{BR=1}^{N^{BR}} C^{BR} \quad (12)$$

$$EL_{Cost} = 8760 \times C_l \times \phi \times \sum_{BR=1}^{N^{BR}} (I^{BR})^2 \times R^{BR} \quad (13)$$

$$\lambda = 0.15 \times \psi + 0.85 \times \psi^2 \quad (14)$$

$$ENS_{Cost} = C_i \times ENS \quad (15)$$

Where, ρ = Proposed Study-0 (PS-0), δ = Proposed Study-1 & 2 (PS-1 & PS-2), and V = Voltage at each bus. The branch numbers, current of respective branch, BR^{th} branch resistance, main feeders BR^{th} branch cost, the fixed-cost annual-recovery rate, the factor of load, & factor of loss are represented by using the variables N^{BR}, I^{BR}, R^{BR}, C^{BR}, μ, λ, & ψ.

Environmental Emission Components (EEC): CO_2, SO_2, and NO_X have also been considered as environmental performance parameters. It is assumed the grid utility that supplies power to the consumers has conventional generation as thermal power generation; hence the EEC are involved in it. These EEC have a detrimental impact on both the environment and human health. The CO_2, SO_2, and NO_X each have Pollutant Emission Factors (PE_F) of 632.0 g/kWh, 2.74 g/kWh, and 1.34 g/kWh, respectively [45].

$$EEC^{\rho\ or\ \delta} = PE_F \times P_{GRID}^{\rho\ or\ \delta} \tag{16}$$

This work is carried out using APSO and TLBO techniques [5, 6]. The optimal solution of the MO_{FF} can be obtained using APSO and TLBO by initializing the system parameters as swarm and class, respectively. The detailed procedure to find the optimal solution for the presented work using APSO and TLBO based on the MO_{FF} is given in Figure 1.

4 Results and Discussion

The optimum planning of multiple SDG and DSTATCOM with RDN reconfiguration impact using the APSO and TLBO based on the considered MO_{FF} is presented in this work. For the result analysis of this work, the BFS-LFA has been used. The IEEE 69 [17] and 118 [38] bus RDN is considered with three case studies (PS-0, PS-1 and PS-2) to demonstrate the proposed methodology's effectiveness.

4.1 Analysis of 69-Bus IEEE RDN

The obtained results using APSO and TLBO for PS-0, PS-1 and PS-2 are illustrated in Tables 1–5 and Figures 2–5 in a comparative manner. In PS-0, the AP_{Loss} is 0.225 MW, RP_{Loss} is 0.1022 MVAr, maximum SV_D is 0.1908 p.u., FCL_{Line} is 6.6534 kA, and the SS_R is 84.36%, as shown in Table 3 and Figures 3–5. In this case, the CO_2 is 2546.96 kg/h, SO_2 is 11.0422 kg/h, and NO_X is 5.4002 kg/h, as tabulated in Table 5.

In PS-1 using APSO, the three SDG (P_{SDG}) and three DSTATCOM (Q_{DSTAT}) are optimally allocated at buses 51, 50 and 62 with their respective optimal sizes as shown in Table 1. For this implementation, the MO_{FF} is converged and minimized to 0.1094 in 100 trials (T_r) for 100 iterations with an approximate computation time (t_c) of 1083.4572 seconds per T_r.

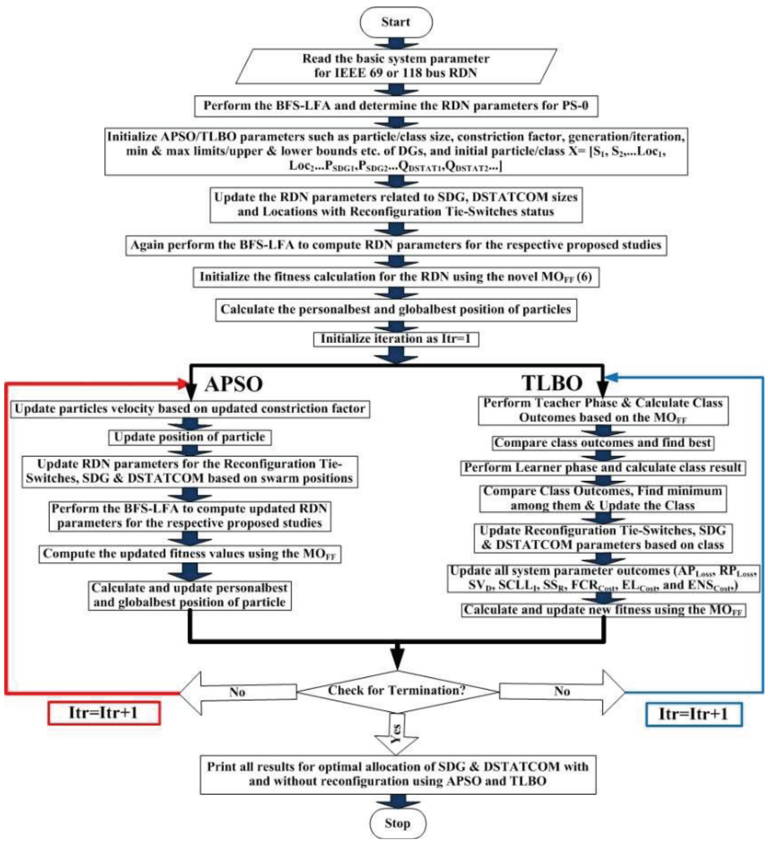


Figure 1 Flowchart for APSO & TLBO.

Hence, it's a global solution of APSO for MO_{FF} optimization, as illustrated in Table 2 and Figure 2(a). The PS-1 result analysis shows that the AP_{Loss} is 0.0168 MW, RP_{Loss} is 0.0081 MVAr, and the maximum SV_D is 0.1217 p.u. In addition, the FCL_{Line} is 0.4234 kA, and the SS_R is 95.97%, demonstrated in Table 3 and Figures 3(a)–5(a). Consequently, the economic benefit characteristics have improved with a reduced total cost of 25129.2262 \$/year, which was 112876.87 \$/year in PS-0. It has been achieved because the FCR_{Cost}, EL_{Cost}, and ENS_{Cost} are reduced to 18230.3271, 5842.7864 and 1056.1127 \$/year, respectively, given in Table 4. The environmental emissions CO_2, SO_2, and NO_X are decreased to 1219.0648 kg/h, 5.2852 kg/h, and 2.5847 kg/h compared to PS-0, i.e., the PS-0 has more influence of EECs as shown in Table 5.

Table 1 Optimal Location and Sizes of SDG and DSTATCOM with Tie-Switch Status in 69 and 118 bus RDN

	P_{SDG} (MW)			Q_{DSTAT} (MVAr)			Optimal Location	Tie-Switch Status (S^1-S^5 for 69-Bus &		
Cases	P_{SDG1}	P_{SDG2}	P_{SDG3}	Q_{DSTAT1}	Q_{DSTAT2}	Q_{DSTAT3}	(Loc)	S^1-S^9 for 118-Bus)	Technique	Test System
PS-0	—	—	—	—	—	—	—	—	—	69-Bus
PS-1	1.04	1.17	1.63	0.45	0.33	1.24	51, 50, 62	—	APSO	
PS-2	1.58	2.23	0.49	-0.31	1.30	0.43	28, 61, 20	1, 1, 1, 0, 1		
PS-1	1.84	0.40	1.50	1.02	0.49	0.28	61, 24, 49	—	TLBO	
PS-2	0.68	1.83	3.40	1.09	1.43	-0.88	11, 62, 4	1, 1, 1, 1, 1		
PS-0	—	—	—	—	—	—	—	—	—	188-Bus
PS-1	2.88	2.63	4.38	7.72	1.75	0.66	29, 74, 50	—	APSO	
PS-2	7.57	0.00	2.41	-0.72	0.61	0.90	7, 118, 111	1, 1, 1, 1, 1, 1, 1, 1, 1		
PS-1	4.64	2.43	2.01	3.79	1.84	3.33	32, 75, 113	—	TLBO	
PS-2	3.52	2.38	7.01	2.40	1.00	1.75	65, 112, 5	1, 1, 1, 1, 1, 1, 1, 1, 1		

Table 2 The MO_{FF} of 69-bus and 118-bus IEEE RDN

Study/ Technique	IAP_{Loss}		IRP_{Loss}		ISV_D		$IFCL_{Line}$		ISS_R		MO_{FF}		Computation Time		Trial Run	
Technique	APSO	TLBO	APSO	TLBO	APSO	TLBO	APSO	TLBO	APSO	TLBO	APSO	TLBO	APSO	TLBO	For Both	Test System
PS-1	0.0749	0.0571	0.0791	0.0738	0.1107	0.0092	0.0636	0.0281	0.2580	0.1987	0.1094	0.0607	1083.4572	978.5176	100	69-Bus
PS-2	0.0426	0.0486	0.0576	0.0585	0.0970	0.0070	0.0604	0.0210	0.2564	0.1224	0.0834	0.0547	1189.8050	1077.5111	100	
PS-1	0.5544	0.3842	0.5148	0.3651	0.0947	0.0445	0.3791	0.5307	0.6003	0.7140	0.4099	0.3504	2208.7320	1707.7821	100	118-Bus
PS-2	0.3243	0.2671	0.3516	0.2394	0.0429	0.0332	0.3519	0.3748	0.5800	0.5971	0.2891	0.2522	2472.1958	2181.1785	100	

Table 3 AP_{Los}, RP_{Loss}, SV_D, FCL_{Line}, and SS_R of both the systems

Study/ Technique	AP_{Loss} (MW)		RP_{Loss} (MVAr)		SV_D (p.u.)		FCL_{Line} (kA)		SS_R in %		Test
Technique	APSO	TLBO	APSO	TLBO	APSO	TLBO	APSO	TLBO	APSO	TLBO	System
PS-0	0.225	0.225	0.1022	0.1022	0.1908	0.1908	6.6534	6.6534	84.36	84.36	69-Bus
PS-1	0.0168	0.0128	0.0081	0.0075	0.1217	0.1053	0.4234	0.1914	95.97	96.61	
PS-2	0.0109	0.0102	0.0059	0.0040	0.1067	0. 1070	0.4018	0.0006	95.99	98.14	
PS-0	1.2981	1.2981	0.9787	0.9787	0.2312	0.2312	22.7339	22.7339	98.33	98.33	188-Bus
PS-1	0.7197	0.4987	0.5039	0.3574	0.1947	0.1445	8.6183	12.0640	99.00	98.81	
PS-2	0.4210	0.3468	0.3441	0.2343	0.1429	0.1332	8.0008	8.5201	99.03	99.00	

Table 4 The FCR_{Cost}, ENS_{Cost}, and EL_{Cost}

Study/ Technique	FCR_{Cost} ($/Year)		EL_{Cost} ($/Year)		ENS_{Cost} ($/Year)		Total Cost ($/Year)		Test
Technique	APSO	TLBO	APSO	TLBO	APSO	TLBO	APSO	TLBO	System
PS-0	18230.3271	18230.3271	78051.833	78051.833	16594.715	16594.715	112876.87	112876.87	69-Bus
PS-1	18230.3271	18230.3271	5842.7864	3795.1948	1056.1127	631.8908	25129.2262	22657.4126	
PS-2	18247.2055	18247.2055	3322.2765	3677.7492	1002.1959	347.8743	22571.6779	22272.8290	
PS-0	33338.9837	33338.9837	450302.7888	450302.7888	56701.8942	56701.8942	540343.6667	540343.6667	188-Bus
PS-1	33338.9837	33338.9837	249649.9576	173002.3069	21495.4521	30089.5192	304484.3934	236430.8097	
PS-2	38151.9331	38151.9331	146030.8638	120290.2567	19955.3341	21250.4248	204138.1310	179692.6147	

Table 5 Environmental Emission (E_E) in PS-0, PS-1, and PS-2 for 69 and 118 bus RDN

	E_E in PS-0 (kg/h)		E_E in PS-1 (kg/h)		E_E in PS-2 (kg/h)		Test
EEC	APSO	TLBO	APSO	TLBO	APSO	TLBO	System
CO_2	2546.96	2546.96	1219.0648	705.4584	473.4312	352.5296	69-Bus
SO_2	11.0422	11.0422	5.2852	3.0584	2.0525	1.5283	
NO_x	5.4002	5.4002	2.5847	1.4957	1.0038	0.7474	
CO_2	15174.32	15174.32	8930.16	8563.60	8310.80	6408.48	188-Bus
SO_2	65.7874	65.7874	38.7162	37.1270	36.0310	27.7836	
NO_x	32.1734	32.1734	18.9342	18.1570	17.6210	13.5876	

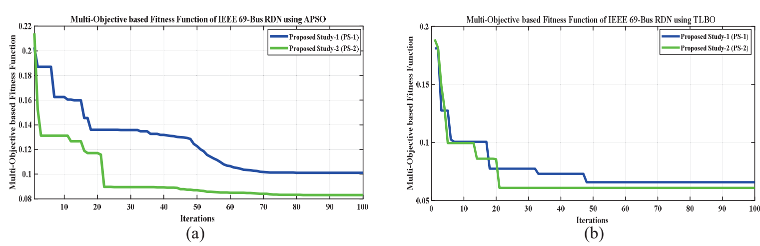


Figure 2 MO_{FF} of the 69-bus IEEE RDN using; (a) APSO, (b) TLBO.

In PS-2 using APSO, the three P_{SDG} and three Q_{DSTAT} are optimally allocated at buses 28, 61 and 20 with the impact of five reconfiguration tie-switches. If any tie-switch (S) is active, then S will be 1; else, 0. The optimal values of P_{SDG}, Q_{DSTAT} and S are given in Table 1. The optimized value

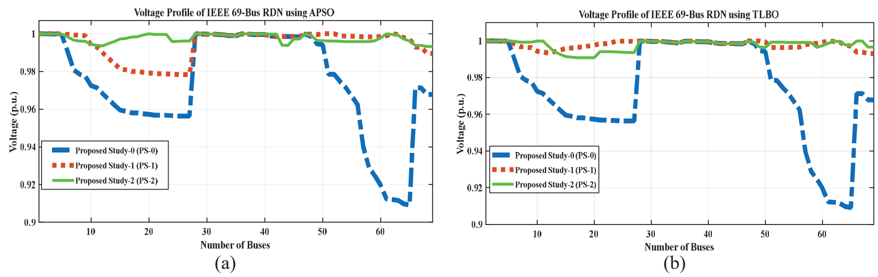


Figure 3 System voltage profile of 69-bus IEEE RDN using; (a) APSO, (b) TLBO.

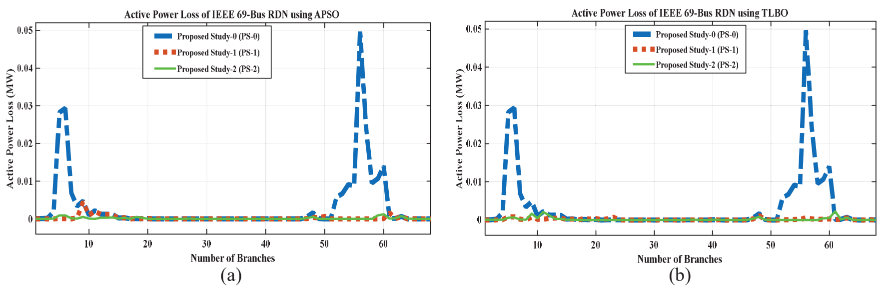


Figure 4 Active Power Loss of 69-bus IEEE RDN using; (a) APSO, (b) TLBO.

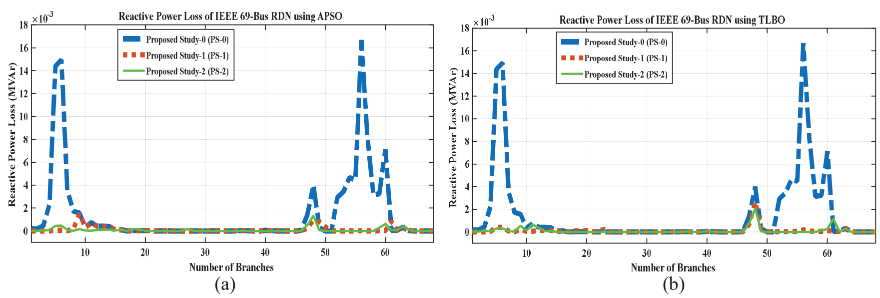


Figure 5 Reactive Power Loss of 69-bus IEEE RDN using; (a) APSO, (b) TLBO.

of MO_{FF} using APSO is converged at 0.0834 in 100 T_r for 100 iterations with an approximate t_c of 1189.8050 seconds per T_r, as illustrated in Table 2 and Figure 2(a). The PS-2 result includes the AP_{Loss} of 0.0109 MW, RP_{Loss} of 0.0059 MVAr, maximum SV_D of 0.1067 p.u., FCL_{Line} of 0.4018 kA, and SS_R of 95.99%, are illustrated in Table 3 and Figures 3(a)–5(a) respectively. Afterwards, the total cost is reduced to 22571.6779 \$/year, which was 112876.87 \$/year in PS-0, which reveals economic benefit improvement. It has been achieved as the FCR_{Cost}, EL_{Cost}, and ENS_{Cost} are reduced to

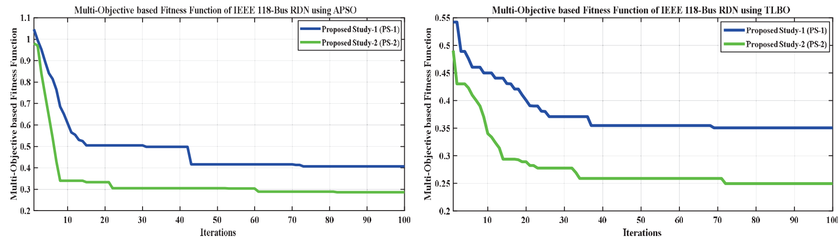
18247.2055, 3322.2765 and 1002.1959 \$/year, respectively, given in Table 4. The production of CO_2, SO_2, and NO_X has also been decreased in PS-2 using APSO with the value of 473.4312 kg/h, 2.0525 kg/h, and 1.0038 kg/h, respectively compared with PS-0 and PS-1 as seen in Table 5.

Similarly, the implementation of PS-1 and PS-2 using TLBO is performed, and its corresponding optimal values for P_{SDG}, Q_{DSTAT}, bus locations and S are tabulated in Table 1. For PS-1, the MO_{FF} is optimized to 0.0607 in 100 T_r for 100 iterations with an approximate t_c of 978.5176 seconds per T_r, as given in Table 2 and Figure 2(b). The PS-1 outcomes reveal that the AP_{Loss} is 0.0128 MW, RP_{Loss} is 0.0075 MVAr, maximum SV_D is 0.1053 p.u., FCL_{Line} is 0.1914 kA, and SS_R is 96.61%, shown in Table 3 and Figures 3(b)–5(b). The cost related to FCR_{Cost}, EL_{Cost}, and ENS_{Cost} are reduced to 18230.3271, 3795.1948 and 631.8908 \$/year, respectively, given in Table 4. Inevitably, the economic benefit has enhanced with a reduced total cost of 22657.4126 \$/year, which was 112876.87 \$/year in PS-0. The reduced EECs such as CO_2, SO_2, and NO_X are 705.4584 kg/h, 3.0584 kg/h, and 1.4957 kg/h, respectively compared to PS-0, which can be seen in Table 5.

Interestingly for PS-2 implementation, the MO_{FF} is optimized to 0.0547 using TLBO in 100 T_r for 100 iterations with an approximate t_c of 1077.5111 seconds per T_r which is a global solution, illustrated in Table 2 and Figure 2(b). The PS-2 results using TLBO include the AP_{Loss} of 0.0102 MW, RP_{Loss} of 0.0040 MVAr, maximum SV_D of 0. 1070 p.u., FCL_{Line} of 0.0006 kA, and SS_R of 98.14%, shown in Table 3 and Figures 3(b)–5(b). Consequently, the economic benefit characteristics have been increased with a reduced total cost of 22272.8290 \$/year, which was 112876.87 \$/year in PS-0. It has been achieved as the FCR_{Cost}, EL_{Cost}, and ENS_{Cost} are reduced to 18247.2055, 3677.7492 and 347.8743 \$/year, respectively, given in Table 4. The production of EECs viz CO_2, SO_2, and NO_X are reduced to 352.5296 kg/h, 1.5283 kg/h, and 0.7474 kg/h, respectively as presented in Table 5. This is because the most percentage of the demand power is supplied by the planned renewable SDGs.

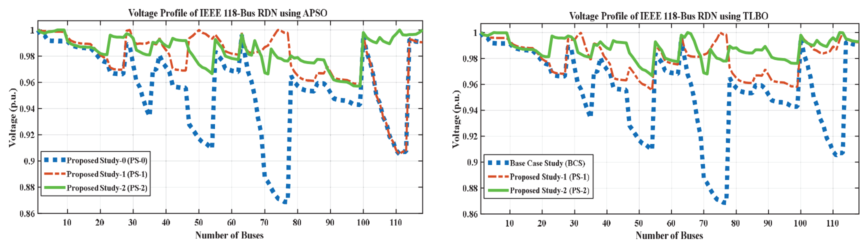
4.2 Analysis of 118-Bus IEEE RDN

The comparative result analysis of 118 bus RDN for PS-0, PS-1 and PS-2 using APSO and TLBO is illustrated in Tables 1 to 5 and Figures 6 to 9. For PS-0, the AP_{Loss} is 1.2981 MW, RP_{Loss} is 0.9787 MVAr, maximum SV_D is 0.2312 p.u., FCL_{Line} is 22.7339 kA, and the SS_R is 98.33%, demonstrated in Table 3 and Figures 7–9. In this case, the CO_2 is 15174.32 kg/h, SO_2 is 65.7874 kg/h, and NO_X is 32.1734 kg/h, as tabulated in Table 5.



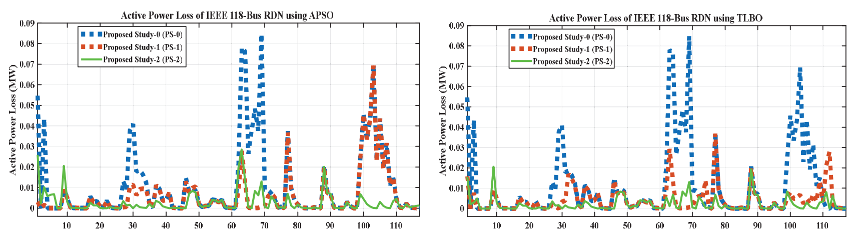
(a) (b)

Figure 6 $\mathrm{MO_{FF}}$ of the 118-bus IEEE RDN using; (a) APSO, (b) TLBO.



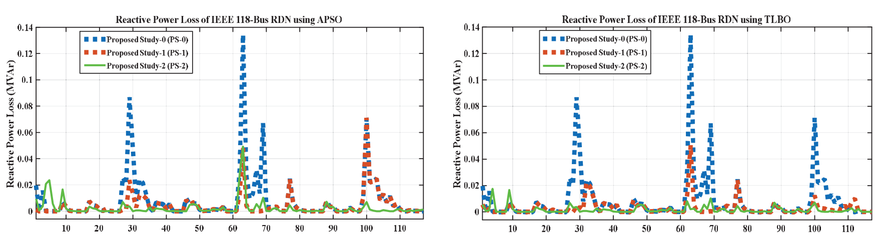
(a) (b)

Figure 7 System voltage profile or system voltage deviation of 118-bus IEEE RDN using; (a) APSO, (b) TLBO.



(a) (b)

Figure 8 Active Power Loss of 118-bus IEEE RDN using; (a) APSO, (b) TLBO.



(a) (b)

Figure 9 Reactive Power Loss of 118-bus IEEE RDN using; (a) APSO, (b) TLBO.

The implementation of three P_{SDG} and three Q_{DSTAT} in PS-1 using APSO are simultaneously allocated at buses 29, 74 and 50 with their optimal sizes, as shown in Table 1. Hence for PS-1, the MO_{FF} is optimized to 0.4099 using APSO in 100 T_r for 100 iterations with an approximate t_c of 2208.7320 seconds per T_r, illustrated in Table 2 and Figure 6(a). With this PS-1 implementation, the AP_{Loss}, RP_{Loss}, maximum SV_D, and FCL_{Line} are reduced to 0.7197 MW, 0.5039 MVAr, 0.1947 p.u., and 8.6183 kA, respectively, mentioned in Table 3 and Figures 7(a)–9(a). In addition, the economic benefit and SS_R have also improved; their related values are given in Table 4. The environmental emissions CO_2, SO_2, and NO_X are decreased to 8930.16 kg/h, 38.7162 kg/h, and 18.9342 kg/h compared to PS-0, i.e., the PS-0 has more influence of EECs as shown in Table 5.

In PS-2 using APSO, the simultaneous optimal placement of three P_{SDG} and three Q_{DSTAT} at 7, 118 and 111 buses are carried out with the impact of nine reconfiguration tie-switches. The optimal values of P_{SDG}, Q_{DSTAT} and S are given in Table 1. The MO_{FF} is optimized to 0.2891 in 100 T_r for 100 iterations with an approximate t_c of 2472.1958 seconds per T_r for PS-2 using APSO. It is clear that this is a global solution of APSO for this MO_{FF} optimization, illustrated in Table 2 and Figure 6(a). These DGs allocations in PS-2 reveal a reduction in AP_{Loss}, RP_{Loss}, and maximum SV_D, with enhanced fault current tolerance capability and SS_R, as illustrated in Table 3 and Figures 7(a)–9(a). In the same instance, the total cost is reduced to 204138.1310 \$/year, as it was 540343.6667 \$/year in PS-0; hence the economic benefit has increased. It's achieved as the FCR_{Cost}, EL_{Cost}, and ENS_{Cost} are reduced to 38151.9331, 146030.8638 and 19955.3341 \$/year, respectively, given in Table 4. The production of CO_2, SO_2, and NO_X has also decreased in PS-2 using APSO with the value of 8310.80 kg/h, 36.0310 kg/h, and 17.6210 kg/h, respectively compared with PS-0 and PS-1 as seen in Table 5.

Similarly, using TLBO, the PS-1 and PS-2 are implemented separately, and their corresponding optimal values for P_{SDG}, Q_{DSTAT}, bus locations and S are tabulated in Table 1. For PS-1, MO_{FF} is optimized and converged at 0.3504 in 100 T_r for 100 iterations with an approximate t_c of 1707.7821 seconds per T_r, illustrated in Table 2 and Figure 6(b). The obtained technical parameters result includes the AP_{Loss} of 0.4987 MW, RP_{Loss} of 0.3574 MVAr, maximum SV_D of 0.1445 p.u., FCL_{Line} of 12.0640 kA, and SS_R of 98.81%, given in Table 3 and Figures 5(b)–7(b). Correspondingly, the economic benefit has increased with the reduction in FCR_{Cost} of 33338.9837, EL_{Cost} of 173002.3069, and ENS_{Cost} 30089.5192 \$/year, respectively, given

Table 6 Comparison of the proposed work with other already-published works of 69-bus and 118-bus RDN

Existed/Work	Method of	69-Bus RDN Loss (kW)		118-Bus RDN Loss (kW)	
Proposed	Optimization	Magnitude	% Reduction	Magnitude	% Reduction
Rahim, M. N. A.,	FA	126.8	43.64	659.17	49.22
et al. [38]	EA	150.4	33.15	712.29	45.12
Kanwar, Neeraj,	TLBO	42.25	81.22	—	—
et al. [39]	IS-TLBO	39.63	82.38	—	—
Proposed	APSO	10.9	95.15	421.00	67.57
Work	TLBO	10.2	95.47	346.80	73.28

in Table 4. The reduced EECs such as CO_2, SO_2, and NO_X are 8563.60 kg/h, 37.1270 kg/h, and 18.1570 kg/h, respectively compared to PS-0, which can be seen in Table 5.

Finally, for PS-2, the MO_{FF} is converged and optimized to 0.2522 value using TLBO in 100 T_r for 100 iterations with an approximate t_c of 2181.1785 seconds per T_r, shown in Table 2 and Figure 6(b). The obtained results include the AP_{Loss} of 0.3468 MW, RP_{Loss} of 0.2343 MVAr, maximum SV_D of 0.1332 p.u., FCL_{Line} of 8.5201 kA, and SS_R of 99.00%, shown in Table 3 and Figures 7(b)–9(b). Consequently, the economic benefit characteristics have improved with a reduced total cost of 179692.6147 \$/year, which was 540343.6667 \$/year in PS-0. It has been achieved because the FCR_{Cost}, EL_{Cost}, and ENS_{Cost} are reduced to 38151.9331, 120290.2567 and 21250.4248 \$/year, respectively, given in Table 4. The production of EECs viz CO_2, SO_2, and NO_X are reduced to 6408.48 kg/h, 27.7836 kg/h, and 13.5876 kg/h, respectively as presented in Table 5. This is because the most percentage of the demand power is supplied by the planned renewable SDGs.

Hence the final proposed work, i.e., PS-2 results using APSO and TLBO, are compared with existing research from the literature [38, 39] in Table 6 and evaluated its efficacy. As a result of this analysis, it is noted that the Table 3 results are significantly better than the existing ones.

5 Conclusion

This paper proposes a techno-economic and environmental based approach for the optimum planning of multiple SDG and DSTATCOM with network reconfiguration impact. The APSO and TLBO techniques are employed to accomplish this work. In the MO_{FF}, the AP_{Loss}, RP_{Loss}, SV_D, FCL_{Line}, and

SS_R of the RDN are simultaneously considered to enhance the service quality of the distribution system. The economic-benefit measures, along with the impact of environmental emission components, have also been addressed in light of various system costs, such as FCR_{Cost}, EL_{Cost}, and ENS_{Cost}. The IEEE 69 and 118 bus RDN are considered with three case studies to demonstrate the effectiveness of the proposed methodology. These three case studies (PS-0, PS-1, and PS-2) results for 69 and 118 bus RDN are presented in the result and discussion section in a close comparative manner for analysis using the APSO and TLBO. In this analysis, the value of AP_{Loss} is 0.0096 & 0.0102 MW, RP_{Loss} is 0.0059 & 0.0040 MVAr, SV_D is 0.1067 & 0.1070 p.u., and SS_R is 95.99% & 98.14%, respectively are achieved using APSO & TLBO for PS-2 of 69 bus RDN. In contrast, the FCL_{Line} is reduced to 0.4018 & 0.0006 kA, which was 6.6534 kA in PS-0 using APSO & TLBO. Consequently, the fault current tolerance capability of the RDN has improved by 93.96% & 99.99%. Similarly, for 118 bus RDN, in PS-2 using APSO & TLBO, the AP_{Loss} is 0.4210 & 0.3468 MW, RP_{Loss} is 0.3441 & 0.2343 MVAr, SV_D is 0.1429 0.1332 p.u., and SS_R is 99.03% & 99.00%, respectively. In contrast, the FCL_{Line} is 8.0008 & 8.5201 kA, which was 22.7339 kA in PS-0 using APSO & TLBO. Consequently, the fault current tolerance capability of the RDN has improved by 64.81% & 62.52%. It has also been noticed that the environmental emissions, total cost, and total power generation for both 69 and 118 bus RDNs have decreased; therefore, the system's environmental and economic benefits have improved. The comparative result analysis reveals that better performances have been achieved based on the considered MO_{FF} in terms of techno-economic and environmental perspective, consistency, convergence, and computation time using TLBO rather than APSO. Hence, the proposed work based on the novel MO_{FF} is superior compared to the existing ones, which signifies the usefulness of this work.

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