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REVIEW PAPERS

Optimal DSTATCOM, PVAs and WTGUs allocation for electrical distribution system performance improvement using improved TLBO

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Abstract The performance of the Electrical Distribution System (EDS) depends on how efficiently it utilizes the distribution lines, provides power flow with minimum losses, and provides a better voltage profile to utilities. The Distribution Static Synchronous Compensators (DSTATCOM) or Distribution Generation (DG) (like number of Photovoltaic Array (PVA) or number of Wind Turbine Generation Unit (WTGU)) play a major role in the EDS system to improve its performance. The right location and right size of DSTATCOM, or DG is a challenging problem for acquiring their maximum possible benefits to improve EDS performance. This paper proposes a constrained generalized multi-objective performance index (MOPI) objective function proposed with EDS performance indices. Improved Teaching Learning Based Optimization (ITLBO) is used by eliminating the convergence issue of basic Teaching Learning Based Optimization (TLBO) to solve the proposed objective function. DSTATCOM, PVAs, and WTGUs are considered for placement and sizing at different locations for EDS performance improvement by optimizing the MOPI objective function with ITLBO. The optimal solution helps to minimize the power losses, enhance the consumer voltage profile and voltage stability, increase the line loadability margin, and reduce the burden of consumer loss allocation in EDS. The performance test is conducted on 33 node EDS and showed the efficiency of the proposed solutions using the MATLAB software.

Keywords Electrical distribution system · Distribution static synchronous compensators · Photovoltaic array · Wind turbine generation unit

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1 Introduction

EDS is the sub-part of the power system infrastructure that delivers electrical power from the high-voltage transmission network to the customers. EDS has a high R/X ratio compared with transmission systems. Due to this, high losses in EDS and intern may lead to voltage instability. In EDS feeders, almost 13% of generated electrical power is wasted due to power losses. Due to all these factors, EDS performance is degrading day by day. The economic and environmental benefits of renewable energy sources are increasing the penetration of renewable DG sources like PV, WTGU, and biomass into EDS. According to the International Energy Agency, energy from renewable sources will reach 37% by 2040. Between 2010 and 2016, the global installed solar and wind capacity rose from 40 to 227 GW (Eia 2015). Along with DGs, EDS DSTATCOMs allocation is more advantages such as branch loss reduction, customer node voltage profile improvement, power quality increase, load balancing, etc.. When compared to available traditional reactive power compensation methods, DSTATCOM has more advantages, including low cost, compact size, fewer power losses, high regulatory capacity, and less harmonic production. From a utility perspective, EDS performance improved in terms of reduced power loss, improved consumer node voltage profile, network upgrading, and reduced peak demand supply from the substation. The optimal allocation of DSTATCOM and DG in the EDS is a challenging topic for power system researchers.

Devi and Geethanjali (2014) proposed sizing for DSTATCOM and DG in the radial EDS. Simultaneous DSTATCOM and DG allocation is used to reduce EDS power loss using the Particle Swarm Optimization (PSO) algorithm. Sanam et al. (2016) utilized the Exhaustive Search Method (ESM) to reduce EDS losses and improve the EDS node voltage profile using DSTATCOM and DG optimum sizing at optimal EDS sites. Kanwar et al. (2015) used improved Cat Swarm Optimization (ICSO) method to obtain global search capabilities. It also optimizes DSTATCOM and DG placement in the EDS. Tolabi et al. (2015) used fuzzy logic and Ant Colony Optimization (ACO) to handle simultaneous network reconfiguration, DG and DSTATCOM allocation. This article aims to reduce power loss, improve the voltage profile, and load balance in the feeder. Chabok and Ashouri (2016) employed discrete imperialistic competition and Nelder-Mead Algorithms to allocate DSTATCOMs in DG's existing EDS. Yuvaraj and Ravi (2018) proposed a bio-inspired Cuckoo Search Algorithm (CSA) method for combining DSTATCOM and DG in the EDS. CSA is used to identify the appropriate size of DSTATCOM and DGs. The objective function for minimizing power loss, reducing operating expenses, and increasing the voltage profile of the EDS was established by Devabalaji and Ravi (2016). The authors used the Loss Sensitivity Factor (LSF) to examine the location of DSTATCOM and DG, and the Bacterial Foraging Optimization Algorithm (BFOA) was proposed to compute the DSTATCOM and DG size. Yuvaraj and Ravi (2017) explore long-term scheduling for DSTATCOM and DG in EDS. This function reduces power loss, improves VSI, and reduces Total Voltage Deviation (TVD) considering equality and inequality constraints. The Lightning Search Algorithm (LSA) was utilized to address the metaheuristic optimization problem for DSTATCOM and DG size. Iqbal et al. (2018) suggested improving the node voltage in active EDS by reducing power losses. Various DGs such as biomass, solar, and wind renewable energy sources are placed in the EDS to reduce losses. However, this approach has not injected any reactive power required by EDS, resulting in numerous nodes exhibiting a poor voltage profile. According to Essallah et al. (2019), the appropriate location of DG depends on the load circumstances. The Sine Cosine Algorithm (SCA) with Chaos Map Theory for optimum multiple DG allocation technique for distribution systems was proposed by Selim et al. (2020). Various authors (Abualigah and Diabat 2021; Wang et al. 2021; Silva Santos et al. 2021; Wang et al. 2020; Singh 2022; Kumar Ram et al. 2022; Padhi et al. 2020) discussed modern optimization algorithm methods where expert analysis was needed to handle the algorithm's specific parameters. The literature review found minimal work on simultaneous placement and size of PVAs, WTGUs, and DSTATCOM to decrease power losses and improve the voltage profile in EDS. The paper aims to improve EDS performance based on different EDS performance indices. No author has observed voltage stability, consumer loss allocation, or line loadability margin in previous research literature.

The output power of PVA and WTGU renewable generation sources mainly depends upon environmental conditions. So proper planning is needed before the allocation of DSTATCOM, PVAs, and WTGUs to EDS. This proposed method presents MOPI minimization optimization using the ITLBO approach and is applied to solve DSTATCOM, PVAs DG, and WTGUs DG allocation problems in the EDS effectively by placing them individually and in combination. ITLBO is used due to the great advantage of the TLBO method where there is no need for the algorithm specific parameters. The objectives of this approach are to increase power loss reduction, maintain a better voltage profile, voltage stability enhancement, line loadability margin improvement, and reduce the customer loss allocation burden. Before placement of DSTATCOM and renewable-based PVA and WTGU DGs in the system, the exact output power needs to be determined because the output power of PVA and WTGU mainly depends upon solar irradiance, temperature, and wind speed of the particular location, respectively. The solar irradiance and wind energy are modelled by selecting the average solar irradiance and average wind speed, respectively. After determining the power output of PVA and WTGU, the best locations are found, and a number of PVAs and WTGUs are placed at the identified locations along with DSTATCOM. This is carried out by ITLBO by optimizing the minimization MOPI objective function. The WTGUs are operating at unity, 0.95 lead and 0.95 lag to observe the performance of the EDS system with DSTATCOM and PVA. Finally, the developed methodology of performance improvement is examined on 33-node EDS test systems.

Further, the paper is subdivided into various sections: Sect. 2 demonstrates EDS performance objectives; Sect. 3

demonstrates multi-objective problem statement; Sect. 4 demonstrates basic TLBO method; Sect. 5 demonstrates the Improved TLBO method; Sect. 6 explains computation method for the size of the PVA panel and WTGU; Sect. 7 gives constraints of the multi-objective function; Sect. 8 explains the complete flow chart for DSTATCOM, PVAs, and WTGUs placement and sizing using ITLBO; and Sect. 9 gives the outcome of the process of simulation and details of comparisons. Finally, we conclude the total work with a summary in Sect. 10.

2 EDS performance objectives

To effectively handle EDs operational performance, a multi-object function with six performance objects is developed. The EDS performance object function objectives (indices) are mentioned below.

2.1 Index for active power losses (IAPL) and index for reactive power losses (IRPL) based on available load

When EDS power losses (via load flow solution (Ramana et al. 2013)) are minimized, the EDS performs optimally. The active and reactive power loss indices based on total active and reactive demands are stated as follows.

$$IAPL = \left(\sum_{pq=1}^{br} P_{loss}(pq) / \sum_{q=1}^{nd} PL(q) \right) \tag{1}$$

$$IRPL = \left(\sum_{pq=1}^{br} Q_{loss}(pq) / \sum_{q=1}^{nd} QL(q) \right) \tag{2}$$

wherebr is total number of branches of EDSnd is total number of nodes of EDS

$\sum_{pq=1}^{br} P_{loss}(pq)$and $\sum_{pq=1}^{br} Q_{loss}(pq)$ are total APL (kW) and total RPL (kVAr).

$\sum_{q=1}^{nd} PL(q)$and $\sum_{q=1}^{nd} QL(q)$ are total active (kW) and reactive (kVAr) load.

For enhancing EDS performance, total EDS losses will be reduced to near-zero IAPL and IRPL values. Reducing of the real power losses improves the system efficiency by transferring the power via EDS lines, where as reducing the reactive power losses helps the system reliability and security.

2.2 Index for node voltage deviation (IVDI)

The EDS node voltage should be kept within the limitations. Voltage variations outside the prescribed limits can cause EDS block out. The voltage deviation index (VDI) measures voltage deviations from defined voltage limits (Rau and Wan 1994).

$$VDI = \sqrt{\sum_{q=1}^{nd} \frac{\left| V(q) - V_{limit} \right|^2}{Nv}} \tag{3}$$

where

V_{limit} is upper limit voltage if the upper limit violation or lower limit voltage if a lower limit violation, $0.925 \le V(q) \le 1.025 p.u.$

$V(q)$ is the voltage at the qth node

Nv Voltage violation nodes

$$\text{Index for Voltage Deviation Index } (IVDI) = VDI \tag{4}$$

The minimizing value of IVDI is the improvement of the voltage profile, which enhances EDS voltage regulation. Optimizing EDS performance will reduce system node voltage variation to zero.

2.3 Consumer loss allocation index based on total APL (ICPL)

End node consumers with large loss allocation burdens must be considered, and any performance improvement approach must always provide the best solution to decrease their loss allocation. Based on the overall system APL (Ramana et al. 2019), the index was created to lower the maximum loss allocation consumer.

$$ICPL = \max_{q=1 to nd} \left(CP_{loss}(q) \backslash \sum_{pq=1}^{br} P_{loss}(pq) \right) \tag{5}$$

where

$CP_{loss}(q)$ is the loss allocation of qth consumer.

The burden of excessive loss allocation to consumers will be decreased using proper EDS objective function optimization, and the ICPL will be near zero.

2.4 Index for VSI (IVSI)

The voltage stability index can be used to calculate EDS voltage stability and take necessary action if the index shows low voltage stability. Thus, stability is required for good operation and to avoid blocking the system (Chakravorty and Das 2001).

$$VSI(q) = V(p)^4 - 4(P(pq)X(pq) - Q(pq)R(pq))^2 - 4V(p)^2(P(pq)R(pq) + Q(pq)X(pq))$$

$$q = 2, 3, 4 \ldots nd \tag{6}$$

where

P(pq) is the active power flow through the branch *pq*.

Q(pq) is the reactive power flow through the branch *pq*.

For secure and stable operation $VSI(q) > 0$ for all the nodes. The node where $VSI(q)$ is found to be minimum is the most sensitive to the voltage collapse. The index of VSI is defined as

$$IVSI = \min_{q=1tond}(VSI(q)) \tag{7}$$

The EDS stability intensity may be evaluated using the IVSI. If the EDS index reveals instability, intervention is necessary. The VSI value is larger than zero if the EDS operates in a stable and secure condition.

2.5 Index for LLM (ILLM)

The EDS branches power flow varies as EDS performance improves. The maximum loading allowed with branch LLM (Yu et al. 2008) is the branch's allowable limit for preventing system instability. The ILLM index in EDS provides information on the minimum loading of LLM from all branches of LLMs.

$$ILLM = \min_{pq=1tobr}\left(\frac{LLM(pq)}{LML(pq)}\right) \tag{8}$$

To operate the EDS system with high LLM values and use the existing lines to handle future load growths, the ILLM value must be increased.

3 Defining the EDS performance improvement multi-objective optimization problem

The multi-objective performance index (MOPI) of the EDS is calculated by including the individual objective functions. The MOPI has multiple indices presented to optimize EDS and enhance the performance of EDS. The largest values of IVSI and ILLM are to enhance voltage stability and line loadability such that all the line flows should be within their permissible limits for accepting the additional load growth of EDS, respectively. The lowest values of IAPL, IRPL, IVDI, and ICPL are to reduce APL and RPL, improve the voltage profile, and reduce the loss allocation to the consumer of the EDS. For good performance of EDS, the individual objectives are normalized between zero and one. Individual objectives are given weighting factors to form a single objective optimization problem.

The optimization used by MOPI is given by

$$MOPI = w_1.IAPL + w_2.IRPL + w_3.IVDI + w_4.ICPL + w_5.\left(\frac{1}{IVSI}\right) + w_6.\left(\frac{1}{ILLM}\right) \tag{9}$$

where

$$\sum_{s=1}^{6} w_s = 1 \cap w_s \in [0, 1]$$

The weighting factors are decided by planners and designers of EDS and play a very important role in the multi-objective problem. In the proposed technique, IAPL is the objective function first part inward with an important weighting factor of 0.25. The objective function's second part is the IRPL, which receives 0.15 as a weight factor. Because of the system's consumer voltage profile, the IVDI is given a weighting factor of 0.15. The ICPL receives 0.2 as the fourth objective function to examine the loss allocation load to the consumer. The inverse of IVSI is given a value of 0.10, indicating whether the system is operating away from the voltage collapse point. The information concerning line loadability is given by the inverse of ILLM, which receives 0.15. The ITBLO algorithm must be simulated in order for the teaching–learning process to traverse the feasible region and reach its limit in the search space. The goal of the problem formulation is to minimize the MOPI function while meeting voltage and power constraints.

4 TLBO algorithm

Teaching–learning is an essential preparation where each student prepares to become proficient in something from other students to upgrade themself. Teaching–Learning-Based Optimization (TLBO) (Rao et al. 2011) introduces the conventional classroom teaching–learning process. The algorithm mimics two essential modes of process: (i) knowledge from the teacher (called as the teacher phase) and (ii) knowledge exchange between learners (called as the learner phase). TLBO method is basically a population-based optimization, where a group of learners (i.e., students) are taken from the population and the distinctive subjects considered to the learners closely resembling the various design parameters of the optimization objective function (problem). The results of the learner closely resemble the solution of the optimization objective function (problem). The best solution of TLBO in each iteration is considered as a teacher. TLBO method is used common control parameters such as population, number of iterations and there is no need of any optimization execution specific parameters as required in meta-heuristic optimization techniques which needs better tuning for global optimization solution (for Genetic Algorithm (GA) (Cus and Balic 2003) needs selection, crossover and mutation probabilities, and PSO (Kennedy and Eberhart 1995) needs inertia weight, social and cognitive parameters). Various stages of TLBO described below.

4.1 Teacher phase

This is the first part of TLBO where learners acquire knowledge from a teacher. Teacher always tries to enhance the classroom mean result depends on the teacher capability of the subject taught. At iteration k, s is number classroom subjects (i.e. design variables $v = 1, 2, \ldots, s$) with subject (each) score as X_v, l is learners (i.e. size of population $p = 1, 2, \ldots, l$), mean of class $M_{v,k}$ in v subject during the iteration k and the best result of the all learners for all subjects in the overall population is $X_{v,pbset,k}$. Efficient learner is observed as a teacher who shared the knowledge to learners at maximum extent. The difference between teacher of all subjects to the available mean of individual subject is computing by

$$\begin{aligned} Diff\_Mean_{v,k} &= r_k \times \left[X_{v,pbest,k} - T_{F,k} \times M_{v,k}\right] \mathrm{Diff\_Mean_{s,p,t}} \\ &= \mathrm{r_t} \times \left[\mathrm{X_{s,pbest,t}} - \mathrm{T_F} \times \mathrm{M_{s,t}}\right] \mathrm{Diff\_Mean_{s,p,t}} \\ &= \mathrm{r_t} \times \left[\mathrm{X_{s,pbest,t}} - \mathrm{T_F} \times \mathrm{M_{s,t}}\right] \end{aligned} \tag{10}$$

where

$T_{F,k}$ is teaching factor i.e., 1 or 2.

Teaching factor is computing via

$$T_{F,k} = round\left[1 - r_k\right] \mathrm{T_F} = \mathrm{round}[1 - \mathrm{rand}(0,1) \times \{2 - 1\}] \tag{11}$$

wherer_k is generated random number in range [01]

Each subject score is increasing with addition of $Diff\_Mean_{v,p,k}$, mathematically,

$$X'_{v,p,k} = X_{v,p,k} + Diff\_Mean_{v,k} \tag{12}$$

The existing subject score replace if new subject score is better than the existing subject score.

4.1.1 Learner phase

Second part of the TLBO method is learner phase where learners get the knowledge form other learners, mathematically select two learners x and y randomly after the end of the teacher phase such that $f(X'_{x,k}) \neq f(X'_{y,k})$

$$X''_{v,x,k} = X'_{v,x,k} + r_k \times \left(X'_{v,x,k} - X'_{v,y,k}\right), Iff\left(X'_{x,k}\right) < f\left(X'_{y,k}\right) \tag{13}$$

$$X''_{v,x,k} = X'_{v,x,k} + r_k \times \left(X'_{v,y,k} - X'_{v,x,k}\right), Iff\left(X'_{y,k}\right) < f\left(X'_{x,k}\right) \tag{14}$$

The eqns. (13) and (14) are considered for minimization optimization problem as we are interested in minimization of objective function.

5 Improved TLBO

The ITLBO algorithm (Rao and Patel 2013) is the enhanced revision by introducing the number of teachers, adapting different teacher factors for an individual group, learning leaners through tutorials and discussions and self-learning during learner phase to the basic TLBO algorithm.

5.1 Number of teachers

All students are divided and assigned to different groups. Individual groups assign the teacher who performed top in their subjects. Each group teacher teaches the learners and brings the learners to the teacher level of that group, if learners of the particular group reach the teacher level in the particular group, the learners of that group are assigned to another better teacher. This improvement is the same as the population sorting mechanism used in other optimization algorithms such as swarm intelligence and evolution.

5.2 Adaptive teaching factor

In the basic TLBO algorithm, teaching factor (TF) is 1 or 2 which means the learner can learn completely from the teacher or nothing he will learn from a teacher and these two possibilities during the entire optimization process. This will trap the local optimum solution and also show slow convergence. In real-time teaching–learning processing, the learner can learn from a teacher in any proportionate way. So, for the learner, it does not end state and various in between of these two possibilities. A larger value of TF speeds up the optimization search and reduces exploration capacity. Teaching factor is improved with the following,

$$T_{F,g,k} = \frac{f\left(X_{x,g,k}\right)}{f\left(X_{g,k}\right)} if\, f\left(X_{g,k}\right) \neq 0 \tag{15}$$

$$T_{F,k} = 0\, if\, f\left(X_{g,k}\right) = 0 \tag{16}$$

where$f(X_{x,g,k})$ is the result of the x student related to group g by taking into account all subjects in iteration k.$f(X_{g,k})$ is the result of the same group of teachers in the same iteration k

Hence, teaching factor changes automatically depend on the result of learner and teacher during the search.

5.3 Learning through the tutorial

Teacher phase is modified by including the tutorial hours, during the tutorial hours or by discussing learner can enhance knowledge from fellow classmates or teacher which is considered in ITLBO algorithm. Mathematical model of this modification can be shown as follows:

$$X''_{v,x,g,k} = X_{v,x,g,k} + Diff\_Mean_{v,g,k} + r_k \times \left(X_{v,x,g,k} - X_{v,y,g,k}\right)$$

$$Iff\left(X_{v,x,g,k}\right) < f\left(X_{v,y,g,k}\right), x \neq y \tag{17}$$

$$X''_{v,x,g,k} = X_{v,x,g,k} + Diff\_Mean_{v,g,k} + r_k \times \left(X_{v,y,g,k} - X_{v,x,g,k}\right)$$

$$Iff\left(X_{v,y,g,k}\right) < f\left(X_{v,x,g,k}\right), x \neq y \tag{18}$$

where

$$Diff\_Mean_{v,g,k} = r_k \times \left[X_{v,g,k} - T_{F,g,k} \times M_{v,g,k}\right] \tag{19}$$

In above eqns. (17) and (18), the first element on the right indicates learning in the classroom and the second element indicates learning through tutorials.

5.4 Self-motivated learning

Learner phase is modified by including the self-learning. During the self-learning learner can gain the knowledge in the absence of teacher which is considered in ITLBO algorithm. Mathematical model of this modification can be shown as follows:

$$\begin{aligned} X''_{v,x,g,k} = X'_{v,x,g,k} &+ r_k \times \left(X'_{v,x,g,k} - X'_{v,y,g,k}\right) \\ &+ r_k \times \left(X_{v,g,k} - E_{F,k} \times X'_{v,x,g,k}\right) \end{aligned}$$

$$Iff\left(X'_{v,x,g,k}\right) < f\left(X'_{v,y,g,k}\right), x \neq y \tag{20}$$

$$\begin{aligned} X''_{v,x,g,k} = X'_{v,x,g,k} &+ r_k \times \left(X'_{v,y,g,k} - X'_{v,x,g,k}\right) \\ &+ r_k \times \left(X_{v,g,k} - E_{F,k} \times X'_{v,x,g,k}\right) \end{aligned}$$

$$Iff\left(X'_{v,y,g,k}\right) < f\left(X'_{v,x,g,k}\right), x \neq y \tag{21}$$

where

$X_{v,g,k}$ $X_{s,g,t}$ $X_{s,g,t}$ is the grade of the teacher in iteration t associated with group g in v subjects.

E_F is the exploration factor and its value is decided randomly as:

$$E_{F,k} = round\left[1 + r_k\right] \tag{22}$$

In above eqns. (20) and (21), the first element to the right represents learning through interaction with other students, and the second term represents self-motivated learning.

Knowledge from the teacher and tutorial sessions are available throughout the teacher phase of ITLBO. During the learner phase, the student can learn from peers and self-learn, which helps exploit search space. The ITLBO method computes the teaching and learning phases in each iteration until optimization is completed. So, each cycle includes both exploration and exploitation to discover a more optimal solution. The teaching factor is also changed for ITLBO, which speeds up the search for the best solution and improves convergence. ITLBO also does not need any algorithm-specific parameters. So, accelerating optimization reduces computing time, and balancing exploration and exploitation yields results.

6 Size of PVA and WTGU

To calculate the PVA and WTGU sizes, it is considered based on assumption that test systems are placed near Anantapuram (state: Andhra Pradesh, Country: India) and related data to these locations, i.e. solar irradiance (http://www.synergyenviron.com/tools/solar-irradiance/india/andhra-pradesh/anantapur), ambient temperature (http://www.synergyenviron.com/tools/solar-irradiance/india/andhra-pradesh/anantapur) and wind speed (https://www.worldweatheronline.com/lang/en-in/anantapur-weather-averages/andhra-pradesh/in.aspx). The latitude and longitude of the Anantapuram location are 14.55 N and 77.75 E respectively. PVA and WTGU specification are taken from (Wei et al. 2007) to calculate PVA size and WTGU size. The PVA and WTGU size are fixed and once the location of PVAs and WTGUs are selected along with DSTATCOM, the number of PVA and number of WTGU will change based on the optimal size.

7 Constraints for MOPI optimization for DSTATCOM, PVAs and WTGUs allocation

The following equality and inequality constraints are considered for DSTATCOM, PVAs and WTGUs planning and optimization in EDS for the generalized MOPI function to minimize in order to keep the operating condition within the limit.

7.1 Equality constraints

7.1.1 Active power conservation limits

The algebraic sum of all active power including active power branch losses and produced active power from the PVAs and WTGUs over the complete EDS should be equal to zero

$$P_{s/s} = \sum_{q=1}^{nd} PL(q) + \sum_{pq=1}^{br} P_{loss}(pq) - \sum_{p=1}^{npva} N_{PVA}(p) * P_{PVA} - \sum_{w=1}^{nwt} N_{WT}(w) * P_{WT} \tag{23}$$

where$npva$ is total locations of PVAs placed in EDSnwt is total locations of WTGUs placed in EDS

$N_{PVA}(p)$ is number of PVAs placed at location p.

$N_{WT}(w)$ is number of WTGUs placed at location w.

P_{PVA} is the size of PVA in kW.

P_{WT} is the size of WTGU in kW.

7.1.2 Reactive power conservation limits

The algebraic sum of all reactive power including reactive power branch losses and produced reactive power or absorbed reactive power from the DSTATCOM and WTGU over the complete EDS should be equal to zero

$$Q_{s/s} = \sum_{q=1}^{nd} QL(q) + \sum_{pq=1}^{br} Q_{loss}(pq) - j\sum_{s=1}^{ns} Q_{DSTATCOM}(s) \pm \sum_{w=1}^{nwt} N_{WT}(w) * P_{WT} * \sqrt{\frac{1-cos^2\theta}{\cos\theta}} \tag{24}$$

where

$Q_{DSTATCOM}(s)$ is the size of DSTATCOM at the location s in kVAr.

7.2 Inequality constraints

7.2.1 Injected active power of PVAs and WTGUs

The injected active power by all WTGUs at various candidate nodes should be within their minimum and maximum limits.

$$P^{min}_{PVA+WT} \le \sum_{p=1}^{npva} N_{PVA}(p) * P_{PVA} + \sum_{w=1}^{nwt} N_{WT}(w) * P_{WT} \le P^{max}_{PVA+WT} \tag{25}$$

where

P^{min}_{PVA+WT} $\mathrm{P}^{\min}_{\mathrm{PVA}}$ $\mathrm{P}^{\min}_{\mathrm{PVA}}$ is minimum PVA and WTGU value of real power i.e. single PVA and WTGU value.

P^{max}_{PVA+WT} is total active power load available in EDS i.e. $\sum_{q=1}^{nd} PL(q)$.

7.2.2 Injected reactive power of DSTATCOMs and WTGUs

The injected reactive power by all WTGU at various candidate nodes should be within their minimum and maximum limits.

$$Q^{min}_{DSTATCOM+WT} \le j\sum_{s=1}^{ns} Q_{DSTATCOM}(s) + \sum_{w=1}^{nwt} N_{WT}(w) * P_{WT} * \sqrt{\frac{1-cos^2\theta}{\cos\theta}} \le Q^{max}_{DSTATCOM+WT} \tag{26}$$

where

$Q^{min}_{DSTATCOM+WT}$ is minimum DSTATCOM and WTGU value of reactive power i.e. single WTGU size or 5 kVAr in case of DSTATCOM.

$Q^{max}_{DSTATCOM+WT}$ is total reactive power load available in EDS i.e. $\sum_{q=1}^{nd} QL(q)$.

7.2.3 Line thermal limit (Kumar et al. 2010)

For thermal and stability measure, the constraint of maximum power flow in the branch is needed to measure. The carrying power capacity of the branch is represented by MVA limit ($S(pq)$)throw any branch pq must within the maximum thermal capacity ($S^{max}(pq)$) of the branch

$$S(pq) \le S^{max}(pq) \tag{27}$$

8 Flow Chart for DSTATCOM, PVAs and WTGUs placement and sizing using ITLBO algorithm

The MOPI function Eq. (9) is minimized to optimize the ideal location and size of DSTATCOM, PVAs, and WTGUs at three sites (one at each location). The ITLBO algorithm parameters (number of generations, population size (i.e., number of learners), number of teachers, and number of subjects), constraints (equality and inequality), and the EDS specification (which includes node and line data) can be included as inputs of the ITLBO. Select the locations as an integer number between 2 and the maximum number of EDS nodes (as 1 is the substation) and the size of the corresponding location for DSTATCOM, PVAs, and WTGUs. Figure 1 illustrates the flowchart diagram of the approaches utilized in optimizing the optimal DSTATCOM, PVA, and

WTGU placement and size utilizing the ITLBO. After initializing the ITLBO populations' locations, size, and numbers, the MOPI objective function evaluation checks equality and inequality requirements for a particular population size and generates EDS performance indices. As illustrated in Fig. 1, ITLBO identifies the number of teachers, learners under each group, teaching phase, and learner phase for the following iteration. Convergence occurs when the optimum global solution does not improve after a specified number of iterations.

9 Result and analysis

A standard 33 node EDS (Sahoo and Prasad 2006) consists of 32 branches and 33 nodes with a total load demand of 3715 kW and 2300 kVAr. The system operates at a base

Fig. 1 Flow chart for DSTATCOM, PVAs and WTGUs Placement and Sizing using ITLBO

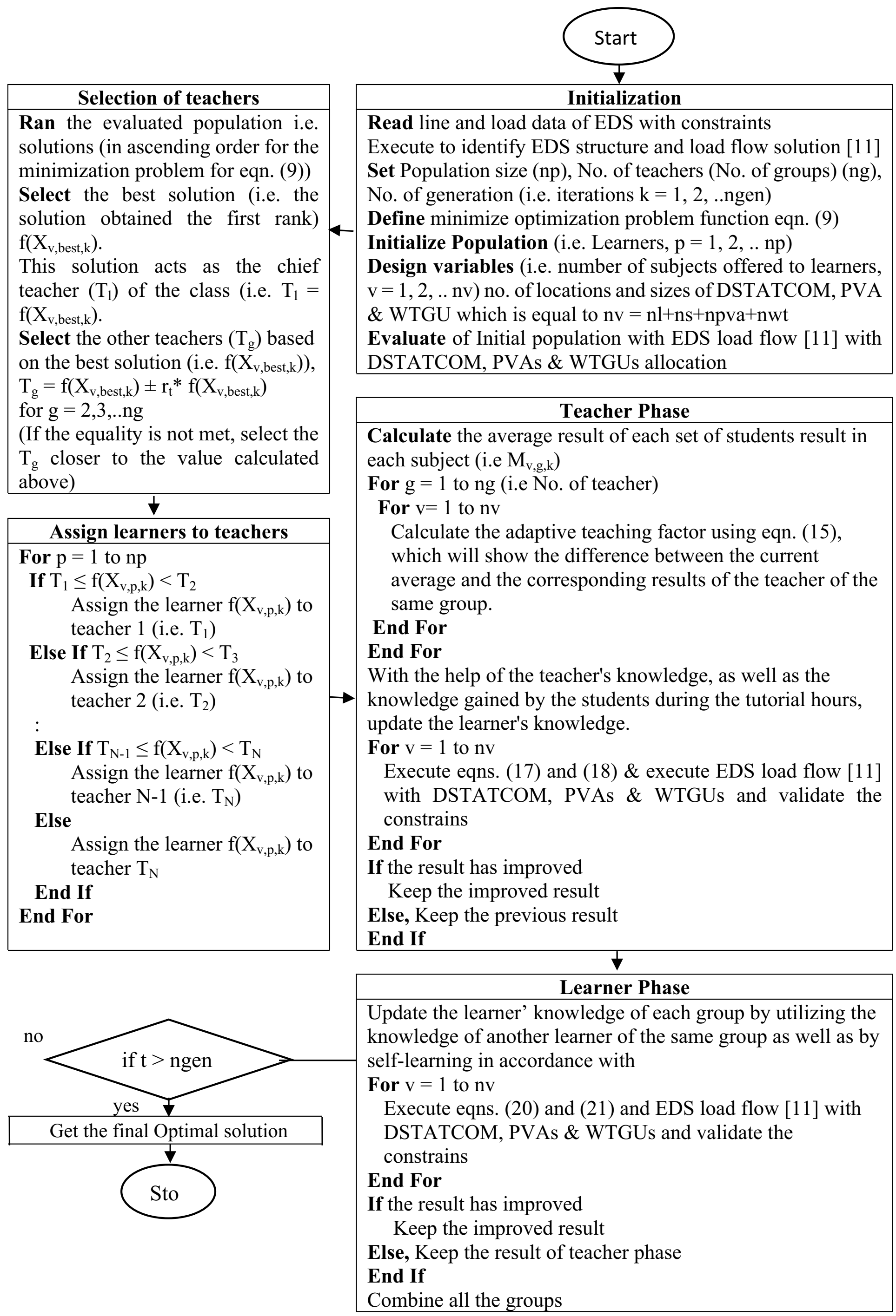

Table 1 Summary of the results to observe the performance of DSTATCOM, PVAs &WTGUs placement at three locations in the 33 node EDS

Case	Method	Size in DSTATCOM in kVAr, PVAs and WTGUs in kW (Location)	Power Factor	APL (kW)	RPL (kVAr)	$\lvert V \rvert_{min}$ (p.u)	VDI	VSI_{min} (p.u.)	LLM_{min} (MW)	$PLAM_{max}$ (kW)
Base Case		–	–	210.97	143.12	0.90378	0.32299	0.66901	15.64	22.61
DSTATCOMs at 3 Locations	Proposed Method	350 (14) 520 (24) 1010 (30)	–	138.57	94.48	0.93142	zero	0.75454	17.29	21.54
	LSA (Yuvaraj and Ravi 2017)	341 (14) 516 (24) 1013 (30)	–	138.45	94.42	0.93134	zero	0.75394	17.18	24.15
PVAs at 3 Locations	Proposed Method	750 (14) 1100 (24) 1100 (30)	–	72.83	50.79	0.96933	zero	0.88436	18.74	10.51
	BFOA (Devabalaji and Ravi 2016)	779 (14) 880 (25) 1083 (30)	–	73.54	51.09	0.96850	zero	0.88081	18.42	12.32
WTGUs at 3 Locations	Proposed Method	773.36 (14) 1063.37 (24) 1063.37 (30)	Unity	72.80	50.70	0.96849	zero	0.88076	18.77	10.67
			0.95 lead	30.90	22.52	0.97967	zero	0.92212	18.83	7.63
			0.95 lag	142.95	98.30	0.95420	zero	0.83103	18.16	17.32
	QOTLBO (Sultana and Roy 2014)	600 (14) 598 (25) 934 (30)	Unity	90.94	62.03	0.94919	zero	0.81372	17.95	29.21
			0.86 (14) 0.71 (25) 0.70 (30) lead	34.78	24.34	0.96899	zero	0.88369	18.64	8.62
			lag	230.42	157.97	0.92754	zero	0.74207	17.15	54.84
DSTATCOM, PVAs& WTGUs at 3 Locations	Proposed Method	1360 (6) 1000 (11) 1160.04 (30)	Unity	47.73	35.37	0.97688	zero	0.91280	19.04	7.83
			0.95 (lead)	36.29	27.24	0.98037	zero	0.92589	19.18	7.22
			0.95 (lag)	68.78	50.27	0.97323	zero	0.89923	18.90	17.13

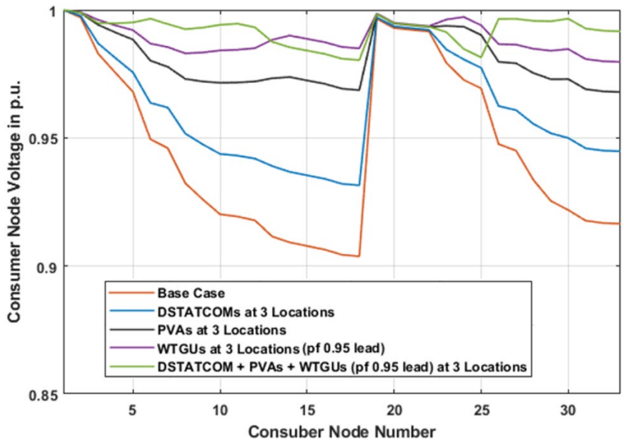

Fig. 2 Voltage profile improvement for DSTATCOM, PVAs and WTGUs placement at three locations in 33 node EDS

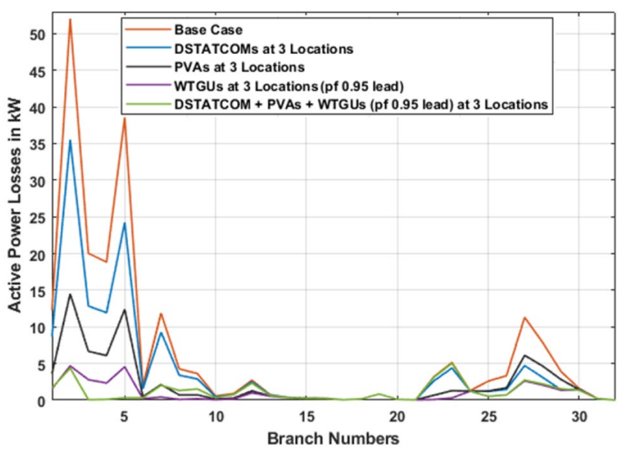

Fig. 3 Active power losses for DSTATCOM, PVAs and WTGUs placement at three locations in 33 node EDS

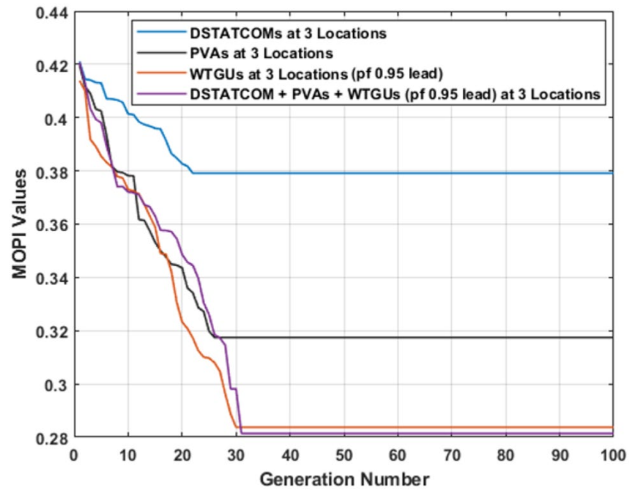

Fig. 4 ITLBO convergence with MOPI objective function for DSTATCOM, PVAs and WTGUs placement at three locations in 33 node EDS

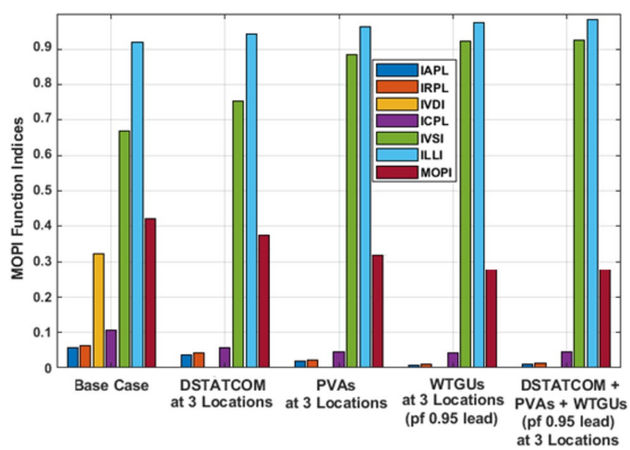

Fig. 5 Analysis of MOPI Function Indices for DSTATCOM, PVAs and WTGUs placement at three locations in 33 node EDS

voltage of 12.66 kV and a base power of 100 MVA. The real and reactive power losses without any compensation (without DSTATCOM, number of PVAs and number of WTGUs) in the EDS are 210.98 kW and 143.12 kVAr with a minimum voltage of 0.90378 p.u in a 33 node test system.

The MOPI optimization using ITLBO is performed on the 33 node EDS for DSTATCOM, PVAs, & WTGUs (with pf unity, 0.95 (lead & lag)) placement with three locations respectively, as shown in flowchart Fig. 1. For solving the ITLBO, 50 students are considered with 5 teacher groups, and the number of subjects depends on the number of DSTATCOM and DG placements and corresponding sizes. The locations & sizes of DSTATCOM in kVAr, PVAs in kW and WTGUs in kW, APL in kW, RPL in kVAr, |V|min in p.u., VSImin in p.u., PLAMmax in kW and LLMmin in MW for the proposed MOPI optimization using ITLBO for DSTATCOM, PVAs, WTGUs (with pf unity, 0.95 (lead & lag)) at three locations in Table 1. From the Table 1, the proposed method has reduced the total real and reactive power losses, enhanced the minimum voltage, minimum VSI & line loadability, and reduced the consumer loss allocation for 33 node EDS with DSTATCOM, PVAs, and WTGUs placement at different locations. The size of DSTATCOM, number of PVAs (1 PVA = 25 kW), and number of WTGUs (1 WTGU = 96.67 kW with pf unity, 0.95 (lead & lag)) placement at three locations are 1360 kVAr DSTATCOM, 40 PVAs, and 12 WTGUs, respectively, and it has been observed that WTGUs placement with pf 0.95 lead has given better EDS performance results along with the DSTATCOM and PVAs compared with WTGUs placement with unit or 0.95 lag pf along with DSTATCOM and PVAs placement and sizing at different locations. From the Table 1, it can be noticed that the active and reactive power loss has been reduced to 36.29 kW and 27.24 kVAr for DSTATCOM, PVAs & WTGUs (with pf 0.95 (lead)) placement at three locations from 210.98 kW and 143.12 kVAr respectively by using the proposed MOPI optimization using the ITLBO based method. The power loss reduction is slightly lower compared with the WTGUs placement (with pf 0.95 lead) at three locations and is high compared with DSTATCOM or PVAs placement at three locations in the 33 node EDS. Better improvement has observed to increase the minimum node voltage from 0.90378 p.u. to 0.98037 p.u., increase the minimum VSI from 0.66901 p.u. to 0.92589 p.u., decrease the VDI from 0.32299 to with the voltage limits, increase the minimum LLM from 15.64 MW to 19.18 MW, and decrease the maximum customer loss allocation from 22.61 kW to 7.22 kW with DSTATCOM, PVAs, & WTGUs (with pf 0.95 lead) placement at three locations from Table 1. Each indivisual method has been compared with the existing methods to show the performance of the proposed method.

From the above discussion, it can be concluded that the MOPI optimization using ITLBO compared with existing methods has effectively reduced the losses and also improved EDS performance with respect to enhancing the minimum voltage, improving the voltage stability, reducing the VDI, improving the LLM, and reducing the loss burden of consumers.

Figures 2–3 shows the enhancement in node voltage profile and active power loss reduction under DSTATCOM, PVAs, and WTGUs placement at three locations in the 33 node EDS. Figure 4 shows the convergence of the MOPI optimization using ITLBO and most of the cases with the DSTATCOM, PVAs, & WTGUs (with pf 0.95 lead) placements at three locations. The ITLBO solution obtained the optimal value before 30 iterations for 33 node EDS. The good optimal solution is based on the objective function and has a global solution. The number of iterations for convergence has increased as the complexity of the problem has increased.

Figure 5 shows the MOPI objective function indices values for different WTGUs placement in 33 node EDS. From Fig. 5, it has been observed that IAPL, IRPL, IVDL, & ICPL are decreased, whereas IVSI & ILLM are increased and MOPI has decreased for getting the best performance of EDS from the base case to DSTATCOM, PVAs, and WTGUs (with pf 0.95 lead) placement at three locations in 33 node EDS.

10 Conclusions

A generalized MOPI objective function has been developed for observing EDS performance based on total system losses, voltage deviation, voltage stability, line flows, and loss burden to end node consumers. The ITLBO technique has been used to solve the minimizing MOPI objective function for various cases to find optimal places and sizes for the individual and combination of DSTATCOM, PVAs, and WTGUs (with different pfs) at three distinct locations. In all instances in which the results are compared with existing methods, it has been observed that the proposed technique has better efficiency. EDS performance has been shown to be good with the combination of DSTATCOM, PVAs, and WTGUs compared with the individual DSTATCOM, or PVAs, or WTGUs in three distinct places. The proposed method has reduced the active and reactive losses by nearly 83% and 81%, respectively. The voltage profile has improved by 8.5% with no deviation in voltage limits, the voltage stability has improved by 38.4%, the additional loading handling has increased by 22.6%, and the loss burden on end node consumers has been reduced by 68%. The obtained results have shown that the proposed approach reduces the power loss in compromise with the existing methods and has also been shown to have greater performance in improving the node voltage profile by reducing the VDI, enhancing the minimum VSI, enhancing the minimum LLM, and reducing the consumer loss allocation in the EDS. Hence, overall EDS performance has been enhanced with the proposed method.

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Declarations

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