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Transmission congestion management considering multiple and optimal capacity DGs

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Abstract Transmission congestion management became a grievous issue with the increase of competitiveness in the power systems. Competitiveness arises due to restructuring of the utilities along with the penetration of auxiliary services. The present study depicts a multi objective technique for achieving the optimal capacities of distributed generators (DG) such as solar, wind and biomass in order to relieve congestion in the transmission lines. Objectives like transmission congestion, real power loss, voltages and investment costs are considered to improve the technical and economical performances of the network. Multi objective particle swarm optimization algorithm is utilized to achieve the optimal sizes of unity power factor DG units. The insisted methodology is practiced on IEEE-30 and IEEE-118 bus systems to check the practical feasibility. The results of the proposed approach are compared with the genetic algorithm for both single and multi-objective cases. Results revealed that the intimated method can aid independent system operator to remove the burden from lines in the contingency conditions in an optimal manner along with the improvement in voltages and a reduction in real power losses of the network.

Keywords Transmission congestion, Optimal power flow, Distributed generation, Particle swarm optimization

1 Introduction

In the present restructured environment, new technologies are employed on electric utilities to gain maximum profits while supplying reliable power to the consumers. Unbundling of vertically integrated power system into various sectors like generation, transmission and distribution, exposes the market for a variety of services provided by the utilities. This disintegration converts the monopolistic behavior of electricity markets into a competitive one. Uncertainties like imperfect scheduling of generators and transmission line contingencies should be conquered and relieved at the earliest to make optimum utilization of available transmission network in order to achieve maximum profits [1, 2].

Generator rescheduling and load shedding are proposed as the control actions for alleviating the congestion in the network lines. In this view, a method based on local optimization is employed to achieve the best solution [3]. In addition, sensitivities of the overload lines with respect to the bus injections are also considered along with the previous mechanisms [4]. Similarly, objectives like over load alleviation and production cost minimization are considered in a multi-objective based TCM study. PSO based solution methodology is utilized in achieving the global optimal values [5]. In [6], clustering algorithm is utilized to identify the most sensitive zones for congestion employing the real and reactive transmission congestion distribution factors.

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Later, the problem of TCM is limited to generator rescheduling only. In this, rescheduling cost is minimized while managing congestion by altering the output levels of the participating generators which are selected based on generator sensitivity factors. Many algorithms have been proposed to alter the preferred active power generations for alleviating congestion in the network lines. Initially, PSO is proposed to reschedule the outputs of participating generators to obtain the minimum deviations [7]. Further, Adaptive bacterial foraging algorithm with Nelder–Mead (ABFNM) is employed to minimize the congestion (rescheduling) cost of standard IEEE-30 bus system [8].

Many procedures reveal the usage of static VAR compensators and flexible ac transmission systems (FACTS) for the congestion management problem. In this, Benders decomposition is utilized as an efficient algorithm to place the static VAR compensators and FACTS devices optimally for relieving congestion in the lines [9, 10]. In [11], the TCM problem is solved using a qualitative bidding strategy which is achieved through a dynamic game. Rescheduling of generator outputs and transaction curtailments together are employed to manage the congestion that is caused due to bi-lateral and multi-lateral transactions [12]. Similarly, three different frameworks Monte Carlo Simulation (MCS), Lattice Rank-1 MCS and Lattice Rank-2 MCS are employed to control the congested line power flows [13].

On the other hand, due to heavy competition in the electricity markets load side governing is more preferred instead of supply side governing in the case of TCM [14]. In this regard, auxiliary services are penetrated in the present competitive electricity markets to improve reliability and security of the power system [15]. Auxiliary services like distributed generators in addition with the conventional generators provide better stand in loss reduction, voltages improvement and congestion relieving. The most proven DGs are diesel, solar thermal systems, biomass and wind.

Lot of research works reveals the application of DGs in distribution systems for voltage improvement and reducing real power losses thereby enhancing the performance of the network. Artificial intelligence based solution methods are applied to obtain the optimal capacities using single and multi-objective functions. Objectives like power flows, loss reduction, voltage improvement and cost factors are considered simultaneously to obtain the optimal capacity DGs [16].

Many researches in the past utilized various artificial intelligence and sensitivity based techniques for obtaining the optimal places and capacities of DGs to be integrated with the distribution network. In view of this, sensitivities based on real and reactive power losses are evaluated to obtain the size of DG in a weakly mesh distribution network [17]. Hybrid PSO (HPSO) is employed to minimize the system loadability for obtaining the optimal place and sizes of DGs for various radial test bus systems [18]. Weighted aggregation PSO (WAPSO) is employed to obtain the size, type and location of DG to be connected with the practical Indian distribution systems [19]. Many algorithms like fireworks optimization algorithm [20] and bacterial foraging algorithm (BFA) [21] are also implemented to obtain DGs placement and their capacities. Some of the researches concentrated on reducing the search space for the above mentioned procedures [22]. A method based on network reconfiguration along with DG insertion is proposed in [23]. Later, the results were further improved with the implementation of improved bat algorithm (BAT) [24].

DGs are also integrated in transmission networks to control the power flows and to increase the performance of the network. Z_{BUS} based contribution factors are determined to optimally insert the DGs for the TCM problem. A 60 MW DG was inserted at the optimal location to alleviate the congestion in the line 1–3 [25] of standard IEEE 30-Bus system. Likewise, genetic algorithms (GA) are applied to determine the optimal capacities for the TCM problem by considering voltage improvement factors and real power loss reduction factors [26, 27]. LMP based DG integration is proposed for TCM problem [28]. Many random search methods, such as genetic algorithms (GA) and simulated annealing (SA) have recently received much interest for obtaining the optimal capacities of DGs in the distribution systems and transmission systems. Although GA has been successfully employed to complex optimization problems, recent researches revealed some deficiencies in the performance and its search capability when it was presented before highly correlated objective function [29].

So far, many of the researches aimed to obtain the optimal capacity DGs comprising of either only technical [15, 26] or only economical factors for the TCM problem [28]. Also, the researches in the past did not adopt the weight selection strategies considering multi objectives [26] and aim the optimal capacity DGs for the TCM problem [25]. The optimal sizing of DGs that are obtained by considering technical factors may direct towards the higher investment costs of DG with a little improvement in the technical performances of the system and may become financial burden which leads to economical infeasibility. Similarly, in case of considering only economical factors, the technical performance may be degraded and may not fulfill the present and future transaction curtailments. Hence, to overcome the above research gaps, in this work authors aimed to obtain the optimal capacities of DGs to improve technical performance along with optimal investment on DG units, which is an important and a new contribution to this field.

In this work, the demand side management based multi-objective technique is proposed for the TCM problem. Objectives like transmission congestion, voltage improvement, real power loss reduction and investment cost are considered simultaneously by including them with normalized weighting factors to achieve the optimal sizes of DGs. The results of proposed multi-objective optimization problem are evaluated by the application of both GA and PSO for various single and multi-objective cases.

The timeline of the paper is as follows: Sect. 2 shows the formulations for optimal power flow, congestion management problem and artificial intelligence methodology. Section 3 describes the step by step procedure for solving the TCM problem. The results obtained are presented in Sect. 4. Finally, conclusions are deducted in Sect. 5.

2 Problem formulation

2.1 Optimal power flow (OPF)

In a deregulated environment, the OPF problem is structured by minimizing production cost of generators subjected to power balance constraints and line flow constraints [30]. The OPF problem can be mathematically formulated as:

$$\min C = \sum_{i=1}^{N_g} F_{gi} \tag{1}$$

Subjected to:

1) Power balance constraints:

$$P_{gi} = P_{di} + \sum_{j=1}^{N} |V_i||V_j|\left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right) \quad \forall i = 1, 2, \ldots, N \tag{2}$$

where P_{di}, P_{gi} are real power demand and generation at i^{th} bus; δ_{ij} is $\delta_j - \delta_i$; N is total number of buses.

$$Q_{gi} = Q_{di} + \sum_{j=1}^{N} |V_i||V_j|\left(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}\right) \quad \forall i = 1, 2, \ldots, N \tag{3}$$

where G_{ij} and B_{ij} are the conductance and susceptances of the line $i - j$ respectively.

2) Power flow constraints:

$$|Pl_{ij}| \le Pl_{ij}^{\max} \quad \forall ij \in N_l \tag{4}$$

where Pl_{ij}, $Pl_{ij}^{\max}$ are power flow in the line $i - j$ and its maximum limit respectively; N_l is total number of lines.

3) Other in-equality constraints:

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad \forall i = 1, 2, \ldots, N_g \tag{5}$$

$$\delta_i^{\min} \le \delta_i \le \delta_i^{\max} \quad \forall i = 1, 2, \ldots, N \tag{6}$$

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \forall i = 1, 2, \ldots, N \tag{7}$$

where $P_{gi}^{\min}$, $P_{gi}^{\max}$ are minimum and maximum limit of i^{th} generator respectively; δ_i, $\delta_i^{\min}$, $\delta_i^{\max}$ are voltage angel of i^{th} bus and its minimum maximum limits respectively; N_g is total number of generators. The production function (\$/h) of i^{th} generator can be mathematically represented by

$$F_{gi} = \frac{1}{2}a_{gi}P_{gi}^2 + b_{gi}P_{gi} + c_{gi} \tag{8}$$

where a_{gi}, b_{gi} and c_{gi} are the fuel cost coefficients of i^{th} generation company.

In this work all the inequality constraints are transformed to the penalty functions and are added to the main objective function to construct the final fitness function to be minimized.

2.2 Congestion management problem with optimal capacity DGs considering economical factors

The main causes of congestion are line outages, sudden increase in load, reduction in thermal limits and due to a combination of bi-lateral and multi-lateral transactions. Once congestion occurs, independent system operator (ISO) follows various procedures to alleviate the extra power flows in the transmission lines. Various procedures like Generators active power rescheduling, load shedding, insertion of FACT devices and insertion of optimal capacity distributed generators are mainly utilized. In this work, the optimal capacity distributed generators are inserted for TCM problem. After deciding the optimal locations for placing the DGs, TCM problem is formulated to incorporate the effect of DGs. To include the effect of DGs by considering the economic factors, the objective function (1) is altered as follow:

$$\min C = \sum_{i=1}^{N_g} F_{gi} + \sum_{i=1}^{N_{DG}} F_{DG,i} \tag{9}$$

In (9), $F_{DG,i}$ in (\$/h) is the production cost function of i^{th} DG obtained from the slope $a_{DG,i}$ and intercept $b_{DG,i}$ of DG offer as shown below:

$$F_{DG,i} = \frac{1}{2}a_{DG,i}P_{DG,i}^2 + b_{DG,i}P_{DG,i} \tag{10}$$

Further, the constraint (2) is also altered to involve the effect of DG and represented as follow:

$$P_{gi} = P_{di} + \sum_{j=1}^{N} |V_i||V_j|\left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right) \quad \forall i = 1, 2, \ldots, N, i \neq k \tag{11}$$

$$P_{gi} + P_{DG,k} = P_{di} + \sum_{j=1}^{N} |V_i||V_j|\left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right) \quad i = k \tag{12}$$

The limits on DGs active power generation is also included along with conventional generators limits.

$$0 \leq P_{DG,k} \leq P_{DG}^{\max} \tag{13}$$

where $P_{DG}^{\max}$ is maximum penetration of k^{th} DG.

The TCM problem with DG consists of objective function (9) subjected to constraints given by (3)–(7) and (11)–(13). The maximum power delivered by DG units is restricted to its installed capacity for operating the power system during the congestion hours. The maximum capacity of DG is taken as 20% of the systems total demand. The DGs are inserted as negative power injections at the load pockets during the load flow analysis.

2.3 Congestion management problem with optimal capacity DGs considering technical and economical factors

In the present work congestion management with voltage and real power losses improvement are considered as technical factors and production costs of both distributed and conventional generators are considered as economical factor for obtaining the optimum capacities of DG units. The following sub-section shows the various factors that are considered in this work.

2.3.1 Transmission congestion

Congestion relieving is the main aim of present work. In view of this, a factor resembling the ratio of the real power flowing through the line after the placement of DG(s) to its line limits is computed for all the transmission lines. The highest of all such fractions is considered as transmission congestion factor (*TC*). It can be mathematically represented as follow:

$$TC = 200 \cdot \max\left(\frac{Pl_{ij}^{DG}}{Pl_{ij}^{\max}}\right) \tag{14}$$

where Pl_{ij}^{DG} and $Pl_{ij}^{\max}$ are the real power flows in the line $i - j$ after including DG in network and the line limiting capacity respectively.

2.3.2 Voltage improvement (VD)

The ratio between the sum of squares of the deviations of voltage magnitudes from 1 p.u. before and after including DG in the network is considered as voltage improvement factor. This is mathematically defined as follow:

$$VD = 200 \cdot \frac{\sum_{i=1}^{N}\left(V_i^{DG} - 1.0\right)^2}{\sum_{i=1}^{N}\left(V_{i,0} - 1.0\right)^2} \tag{15}$$

where V_i^{DG} is voltage magnitude of i^{th} bus after placement of DG; $V_{i,0}$ is voltage magnitude of i^{th} bus before the placement of DG.

2.3.3 Real power loss (RPL)

The purpose of considering this parameter is to reduce the real power loss in the power system network. This can be mathematically defined as:

$$RPL = 200 \cdot \frac{P_{Loss}^{DG}}{P_{Loss}^{0}} \tag{16}$$

where P_{Loss}^{DG} is real power loss after including the DG; P_{Loss}^{0} is real power loss before including the DG.

2.3.4 Cost factor (CF)

The main aim of the *CF* is to obtain the optimum investment costs of all the three types of DGs and conventional generators simultaneously. This is mathematically defined as:

$$CF = \sum_{i=1}^{N_g} F_{gi} + \sum_{i=1}^{N_{DG}} F_{DG,i} \tag{17}$$

2.4 Mathematical modeling for achieving optimum sizing of DGs

In this work the problem of optimal sizing of DGs is intended to improve the technical performance along with optimal investments on DG units. In the present multi-objective approach, weighted technical parameters and economical parameters are considered simultaneously to achieve the sizes of DGs. Computation of multi-objective solutions without weight selection strategy may lead to inappropriate solution [26].

In recent, the weights for respective objectives were selected based on the "hypothesis of relevance of objectives" which is deducted from planner's experience. However the process is not methodical and may misguide the entire planning process [18, 31]. Hence in this work all the objectives are considered simultaneously for the optimization by using the weighting factors for the incorporation of

DGs with the aim of improving technical and economical performances of transmission network [16]. The multi-objective function for obtaining optimum sizing of DGs is formulated by combining the technical and economical parameters with the weighting factors represented as follow:

$$J = h_1 \cdot TC + h_2 \cdot VD + h_3 \cdot RPL + h_4 \cdot CF \tag{18}$$

where h_1, h_2, h_3 and h_4 are the weighting factors of TC, VD, RPL and CF respectively.

The multi-objective minimization problem is formulated to minimize the function J (18) subject to the constraints mentioned in (3)–(7), (11)–(13) and an extra constraint as follow:

$$\sum_{i=1}^{4} h_i = 1 \quad h_i \in [0 \quad 1] \tag{19}$$

2.5 Optimum sizing of DGs using particle swarm optimization

The classical particle swarm optimization (PSO) technique used for optimizing complex objective functions is first introduced by Kennedy and Eberhart [32]. This is kind of evolutionary computation technique has wide applications in solving problems constituting nonlinearity, non-differentiability, multiple optima and high dimensionality [29]. PSO is based on the parallel exploration of the search space by a swarm-a set of "particles", the solutions or alternatives. Its key concept is that the potential solutions are flown through search space and are accelerated towards better or more optimum solutions. Every particle in PSO is associated with two vectors, position vector and velocity vector. The position vector of p^{th} particle is represented as $z_p = (z_{p1}, z_{p2}, \ldots, z_{pd})$ and velocity vector of p^{th} particle is represented as $v_p = (v_{p1}, v_{p2}, \ldots, v_{pd})$. PSO starts with a population of random solution "particles" in a d dimension space. Each particle preserves the best solution and its respective coordinates so far achieved. The best solution is called F_{best} and the coordinates associated with best solution are called P_{best}. The best previous positions of the particles in every iteration are recorded in $P_{best,p} = (P_{best,p1}, P_{best,p2}, \ldots, P_{best,pd})$. The PSO algorithm stores the overall best value and its respective coordinates as G_{best}. The optimization technique updates its velocity and position of each particle at every step towards P_{best} and G_{best} to obtain the best solution so far. The particles in the swarm are updated iteratively according to the equations as follow:

$$\begin{aligned} v_{pd}^{j+1} &= u \cdot v_{pd}^{j} + c_1 \cdot rand_1 \cdot \left(P_{best,pd} - x_{pd}^{t}\right) \\ &\quad + c_2 \cdot rand_2 \cdot \left(G_{best,p} - x_{pd}^{t}\right) \end{aligned} \tag{20}$$

$$z_{pd}^{j+1} = z_{pd}^{j} + v_{pd}^{j+1} \tag{21}$$

where n is number of particles; m is number of members; j is iteration count; v_{pd}^{j} is velocity of p^{th} particle at j^{th} iteration; u is inertia weight vector; c_1 and c_2 are acceleration constants; $rand_1$ and $rand_2$ are random numbers between 0 & 1; z_{pd}^{j} is position of p^{th} particle at j^{th} iteration; $P_{best,pd}$ is local best of p^{th} particle; $G_{best,p}$ is global best of p^{th} particle.

The weighting factor is evaluated based on the equation as follow:

$$u = u_{\max} - \frac{u_{\max} - u_{\min}}{N_{iter,\max}} \cdot N_{iter} \tag{22}$$

where $u_{\max}$ and $u_{\min}$ are maximum and minimum value of inertia weight respectively; N_{iter} is iteration count; $N_{iter,\max}$ is maximum number of iterations.

3 Flow chart for proposed methodology

The proposed method aims to achieve the optimal capacity DG units in order to relieve congestion in transmission lines along with improvement and both real power losses and voltages of the network. The optimal capacities of the DG units are achieved by implementing MO-PSO approach. The flow chart for proposed MO-PSO approach is shown in Fig. 1.

4 Result analysis

In this work, optimal capacities of DGs are obtained based on the multi-objective approach in order to relieve the congestion in transmission lines of the network. The effectiveness of the proposed approach is examined on IEEE-30 and IEEE-118 bus systems. To check the suitability of proposed approach, case studies including single objective and multi-objectives are considered separately. The case studies in terms of single and multi-objective are shown in Table 1.

The locations of DGs are selected based on Z_{BUS} based contribution factors which was proposed in [25]. Three types of DGs like Solar, Wind and Biomass are considered and their production cost functions are modeled as $a_{DG,i} = 0$ and $b_{DG,i} = 30\,(\$/\mathrm{MWh})$ throughout the work. Following assumptions are made in order to continue the work.

1) Only one DG is connected to the same bus at a time [19].
2) Similarly, the system considered for the study is operated in balanced mode [19].

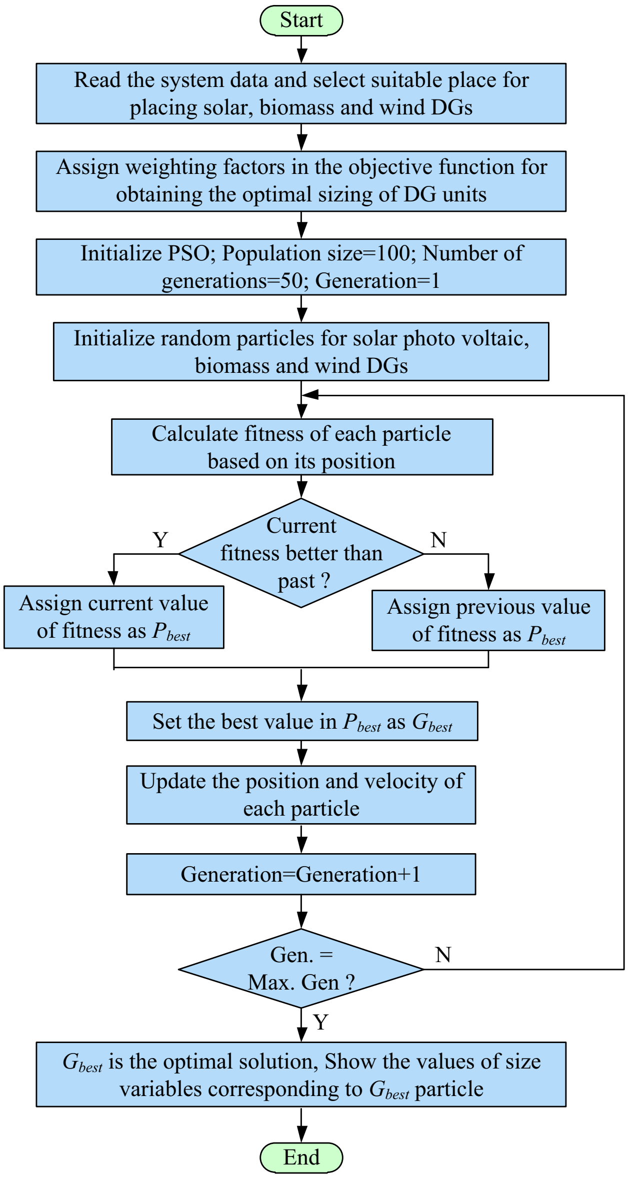

Fig. 1 Flow chart for proposed approach

The optimal capacities of DGs are achieved based on the proposed MO-PSO approach and the results obtained are compared with results of genetic algorithm (GA) and method reported in [25]. The control parameters for both PSO and GA approaches are depicted in Table 2.

Table 2 Control parameters for GA and PSO

GA	PSO
Maximum iteration = 100	Maximum iteration = 100
Population size = 20	Population size = 20
Stall generation limit = 100	$c_1 = c_2 = 2$
	$u_{\max} = 0.9$, $u_{\min} = 0.4$ [29]

4.1 Case 1: IEEE-30 bus test system

The proposed approach is evaluated on standard IEEE-30 bus system which has 6 generators, 21 loads and 41 transmission line sections. The generators cost coefficients, their maximum and minimum limits, bus and line data related to the IEEE-30 bus can be obtained from [8]. In Case 1A, the considered network has no DG and the base MVA is considered as 100 MVA. OPF is performed to obtain the power flows in the lines, voltages at buses and the real power losses. As bus 1 is reference, the output of all generators except at bus 1 are considered as variables for the OPF run. The results of OPF are shown in Table 3. It is clear that the total fuel cost obtained using proposed approach is 801.8437 ($/h) which is minimum as compared to the GA.

The contingency scenario is created by reducing the line limit of the line 1–3 from 75 to 60 MW. This implies the line 1–3 is loaded with more 5.65% of its maximum line loading. Hence in this work, multiple DGs with their optimal capacities are inserted to mitigate the congestion in the line. For the present case study 60 MW is considered as maximum limit of DG ($P_{DG}^{\max}$) during the run of reported algorithms. The preferable locations for inserting the optimal capacity DGs with respect to the congested line 1–3 are shown in Table 4. The optimal capacities of DGs at the top three locations are obtained using PSO and GA with the proposed multi-objective function described in (18).

During Case 1C, the objective function is formed with the cost factors of the both conventional and distributed generators. Hence in this case, the weighting factor is set to 1 for both the cost factors of DGs and the conventional generators. The results obtained through reported

Table 1 Case studies considered for present study

Test case	Test system	Description	Form of objective
Case 1A/2A	IEEE-30/118 bus	Without DG	Single
Case 1B/2B	IEEE-30/118 bus	With 60 MW DG [25]	Single
Case 1C/2C	IEEE-30/118 bus	With optimal capacity DGs with only *CF*	Single
Case 1D/2D	IEEE-30/118 bus	With optimal capacity DGs with all factors	Multi

Table 3 Results of OPF according to Case 1A for IEEE-30 bus system

Generator number	PSO (MW)	GA (MW)
1	176.6624	177.217
2	48.8103	48.471
3	21.4607	21.588
4	21.7339	21.9621
5	12.1028	11.882
6	12.0	12.0
Generation cost ($/h)	801.8437	803.032
Losses (MW)	8.89	9.3507
Power flow in line 1–3 (MW)	63.36	62.21

Table 4 Optimal locations for inserting DGs in IEEE-30 bus system

Bus number	Description	Type of DG
3	Optimal	Solar
4	Sub-optimal	Biomass
13	Sub-optimal	Wind
12	Sub-optimal	–
14	Sub-optimal	–

Table 5 Sizing of DGs in various case studies for IEEE-30 bus system

Bus number	Case 1B (MW)	Case 1C		Case 1D	
		GA (MW)	PSO (MW)	GA (MW)	PSO (MW)
3 (Solar)	60	19.952	8.1647	10.098	2.073
4 (Wind)	–	39.868	0	8.728	3.374
13 (Biomass)	–	0.099	0	1.044	4.517
Total DG capacity	60	59.199	8.1647	19.87	9.964

approaches during this case study are shown in Table 5. The total DG power injection using PSO is 8.1647 MW, whereas it is 59.91 MW by GA. After the insertion of optimal capacity DGs at suitable sites it has been observed that the power flow in the congested line 1–3 is reduced by 8.3, 11.1 and 5.3% of its maximum line limit by PSO, GA and according to Case 1B respectively. The convergence curves of PSO and GA approaches during Case 1C run are shown in Fig. 2. Form the figure it is clear that the PSO approach converges in less number of iterations and gives better solution as compared to GA.

Similarly, in Case 1D, the weighting factors are kept at 0.25 for each of the objectives in order to have equal weightage during the execution. The optimal capacities

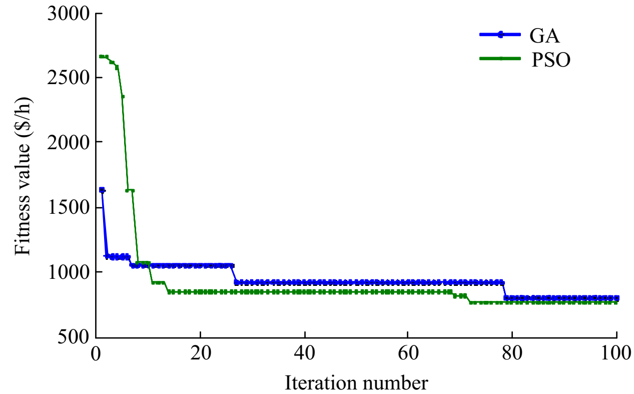

Fig. 2 Convergence curve in Case 1C for IEEE-30 bus system

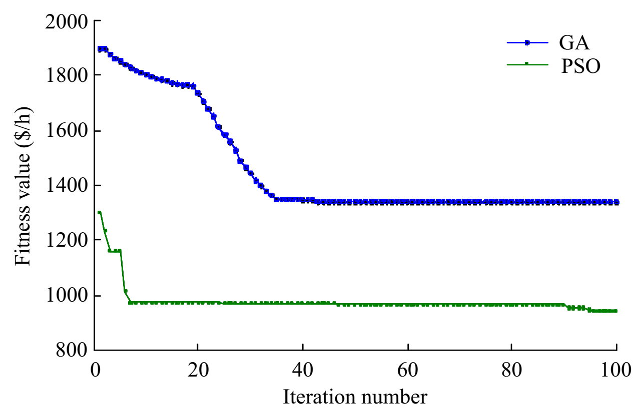

Fig. 3 Convergence curve in Case 1D for IEEE-30 bus system

that are obtained during this case are presented in the Table 5. The convergence curves of both PSO and GA approaches during Case 1D run are shown in Fig. 3. In this case, the total DG power penetration is increased to 9.964 MW by the proposed PSO approach whereas; it is reduced to 19.87 MW by GA. The result obtained after inserting the optimal capacity DGs to the network are presented in Table 6. From the table it is noticed that, the power flows and real power losses in Case 1D have been further decreased by the proposed multi-objective approach as compared to the other single objective approaches.

A comparison with the similar researches in terms of real power flow, real power losses, maximum and minimum values of voltages have been shown in Table 6. Large decrement is observed in the real power losses before and after the placement of the optimum size of DGs. It is noticed that, the power flow in the congested line has been reduced but the real power losses have been increased in Case 1B. Figure 4 shows the voltage magnitudes of each bus in p.u. for different case studies. It discloses that the voltage magnitudes have been improved greatly after

Table 6 Comparative results of various approaches in different case studies for IEEE-30 bus system

Parameter	Case 1A	Case 1B [25]	Case 1C		Case 1D	
			GA	PSO	GA	PSO
Power flow in line 1–3 (congested line) (MW)	63.36	56.82	53.34	54.97	52.21	54.97
Real power losses (MW)	11.834	14.097	7.8234	8.9453	5.6056	8.2021
Maximum value of voltage magnitude in p.u.	1.0822	1.082	1.082	1.082	1.082	1.082
Minimum value of voltage magnitude in p. u.	0.992	0.994	0.9966	0.9959	0.9956	0.9957
DG cost ($/h)	0	1800	1797.597	244.941	596.1	298.214

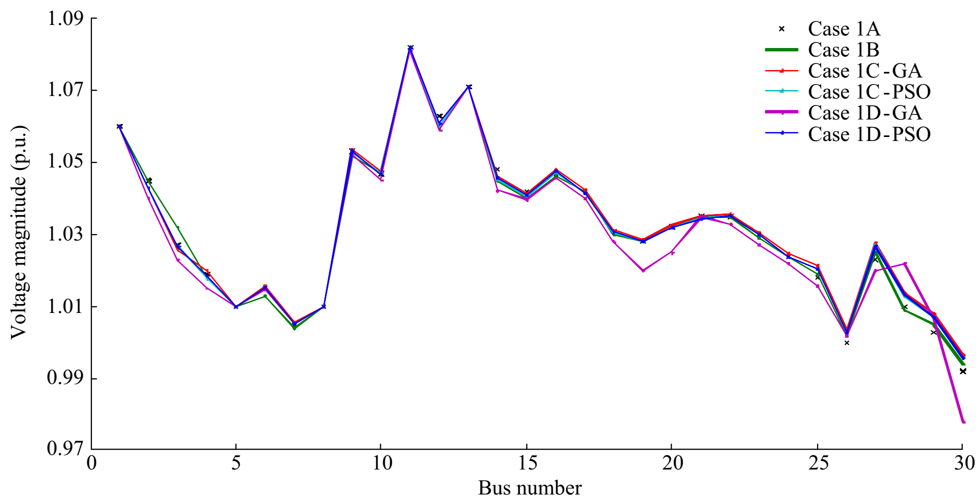

Fig. 4 Voltage profile of IEEE-30 bus system at different stages

inserting the optimum sizing of DGs according to the Cases 1C and 1D.

It is also noticed that the voltage magnitudes at the load buses have been improved greatly through the multi-objective approach by PSO as compared to GA and other single objective approaches. This proves the superiority of the proposed approach as compared to GA and the approach reported in [25] for IEEE-30 bus network. Further, the proposed congestion management approach is also practiced on large test bus system to check the practical feasibility. The following sub-section discuses the various results related to the large test bus system.

4.2 Case 2: IEEE-118 bus system

In this sub-section, the proposed approach is applied on IEEE-118 bus system. The test system has 54 generators, 186 transmission lines and 99 loads. The total load on the system is 4242 MW. The generators cost coefficients, their maximum and minimum limits, bus and line data related to the IEEE-118 bus can be obtained from [33]. As the bus 69 is reference, generator outputs except the reference bus generator are considered as variables for the OPF run. The results of the OPF are tabulated in the Table 7. The results of OPF obtained through proposed approach are compared with the other similar works like PSO, ALC-PSO, ICBO. The total fuel cost obtained using the proposed approach is 130062.8620 ($/h) which is minimum as compared to GA and ICBO approaches. In Case 2A, the test system does not have DG allocation. The real power losses and power flow in the line 26–30 are 87.620 and 170.60 MW respectively. This implies, the line 26–30 is congested when its limit is reduced from 175 to 150 MW. That means the line 26–30 is loaded with more 13.745% of its limit. Hence, MO-PSO is implemented to alleviate the congestion in the line.

In this case 20% of total load is 848.4 MW, hence 850 MW is considered as maximum capacity of the DG to be connected. But practically DGs are of low ratings so, in this work maximum available capacity of DG is taken as 60 MW. According to this, 14 DGs are required to be inserted in the IEEE-118 bus system to relieve congestion

Table 7 Results of OPF according to Case 2A for IEEE-118 bus system

Generator	PSO (MW)	ALC-PSO [33] (MW)	ICBO [34] (MW)	GA (MW)
1	20.69	27.5202	370.42	0
4	0	0	30.0012	86.897
6	0	0	30.006	72.6573
8	0	0	30.0004	42.2068
10	390	401.6008	30.0017	14.9294
12	86.36	85.5017	316.815	30.4277
15	26.57	18.3415	68.0579	68.1198
18	10.59	11.1001	30.0344	24.8773
19	39.68	23.321	30.0022	21.392
24	2.96	0	30.0009	57.654
25	177.98	195.27	30.0031	100
26	265	278.986	152.2583	202.6975
27	25.13	15.2378	221.2265	112.208
31	7.4	7.2651	30.0023	3.1887
32	12.12	13.6541	32.1001	16.142
34	17.78	2.4891	30.0468	55.4852
36	27	8.9856	30.0023	100
40	23	49.9442	30.0002	100
42	61.23	42.0478	30.0011	22.7333
46	18.35	19.1282	30.0074	17.4502
49	192.53	193.6081	35.7188	79.6501
54	53.61	50.1543	162.5469	14.6998
55	42.97	31.659	44.4008	101.479
56	26.54	34.7532	30.3515	100
59	146.35	147.6018	30.0022	100
61	147.23	149.8376	126.396	154.0434
62	0	0.0022	123.5531	148.2644
65	333.21	346.2842	30.0022	33.2415
66	344.01	348.1853	290.6133	271.7695
69	447.72	462.8761	290.485	100
70	0	0	30.0008	100
72	0	0	30.0018	0.0522
73	0	0	30.0016	89.0752
74	23.79	17.0971	30.0015	10.1664
76	19.55	24.2712	30.0023	52.6154
77	0	0	30.0046	16.7157
80	424	416.045	350.109	528.7858
85	0	0	30.0038	65.4129
87	3.48	3.7122	31.2	6.4411
89	483.78	505.012	378.9986	239.0351
90	0	0	30.0003	116.3091
91	0	0	30.0006	82.0595
92	0	0	30.0004	44.4655
99	0	0	30	39.6494
100	227.52	232.1064	176.5001	184.1041
103	38.56	39.021	42.0025	78.9053
104	18.95	0	30.0007	40.2184
105	12.25	11.5314	30.019	13.2081
107	31.29	26.4823	30.0016	76.2585
110	12.03	0	30.0008	18.0738
111	34.71	35.9456	40.8017	0
112	38.47	39.5123	30.0005	86.897
113	6.75	0	30.0048	72.6573
116	0	0	30.017	42.2068
Generation cost ($/h)	130062.86	129546.08	135121.57	142000.00
Power flow in line 26–30 (MW)	170.60	–	–	172.58

Table 8 Sizing of DGs in various case studies for IEEE-118 bus system

Preferable locations	Case 1B (MW)	Case 1C		Case 1D	
		GA (MW)	PSO (MW)	GA (MW)	PSO (MW)
9	60	8.19	0	6.42	0.134
8	60	4.26	0.8403	18.117	0.826
10	60	5.23	1.9578	0	0.112
30	–	7.61	1.447	20.166	0.618
26	–	1.26	7.421	5.387	8.216
38	–	3.14	0	4.322	0.510
25	–	0	0	0	0
65	–	0	0	7.785	0.620
66	–	45.15	0.2234	12.611	0
64	–	30.61	3.2563	0.8571	1.240
61	–	14.22	0.8676	15.621	0.560
67	–	0	6.7299	0.584	5.432
68	–	30.68	1.3526	10.480	0.726
116	–	2.28	1.3258	24.610	0.528
Total DG penetration	180	152.63	25.4217	126.96	19.52

in the line 26–30. The preferable locations for inserting the optimal capacity DGs with respect to the congested line 26–30 are shown in first column of Table 8.

The near optimal solutions for the TCM problem are obtained through both the GA and PSO approaches as reported. During the Case 2C weighting factors are set to 1 and during the Case 2D those are set to 0.25. The results obtained in the both cases are reported in Table 8. The convergence curves for both the approaches during Cases

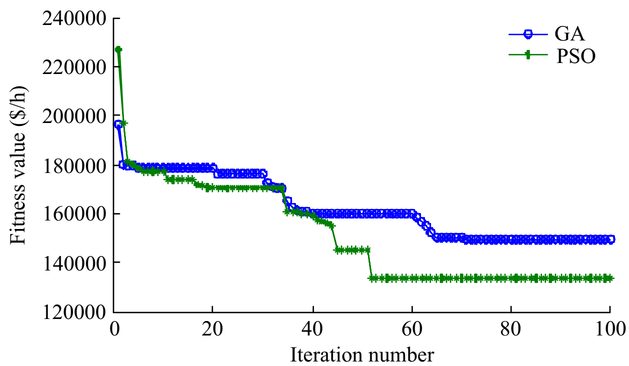

Fig. 5 Convergence curve in Case 2C for IEEE-118 bus system

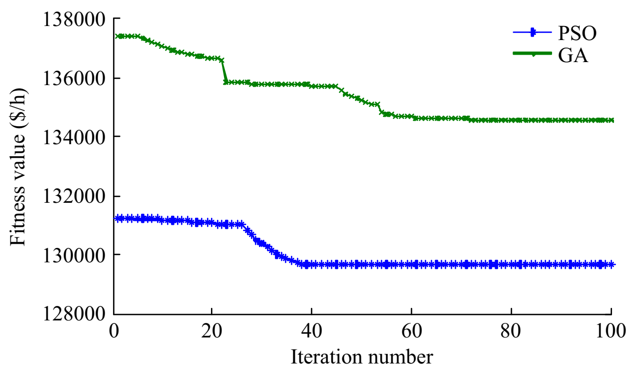

Fig. 6 Convergence curve in Case 2D for IEEE-118 bus system

2C and 2D run are shown in Figs. 5 and 6 respectively. According to Case 2B, 60 MW DGs at buses 9, 8, 10 will not alleviate the transmission line congestion. Further, the results of proposed approach are also compared with other single and multi-objective approaches using GA. This comparative analysis is shown in Table 9.

It is confirmed that, the real power losses and power flow in the congested lines have been greatly reduced with the implementation of proposed multi-objective approach using PSO. The Fig. 7 shows voltage magnitudes of each bus in p.u. before and after connecting the DGs in different cases. The figure reveals advancement in voltages after connecting the optimum sizing of DGs according to the proposed approach. It is noticed that change is not observed for the maximum voltage level, but a slight decrement is observed after connecting the optimum size of DGs according to Case 2C. The results declare the superiority of the proposed PSO approach over the GA and other single objective approaches. The results of the proposed approach also reveal that the congested lines are alleviated completely without overloading any other lines in the power system network. The entire results reveal that the power flows, real power losses and voltages have been greatly improved by inserting optimum capacity DGs by the proposed MO-PSO approach.

Table 9 Comparative results of various approaches in different case studies for IEEE-118 bus system

Parameter	Case 2A	Case 2B [25]	Case 2C		Case 2D	
			GA	PSO	GA	PSO
Power flow in line 26–30 (congested line) (MW)	170.60	183.42	149.68	144.729	150	145.62
Real power losses (MW)	87.620	102.56	90.12	87.572	88.16	84.32
Maximum value of voltage magnitude in p.u.	1.0742	1.05	1.65	1.068	1.068	1.065
Minimum value of voltage magnitude in p.u.	0.952	0.943	0.96	0.9519	0.962	0.974
DG cost ($/h)	0	5400	4578.9	762.651	3808.8	585.66

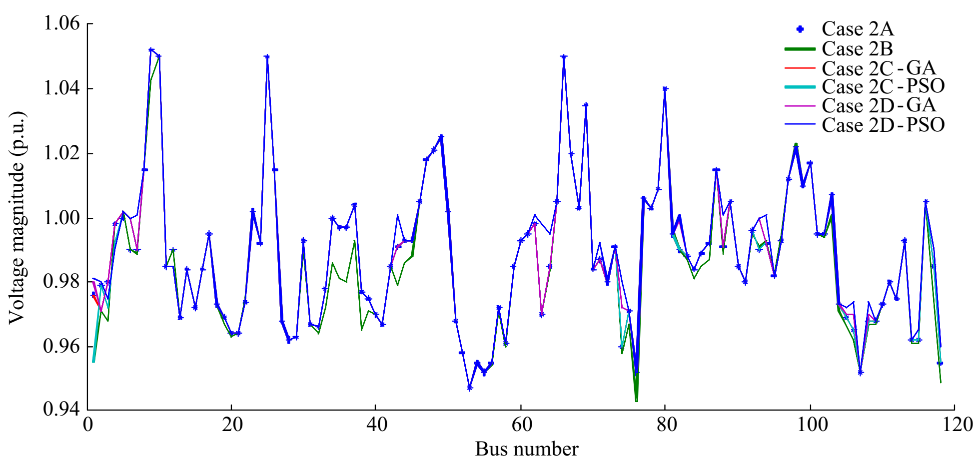

Fig. 7 Voltage profile of IEEE-118 bus system at different stages

5 Conclusion

In this paper, MO-PSO based transmission congestion management problem has been proposed. Optimal sizing of renewable DGs are integrated in order to relieve the congestion in a transmission line. The multi-objective approach comprises of both the technical and economical factors like congestion, real power losses, voltage improvement and DGs investment cost respectively. The multi-objectives are made as single objective by fastening them with normalized weighting factors. Three types of renewable DGs such as solar, biomass and wind systems are integrated with the main grid at optimal locations. The feasibility of the proposed approach is checked on standard test systems like IEEE-30 bus and IEEE-118 bus test systems. It is observed that the proposed approach reduces real power losses up to 30.7 and 3.77% in the case of 30 and 118 bus test systems respectively. It was also observed that voltage profile is improved at all load buses significantly in both the test systems. The entire study depicts that the critical contingency condition has been relieved completely and a wide scope has been opened for the ISO to improve the bidding strategies in an optimal manner. Finally it can be concluded that the proposed method is efficient and feasible for solving the real time complex power system problems.

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