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Proceedings Paper:

Yin, M and Li, K (2020) Optimal Allocation of Distributed Generations with SOP in Distribution Systems. In: Proceedings of 2020 IEEE PES General Meeting. 2020 IEEE PES General Meeting, 03-06 Aug 2020, Online. .

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Optimal Allocation of Distributed Generations with SOP in Distribution Systems

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Abstract—The concept of flexible AC transmission systems (FACTS) that has been successfully used in power flow control could potentially benefit the distribution networks equally, in particular for supporting the integration of distributed generations (DGs). This paper considers an emerging distributionlevel FACTS (D-FACTs) device, namely soft open point (SOP) that provides both active and reactive power flow capabilities. To use distributed generations (DGs) at distribution level to accommodate local increasing energy consumption can reduce the power losses due to long distance power transmission, while maximizing the utilization of local renewable and clean energies. This paper investigates the optimal sizing and location of DG units with smart inverters assisted with SOPs in the distribution systems. To solve the non-convex and non-linear optimization problem, a fast IPOP-CMA-ES algorithm is proposed and its efficiency is validated in a modified IEEE 33-bus test system under different operating conditions. Simulation results have revealed that the optimal DG allocation can achieve up to 93.26% power loss reduction and 93.62% voltage deviation reduction, while the line congestion level revealed by load balancing index has significantly dropped from original 6.26 to 0.35 only.

Index Terms—Distributed generation (DG), optimal DG location, power flow control, distribution-level FACTS (D-FACTS), soft open point (SOP), fast IPOP-CMA-ES algorithm.

I. INTRODUCTION

The last decade has witnessed massive applications of active components, such as distributed generators (DGs) in the development of distributed networks around the world [1]. According to different power sources and grid connection types, DGs show different characteristics. An inverter-based DG unit could supply real power and either generate or consume reactive power. By utilizing the cost effective and environmentally friendly renewable energy sources (RES) such as wind energy, it will relieve the pressure induced by the increasing demand, pollutant and green house gas emissions from thermal generators, and delay network reinforcement at the operation stage. Studies show that the capacity and location of DGs are not identical in distribution network [2]. Improper placement will deteriorate the power flow that causes negative impacts on the system reliability. Due to the high R/X ratio in distribution systems, it is of great significance to find suitable place and proper size of DG units to minimize the loss.

The soft open point has been proposed as a promising D-FACTS design to replace the normally opened tie-switches to improve the active/reactive power control capabilities among feeders with reasonable cost [3]. In [4], the authors have judiciously examined the benefits of a distribution network assisted with SOPs by their flexible power control capabilities. SOP has been demonstrated to be supportive to DG penetration. Therefore, the power loss and voltage profile can be enhanced by optimal allocation of DGs with SOP in the distribution system. For example, Shafik et al. [5] have proposed a model to detect the number, sitting and sizing of DG units with and without SOP based on power losses, voltage profile and DG penetration level, but the reactive capability of DG units was not considered.

The aforementioned performance of DG units and SOP formulates a non-linear, higly-constrained optimization problem to determine the size and location of DG units. The main objective for such a problem is to minimize the power losses while satisfying the physical operation constraints predefined by distribution system operators (DSO). Various optimization techniques were investigated for solving optimal sizing and sitting of DGs in the literature. Basically they can be categorised into three groups: classic approaches, analytical approaches and metaheuristic approaches. The computation of the classic approaches such as linear programming (LP) and mix-integer non liner programming (MINLP) is fast. However, the utilization of convex relaxations or linearization sometimes does not meet the practical situations [6]. Analytical approach introduces sensitivity index to locate the DG, but the approach can not guarantee the global optimum and computation is time consuming [7]. Metaheuristic algorithms based on artificial intelligence now become popular for handling non-convex and non-linear problems in the power systems. Some of these methods include the Genetic Algorithm (GA) [8] and modified Particle Swam Optimization (PSO) [5]. These methods do not need preconditioning of objective function and converge to near global optimum in acceptable time. In this paper, a fast Covariance Matrix Adaptation Evolution Strategy with an Increasing Population size (IPOP-CMA-ES) is used. The main contribution of this paper is to propose an efficient algorithm for DG allocation considering DG reactive capability and power flow control assisted with SOP in regard to power losses, voltage profile and congestion management.

The remainder of the paper is organized as follows. Section II introduces the envisaged SOP and DG models. Section III formulates the optimization problem. Section IV details the proposed optimisation method and its adaptation. Section V interrogates simulations and provides numerical results. Finally Section VI concludes the paper.

II. MATHEMATICAL MODELS

A. Modelling of Soft Open Point (SOP)

A back-to-back voltage source converter (VSC) based SOP is placed between two feeder ends to replace the traditional tie-line switch. In the power flow control mode [9], one VSC works with P-Q control scheme while the other operates with the $V_{dc}-Q$ control scheme. It provides decoupled active power and reactive power control at both terminals. Fig. 1 shows a power injection model of SOP connected to two feeders. P_m^{SOP} and P_n^{SOP} denote the active power of SOP entering feeder ends at bus m and n, respectively. It follows

$$P_m^{SOP} + P_n^{SOP} + P_{loss}^{SOP} = 0, \forall (m, n) \in N_{SOP}$$
(1)

where P_{loss}^{SOP} is the internal power loss of the SOP and N_{SOP} is the set of all SOPs. As to a high efficiency SOP, P_{loss}^{SOP} is very small and can be neglectable. The reactive power outputs of SOP are independent, which implies that both power compensation and absorption are available.



Fig. 1: power injection model of SOP

The operational limits of power entering the feeders are constrained by the capacities of the two back-to-back VSCs, it follows

$$(P_m^{SOP})^2 + (Q_m^{SOP})^2 \leqslant (S_m^{SOP})^2$$
(2)

$$(P_n^{SOP})^2 + (Q_n^{SOP})^2 \leqslant (S_n^{SOP})^2 \tag{3}$$

where S_m^{SOP} and S_n^{SOP} are the rating power of VSC1 and VSC2. The steady-state model represents the capability of SOP to control the active/reactive power flow of the joint feeders, as well as the volt/VAR control at the terminals.

B. Modelling of Inverter-based Distributed Generation (DG)

DG unit possesses smaller unit size and can be powered by renewable sources including the popular wind turbines (WT) and photovoltaic (PV) panels. Through the power electronic device, i.e. inverter interface, DG unit is connected to the distribution network. The reactive power is dynamically adjustable due to power factor required by DSO. The capacity and operation constraints of the inverter-based DG is mathematically formulated as:

$$S_{min}^{DG} \le S^{DG} \le S_{max}^{DG} \tag{4}$$

$$pf_{min}^{DG} \le pf^{DG} \le 1 \tag{5}$$

$$P^{DG} = S^{DG} \cdot pf^{DG} \tag{6}$$

$$Q^{DG} = \pm S^{DG} \cdot \sin\left(\cos^{-1}(pf^{DG})\right) \tag{7}$$

where S^{DG} , P^{DG} , Q^{DG} are the apparent, active and reactive power output of DG respectively. pf^{DG} is the power factor which is maintained within $[pf_{min}^{DG} \text{ lagging, } pf_{min}^{DG} \text{ leading}]$.

III. PROBLEM FORMULATION

Denote a branch l by (i, j) or $i \to j$ if it points from bus i to bus j where $(i, j) \in N_{br}$. P_{ij} and Q_{ij} are the real power and reactive power at the sending end of a branch, respectively. The branch impedance is simplified as $z_{ij} = r_{ij} + jx_{ij}$.

Therefore, the real power loss in the branch (i, j) is

$$P_{ij}^{Loss} = \frac{P_{ij}^2 + Q_{ij}^2}{|V_i|^2} r_{ij} \tag{8}$$

where $|V_i|$ is the voltage magnitude on bus *i*.

A. Objective Function

The objective of optimal DG allocation with SOP in distribution system is to minimize the total power loss for efficient energy utilization. It can be formulated as follows:

min
$$P^{TLoss}(\mathbf{x}) = \min \sum_{ij=1}^{N_{br}} P_{ij}^{Loss}, \forall (i,j) \in N_{br}$$
 (9)

where P^{TLoss} is the total power losses of all branches. The decision variables **x** include the bus number n^{DG} , capacity S^{DG} and power factor pf^{DG} of DG and SOP generated/absorbed power at two terminals $P^{SOP}_{m,n}$ and $Q^{SOP}_{m,n}$.

B. Constraints

1) Distribution Power Flow Equations: At every bus, based on the definition of Ohm's law and power balance, total active/ reactive power satisfies the branch flow equations [10].

$$p_j = \sum_{k:j \to k} P_{jk} - \sum_{i:i \to j} \left(P_{ij} - r_{ij} \frac{P_{ij}^2 + Q_{ij}^2}{|V_i|^2} \right), \forall j \quad (10)$$

$$q_j = \sum_{k:j \to k} Q_{jk} - \sum_{i:i \to j} \left(Q_{ij} - x_{ij} \frac{P_{ij}^2 + Q_{ij}^2}{|V_i|^2} \right), \forall j \quad (11)$$

$$|V_j|^2 = |V_i|^2 - 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) + (r_{ij}^2 + x_{ij}^2)\frac{P_{ij}^2 + Q_{ij}^2}{|V_i|^2},$$

$$\forall (i,j) \in N_{br}$$
(12)

where p_j and q_j are net injection real and reactive power that are equal to total generation minus load $p_j = P_j^G - P_j^L$ and $q_j = Q_j^G - Q_j^L$ at bus *j*. SOP and DG can be regarded as generator or negative load. In the study, an iterative method based on the Backward/Forward Sweep (BFS) is utilized for power flow calculation.

2) Voltage constraint: the voltage at each bus should be within the permissible limits and remains 1 p.u. at substation.

$$V_{i,min} \le V_i \le V_{i,max}, \forall i \in N_{bus}$$
(13)

$$V_{sub} = 1 \ p.u. \tag{14}$$

3) Branch constraint: The current of each line is maintained within the limits

$$|I_{ij}| \le I_{ij,max}, \forall (i,j) \in N_{br}$$
(15)

Besides, a series of technical and operational constraints of SOP and DG are subject to Equation (1)-(5).

IV. OPTIMIZATION METHOD AND ALGORITHM

A. Overview of CMA-ES Algorithm

Covariance Matrix Adaptation Evolution Strategy (CMA-ES) [11] was proposed by Hansen and Ostermeier in 2010. It inherits the merits of Evolution Strategy (ES) that uses weighted recombination of μ parents through adaptive covariance matrix to generate λ offsprings. The core idea of CMA-ES or called $(\mu/\mu_W, \lambda)$ -ES algorithm is to learn the dependencies and relative ratios along different directions of a multivariate normal distribution $\mathcal{N}(m, \sigma^2 C)$. Mean value m, step-size σ and covariance matrix C will be strategically evolved in every iteration step. The pseudocode of the algorithm can be found at the right column. The details of the parameters can be found in [12].

The algorithm conducts three major steps: selection and recombination, adapting the covariance matrix and step-size control. One iteration is implemented as follows: 1) Generate λ samples according to multivariate normal distribution $\mathcal{N}(m_g, \sigma_g^2 C_g)$. 2) Evaluate the fitness based on the objective function and take out the best μ individuals to update the distribution mean value m_{g+1} along the weighted average $\sum_{i=1}^{\mu} \omega_i$. 3) Construct the evolution path $p_{c,g+1}$ by accumulating consecutive steps that can cancel the movements of opposite directions. 4) Update the covariance matrix along with rank-one term and rank- λ term. 5) Adapt the step-size by constructing a conjugate evolution path $p_{\sigma,g+1}$.

B. Fast IPOP-CMA-ES Algorithm

Introducing a new start trigger for CMA-ES with increasing population size (IPOP) is proven to be a simple and effective strategy for global optimization [13]. By comparing the iterating CMA-ES solutions, the best one in the loop is chosen to be the algorithm result. In each iteration, the calculation stops when convergence is observed or its parameters do not indicate further improvement [14]. A new start is then launched by increasing the population size with a factor of 2. The default stagnation factor is set to $10 + \lceil 30n/\lambda \rceil$.

Learning faster So far the rank-one update guarantees the direction of the best solution appears with maximum likelihood in the next iteration. However, the true potential is still underestimated. In this study, the historical best candidate $x_{best,g-1}$ will be part of the offsprings in next iteration if it is superior to the current best one as below:

$$x_{best,g} = \begin{cases} x_{best,g-1} & f(x_{1:\lambda,g}) \ge f(x_{best,g-1}) \\ x_{1:\lambda,g} & f(x_{1:\lambda,g}) < f(x_{best,g-1}) \end{cases}$$
(16)

$$z_{best,g} = \begin{cases} z_{best,g-1} & f(x_{1:\lambda,g}) \ge f(x_{best,g-1}) \\ (BD)^{-1} \frac{x_{best,g} - m_g}{\sigma_g} & f(x_{1:\lambda,g}) < f(x_{best,g-1}) \end{cases}$$
(17)

Algorithm 1 $(\mu/\mu_W, \lambda)$ -ES algorithm

- 1: Set λ , $\omega_{i=1...\lambda}$, c_{σ} , d_{σ} , c_c , c_1 and c_{μ}
- 2: Initialize m,σ , $p_{\sigma} = 0, p_c = 0$, C = I and g = 0
- 3: while not terminate do
- 4: eigenvalue decomposition $C_q = BD^2B^T$
- 5: for k = 1 to λ do
- 6: $z_k \sim \mathcal{N}(0, \mathbf{I})$
- 7: $y_k = BDz_k \sim \mathcal{N}(0, C_g)$

8:
$$x_k = m_g + \sigma_g y_k \sim \mathcal{N}(m_g, \sigma_g^2 C_g)$$

- 9: end for
- 10: sort $f(x_{1:\lambda}) \leq f(x_{2:\lambda}) \leq \dots \leq f(x_{\lambda:\lambda})$ // sort fitness
- 11: $m_{g+1} \leftarrow \sum_{i=1}^{\mu} \omega_i x_{i:\lambda}$ // selection and recombination

12:
$$p_{c,g+1} \leftarrow (1-c_c)p_{c,g} + \sqrt{c_c(2-c_c)\mu_{eff}} \frac{m_{g+1}-m_g}{\sigma_g}$$

13:
$$C_{g+1} = (1 - c_1 - c_\mu)C_g + c_1p_{c,g+1}p_{c,g+1}^+ + \frac{c_\mu}{\sigma_g^2}\sum_{i=1}^{\mu}\omega_i(x_{i:\lambda} - m_g)(x_{i:\lambda} - m_g)^T$$
 // covariance matrix adaptation

14: $p_{\sigma,g+1} \leftarrow \sqrt{c_{\sigma}(2-c_{\sigma})\mu_{eff}}C_g^{-1/2}\frac{m_{g+1}-m_g}{\sigma_g} + (1-c_{\sigma})p_{\sigma,q}$

15:
$$\sigma_{g+1} = \sigma_g \cdot \exp(\frac{c_\sigma}{d_\sigma}(\frac{\|\mathbf{p}_{\sigma,g+1}\|}{\mathbf{E}\|\mathcal{N}(0,\mathbf{I})\|} - 1))$$
 // step-size control

16: $g \leftarrow g + 1$

17: end while

where BD is derived from the eigenvalue decomposition of covariance matrix C_q in the current iteration.

V. SIMULATION RESULTS AND DISCUSSION

To evaluate the effectiveness, the proposed algorithm is implemented in MATLAB on a PC with Intel Core i5 2.70 GHz CPU and 16 GB RAM.

A. Experimental Set-up

In this paper, a modified 12.66kV IEEE 33-bus system is used to investigate the DG allocation with SOP. The system consists of 33 buses and 32 branches. The line and topology data can be found in [15]. The basic total load is 3715 kW and 2300 kVAR. A single line diagram is presented in Fig. 2. The modified system is equipped with SOP in replace of normally open tie-line between bus 18 and 33. The voltage range of all buses except the substation is set to [0.95, 1.05] p.u.. The power factor of DG is considered to be within [0.95 lagging, 0.95 leading] according to grid codes [16].

The base case where the system has no DG and SOP is firstly examined and is used as a benchmark to evaluate the performance of DG allocation. The total real power loss is 212.50 kW. In the study, five cases with different configurations are considered as follows:

- 1) one DG without reactive capability and no SOP insertion
- 2) one DG with reactive capability and no SOP insertion
- 3) one DG with reactive capability and SOP installation
- 4) two DGs with reactive capability and SOP installation
- 5) three DGs with reactive capability and SOP installation



Fig. 2: A single line diagram of a modified IEEE 33-bus distribution system

Apart from power loss, the system technical performance is evaluated by two indexes. Load balancing index (LBI) represents the congestion level in the system.

$$LBI = \frac{1}{N_{br}} \sum_{i=1}^{N_{br}} \left(\frac{|I_{ij}|}{I_{ij,rate}} \right)^2$$
(18)

where $|I_{ij}|$ and $I_{ij,rate}$ are the current magnitude and rating of branch (i, j) respectively. Voltage deviation index (VDI) is used for evaluating the voltage magnitude deviation from unity at each bus.

$$VDI = \frac{1}{N_{bus}} \sum_{i=1}^{N_{bus}} \left(\frac{|V_i| - V_{norm}}{V_{norm}}\right)$$
(19)

where V_{norm} is the nominal voltage.

B. Numerical Results and Analysis

1) Algorithm Assessments: The simulation results of placement of single and multiple DG units are presented in Table 1. The proposed algorithm is compared with GA [8] and MPSO [5]. It is evident that the proposed algorithm fast IPOP-CMA-ES is superior in finding the optimum to its competitors in all five cases. For instance, in case 5, it reaches the maximum power loss reduction of 93.26% compared to the base case, whereas GA and MPSO achieves 89.44% and 89.94% reduction respectively. However, this improvement is achieved at the cost of the computation efficiency as shown in the Table 1. For the DG placement problem, the computation time is not the most important aspect to consider, and the proposed algorithm is appropriate to be used in the study.

2) Effectiveness of reactive capability of DG: The reactive capability of DG unit contributes to better energy usage. By introducing the reactive power, the system power loss reduces from 115.84 kW in case 1 to 78.81 kW in case 2. Meanwhile, LBI drops from 3.02 to 1.78 which presents a significant improvement on the transmission line congestion.

3) Effectiveness of SOP capacity: Fig. 3 illustrates the power loss under the optimal allocation of one DG with several different SOP capacities. It reveals that the capacity of SOP is negatively correlated with power loss. However, for capacity above 600 kVA, the reduction of power loss can be ignored.

To maximize the economic benefit, the capacity of SOP is set to 600 kVA.



Fig. 3: Power loss of single DG system with different SOP capacity

4) Effectiveness of DG numbers: Cases 3, 4 and 5 consider different DG numbers. The advantage of introducing more DG units with SOP in the distribution system is evident. The power loss is reduced by more than half from 43.25 kW to 14.32 kW with an increase of 1277 kVA DG power.



Fig. 4: Voltage profile of the system with single and multiple DG units and SOP

Fig. 4 illustrates the improvement of voltage profile with different number of DG units assisted with SOP. In the case of 3 DG units with SOP, the voltage is almost flat and VDI is reduced to 0.34 % from 5.38 % in the base case and LBI is

Scenario	Method	Bus no.	DG power (kVA)	Power factor	Computation time (s)	Total power loss (kW)
Base Case						212.50
Case 1	fast IPOP-CMA-ES	7	2897	1	8.9	115.50
(One DG without reactive	GA [8]	6	3179	1	5.0	116.61
capability and no SOP)	MPSO [5]	7	2898	1	3.4	115.51
Case 2	fast IPOP-CMA-ES	6	2992	0.95	24.9	78.81
(One DG with reactive	GA [8]	6	2838	0.96	9.1	81.55
capability and no SOP)	MPSO [5]	6	2982	0.95	12.9	79.12
Case 3	fast IPOP-CMA-ES	30	1880	0.97	53.4	43.25
(One DG with reactive	GA [8]	29	2121	0.96	29.4	51.27
capability and with SOP)	MPSO [5]	30	1922	0.96	26.4	47.41
Case 4	fast IPOP-CMA-ES	24, 30	1271, 1756	0.95, 0.95	82.4	25.17
(Two DG with reactive	GA [8]	8, 30	1540, 1265	0.95, 0.98	25.2	47.69
capability and with SOP)	MPSO [5]	11, 29	1059, 1306	0.98, 0.97	24.4	34.29
Case 5	fast IPOP-CMA-ES	11, 24, 30	768, 1175, 1214	0.98, 0.95, 0.97	116.3	14.32
(Three DG with reactive	GA [8]	14, 24, 29	796, 920, 1291	0.98, 0.95, 0.98	25.2	22.43
capability and with SOP)	MPSO [5]	11, 24, 30	796, 1412, 1363	0.97, 0.98, 0.97	31.7	21.38

TABLE I: Comparisons of simulation results of power losses with single and multiple DG units and SOP

also reduced to a low level, standing at only 0.35 compared with 6.26 in base case.

VI. CONCLUSION

This paper presents a novel algorithm called fast IPOP-CMA-ES for solving optimal DG allocation problem with a D-FACTS device, namely SOP. The proposed algorithm is validated on a modified IEEE 33-bus system with five different cases and compared with two popular optimization algorithms GA and MPSO. Different factors are considered while valuing the placement of DG units, including the DG reactive capability, DG number and SOP capacity. Simulation results reveal that the proposed algorithm outperforms the other two well-known approaches. It is also shown that the system performance will be greatly enhanced as the DG number increases when SOP is applied. For example, inclusion of 3 DG units will result in a 93.26 kW reduction in terms of power loss. In addition, the line congestion level reflected by LDI is significantly dropped by 94.41% and the voltage profile is improved with a 93.26% deviation reduction. The algorithm can also be applied to practical cases involving probabilistic load models. Future work will be dedicated to cases considering the load dynamics in the optimization problem.

ACKNOWLEDGMENT

The work was partially funded by EPSRC under grant EP/R030243/1.

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