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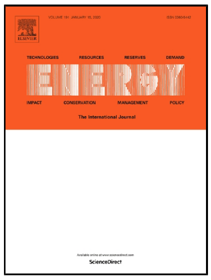

Optimal Placement, Sizing and Power Factor of Distributed Generation: A Comprehensive Study Spanning from the Planning Stage to the Operation Stage

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Optimal Placement, Sizing and Power Factor of Distributed Generation: A Comprehensive Study Spanning from the Planning Stage to the Operation Stage

Phung Dang Huy [a], Vigna K. Ramachandaramurthy [a], Jia Ying Yong [a,1], Kang Miao Tan [a] and Janaka B. Ekanayake [b,c]

[a] Institute of Power Engineering, Department of Electrical Power Engineering, College of Engineering, Universiti Tenaga Nasional, Malaysia

[b] Institute of Sustainable Energy, Universiti Tenaga Nasional, Malaysia

[c] Department of Electrical and Electronic Engineering, University of Peradeniya, Sri Lanka

Abstract—In this paper, an optimised framework utilising a Differential Evolution algorithm is presented to optimally integrate multiple distributed generation sources simultaneously into the distribution grid. By considering the important power system constraints, the proposed algorithm optimises the location, sizing and power factor setting for each distributed generation source to minimise network losses and maximise distributed generation integration. Various case studies were conducted at constant or varying levels of load and generation in both the planning stage and the real-time operation stage. The results of all case studies revealed that the proposed Differential Evolution-based algorithm delivered better performance in terms of network loss reduction and maximised distributed generation compared to other existing methods. The network loss reduction of 95.71% was achieved when all three parameters of placement, sizing and power factor of distributed generation were optimised simultaneously. In addition, a practical framework with a varying optimal power factor for distributed generation was designed. The optimal power factor setting for each distributed generation source was dynamically adjusted during real-time power grid operation, resulting in further minimisation of the system loss reduction. The overall loss reduction achieved was 96.04% relative to the base case of no distributed generation connection.

Keywords—Differential Evolution, distributed generation, optimal allocation, optimisation, power factor

1. Introduction

In recent decades, global warming has resulted in worldwide desert expansion, temperature increase and rise in sea level. If this global warming issue is not addressed properly, some of the main landmasses and islands will eventually become uninhabitable. In the energy sector, the conventional electricity generation process based on the burning fossil fuels emits greenhouse gases, which are known to be the main cause of

[1] Corresponding author, email: yongjiaying89@gmail.com or jiaying@uniten.edu.my; Tel. +6017 2597352; Fax +603 89212116

global warming. The use of Renewable Energy (RE) serves as an excellent countermeasure to the effects of global warming because RE is a non-depleting indigenous resource that produces insignificant waste pollutants [1]. Therefore, RE-based Distributed Generation (DG) has emerged as a preferred choice in the energy sector to reduce the amount of greenhouse gases emission [2].

Despite the environmental benefits, the technical aspects of RE-based DG integration to the power grid must be carefully assessed because these resources are intermittent in nature and rely heavily on weather conditions [3]. While integrating a small portion of RE into a large power grid is relatively easy to accomplish, the escalating penetration of RE is posing new challenges to both system planning and operation [4]. In the literature, researchers have reported various technical impacts on the grid due to DG connection to the power network [5]. The main impacts are grid voltage rise, reverse power flow and power quality problems. Severe grid voltage rise occurs if DG sources are connected in a weak power network [6]. Reverse power flow, which occurs during periods with high DG power generation and low demand, may affect the existing power protection schemes [7]. Moreover, power quality problems, such as harmonics and flickers, are caused by the switching of DG inverters [8].

In order to maximise the DG potential without compromising the power grid performance, the development of appropriate optimal strategies for DG allocation has become a crucial task. Various methods and strategies for DG allocation have been introduced in the literature. The simplest method is the direct search method, which guarantees a global optimal solution in its search boundary [9]. The major drawback of this method is that it requires lengthy computation time to search through all the available options and hence requires limitation of the number of controlling variables. On the contrary, the analytical method requires a short computation time [10]. Nevertheless, this method requires assumptions be made for several factors. Because power system functions are principally complex and not all of them are differentiable, the use of the analytical method becomes limited for solving power system problems [11]. Furthermore, the Evolutionary Algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) integrates the good qualities of the aforementioned methods. These algorithms can deliver global or near global optimal results within an acceptable period without reducing the search space and limiting the considerations [12].

It is also important to place the DG source of practical size at the optimal location because inappropriate selections of the location and size of DG sources may lead to greater system losses [13]. Reports of extensive research studies on optimal DG allocation can be found in the literature. Although the formulation of the objective function in these optimisation algorithms differed from study to study, the main goals were generally to minimise system loss, cost and emissions as well as to improve the voltage profile and grid resilience. For example, the authors in [14] proposed a Mixed-Integer Linear Programming (MILP) formulation to optimise DG location and sizing simultaneously, with the loss expressions considered in the algorithm for better accuracy of system representation. An optimal DG allocation strategy was proposed in [15] to minimise the annual comprehensive cost of the distribution network and the active power cut-off of DG via active management. Alternatively, a multi-objective DG planning model considering correlations among the dynamic parameters was presented in [16], with the objectives of minimising annual total costs and system risks. In [17], comparative analyses of various optimisation techniques on the protection coordination of optimally allocated DGs were presented. Furthermore, some studies assessed the long-term investments in RE-based DG in isolated microgrids, such as remote communities and islands. A multi-objective optimisation algorithm was proposed in [18] to optimise sizing and placement of solar photovoltaic (PV) and batteries in an off-grid system to achieve minimisation of electricity cost, carbon emissions and grid voltage deviations. An efficient planning algorithm with the optimal allocation of DGs, energy storages and converters for microgrid was presented in [19] to achieve reliable supply and cost savings. Similarly, a hybrid microgrid planning model with the objective of minimising the total planning costs by determining the optimal DG sizing and location was demonstrated in [20]. In [21], the study revealed that investing in new PV generation would improve the overall microgrid system costs because the diesel DG was more costly due to logistics of fuels.

In the literature, the optimal setting of the DG source's power factor has not been extensively investigated. The power factor of DG source is usually pre-assumed to be set to a specific value before the main optimisation process occurs. This assumption may result in the optimisation algorithm reaching a non-optimally global result; hence, this issue should be further assessed. Moreover, the auto-adjustment of DG operating power factor in operation phase has also not been addressed in literature. In fact, the power factor of each DG source installed in the power grid can be optimally and dynamically varied to actively support the system. This approach is feasible for the inverter-based DG sources, such as solar photovoltaic panels and wind turbines, because of the fast switching in the converter's operation. As compared to a fixed power factor setting, the consideration of the optimal setting of a DG source's power factor can bring additional benefits, such as further reductions in system losses and voltage fluctuations.

To address the aforementioned issues, in this paper, an optimised DG framework using the Differential Evolution (DE) algorithm to optimise the location and sizing of multiple DG sources in the power grid as well as to optimise the power factor of each connected DG source is presented. The development of the framework was conducted using the commercial DIgSILENT Powerfactory 15.1 software [22], and the proposed algorithm was programmed in the Python programming language. The commercial DIgSILENT Powerfactory 15.1 software is a leading power system analysis software application for use in analysing generation, transmission, distribution and industrial systems. It covers the full range of functionality from standard features to highly sophisticated applications including distributed generation, real-time simulation and performance monitoring for system testing and supervision. This software also offers great interface on the simulation of distribution network with the integration of RE, as well as the ability of using the popular Python language for automation tasks. The performance of the proposed algorithm was assessed in different case studies of constant or varying amounts of load and generation.

The main contributions of the paper are summarised as follows: (i) an optimal DG algorithm was successfully designed to simultaneously optimise the placement, sizing and power factor of each connected DG to achieve minimisation of network losses and maximisation of DG integration in the planning stage, (ii) the proposed algorithm was also developed to be utilised in the operation phase by adjusting the DG operating power factor automatically to the optimal value and (iii) comparative analyses were performed in various case studies with different number of connected DGs to validate the advantages of the proposed algorithm compared to existing methods in literature with the same inputs and considerations.

The rest of the paper is organised into several sections. Section 2 describes the proposed optimal DG algorithm utilising the DE algorithm. The formulation of algorithm objectives and constraints are discussed in

Section 3, while the modelling of test system with component profiles are presented in Section 4. In Section 5, the results of the optimal DG planning are presented; in particular, the proposed algorithm is compared with other techniques. Section 6 explains the optimal operation of DG sources via variation of their power factors throughout the day. Section 7 concludes the paper.

2. Design of the proposed optimal DG algorithm

In this paper, the proposed optimal DG algorithm is developed using DE. DE, which is an Evolutionary Algorithm (EA) developed by Storn and Price in 1997 [23], has been applied in various scientific fields. DE is simple to be programmed and requires a small number of control variables. In addition, DE can deliver better performance compared to other algorithms of similar type [24]. Although DE is not biologically motivated as for typical EAs, such as GA or PSO, it is a population-based algorithm in which each individual is a vector of dimension D (where D is an integer value predefined by users according to the problem). As suggested by the name of the algorithm, the main operation of DE is vector difference, which initially was an attempt by Storn to solve the Chebychev Polynomial fitting problem. The processes of population initialisation, mutation, crossover and customisation for this study will be described in subsequent subsections.

2.1. Initialisation of the population

As mentioned previously, the dimension of each vector, denoted as D, is to be initially defined, and it should be of value similar to the number of controlling variables. For example, if all three parameters of location, sizing and power factor of three DGs are to be optimised, then D should be set to nine. The total number of individuals in the population, denoted as N, should be set to five to ten times the value of D. The population can be expressed as (1) [23]:

$$\text{Population} = [x_1, x_2, \ldots, x_N]; \text{ in which each individual } x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}] \tag{1}$$

Because DE supports mix-integer optimisation, each parameter of x_i can either be a discrete or continuous value. For the case of three DGs, the first three parameters of x_i denote the locations (Loc.) of the three DGs, which are generated randomly in the range of available bus numbers (integer values). The next three parameters indicate the sizing (Size) of three DGs, and the last three parameters represent their power factor (*pf*) values. All of these parameters are continuous values randomly chosen in their own range. A graphical representation of an individual for this case is illustrated in Fig. 1.

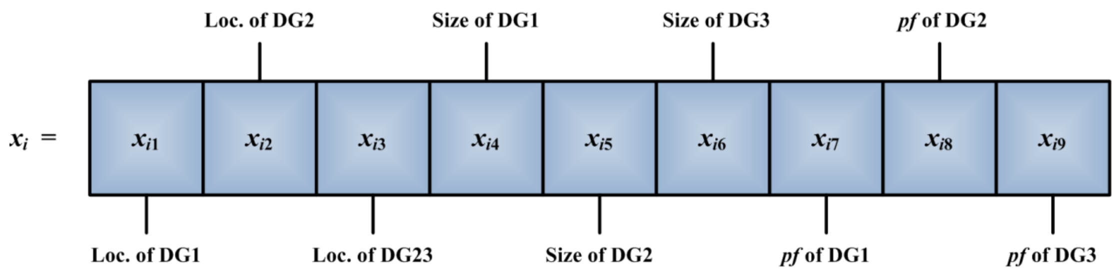


Fig. 1. Example of a 9-dimensional vector in the population for the case of three DGs.

2.2. Mutation process

After population is initialised, N mutated vectors are created by adding a scalar-weighted difference of two vectors into a third vector. For version 'DE/rand', these three vectors are chosen randomly in the population. A mutated vector v_i is calculated as follows [23]:

$$v_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G}) \tag{2}$$

where r_1,r_2,r_3 are random integer numbers $\in [1, N]$ that represent the positions of the vectors in the population; G is the number of the current iteration that denotes the G^{th} generation; and the weight F is a predefined value $\in [0, 2]$ and is set to 0.8 in this study.

All parameters in the mutated vector v_i are likely to have a continuous value after the calculation because of the weight factor multiplication. Hence, some parameter values must be rounded to the nearest integer number, especially for the parameters that represent the location of DGs. Subsequently, all the parameters of the mutated vector are checked to determine whether they remain in their own ranges, which are bound by the constraints. If the condition is not met, then the particular mutated vector should be re-generated. Fig. 2 demonstrates the mutation process for the case of the 2-dimensional population.

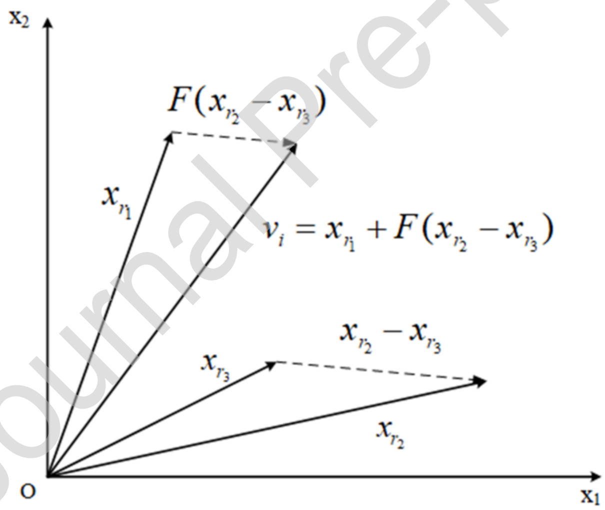


Fig. 2. Example of the DE mutation process for the case of a 2-dimensional population.

2.3. Crossover process

N trial vectors $u_{i,G+1}$ are created during the crossover process by mixing them with the mutated vectors, $v_{i,G+1}$, and the target vector, x_i. The conditions are as follows [24]:

$$u_{ij,G+1} = v_{ij,G+1} \text{ if } randb_j \leq CR \text{ or } j = rr_j, \text{ for } j \in [1, D] \tag{3}$$

or

$$u_{ij,G+1} = x_{ij,G} \text{ if } randb_j > CR \text{ and } j \neq rr_j, \text{ for } j \in [1, D] \tag{4}$$

where the j^{th} parameter of u_i,x_i,$and\ v_i$ is denoted as u_{ij},x_{ij},$and\ v_{ij}$, respectively; $randb_j$ is a uniform random value $\in$ [0, 1] that is re-generated for each parameter j of u_i; CR is the crossover rate, which is a predefined value $\in$ [0, 1] and is set to 0.9 in this study; and rr_j is a random integer $\in$ [1, D] to ensure at least one of the parameters in trial vector u_i has been mixed between $v_{i,G+1}$ and x_i. Fig. 3 illustrates the crossover process for the case of three DGs where the dimension, D, is set to nine.

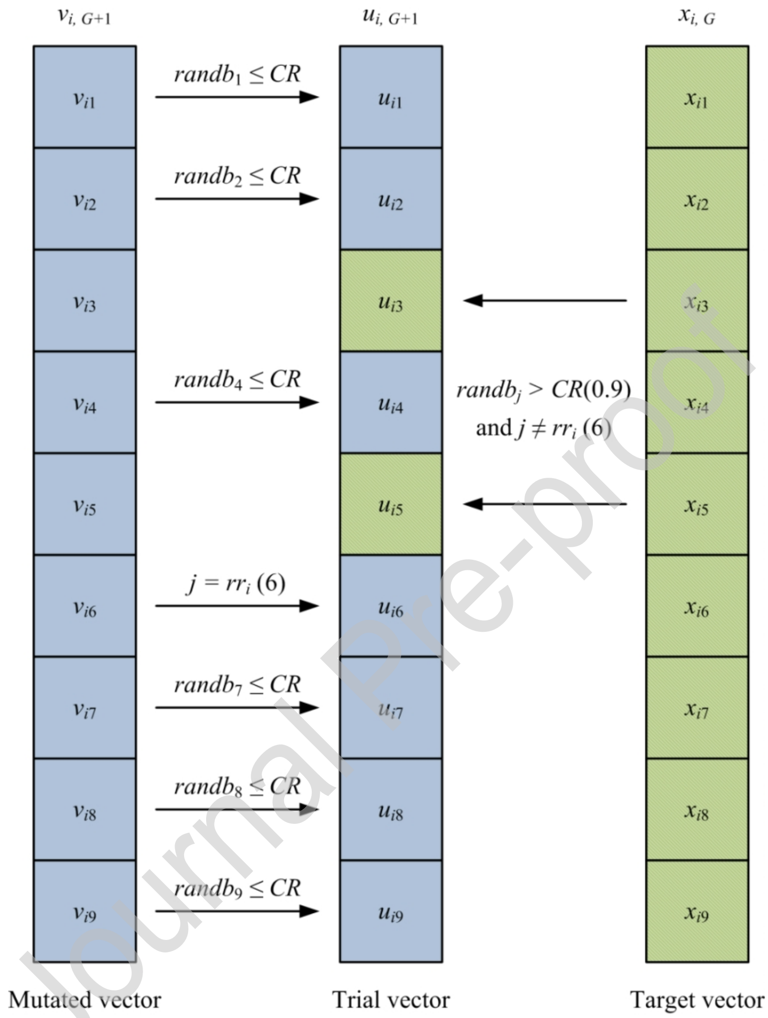


Fig. 3. Example of the DE crossover process to create a trial vector from a mutant and a target vector (9-dimensional).

2.4. Stopping criteria

The population is only required to be initialised in the first generation. Subsequently, the mutation and crossover processes will be repeated to produce new generations, and the iterations will continue. Unlike several studies that used a fixed number of iterations to stop the algorithm, the stopping criteria for this proposed algorithm is that all individuals in the population must have a very close value for each of their parameters. The mathematical representation of the stopping condition is presented as follows [24]:

$$\text{For each } j \in [1, D]\text{: } |x_{aj} - x_{bj}| < \delta_j,\ \forall\ a, b \in [1, N],\ a \neq b \quad (5)$$

The tolerance value of δ_j is set based on the controlling variable that parameter j^{th} represents. For instance, if the parameter represents location of the DG, then δ_j = 1. Moreover, δ_j is set to 0.05 or 0.005 if the parameter represents DG sizing (in kW) or power factor, respectively.

3. Formulation of algorithm objectives and constraints

3.1. Power and energy loss

The network power loss at time t, which is denoted as $P_{loss}(t)$, is determined using load flow analysis in DIgSILENT software. $P_{loss}(t)$ includes the power losses of all the lines in the network and the DG step-up transformer losses. For the case studies that consider load and generation variations, the daily energy loss is also calculated to measure the overall performance. The time step, Δt, is usually predetermined and is set as one hour in this study. The equation for 24-hour energy loss of the system is expressed in (6):

$$E_{loss} = \sum_{t=0}^{24} P_{loss}(t) \,.\, \Delta t \tag{6}$$

3.2. Power infeed

The power infeed, which is denoted as $P_{infeed}(t)$, is the active power that is imported from the upstream substation to the test system and is calculated as follows:

$$P_{infeed}(t) = P_{loss}(t) + P_{load}(t) - \sum \mathrm{P}_{\mathrm{DG}}(t) \tag{7}$$

where $P_{load}(t)$ is total active power of all loads in the system at time t; and $\sum \mathrm{P}_{\mathrm{DG}}(t)$ is the total amount of active power that is generated by the installed DGs at time t.

3.3. Constraints

In this paper, the proposed DG algorithm optimises the placement, sizing and power factor of each connected DG while satisfying several practical constraints. The constraints for this optimisation study are listed as follows:

- Bus voltage must be within ± 5% of its nominal value at any time.

$$0.95\, p.u. \leq V_i \leq 1.05\, p.u., \forall\, i \in 1,2,\ldots, N_{bus} \tag{8}$$

- The power rating of each DG is limited to the maximum demand of the test network.

$$0 \leq P_{DG,j} \leq P_{load,\,max}, \forall\, j \in 1,2,\ldots, N_{DG} \tag{9}$$

- The power factor of each DG is limited to the range from 0.8 (either lagging or leading) to unity.

$$0.8 \le pf_{DG,j} \le 1 \tag{10}$$

- The power infeed at the primary substation should not be negative at any time to alleviate reverse power flow from the test network to the upstream network.

$$P_{infeed}(t) \ge 0,\ \forall\, t \tag{11}$$

4. Modelling of test system with component profiles

4.1. System load curve

The hourly load variation considered in this study is depicted in Fig. 4 by averaging the seasonal load curves that are described in IEEE Reliability Test System (IEEE-RTS) [25].

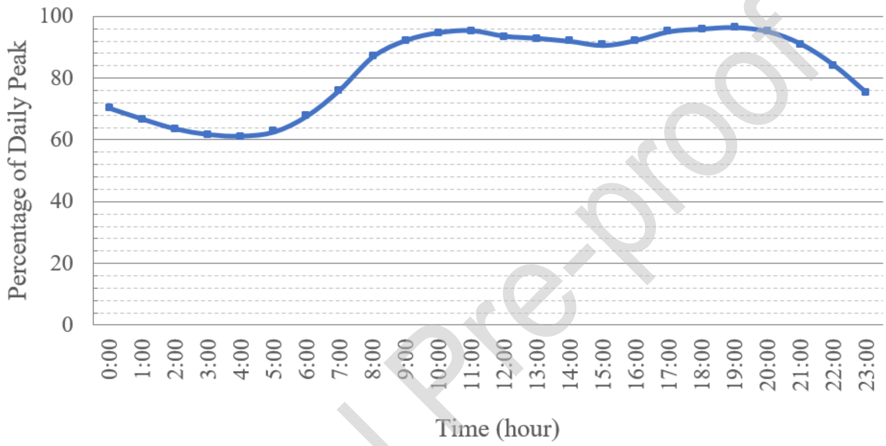


Fig. 4. Hourly load curve of the test system.

4.2. Variation of DG generation

The output variations of solar PV and wind turbine systems are shown in Fig. 5. The curves are produced by averaging the data of solar irradiance and wind speed for one year (July 2014 to July 2015) at a time interval of 15 minutes. This data were recorded by a weather station in the USA [26].

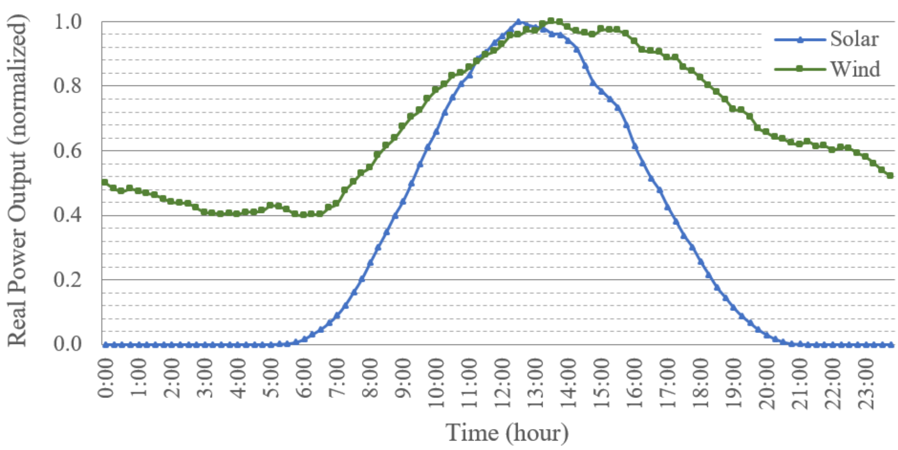


Fig. 5. Hourly output curves of solar PV and wind turbine systems.

4.3. Test system

The network used in this paper consists of 69 buses with a base voltage of 12.66 kV [27]. This network was commonly used by similar studies in literature [11, 27-31]. Hence, the use of this test system allows the results from this research to be directly compared with the findings from similar studies, which can eventually verify the performance of the proposed algorithm. The total base load of the network is at 4 MW and 2.8 MVAr. The initial power loss without any DG installed is 225 kW. By considering the load curve depicted in Fig. 4 and without any DG interconnection, the daily energy loss and energy infeed are 3.75 MWh and 79.47 MWh, respectively. These values will be used as references to benchmark the performance of the proposed optimisation algorithm. Fig. 6 illustrates the test system.

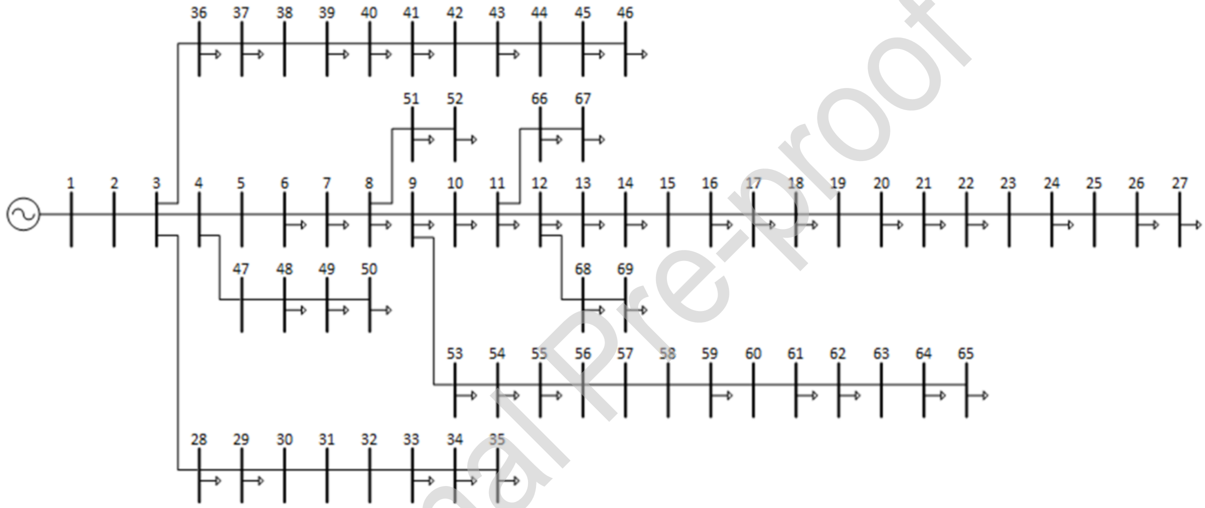


Fig. 6. 69-bus test system under study.

5. Optimal DG planning

In this section, the optimal planning of the integration of single or multiple DG(s) into the test system is presented. The key parameters of each DG system, including location, sizing and power factor, are determined such that the best result of objective function is obtained. The following two case studies are presented: 1) constant load and generation and 2) varied load and generation.

5.1. Constant load and generation

5.1.1. Optimisation results for multiple objectives

As load and generation were constant, the objective for this case study was to minimise the network active power loss with optimal placement and sizing of DG systems. Table 1 shows the optimal results for 1, 2 and 3 DG(s) connection with power factor preset to unity pf. The results were compared with several existing studies to validate the performance of the proposed algorithm. For all cases of single, double and triple DG integration, it can be observed that the proposed algorithm (DE-based) delivered similar or better performance (higher loss reduction) compared to other methods described in [11, 28-30]. It should be noted that the cases of double and triple DGs were not reported in [11] and [30]; hence, results cannot be compared for these cases. The proposed algorithm performed even better when more DGs were connected to the system (such as in the case of 3 DGs), indicating its advantage of solving the problem with a high number of controlling variables or a large search space.

Table 1. Comparative results of interconnection of 1, 2 and 3 DG(s) with unity power factor for case study of constant load and generation.

Scenario	Algorithm	Optimal sizing in kW (Optimal bus number)			P_{loss} (kW)	Loss Reduction (%)
		DG1	DG2	DG3		
No DG	-	-	-	-	225.003	0.00
1 DG	CPLS [11]	1850.0 (B61)	-	-	83.235	63.01
	IA [28]	1900.0 (B61)	-	-	83.244	63.00
	CF-PSO [29]	1806.2 (B61)	-	-	83.372	62.95
	HCF [30]	1900.0 (B61)	-	-	83.244	63.00
	DE	**1872.3 (B61)**	**-**	**-**	**83.218**	**63.01**
2 DGs	IA [28]	1700.0 (B61)	510.0 (B17)	-	71.945	68.02
	CF-PSO [29]	1806.2 (B61)	511.0 (B17)	-	71.705	68.13
	DE	**1870.6 (B61)**	**531.9 (B17)**	**-**	**71.672**	**68.15**
3 DGs	IA [28]	1700.0 (B61)	510.0 (B17)	340.0 (B11)	69.962	68.91
	CF-PSO [29]	1806.2 (B61)	511.0 (B17)	719.0 (B50)	70.188	68.81
	DE	**1718.7 (B61)**	**381.1 (B18)**	**525.2 (B11)**	**69.423**	**69.15**

CPLS is Combined Power Loss Sensitivity; IA is Improved Analytical; CF-PSO is Constriction-Factor Particle Swarm Optimisation; HCF is Heuristic Curve-Fitting; and DE is Differential Evolution (proposed).

Table 2 presents another set of optimal results for 1, 2 and 3 DG(s) integration with non-prefixed power factor. In other words, all three parameters of placement, sizing and power factor were optimised simultaneously with the objective to minimise the network active power loss. Similarly, the results were compared with other studies to prove the performance of the proposed DE algorithm. Again, the comparative results showed that the proposed DE-based algorithm delivered similar or better performance (higher loss reduction) compared to other methods for all the cases of single, double and triple DGs integration. In details, for the case of single DG, all the methods agreed on the best bus (Bus 61), but the proposed DE algorithm had the slight edge over the other methods by giving a better loss reduction. Similar results were also observed for the case of double DGs. For the case of triple DGs, the proposed DE algorithm outputted different optimal buses for DG2 and DG3 with different sizing and power factor, which resulted in significant advantages on the network loss reduction compared to the other methods. Study in [30] did not report any finding for the case of double DGs, while studies in [30] and [31] did not present result for the case of triple DGs. Therefore, their results cannot be compared with the proposed DE algorithm in these cases. Table 2 also shows that the network loss reduction was more effective when the power factor of DGs was optimised rather than prefixed at the beginning of study. Another finding was the optimal power factors listed were all lagging pf; this finding was expected because many under-voltage buses were present in the test network before the interconnection of any DG.

The results in Table 1 and Table 2 have validated the performance of the proposed DE algorithm. The proposed DE algorithm converged and delivered the best optimal results among all the methods, given the same inputs and considerations using the network described in Section 4.3. No major assumption was made and the comparison can be easily verified with a simple simulation. It should be noted that it is apparently impossible to run a direct search algorithm to find the best result in this study, due to the complexity of this problem with too many control variables in the network. A direct search algorithm will take too much time to calculate the power flow for every possible answer. Hence, the proposed DE algorithm was utilized in this paper to optimise the location, sizing and power factor setting for each distributed generation source to minimise network losses and maximise distributed generation integration.

Table 2. Comparative results of interconnection of 1, 2 and 3 DG(s) with optimal power factor for the case study of constant load and generation.

Scenario	Algorithm	Optimal sizing in kVA/Optimal power factor (Optimal bus number)			P_{loss} (kW)	Loss Reduction (%)
		DG1	DG2	DG3		
No DG	-	-	-	-	225.003	0.00
1 DG	IA [28]	2243.0/pf 0.8200 (B61)	-	-	23.184	89.70
	CF-PSO [29]	2207.0/pf 0.8241 (B61)	-	-	23.260	89.66
	HCF [30]	2300.0/pf 0.8500 (B61)	-	-	23.984	89.34
	ABC [31]	2200.0/pf 0.8500 (B61)	-	-	23.920	89.37
	DE	**2242.9/pf 0.8150 (B61)**	**-**	**-**	**23.171**	**89.70**
2 DGs	IA [28]	2195.0/pf 0.8200 (B61)	659.0/pf 0.8200 (B17)	-	7.410	96.71
	CF-PSO [29]	2107.5/pf 0.8272 (B61)	641.6/pf 0.8161 (B17)	-	7.309	96.75
	ABC [31]	2100.0/pf 0.8500 (B61)	600.0/pf 0.8500 (B17)	-	7.999	96.44
	DE	**2140.4/pf 0.8140 (B61)**	**628.7/pf 0.8280 (B17)**	**-**	**7.207**	**96.80**
3 DGs	IA [28]	2073.0/pf 0.8200 (B61)	622.0/pf 0.8200 (B17)	829.0/pf 0.8200 (B50)	5.071	97.75
	CF-PSO [29]	2086.0/pf 0.8318 (B61)	613.4/pf 0.8279 (B18)	845.4/pf 0.8276 (B50)	5.168	97.70
	DE	**2057.8/pf 0.8140 (B61)**	**454.9/pf 0.8340 (B18)**	**608.8/pf 0.8130 (B11)**	**4.268**	**98.10**

IA is Improved Analytical; CF-PSO is Constriction-Factor Particle Swarm Optimisation; HCF is Heuristic Curve-Fitting; ABC is Artificial Bee Colony; and DE is Differential Evolution (proposed).

5.1.2. Result comparison on voltage profile improvement

Besides network power loss reduction, another finding of optimally installing DGs was voltage profile improvement. Fig. 7 shows the voltage profile of all buses in the test network, with the results obtained from the proposed DE algorithm in Table 2. From the results, it can be concluded that better voltage deviation reduction was attained when more DGs were optimally integrated to the test network. Fig. 8 depicts a comparison of the voltage profile results of the proposed algorithm with those of other optimisation techniques presented in the literature. The comparison was conducted for the scenario of 3 DGs interconnection, as presented in Table 2. The proposed DE-based method achieved the lowest value of voltage deviation relative to the other techniques. The acquired standard deviation of voltage level for IA [28], CF-PSO [29] and DE was 0.0018 p.u., 0.0017 p.u. and 0.001 p.u., respectively.

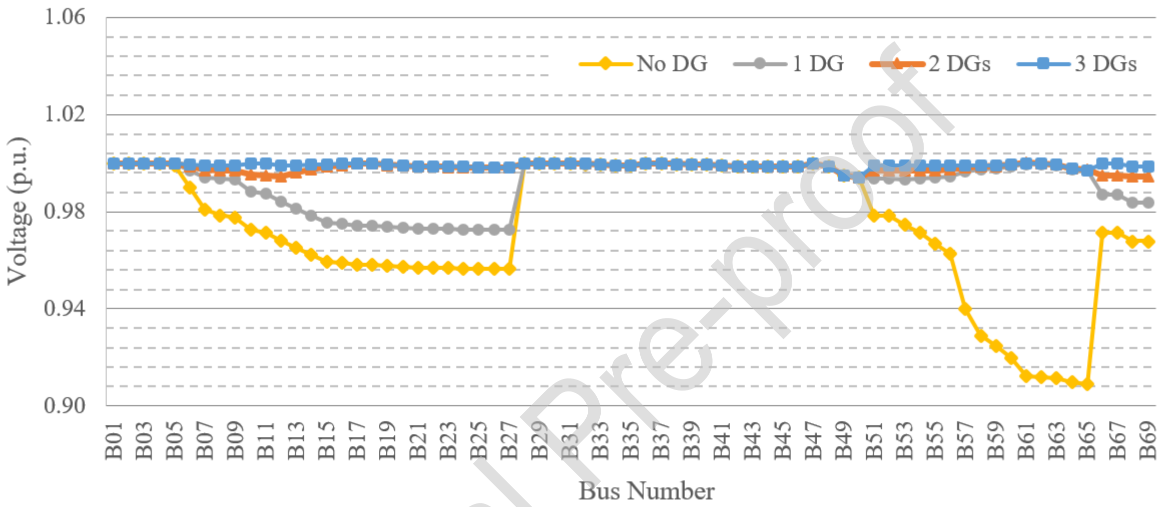


Fig. 7. Voltage profile of the test network with and without DG installation after the implementation of the proposed DE-based algorithm.

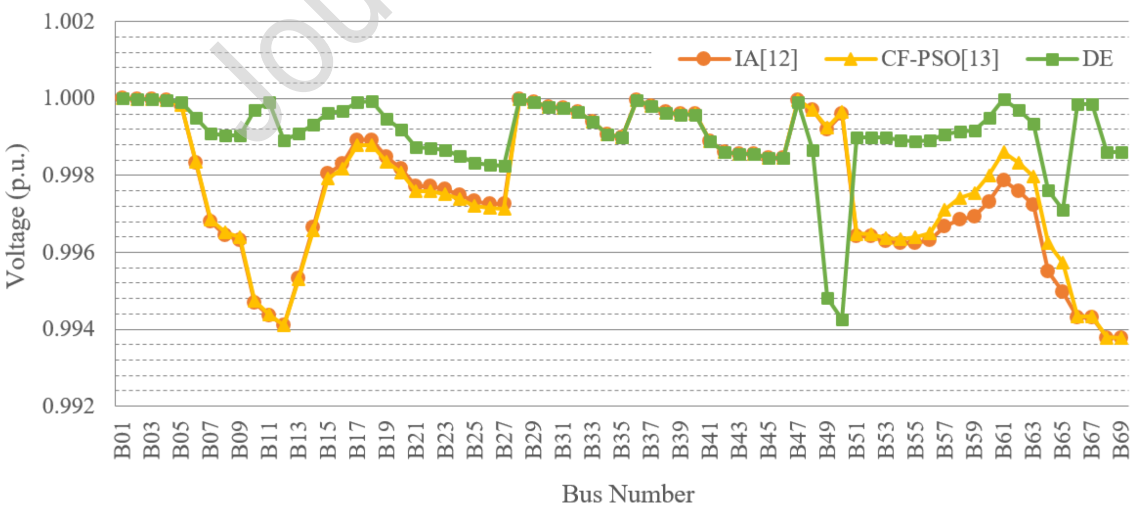


Fig. 8. Result comparison of the voltage profile with optimal installation of 3 DGs using different methods.

5.2. Varied load and generation

5.2.1. Optimisation results for multiple objectives

In this case study, the location, sizing and power factor of 3 DGs of different types, namely, solar photovoltaic (SPV), wind turbine (WT) and biogas generator (BG), were optimised by considering the variation in system generation and loading, as shown in Fig. 4 and Fig. 5. The output of the BG was assumed to be constant throughout the day. The objective functions were chosen from two perspectives, i.e. to minimise the network energy loss from the grid owner's viewpoint and to maximise DGs penetration from the RE developer's viewpoint. To simplify the process, these objectives were converted into the minimisation of energy loss and energy infeed using the formulas described in Sections 3.1 and 3.2. The optimisation of these objectives should be achieved with no violation of the constraints defined in Section 3.3. Table 3 presents the optimal results for each objective as well as when they were combined with the same weight factor of 0.5. The optimal sizing, power factor and placement for each objective are also presented in Table 3.

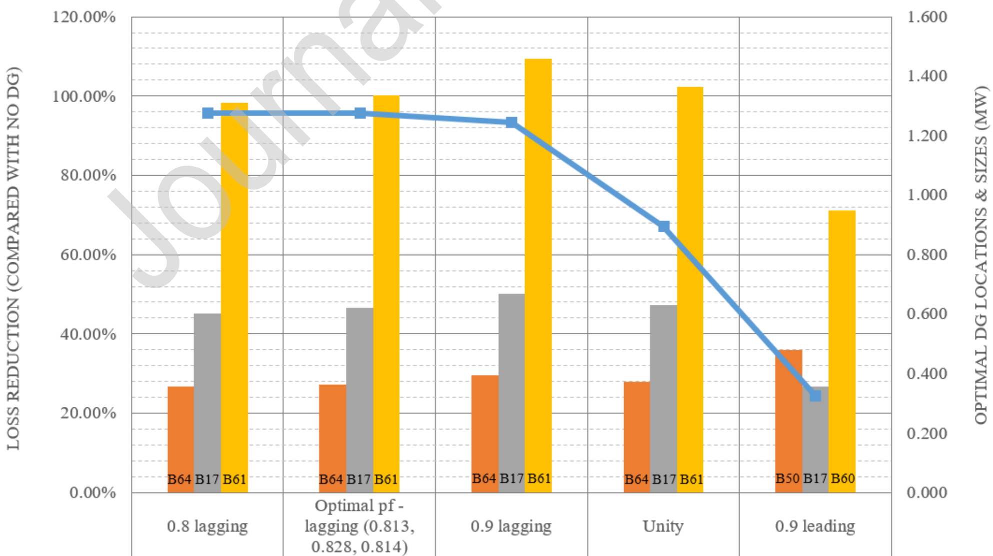
Table 3. Comparative results of interconnection of 1, 2 and 3 DG(s) with optimal power factor for the case study of varied load and generation.

Optimised parameter	Objective function		
	Minimisation of energy loss (grid owner's viewpoint)	Minimisation of energy infeed/maximisation of DG penetration (RE developer's viewpoint)	Minimisation of energy loss and energy infeed (50%–50% weight factor for each objective)
Energy loss (kWh)	161.05	1044.36	363.76
Energy loss reduction (Initially was 3754 kWh)	95.71%	72.18%	90.31%
Energy infeed (kWh)	31231.32	7327.04	7541.61
Energy infeed reduction (Initially was 79469 kWh)	60.7%	90.78%	90.51%
Solar Photovoltaic (SPV)	362.48 kW/pf 0.813 lagging (B64)	100.00 kW/pf 0.802 lagging (B27)	131.23 kW/pf 0.800 lagging (B24)
Wind Turbine (WT)	620.50 kW/pf 0.828 lagging (B17)	1908.55 kW/pf 0.819 lagging (B14)	1768.26 kW/pf 0.931 lagging (B11)
Biogas Generator (BG)	1334.41 kW/pf 0.814 lagging (B61)	1587.39 kW/pf 0.800 lagging (B61)	1634.23 kW/pf 0.853 lagging (B61)

Several findings can be highlighted based on the results in Table 3. When the objective of the optimisation algorithm was to minimise the network energy loss (grid owner's viewpoint), the energy loss reduction achieved compared to base case was 95.71%, which represents an excellent performance. However, the energy infeed was not appropriately reduced, with a reduction of only 60.7%. In contrast, when the objective of the optimisation algorithm was set to minimise the energy infeed or maximise the DG penetration (RE developer's viewpoint), the results obtained were completely opposite, with excellent performance of energy infeed reduction of 90.78%, but a relatively low performance for energy loss reduction of 72.18%. Furthermore, when the objective of the proposed optimisation algorithm was set to achieve both energy loss minimisation and energy infeed reduction with weight factor split evenly to 0.5, excellent optimal results were attained for both objectives with over 90% of reduction accomplished. Therefore, the optimal results of this multiple objectives algorithm appeared to be the best selection in this case study.

5.2.2. Impact of different power factors on the optimisation results

As mentioned before, the assumption of setting the power factor of DGs to fixed values in the initialisation stage might not result in the best solution to the optimal DG problem. Fig. 9 shows the comparative results of the optimal location and sizing of DG when different power factors were applied. It can be observed that if the power factor of DGs was set to unity pf according to a quite common practice of many researches in the literature, the network loss reduction compared to the base case was not significant, with a value of nearly 67%. In contrast, the best network loss reduction with 95.71% was achieved when the power factor of DG was optimised simultaneously with the other parameters of location and sizing. The network loss reduction result was even worse if a leading power factor was set to DGs, and the optimal DG locations were also considerably deviated from the other cases.



	0.8 lagging	Optimal pf - lagging (0.813, 0.828, 0.814)	0.9 lagging	Unity	0.9 leading
Solar PV	0.357	0.362	0.395	0.374	0.481
Wind Turb.	0.601	0.620	0.669	0.631	0.355
Biogas	1.310	1.334	1.458	1.364	0.948
Loss Reduction	95.65%	95.71%	93.44%	67.07%	24.30%

DIFFERENT OPERATING POWER FACTOR OF DGS

Fig. 9. Impact of different operating power factors setting on the optimal result of the DG sizes and locations for the case study with the objective of minimisation of the network energy loss.

6. Optimal DG operation

6.1. Variation of the DG's power factor

The planning study for DG optimisation is a great source of information for engineers to proceed with the installation of DGs in the system. Such optimisation provides the best solution for the particular objective required, assuming that all optimal parameters are fixed during the system lifetime. However, with the recent rapid development of inverter control technology, the ability to continuously adjust the power factor of inverter-based DG has become feasible. This dynamic variation should be implemented in an optimal manner to bring additional benefits to the system compared to the deployment of an optimal fixed power factor value, as presented in the previous section. This implementation can further reduce power losses and mitigate voltage fluctuations, especially when the DGs are based on intermittent resources, such as solar or wind.

In order to compare the results between a fixed power factor and a variable power factor, it is assumed that the 3 DGs of solar, wind and biogas had been installed with optimal parameters of location and size determined by DE method for the objective of minimisation of network energy loss, as presented in the first case in Table 3. The power factor of each DG was optimised every 15 minutes, which matched the time step used in the planning study. As the location and sizing of DG were optimally fixed, the controlling variable only included the power factor of the DGs; as a result, the dimension D for the DE algorithm was set to 3.

Fig. 10 shows the results of optimal power factor variation for each DG, where the result for solar PV technology was only applicable during daytime periods. The additional benefits of varied power factor can be examined by comparing the network power loss between the two cases, as shown in Fig. 11. When the DG's power factor was adjusted continuously and optimally according to the variation in load and generation, the system loss reduction was further minimised. The new daily energy loss was at 148.58 kWh, which was 7.74% lower than its corresponding value of the previous DG planning study (161.05 kWh) presented in Table 3. The overall loss reduction was 96.04% compared to the base case, which was the case without any DG installation.

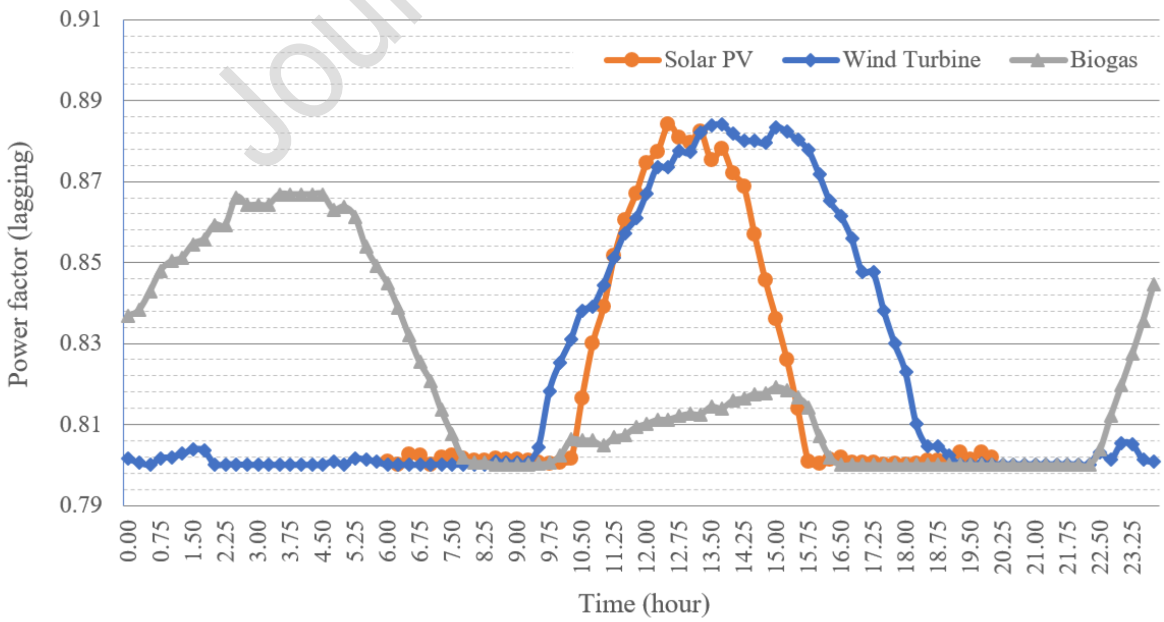


Fig. 10. Optimal variation of the power factor of 3 DGs throughout the day.

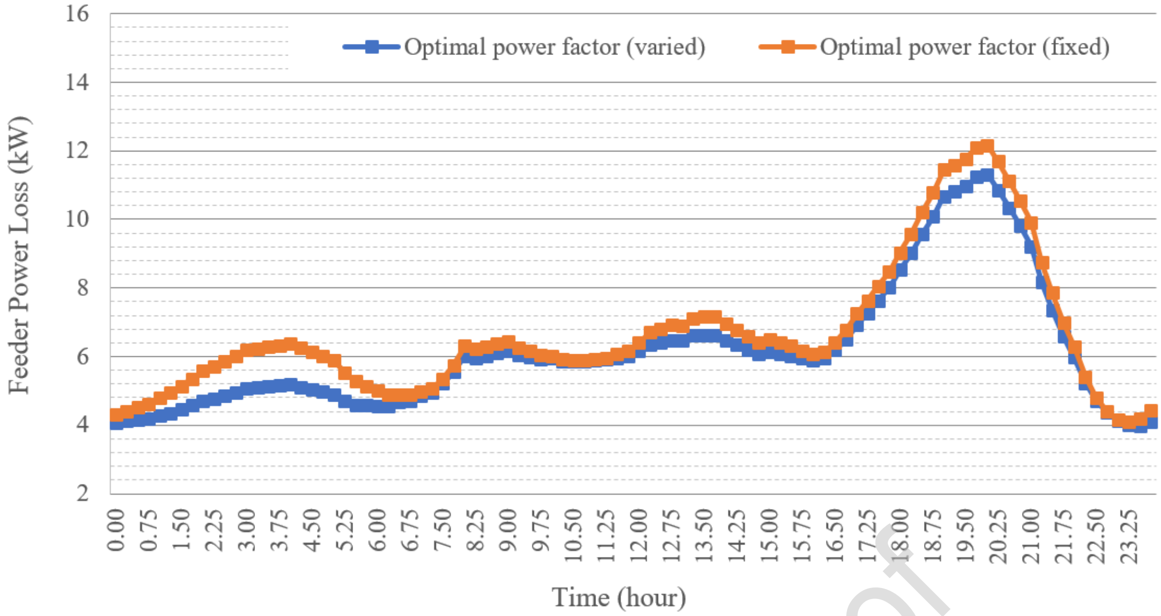


Fig. 11. Result comparison between varied power factor and fixed power factor with the objective function of power loss minimisation.

6.2. Practical application

The advantages of actively adjusting the power factor of DG during its operation compared to a fixed optimal power factor value were clearly highlighted and explained in Section 6.1. Nevertheless, there are several factors that must be considered to ensure the practicality of this application in real-time operation.

- In common distribution feeders, the information of the active power (P) and reactive power (Q) values are only available at the primary substation (beginning of the feeder) and not for the load at each bus.
- Frequent changes of the power factor setting of the biogas generator may cause stresses to the synchronous generator; in contrast, this issue is not a burden for the inverter-based DGs, such as solar PV and WT systems.

The first limitation can be solved by adopting the load estimation method, taking inputs of P and Q readings at the main substation as well as P and Q generated by each DG at every time step. The load estimation can be performed utilising the feeder load scaling function, which is available in DIgSILENT software. This function scales all the load proportionally according their base values to achieve similar P and Q values that are read by power meters in the main substation. Subsequently, the proposed DE algorithm is implemented with the new estimated load values to determine the optimal power factor for DGs during the specific time. For the second concern, the time step for each DG should be set independently in the optimisation algorithm based on the technology. For instance, the time step of three minutes is set for the solar PV and WT systems, while the time step of one hour is set for the BG. Figs. 12 and 13 show the schematic and block diagram of the overall processes for the implementation of varied optimal DG's power factor in real-time operation.

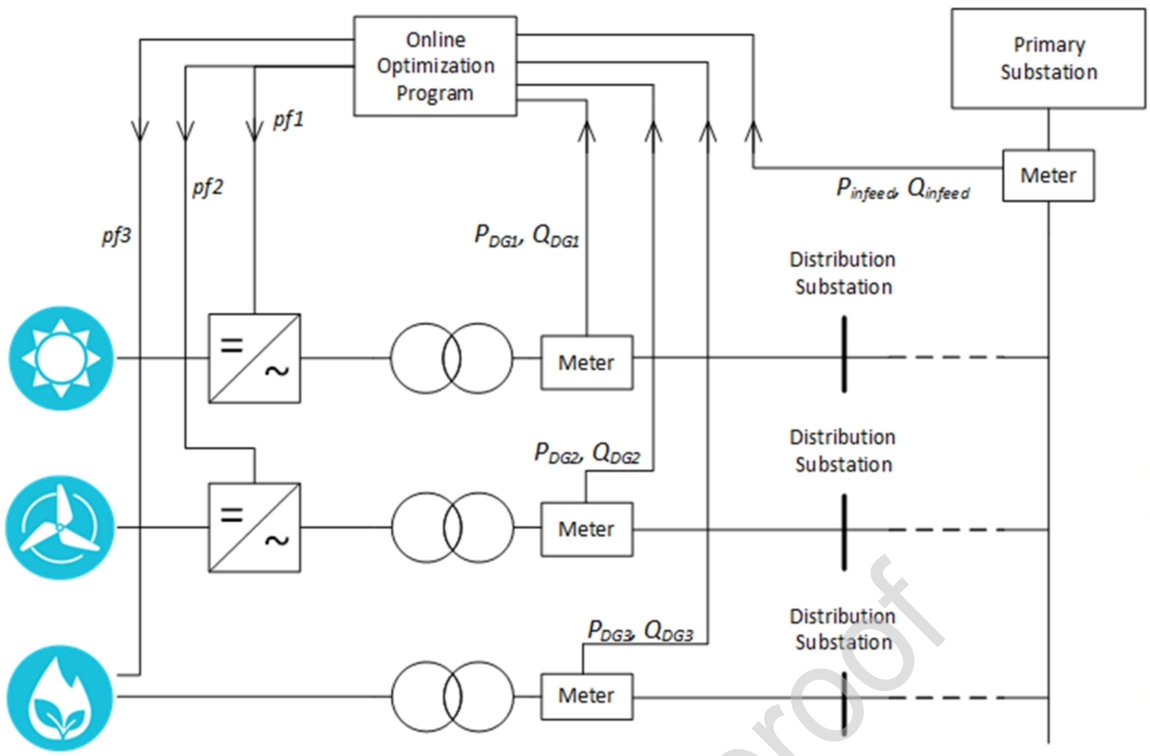


Fig. 12. Schematic diagram showing the inputs and outputs of the optimal DG operation program.

In order to demonstrate the viability of the program, a case study was performed to test its functionality. In this case study, 3 DGs of different types (SPV, WT and BG, with each sized at 1.25 MW) were assumed to be connected to Bus-27, Bus-46 and Bus-65 of the network in Fig. 6. These network buses were at the end of the feeder branches, which are the locations typically preferred by engineers to install DGs for solving the under-voltage problem. Note that this proposed program is applicable to any DG type installed at any network location/bus. Because the program required the absolute values of P and Q flowing at the primary substation as well as P and Q generated by DG at each time step, the curves in Fig. 4 and 5 were not be used for this case study. Instead, a set of absolute values were assumed for these parameters. Figs. 14 and 15 show the required input data of P and Q for upstream network and DG outputs. It can be observed that only six hours during daytime periods were demonstrated because the high sampling rate of three minutes was applied for each time step. The variation in the P value from the upstream network in Fig. 14 was caused by the system being directly affected when DGs changed their outputs.

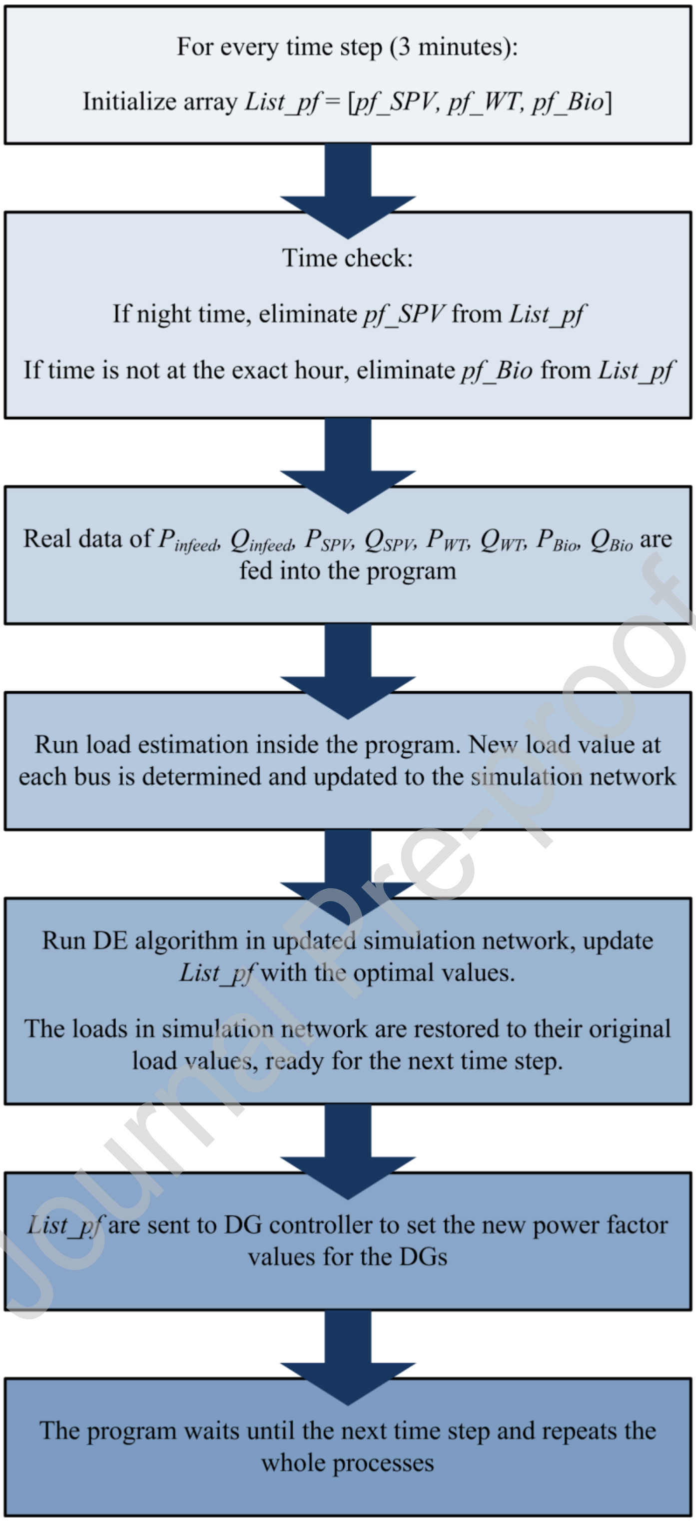


Fig. 13: Processes of varied optimal DG's power factor in real-time operation.

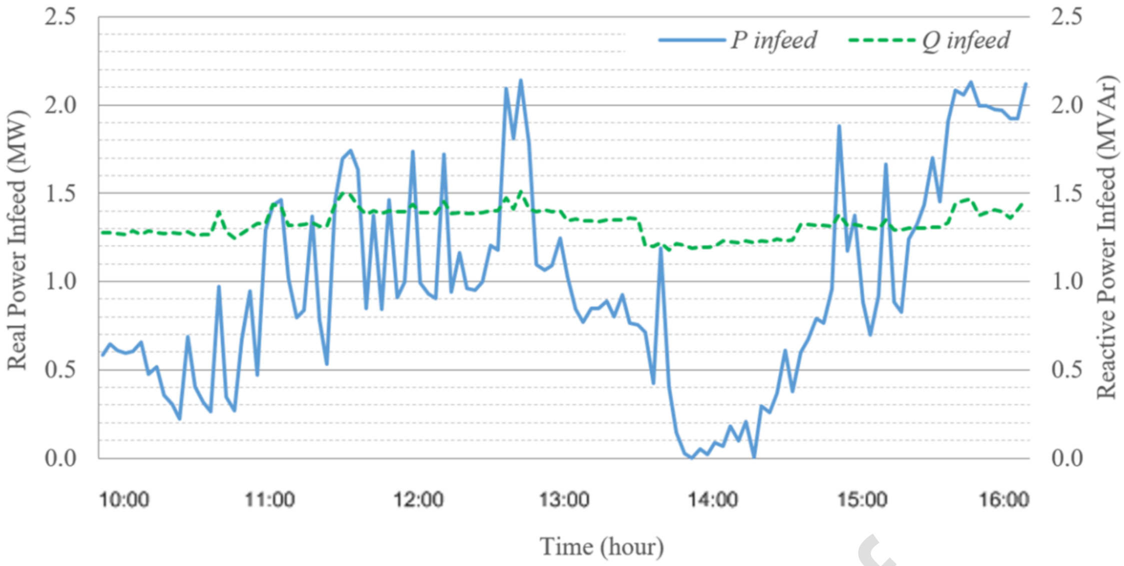


Fig. 14. Input data of P and Q from the upstream grid.

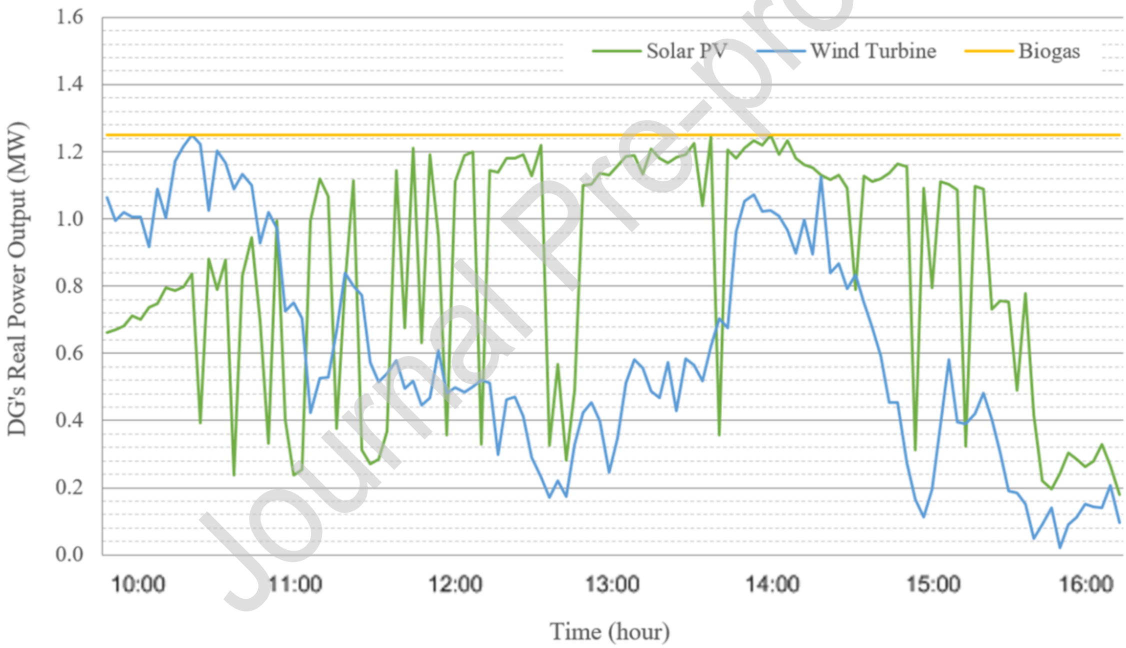


Fig. 15. Input data of the power generated by the DGs.

The program successfully outputted the optimal power factors for 3 DGs at each time step, as illustrated in Fig. 16. The power factor of BG changed hourly, while the power factors of SPV and WT changed every 3 minutes. One of the observations from this case study was that the pattern of the optimal power factor for each type of DG was closely related to the pattern of its real power output, as depicted in Fig. 15. This response was expected because a sudden drop in DG's real power output will cause a drop in its power factor value (lagging) to provide higher reactive power to the network for voltage fluctuation reduction. Moreover, the time taken to output the optimal results for each step was generally between 0.5 and 1.5 seconds, representing relatively fast performance. The proposed program can be applied to any new or existing network for real-time operation with optimal DG's power factor.

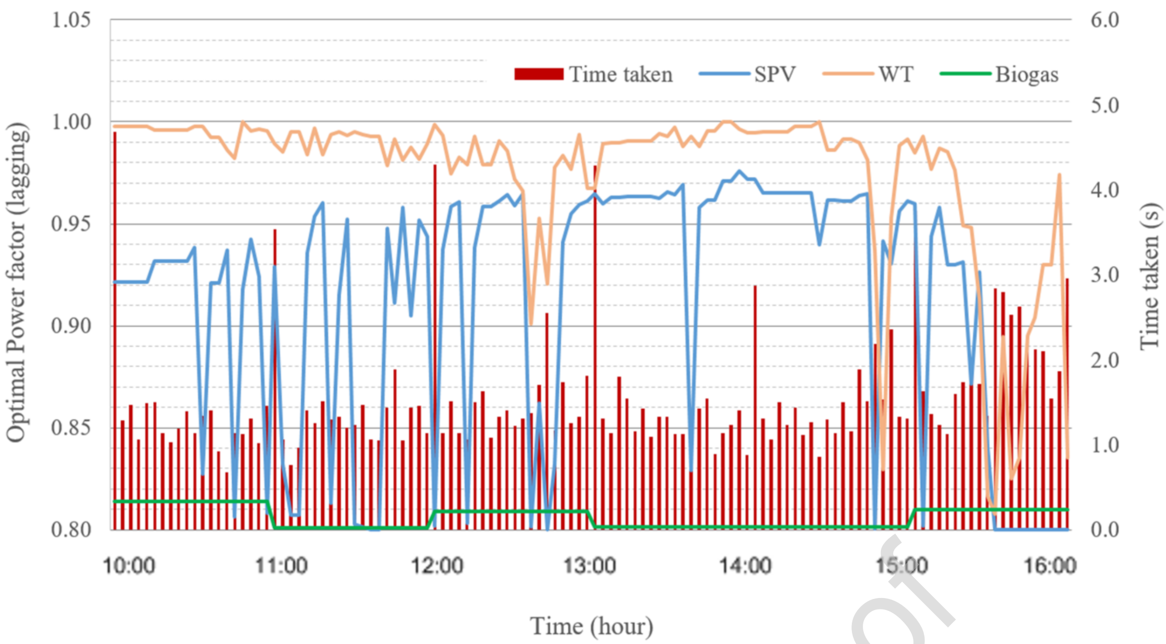


Fig. 16. Program output with optimal power factor for each DG and the time taken to deliver the results.

7. Conclusion

In this paper, a DE-based optimisation algorithm was designed to optimise the placement, sizing and power factor of DGs in a distribution test network. Comprehensive studies were performed for both the planning stage and the real-time operation stage. In DG planning, multiple DGs were integrated into the power grid from the perspectives of both the Distribution Company and RE developers to achieve the objective functions of minimisation of network losses and maximisation of DGs penetration. The case studies were performed for constant or varying amounts of load and generation with the consideration of the crucial power system constraints. The results of all case studies revealed that the proposed DE-based algorithm delivered similar or better performance of network loss reduction compared to other existing methods. Another finding was that a better grid voltage deviation reduction was attained when more DGs were optimally integrated into the test network. Moreover, the network loss reduction was also more effective when the power factors of DGs was optimised instead of being preset at the beginning of the study. The network loss reduction of 95.71% was achieved when the power factor of DG was optimised simultaneously along with other parameters, such as DG's location and sizing.

Furthermore, a novel framework of varied optimal operational power factors for multiple DGs was introduced. When each DG source's power factor was adjusted continuously and optimally according to the variations in the load and generation, the system loss reduction was further minimised. The overall loss reduction achieved was 96.04% compared to the base case of no DG connection. The overall processes of the framework were comprehensively explained, and the practicality of the framework was validated in real-time DG operation.

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Declaration of interests

√ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Phung Dang Huy Vigna K. Ramachandaramurthy Jia Ying Yong Kang Miao Tan Janaka B. Ekanayake

Highlights

- Algorithm design to optimise the placement, sizing and power factor of DG
- Design of DG framework to minimise network losses and maximise DG integration
- Inclusion of various power system constraints for practicality
- Comparative analyses in planning and real-time operation for algorithm validation