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Integrated Clustering Development Using Embedded Meta Evolutionary-Firefly Algorithm Technique for DG Planning

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Abstract

Recent trend changes have created opportunities to achieve numerous technological innovations including the use of distributed generation (DG) to achieve different advantages. A precise evaluation of energy losses is expanding rapidly when DG is connected to the electricity sector due to developments such as increased competition and real time pricing. Nevertheless, non-optimal DG installation either in the form of DG locations and sizing will lead to possible under-compensation or over-compensation phenomena. The integrated clustering resulted from the pre-developed Embedded Meta Evolutionary Programming–Firefly Algorithm (EMEFA) has been used to ensure the optimum allocation and placement of DG. The study also considers the different types of DG. The aim of the technique is to consider the computational time of the optimization process for DG planning in achieving the minimal total loss. Two test systems have been used as test specimens to achieve the efficacy of the proposed technique. In this study, the techniques proposed were used to establish the DG size and the appropriate place for DG planning. The results for total losses and minimum voltage for the system were recorded from the simulation. The result in this study will be compared with the ranking identification technique to ensure the capability of this technique. The power system planner can adopt the

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suitable sizes and locations from the obtained result for the planning of utility in term of economic and geographical consideration.

Keywords: Distributed generation, DG Planning, Evolutionary Programming, Firefly Algorithm, Loss Minimization.

1 Introduction

Several issues such as energy efficiency, environmental impact and security of supply are the major concerns when dealing with the DG installation. As a result, the penetration of DG in the electricity network will increase and may affect the system [1]–[3]. Considering this, various forms of Distributed Generation (DG) technologies have been connected to the system, either to the transmission or distribution system. The installation of DG requires optimisation process to identify the correct location and sizing. Improper sizing and location of DG installation can lead to overcompensation or under compensation. Most optimization methods are inaccurate and stuck in computationally burdensome local minimal phenomena. A reliable optimization technique is therefore essential to deal with this problem. Numerous studies have been reported in this decade in the effort to search for reliable optimization technique. The trend these days consider the integration of several optimization techniques to make them more robust, reliable and flexible. Researchers the proposed techniques as integrated optimization, embedded optimization, cascaded optimization or hybrid optimization. Nevertheless, not all techniques can generally be integrated together to achieve new technique. Thus, a generalization is normally avoided to claim the merit of the proposed technique.

In this paper, a integrated clustering development and Embedded Meta Evolutionary–Firefly Algorithm (EMEFA) was established by incorporating Firefly Algorithm operators into the original Meta Evolutionary Programming. The aim of integrated clustering development and EMEFA technique is to minimise the computational time of the optimisation process for DG planning [4]. A clustering technique and pre-developed EMEFA technology have been proposed in order to achieve an optimal allocation and placement of DG. This also reduces the need for the whole system to install unnecessarily DGs. The proposed technique was tested using several IEEE reliability test systems namely IEEE33-bus and IEEE-69-bus. The results presented in this study could be used by the distribution system utility for the loss reduction scheme. Due to encouraging usage of renewable energy sources, several issues such as energy efficiency, environmental impact and security of supply are the major concern. The system engineers must plan the implementation of DG appropriately.

2 Problem Formulation

Problem formulation refers to the problems to be solved by such study. The proposed integrated clustering and EMEFA based technique are 2 important components in DG planning. This will be conducted under different load models, which also depend on the control variables in each model. Changes in DG types will also influence the performance of the optimization process. Past studies have indicated the importance of considering constant active and reactive power are assumed as constant values (i.e., constant power model). Nevertheless, insufficient data have been the identified setback under different load models.

The 2-Bus power system model is shown in Figure 1. The loss minimisation will be expected subject to the optimal location or sitting of DGs and the corresponding sizing. Equation (1) characterises the total losses. In order to obtain the total line losses, A_{ij} and B_{ij} need to be obtained using equation (2) and (3).

$$P_{loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} A_{ij}\left(P_i P_j + Q_i Q_j\right) + B_{ij}\left(Q_i P_j - P_i Q_j\right) \quad (1)$$

$$A_{ij} = \frac{R_{ij}\cos(\delta_i - \delta_j)}{V_i V_j} \quad (2)$$

$$B_{ij} = \frac{R_{ij}\sin(\delta_i - \delta_j)}{V_i V_j} \quad (3)$$

Where,

P_i and Q_i are real and reactive power of bus *i* respectively

P_j and Q_j are the real and reactive power of bus *j* respectively

R_{ij} is the line resistance between bus *i* and bus *j*

V_i and V_j are the voltage magnitude at bus *i* and bus *j* respectively

δ_i and δ_j are the voltage angle of bus *i* and bus *j* respectively

The effect of DG installation scheme into the distribution system is the aim of this study. Different load models for different DG types will give different impacts to the system performance.

The objective function, Of_1 is written as in (4):

$$\mathrm{Of}_1 = \min\left(P_{loss}\right) \quad (4)$$

Where Total Loss $_0$ = Total loss without DG in MW

Total Loss $_{DG}$ =Total Loss with DG in MW

Figure 1 illustrates the conceptual of DG location dependent on load model. From the figure, 4 load models are considered for different DG types. The load models are very much influenced by the nature of DG types. For example, the DG is installed at bus *n*, consequently the load model also at bus *n*. For the purpose of study, four case studies were considered based on different DG type and load model. The details case study is discussed in the results and discussion.

2.1 DG Types and Model

In DG optimization scheme, loss minimization is the most common objective function; which is **controlled by** the decision variables or control variables for different DG type as tabulated in Table 1 [5]. In this study, the operational power factor is set to be 0.85 which adheres the standard determined by the IEEE standard and Energy Commission of Malaysia. In this study, the voltage constraint is subjected to equation (5). On the other hand, power loss should be set lower than the total loss without DG sources. This will ensure that the DG installation scheme is worth. It is worth to mention that, the over-compensation or under-compensation should not be experienced in this study. Otherwise, the participating entities will discover that the proposed scheme is no worth it. Equations (6) characterises the expected DG installation scheme, while equation (7) presents the objective function of the study. Total losses in the distribution system were set as fitness value. In the selected locations, the simulation was calculated by executing the power flow programme with the injected active and reactive power with the load is modelled at different type.

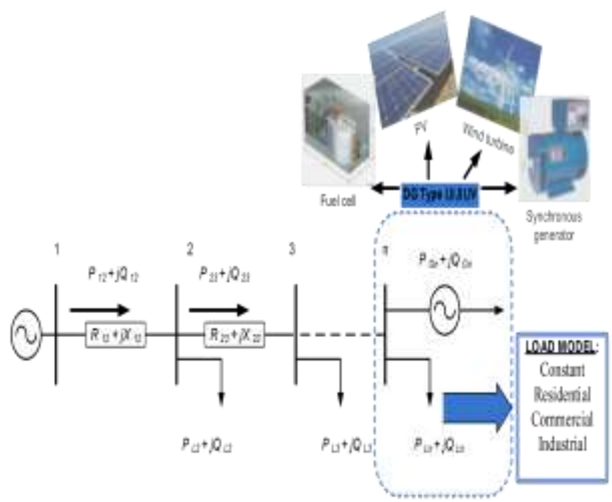

Figure 1 The Conceptual of DG Location Dependent on Load Model

$$0.95\,p.u \le V_{\min} \le 1.5\,p.u \quad (5)$$

$$P_{loss}^{\ with\ DG} < P_{loss}^{\ without\ DG} \quad (6)$$

$$Minimise \sum_{j=1}^{n} P_{loss} \quad (7)$$

Where P_{loss} represent the total power loss in the system and n refers to the number of lines in the system.

Table 1 DG Type and the Variables in DG Modeling for Optimisation Process	
DG Type	DG Modelling
Type I:	$x_i = P_g(MW)$ x_i = *random number*
Type II:	$x_i = Q_g(MW)$ x_i = *random number*
Type III:	$x_i = P_g(MW)$ x_i = *random number* $Q_g = P_g \times \tan^{-1}\theta(MVAr)$
Type IV:	$x_i = P_g(MW)$ x_i = *random number* $Q_g = -(P_g \times \tan^{-1}\theta)(MVAr)$

2.2 Distributed Generation Load Model

Loss minimization scheme has been the most popular scheme in power system study; involving the sitting and sizing of DG under different load models [6]. However, this paper focuses on the proposed clustering technique for the different load model by considering the different DG type. The conducted study focussed on the effect of DG installation subject to changes in load model. Static load model can be characterised by voltage dependent load model. In this model, the load power is characterised by the voltage dependency which increases exponentially based voltage factor. Equations (8) and (9) represent this phenomenon.

$$P_L = P_{oi} V_i^{\alpha} \qquad (8)$$

$$Q_L = Q_{oi} V_i^{\beta} \qquad (9)$$

Where P_L and Q_L are the real and reactive power load at node *i*, P_{oi} and Q_{oi} are active and reactive power at nominal voltage, *V* is the voltage magnitude at a load *i*. *m* and *n* are active and reactive power exponents, respectively. Real and reactive power exponents for commercial, residential, and industrial loads used in the present work are indicated in [7]. Four different models based on the type of load model are used for validation process. This will ensure that the proposed technique will be able to produce results as expected.

3 Integrated Clustering Development and EMEFA Technique for DG Planning

The integrated clustering technique was performed to obtain the suitable location for DG planning. Cluster is formed based on the list of DG in the group of mixture of buses. It is an exploratory method to help us comprehend the amassing structure of the information and data [7]. Load flow study was initially executed at base case. Cluster was subsequently identified by grouping the participating buses being sorted in accordance with the low voltage profile rank. The clustering technique was performed by identifying the group of DG location. The EMEFA technique has been carried out with the objective function of minimizing total losses, taking into consideration the type of DG in the system. The hybrid optimization is expected to enhance the performance, robustness, efficiency, while in turn reducing the computational time when combined them together. Figure 2 and 3 presents the flowchart for the proposed EMEFA based integrated clustering technique and EMEFA Based Approach for Ranking Identification. The outputs from this stage are consequently made use for clustering process of DG. The result in this study will be compared with the ranking identification technique [8] to ensure the capability of this technique and as a benchmark on the DG installation concept. The flowchart of Ranking Identification technique for DG planning is shown in Figure 4. The comparative study for both test systems is summarized in Table 2 using the proposed integrated developments in clusters and EMEFA technology and ranking identity techniques.

Table 2 Case Study for Integrated Clustering Development and EMEFA Technique

IEEE 33 - Bus Test System			IEEE 69 - Bus Test System		
Case Study	Scenario		Case Study	Scenario	
A33 DG Type I	I-1000	Constant	E69 DG Type I	I-1000	Constant
	I-0100	Industrial		I-0100	Industrial
	I-0010	Residential		I-0010	Residential
	I-0001	Commercial		I-0001	Commercial
B33 DG Type II	II-1000	Constant	F69 DG Type II	II-1000	Constant
	II-0100	Industrial		II-0100	Industrial
	II-0010	Residential		II-0010	Residential
	II-0001	Commercial		II-0001	Commercial
C33 DG Type III	III-1000	Constant	G69 DG Type III	III-1000	Constant
	III-0100	Industrial		III-0100	Industrial
	III-0010	Residential		III-0010	Residential
	III-0001	Commercial		III-0001	Commercial
D33 DG Type IV	IV-1000	Constant	H69 DG Type IV	IV-1000	Constant
	IV-0100	Industrial		IV-0100	Industrial
	IV-0010	Residential		IV-0010	Residential
	IV-0001	Commercial		IV-0001	Commercial

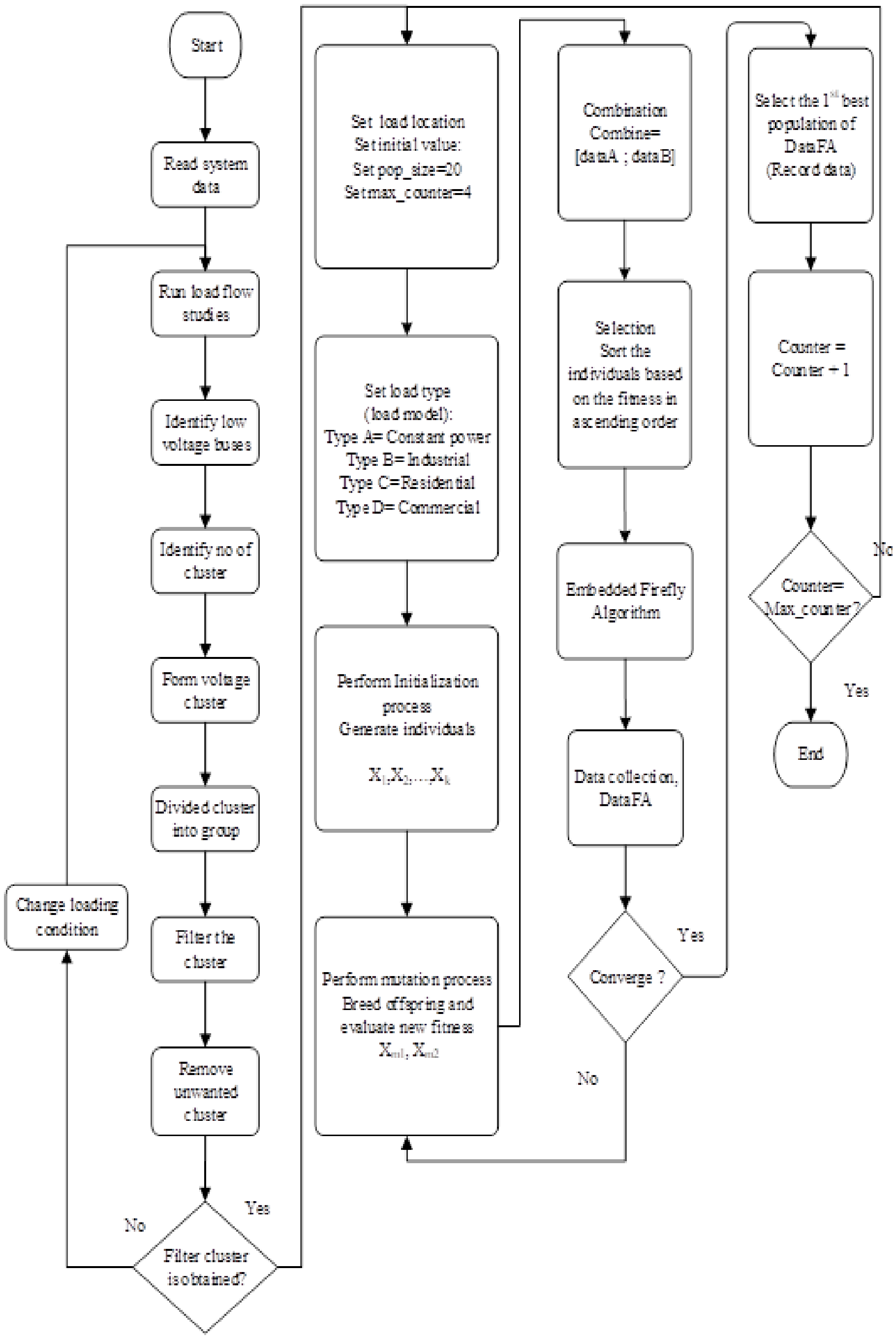

Figure 2 Flowchart for the proposed EMEFA Based Integrated Clustering Technique

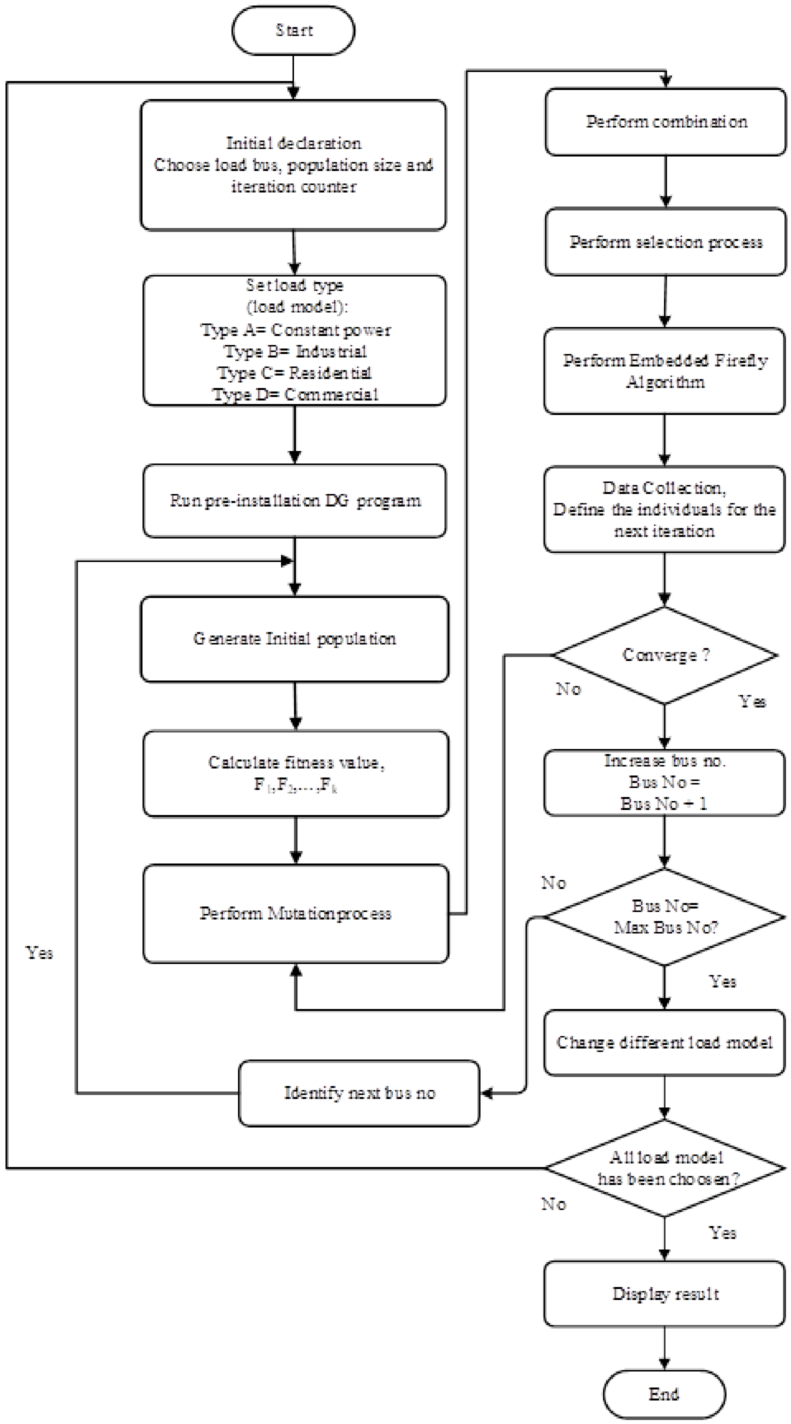

Figure 3 EMEFA Based Approach for Ranking Identification [20]

4 Results and Discussion

Comparative study was conducted between the developed Ranking Identification and integrated clustering development and EMEFA technique in terms of DG placement and the computational time. It was found that the developed program is able to decrease the computational time with accurate DG location and planning for different DG types and load models. In this section, the effect of the loading model on single objective implementation with regard to loss reduction before the DG installation was discussed. The result was compared between the developed Ranking Identification [8]-[9] and integrated clustering development using EMEFA technique in terms of DG location, DG capacity, total losses and computational time.

For scenario I-1000, the ranking identification gives location at bus 25. In Scenario I-1000, type 1 with constant load is considered. The table tabulates the top five locations for DGs installation namely buses 25, 26, 27, 28 and 29. In scenario I-0100, similar process was conducted. For this scenario, buses 30, 25, 26, 29 and 27 are identified as the top five buses for DGs installation. The result for scenario 3 is denoted as I-0010. Buses of bus 30, 25, 26, 27 and 29 are the top five buses sorted in accordance with the system losses. The identification for location of DG was also conducted for scenario I-0001. Buses 30, 25, 26, 27 and 29 are the top five buses to achieve low system losses.

Table 3 Comparative Study on Different Technique and Case Studies (IEEE 33-Bus)

	Scenario	Technique		
			Ranking Identification	Integrated Clustering Development
			Case Study A33	
A33	I-1000	DG Location: DG Capacity: Total Losses: Computational Time:	25 2.2076MW 0.0970MW,0.0704 MVAR 126.4808s	29 1.4785MW 0.1005MW,0.0705MV AR 28.7844s
	I-0100	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.3690MW 0.0767MW, 0.0543MVAR 107.2109s	30 1.3730MW 0.0767MW, 0.0543MVAR 25.7898s
	I-0010	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.3586MW 0.0816MW, 0.0575MVAR 100.9767s	30 1.3616MW 0.0816MW, 0.0575MVAR 24.6353s
	I-0001	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.3440MW 0.0837MW, 0.589MVAR 152.0264s	30 1.3556MW 0.0837MW, 0.590MVAR 28.8820s

	Case Study B33			
B33	II-1000	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.1862MVAR 0.1190MW, 0.0783MVAR 118.1116s	30 1.1884MVAR 0.1190MW, 0.0783MVAR 37.4409s
	II-0100	DG Location: DG Capacity: Total Losses: Computational Time:	30 0.8513MVAR 0.1185MW, 0.0781MVAR 110.3551s	30 0.8260MVAR 0.1184MW, 0.0780MVAR 34.8789s
	II-0010	DG Location: DG Capacity: Total Losses: Computational Time:	30 0.9136MVAR 0.1164MW, 0.0767MVAR 125.3412s	30 0.9071MVAR 0.1164MW, 0.0767MVAR 33.2713s
	II-0001	DG Location: DG Capacity: Total Losses: Computational Time:	30 0.9328MVAR 0.1150MW, 0.0758MVAR 120.9144s	30 0.9415MVAR 0.115MW, 0.0758MVAR 27.2681s

Table 3 Comparative Study on Different Technique and Case Studies (IEEE 33-Bus) (Cont…)

	Scenario	Technique		
			Ranking Identification	Integrated Clustering Development
Case Study C33				
C33	III-1000	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.3386MW, 0.6780MVAR 0.0537MW, 0.0403MVAR 136.5301s	30 1.3418MW, 0.6796MVAR 0.0537MW, 0.0403MVAR 49.0513s
	III-0100	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.3353MW 0.6764MVAR 0.0537MW,0.0402MVAR 171.7971s	30 1.3388MW, 0.6781MVAR 0.0537MW,0.0403MVAR 36.7004s
	III-0010	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.3236MW 0.6704MVAR 0.0538MW, 0.0403MVAR 187.0739s	30 1.3115MW, 0.6663MVAR 0.0537MW, 0.0403MVAR 57.6021s
	III-0001	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.3026MW 0.6597MVAR 0.0537MW, 0.0402MVAR 176.8713s	30 1.3030MW, 0.6600MVAR 0.0537MW, 0.0403MVAR 57.6724s

	Case Study B33			
B33	II-1000	DG Location: DG Capacity: Total Losses: Computational Time:	30 1.1862MVAR 0.1190MW, 0.0783MVAR 118.1116s	30 1.1884MVAR 0.1190MW, 0.0783MVAR 37.4409s
	II-0100	DG Location: DG Capacity: Total Losses: Computational Time:	30 0.8513MVAR 0.1185MW, 0.0781MVAR 110.3551s	30 0.8260MVAR 0.1184MW, 0.0780MVAR 34.8789s
	II-0010	DG Location: DG Capacity: Total Losses: Computational Time:	30 0.9136MVAR 0.1164MW, 0.0767MVAR 125.3412s	30 0.9071MVAR 0.1164MW, 0.0767MVAR 33.2713s
	II-0001	DG Location: DG Capacity: Total Losses: Computational Time:	30 0.9328MVAR 0.1150MW, 0.0758MVAR 120.9144s	30 0.9415MVAR 0.115MW, 0.0758MVAR 27.2681s

The results for clustering technique exhibit the suitable locations are bus 29,30,31,32 and 33 with the lowest total loss value of 0.1005 MW with DG being placed at bus 29. The optimised DG values resulted in this study are the most suitable size at the optimal DG locations. For DG installed at bus 29, the optimal DG size is 1.4785 MW as summarized in the Table 3. This is acceptable since the difference of location of these two buses are within the acceptable top 10 voltage ranking [8]. For the purpose of performance assessment, the total losses for the base case were calculated without DG. The result for IEEE 33-Bus and IEEE 69-Bus are tabulated in Table 3 and Table 4, respectively. Model 1, 2, 3 and 4 represent the conventional categorisation of loads termed as the constant load, industrial load, residential load, and commercial load respectively. This is acceptable since the difference of location of these two buses are within the acceptable top 10 voltage ranking. Similar attempt was performed in the effort to investigate the effectiveness of the proposed approach, the total losses for the base case were calculated without DG. The result for the IEEE 33-Bus and IEEE 69-Bus are tabulated in Table 3 and Table 4.

Model 1, 2, 3 and 4 represent as constant load, industrial load, residential load, and commercial load respectively. From Table 3, constant load exhibits higher total loss value in both categories i.e the power in Watts and VAR. This can be caused by the nature of the load where no load increment is subjected to the system. Apparently model 4 (commercial load) falls as the second load model which dissipates higher loss. Nevertheless, the result shows the value for P_{loss} and Q_{loss} are almost close each other regardless of load models.

Table 4 Comparative Study on Different Technique and Case Studies (IEEE 33-Bus)

Case Study	Scenario	Technique		
			Ranking Identification	Integrated Clustering Development
Case Study E69				
E69	I-1000	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.8767MW 0.0832MW, 0.0405MVAR 697.4667s	61 1.8748MW 0.0832MW, 0.0405MVAR 115.2364s
	I-0100	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.8061MW 0.0406MW, 0.0223MVAR 648.2316s	61 1.7968MW 0.0406MW, 0.0223MVAR 85.6639s
	I-0010	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.6462MW 0.0476MW, 0.0253MVAR 661.31076s	61 1.6395MW 0.0476MW, 0.0254MVAR 85.1576s
	I-0001	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.5384MW 0.0508MW, 0.0267MVAR 637.3487s	61 1.5695MW 0.0508MW, 0.0267MVAR 142.5845s
Case Study F69				
F69	II-1000	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.3241MVAR 0.1520MW, 0.0705MVAR 626.6362s	61 1.3266MVAR 0.1520MW, 0.0705MVAR 49.9417s
	II-0100	DG Location: DG Capacity: Total Losses: Computational Time:	61 0.7421MVAR 0.1460MW, 0.0679MVAR 565.9956s	61 0.7377MVAR 0.1460MW, 0.0679MVAR 62.4488s
	II-0010	DG Location: DG Capacity: Total Losses: Computational Time:	61 0.8699MVAR 0.1246MW, 0.0588MVAR 611.6381s	61 0.8640MVAR 0.1246MW, 0.0588MVAR 70.1239s
	II-0001	DG Location: DG Capacity: Total Losses: Computational Time:	61 0.8983MVAR 0.1109MW, 0.0530MVAR 624.5719s	61 0.9071MVAR 0.1109MW, 0.0530MVAR 61.5281s

Case Study	Scenario	Technique		
			Ranking Identification	Integrated Clustering Development
Case Study E69				
E69	I-1000	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.8767MW 0.0832MW, 0.0405MVAR 697.4667s	61 1.8748MW 0.0832MW, 0.0405MVAR 115.2364s
	I-0100	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.8061MW 0.0406MW, 0.0223MVAR 648.2316s	61 1.7968MW 0.0406MW, 0.0223MVAR 85.6639s
	I-0010	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.6462MW 0.0476MW, 0.0253MVAR 661.31076s	61 1.6395MW 0.0476MW, 0.0254MVAR 85.1576s
	I-0001	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.5384MW 0.0508MW, 0.0267MVAR 637.3487s	61 1.5695MW 0.0508MW, 0.0267MVAR 142.5845s
Case Study F69				
F69	II-1000	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.3241MVAR 0.1520MW, 0.0705MVAR 626.6362s	61 1.3266MVAR 0.1520MW, 0.0705MVAR 49.9417s
	II-0100	DG Location: DG Capacity: Total Losses: Computational Time:	61 0.7421MVAR 0.1460MW, 0.0679MVAR 565.9956s	61 0.7377MVAR 0.1460MW, 0.0679MVAR 62.4488s
	II-0010	DG Location: DG Capacity: Total Losses: Computational Time:	61 0.8699MVAR 0.1246MW, 0.0588MVAR 611.6381s	61 0.8640MVAR 0.1246MW, 0.0588MVAR 70.1239s
	II-0001	DG Location: DG Capacity: Total Losses: Computational Time:	61 0.8983MVAR 0.1109MW, 0.0530MVAR 624.5719s	61 0.9071MVAR 0.1109MW, 0.0530MVAR 61.5281s

G69	III-1000	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.8399MW, 0.9320MVAR 0.0232MW, 0.0144MVAR 866.8819s	61 1.8367MW, 0.9303MVAR 0.0232MW, 0.0144MVAR 152.6264s
	III-0100	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.7961MW, 0.9098MVAR 0.0232MW, 0.0144MVAR 796.9180s	61 1.7966MW, 0.9100MVAR 0.0232MW, 0.0144MVAR 177.8994s
	III-0010	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.6514MW, 0.8365MVAR 0.0232MW, 0.0144MVAR 821.1243s	61 1.6433MW, 0.8323MVAR 0.0232MW, 0.0144MVAR 152.1524s
	III-0001	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.5356MW, 0.7778MVAR 0.0232MW, 0.0144MVAR 774.2687s	61 1.5358MW, 0.7779MVAR 0.0232MW, 0.0144MVAR 182.6403s

Table 4 Comparative Study Based on Different Technique and Case Studies (IEEE 69-Bus) (Cont…)

Case Study	Scenario	Technique		
			Ranking Identification	Integrated Clustering Development
Case Study H69				
H69	IV-1000	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.8326MW -0.9283MVAR 0.0232MW 0.0144MVAR 851.4573s	61 1.8375MW -0.9308MVAR 0.0232MW 0.0144MVAR 174.0700s
	IV-0100	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.7943MW -0.9089MVAR 0.0232MW 0.0144MVAR 862.9201s	61 1.7928MW -0.9081MVAR 0.0232MW 0.0144MVAR 165.9665s
	IV-0010	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.6441MW -0.8328MVAR 0.0232MW 0.0144MVAR 780.8401s	61 1.6443MW -0.8329MVAR 0.0232MW 0.0144MVAR 177.5260s
	IV-0001	DG Location: DG Capacity: Total Losses: Computational Time:	61 1.5402MW -0.7802MVAR 0.0232MW 0.0144MVAR 870.3487s	61 1.5355MW -0.7778MVAR 0.0232MW 0.0144MVAR 216.8659s

The computational times or execution time is recorded for every simulation for both test systems (i.e. IEEE 33-bus and 69-bus RTS). In the realisation of addressing the merit of the study, the analysis was done by calculating the percentage of time reduction in the computational time. In Figure 5, the percentage of time reduction shows for different case study using the data from IEEE 33-Bus. The results show that the percentage of reduction is between 60% to 90% using the of integrated clustering development and EMEFA technique. For this test system, this approach managed to decrease the computational time. The achievable reduction is in between 70% to 90% as compared to the Ranking Identification technique. From the table, the results for total losses and DG capacity for all cases are comparable between proposed technique and ranking identification technique. This study has found that the proposed technique can minimise the computational time and reduce the burdensome on the optimisation method for DG planning. The DG capacities are within the range set earlier in the constraints. The proposed technique outperformed the Ranking Identification technique in most cases. The numerical values can be referred to the corresponding table.

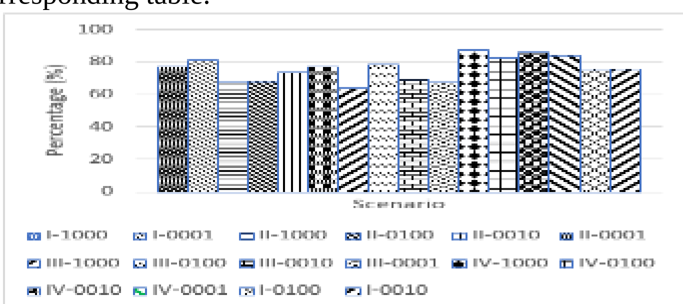

Figure 4 Percentage of Reduction for Computational Time Based on Different Technique and Case Study (IEEE 33-Bus)

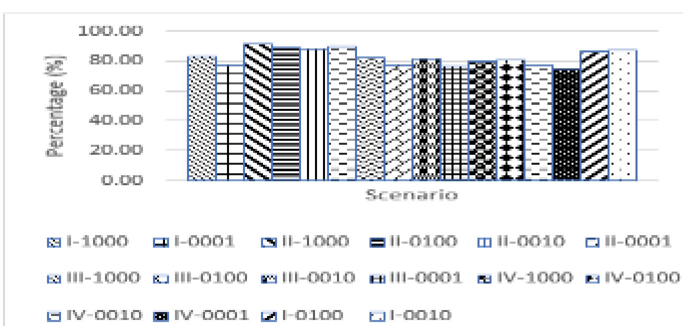

Figure 5 Percentage of Reduction for Computational Time Based on Different Technique and Case Study (IEEE 69-Bus)

5 Conclusion

This paper has presented a rigorous study on the integrated clustering approach for DG planning in power system under several load models. Implementation of several reliability test system models has resulted that the proposed technique is worth for DG planning in power system. The proposed integrated clustering development and EMEFA technique managed to identify the optimal DG sizing under different DG type and load models. The aim of integrated clustering development and EMEFA technique is to minimise the computational time and the burden on the optimisation method for DG planning. This is also meant to reduce unnecessary DG installation for the whole system. The findings from the study are consequently employed in the clustering scheme of DG the power system planning in terms of economic and geographical consideration. Furthermore, the proposed techniques can be further explored for other power system application within considerable variation and alteration.

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