

Investigation of Load Variant Under Power Distribution Network Reconfiguration Using EPSO Algorithm

Abstract. Recently, the power loss issue has emerged as a critical challenge, causing significant disruptions in the nation's infrastructure, economy, and daily lives of its citizens. Despite being a rapidly developing country with a growing demand for electricity, frequent instances of power loss and interruption have resulted in severe consequences such as reduced productivity, financial losses, compromised public safety, and increased inconvenience to individuals and businesses. Due to that reason, this study proposes the Evolutionary Particle Swarm Optimization (EPSO) algorithm which is a hybrid optimization technique that combines the principles of Evolutionary Programming (EP) and Particle Swarm Optimization (PSO) to solve optimization problems by reducing the power losses under Distribution Network Reconfiguration (DNR). Moreover, the consideration of load variants involved in DNR while validating the voltage profile improvement with the best load weightage has been made concurrently. A detailed performance analysis is carried out on IEEE 33-bus test systems to demonstrate the effectiveness of the proposed method. Through simultaneous optimization, it was found that power loss reduction was achieved after conducting power DNR in a radial network connection. Furthermore, the test result also indicated that the EPSO algorithm produced better results in terms of convergence time compared to the conventional PSO algorithm.

Streszczenie. Ostatnio problem utraty mocy stał się krytycznym wyzwaniem, powodującym znaczne zakłócenia w krajowej infrastrukturze, gospodarce i codziennym życiu obywateli. Pomimo tego, że jest to kraj szybko rozwijający się o rosnącym zapotrzebowaniu na energię elektryczną, częste przypadki utraty i przerw w dostawie energii powodują poważne konsekwencje, takie jak zmniejszenie produktywności, straty finansowe, zagrożenie bezpieczeństwa publicznego oraz zwiększone niedogodności dla osób fizycznych i przedsiębiorstw. Z tego powodu w niniejszym badaniu zaproponowano algorytm Evolutionary Particle Swarm Optimization (EPSO), który jest hybrydową techniką optymalizacji, która łączy w sobie zasady programowania ewolucyjnego (EP) i optymalizacji roju cząstek (PSO) w celu rozwiązania problemów optymalizacyjnych poprzez zmniejszenie strat mocy w warunkach Rekonfiguracja sieci dystrybucyjnej (DNR). Co więcej, równolegle uwzględniono warianty obciążenia związane z DNR podczas walidacji poprawy profilu napięcia przy najlepszym obciążeniu. Szczegółowa analiza wydajności jest przeprowadzana na systemach testowych IEEE 33-bus, aby wykazać skuteczność proponowanej metody. Dzięki jednoczesnej optymalizacji stwierdzono, że redukcję strat mocy uzyskano po przeprowadzeniu zasilania DNR w promieniowym połączeniu sieciowym. Ponadto wynik testu wskazał również, że algorytm EPSO dał lepsze wyniki pod względem czasu zbieżności w porównaniu z konwencjonalnym algorytmem PSO. **(Badanie wariantu obciążenia w ramach rekonfiguracji sieci dystrybucyjnej przy użyciu algorytmu EPSO)**

Keywords: Evolutionary Particle Swarm Optimization, Particle Swarm Optimization, Distribution Network Reconfiguration, Load Variants
Słowa kluczowe: Ewolucyjna optymalizacja roju cząstek, optymalizacja roju cząstek, rekonfiguracja sieci dystrybucyjne

Introduction

Distribution systems should be operated at minimum cost, subject to constraints such as radial configuration, serving all loads, operating within the capacity limits of lines, transformers, and equipment, effective coordination of overcurrent protective devices, and maintaining voltage magnitudes within specified limits [1]. Energy losses are a significant and necessary aspect of electricity. It is critical to reliably and precisely define energy losses across long time periods that vary from one day to many months. However, calculating energy losses is difficult owing to somewhat imprecise baseline information on original electric power demands. Calculating the loss of energy in low-voltage distribution systems is especially difficult owing to partly unknown starting information regarding the original electric power demands, which makes an exact evaluation of these losses challenging [2]. Moreover, distribution network reconfiguration is a crucial aspect of power system operation and management in order to improve the overall performance and efficiency of the distribution network [3]–[5]. It involves altering the network topology by adjusting the status of switches by switching them on or off. There are two types of switches: sectionalizing switches and tie switches [6]–[7]. By adjusting the status of switches, it will be possible to optimise power flow, reduce power losses, and improve the voltage profile.

However, numerous constraints need to be fulfilled when reconfiguring the distribution network, such as radial network constraints, node voltage constraints and load variant constraints [8]–[10]. Furthermore, several heuristic methods have been utilized as optimization strategies to address the challenge of local minima issues. This involves changing the states of switches, and toggling them between open and closed positions, in order to perform the

reconfiguration of the distribution network [11]–[13]. For example, Grasshopper Optimization Algorithm (GOA) being used to minimize power losses while considering the constraints of the system structure, ensuring an efficient reduction in power loss [14].

In addition, a Particle Swarm Optimization (PSO) algorithm have been widely used in distribution networks reconfiguration in order to minimize power losses during blackout [15]–[17]. Furthermore, Particle Swarm Optimization (PSO) algorithm also being used to improve voltage profile and minimize power losses of the system [18]–[23]. After a long period of time, algorithms like the one being developed now, Evolutionary Particle Swarm Optimisation (EPSO), were increasingly widely used. Numerous studies on the use of the EPSO algorithm in distribution network reconfiguration to address the problem of power loss have been published [24]–[28]. However, fewer of them consider the variants of load, especially during heavy tiding of the DG, EV, and smart grid system to the distribution network. Hence, in this study, PSO and EPSO's performance has been compared to demonstrate the distribution system losses that are most optimal while considering the weightage of load in the network system. The arrangement of the paper is as follows; Section 2 presents the formulation, constraints, and method to achieve the objective function, and Section 3 discusses the test system. Meanwhile, Section 4 demonstrates the results and discussion while the last section will be the conclusion for the paper presentation.

Formula formulation and constraints Load Flow Formula

In order to evaluate the objective function of the problem, load flow equation was developed as follows;

Apparent Power:

$$(1) \quad S_i = V_i I_i^* = P_i + jQ_i$$

Branch Current:

$$(2) \quad I_i = \frac{\sqrt{(P_i^2 + Q_i^2)}}{|V_i|}$$

Branch Voltage:

$$(3) \quad V_{i+1}^2 = V_i^2 + (R_i^2 + X_i^2) \left(\frac{I_i}{V_i}\right) - 2(R_i P_i + X_i Q_i)$$

Real Power:

$$(4) \quad P_{i+1} = P_i - P_{Li} - R_i \left(\frac{I_i}{V_i}\right)$$

Reactive Power:

$$(5) \quad Q_{i+1} = Q_i - Q_{Li} - X_i \left(\frac{I_i}{V_i}\right)$$

Real Power Loss:

$$(6) \quad P_{loss} = \sum_{n=1}^n |I_i|^2 k_i R_i$$

Reactive Power Loss:

$$(7) \quad Q_{loss} = \sum_{n=1}^n |I_i|^2 k_i X_i$$

Where: S_i =Complex power at bus i ; I_i =Complex power at bus i ; V_i =Sending voltage at bus i ; R_{i+1}, X_{i+1} =Resistance and reactance at branch $(i+1)$; P_{i+1}, Q_{i+1} =Active and reactive power at branch $(i+1)$; P_{loss}, Q_{loss} =Active and reactive power loss at bus i ; n =total number of branches; k_i = The variables representing the topology status of the branches can be defined as 1 indicating a closed circuit and 0 indicating an open circuit.

PSO algorithm equation

PSO algorithm equation was developed as follows:

Particle Velocity update:

$$(8) \quad V_j^{k+1} = (\omega + V_j^k) + (C_1 r_1 (P_{best,j}^k - X_j^k)) + (C_2 r_2 (G_{best,j}^k - X_j^k))$$

Particle Position update:

$$(9) \quad X_j^{k+1} = (X_j^k + V_j^{k+1})$$

Weighting function:

$$(10) \quad \omega(t+1) = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{t_{max}} \times t$$

Where: V_j^k =particle j velocity in k -th iteration; X_j^k =particle j position in iteration k -th iteration; r_1 and r_2 = uniformly distributed random numbers in the interval $[0,1]$; ω =inertia weight; C_1 and C_2 = constants that defined weightage factor of random acceleration terms; $P_{best,j}^k$ =best value of fitness function obtained by particle j in k -th iteration; $G_{best,j}^k$ =best value among the fitness value;

EPSO algorithm equation

EPSO algorithm equation was developed as follows:

Weighting function:

$$(11) \quad \omega_{ik}^* = (\omega_{ik} + \tau' N(0,1))$$

Global best function:

$$(12) \quad G_{best}^* = (G_{best} + \tau' N(0,1))$$

where the random variable $N(0,1)$ follows a Gaussian distribution with a mean of 0 and variance of 1 and the parameters τ' , which govern the learning process, can either be fixed or treated as strategic parameters that are also subject to mutation

Radial Network Constraint

Radial Network structure was composed in considering in the distribution network.

Node Network Constraint

$$(13) \quad V_{min} \leq V_{bus} \leq V_{max}$$

where the minimum voltage is 0.95 and the maximum voltage is 1.05($\pm 5\%$)

Load Variant Constraint

$$(14) \quad P_{s_i} \geq P_{D_i} + \sum_{j \in \beta_{b_i}} (x_{ij} P_{ij})$$

where P_{s_i} is active power supply by substation, P_{D_i} is active power demand at node i , β_{b_i} represents set of nodes, and x_{ij} represents number of circuit that can be reconfigured on branch ij .

Flow of the EPSO implementation is as follows.

Fitness Calculation. A population of particles is initially created with random positions and velocities in the solution space. Each particle that satisfies the given constraints undergoes power flow analysis, and the total power loss is computed using the Newton-Raphson load flow program.

Find Pbest and Gbest. Throughout the search process, the two best values are continually updated and recorded. These values are associated with the best solution achieved by each particle, maintaining the path of its coordinates in the solution space. The first value, denoted as Pbest, represents the best solution found by an individual particle. The second value, Gbest, represents the overall best solution discovered by any particle thus far. Pbest and Gbest correspond to the generation of tie-switches and the associated power loss.

New Velocity and Position. During this step, the velocity and position of the particles are updated by applying equations (8) and (9). The velocity of a particle indicates the movement of switches. Additionally, the total power loss of all switches is calculated by utilizing the new position, X_{new} .

Combination and Tournament Selection. Once the new position X_{new} is obtained, the corresponding fitness value (total power loss) is determined using this new position. Subsequently, the new position X_{new} is combined with the old position set X . The combined set of positions is then subjected to a tournament, where each position competes against others randomly. During this tournament, a position earns a score if its fitness is superior to that of other contenders. The selection strategy employed in this process is based on a priority selection strategy. To implement this strategy, both the old position set X and the new position X_{new} are sorted in descending order based on their power loss values in the system.

Convergence Test. The new position set will undergo convergence testing. If convergence is not achieved, the process will be repeated.

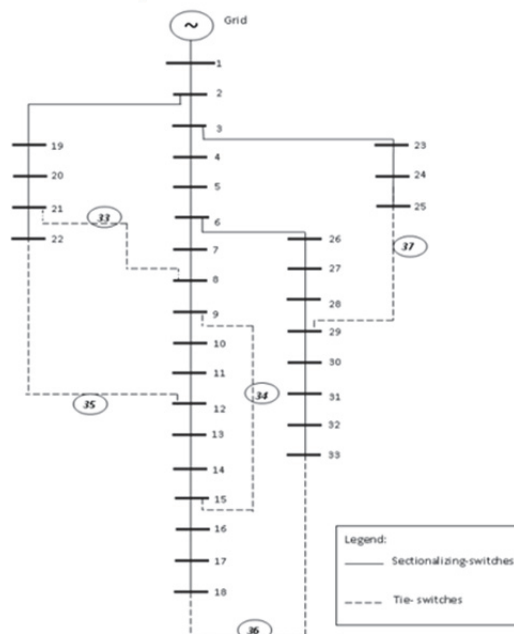


Fig. 1. IEEE 33-bus test radial distribution system

3.0 Test System

In accordance with Fig. 1, this study is applicable to the IEEE 33 bus test system with a radial distribution system. The IEEE 33 bus system consists of one feeder, 32 typically closed switches, and five normally open switches situated on branches 33, 34, 35, 36, and 37. The total optimization variable is represented by the combination of 5 switches for 33 bus system. The system's total load is 3,715kW, and the base apparent power is set at 100MVA. The calculation for maximum and minimum voltages for each bus are set in per unit systems.

Results and analysis

The simulation results were obtained using MATLAB software, and data was collected for three types of loads: low impedance, normal impedance, and high impedance. The normal impedance load was based on the standard parameters of the IEEE 33 bus circuit. The low impedance load was derived by doubling the standard parameters, while the high impedance load was obtained by multiplying the standard parameters by two. A total of 10 results were collected for each load type. However, in order to optimize the system, the three outcomes with the lowest power loss were chosen for each of the low impedance load, normal impedance load, and high impedance load case studies. These outcomes, referred to as Case 1, Case 2, and Case 3, were selected. There are 5 opening switches in each case for every different impedance load study as demonstrated in Table 1 and Table 2, respectively.

Furthermore, by comparing the performance of the PSO and EPSO algorithms, the voltage profile improvement was examined, and the obtained output is presented in Fig. 2 and Fig. 3, accordingly. It was observed that high load impedance draws a lower voltage profile while lower is vice versa for both optimizations' algorithms. The results of the case study for normal load conditions by using PSO are presented in Table 1 shows that, Case 1 draws a power loss of 211.3 kW, while Case 2 and Case 3 exhibit slightly lower power losses at 206.3 kW and 199.6 kW, respectively. The loss reduction percentages for Case 2 and Case 3 are 2.37% and 3.25%, respectively, compared to Case 1. However, for EPSO implementation as in Table 2, the power loss for Case 1 is measured at 129.8 kW, followed by 125.2 kW in Case 2 and 115.2 kW in Case 3. The loss reduction percentages are 3.54% for Case 2 and 7.98% for Case 3 compared to Case 1. The convergence time for optimization ranges from 24.4 seconds in Case 1 to 24.1 seconds in Case 2 and further reduces to 22.3 seconds in Case 3. The switches involved in the optimization process differ across the cases, with specific combinations used for each case.

Table 1. PSO algorithm applied to low, normal and high impedance load

Type of load	Items	Case 1	Case 2	Case 3
Low impedance load	Power loss (kW)	192.6	189.4	183.2
	Loss reduction (%)	-	1.66	3.27
	Convergence time (s)	48.2	46.4	44.4
	Switches	19,21,4,9,28	6,9,13,26,33	5,6,9,13,29
Normal impedance load	Power loss (kW)	211.3	206.3	199.6
	Loss reduction (%)	-	2.37	3.25
	Convergence time (s)	53.5	51.1	48.8
	Switches	3,8,13,25,27	9,19,21,23,31	6,9,18,24,33

High impedance load	Power loss (kW)	255.6	248.3	246.9
	Loss reduction (%)	-	2.86	0.56
	Convergence time (s)	61.3	61.1	58.5
	Switches	7,11,25,27,29	3,7,9,22,32	4,6,9,12,33

Table 2. Results of EPSO algorithm applied to low, normal and high impedance load

Type of load	Items	Case 1	Case 2	Case 3
Low impedance load	Power loss (kW)	102.3	95.2	92.1
	Loss reduction (%)	-	6.9	3.26
	Convergence time (s)	21.2	20.3	18.5
	Switches	3,8,10,21,26	6,8,12,26,29	4,7,9,28,31
Normal impedance load	Power loss (kW)	129.8	125.2	115.2
	Loss reduction (%)	-	3.54	7.98
	Convergence time (s)	24.4	24.1	22.3
	Switches	2,4,9,13,27	5,12,17,19,21	4,7,9,12,32
High impedance load	Power loss (kW)	147.7	141.1	132.5
	Loss reduction (%)	-	4.47	6.09
	Convergence time (s)	38.2	35.1	33.6
	Switches	4,20,21,12,33	2,4,10,13,26	5,9,14,23,26

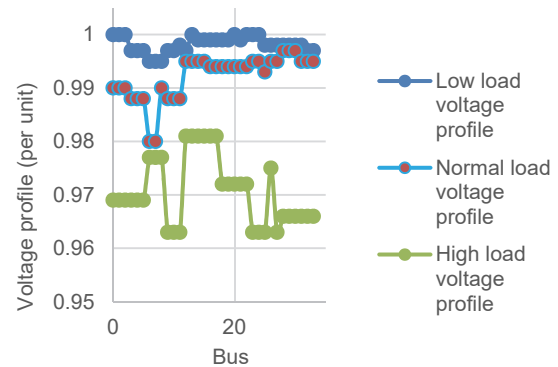


Fig. 2. Voltage profile of each load condition against bus by using PSO algorithm

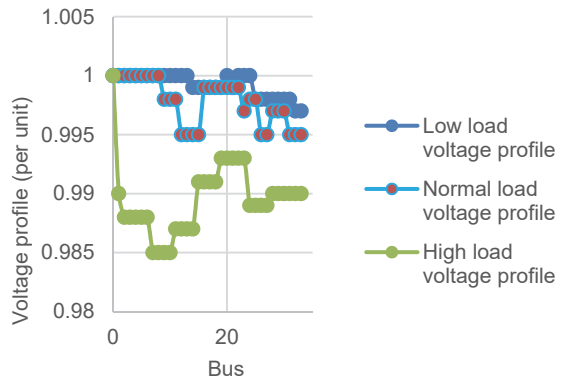


Fig. 3. Voltage profile of each load condition against bus by using PSO algorithm

Based on Fig. 4, it can be observed that the initial circuit has a power loss of 250.6 kW. Implementing the PSO algorithm results in a reduction of power loss to 215.24 kW. However, further improvements are achieved with the EPSO algorithm, which significantly reduces the power loss to 87.07 kW. Comparing the power losses, the PSO algorithm achieves a decrease of 35.36 kW compared to the initial circuit, while the EPSO algorithm demonstrates remarkable performance with a substantial reduction of 163.53 kW, surpassing both the initial circuit and the PSO algorithm. Additionally, the EPSO algorithm exhibits a notable improvement of 128.17 kW in power loss reduction compared to the PSO algorithm. These results highlight the effectiveness of the EPSO algorithm in minimizing power losses and its potential for significant energy efficiency improvements.

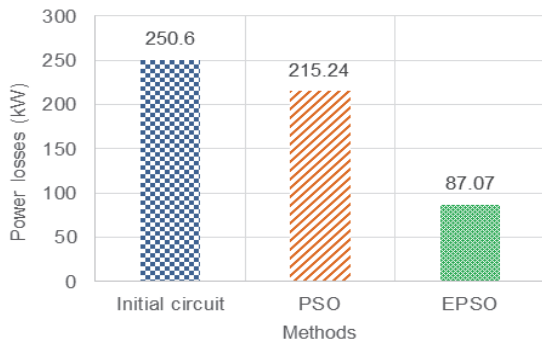


Fig. 4. Comparison of average power losses between PSO and EPSO

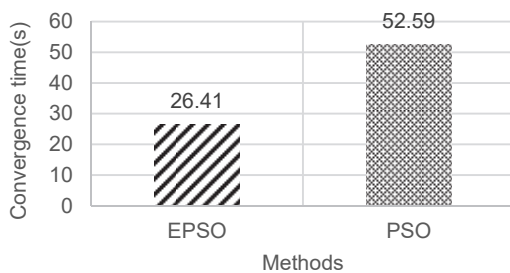


Fig. 5. Comparison of average convergence time between PSO and EPSO

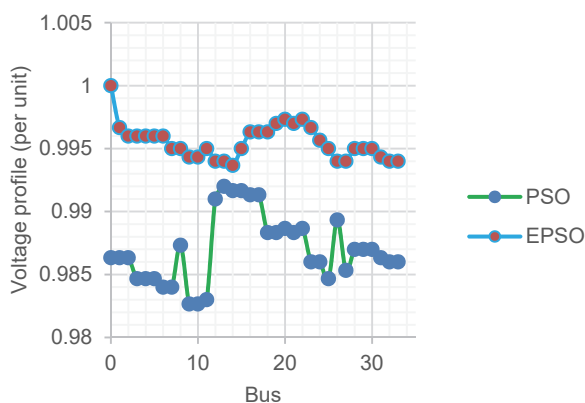


Fig. 6. Comparison of average profile voltage of each bus between PSO and EPSO

Referring to Fig. 5, it can be observed that the EPSO algorithm achieves convergence in 26.41 seconds, whereas the PSO algorithm requires 52.59 seconds. Comparing the convergence times, it is evident that the EPSO algorithm demonstrates significantly faster convergence than the PSO algorithm, taking less than half the time. This indicates the

efficiency of the EPSO algorithm in quickly finding optimal solutions, which can be advantageous in time-critical scenarios and real-time optimization applications. Therefore, in terms of convergence time, the EPSO algorithm outperforms the PSO algorithm, providing faster convergence and more efficient optimization. Based on Fig. 6, it is evident that the average profile voltage of each bus in the PSO algorithm is lower compared to the EPSO algorithm. This suggests that the EPSO algorithm performs better in maintaining higher profile voltages at each bus. According to the power loss, convergence time, and profile voltage analyses, the EPSO algorithm emerges as superior to the PSO algorithm, exhibiting improved performance in all three aspects.

CONCLUSION

In summary, the results obtained from the case study reveal the effectiveness of the EPSO algorithm compared to the PSO algorithm in terms of power loss reduction, convergence time, and profile voltage maintenance under various of load conditions. For power loss reduction, the EPSO algorithm outperforms the PSO algorithm significantly. In terms of convergence time, the EPSO algorithm. This faster convergence indicates the efficiency of the EPSO algorithm in finding optimal solutions more quickly. Regarding the profile voltage, the EPSO algorithm maintains higher average profile voltages at each bus compared to the PSO algorithm. This suggests that the EPSO algorithm is more effective in preserving voltage levels throughout the distribution network. Future work can be done by considering other types of load such as EV charging under those stated conditions.

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Authors: Wong Kok Loong, E-mail: b012020008@student.utem.edu.my; Ts. Dr. Mohamad Fani Sulaima (Corresponding), E-mail: fani@utem.edu.my; Mohamad Naim Mohd Nasir, Email: mohamad.naim@utem.edu.my; Dr. Zulhasrizal Bohari, Email: zulhasrizal@utem.edu.my; Universiti Teknikal Malaysia Melaka, 76100, Hang Tuah Jaya, Melaka

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