Multi-objective long-term reconfiguration of autonomous microgrids through controlled mutation differential evolution algorithm

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Abstract: This study provides a solution for the feeder reconfiguration of autonomous microgrids (MGs). The objective is to minimise power loss, switching costs, and enhance voltage stability index, considering time-variations of loads. The daily load profiles for different seasons (spring, summer, fall, and winter) of different customers (i.e. residential, industrial, and commercial) are considered. In order to reduce the dimensions of the optimisation problem, k-means algorithm is implemented that clusters seasonal/yearly load profile into a few groups. The daily load profile is obtained based on the average of the group which has maximum members. This ensures the selection of a subset of load profiles that effectively represent the entire year's profile to reduce the complexity and execution time of the model. Subsequently, a new method is developed to break the daily load profile into intervals that guarantee less switching frequency for dynamic network reconfiguration. A controlled mutation differential evolution algorithm (CMDEA) compatible with long-term reconfiguration problem is developed with superior performance compared to conventional DEA and invasive weed optimisation algorithm. The CMDEA is employed to solve the reconfiguration problem on 33-bus and 69-bus autonomous MGs. Simulation results validate the effectiveness of the proposed method to reduce operational costs and computational burden in a smart grid environment.

1 Introduction

Smart grids incorporate advanced metering infrastructure (AMI), advanced distribution automation (ADA), advanced telecommunication techniques (ATT), and artificial intelligence (AI), to optimally manage the energy generation, transmission, distribution, and consumption. Smart grids facilitate the implementation and operation of distributed energy resources, energy storage devices, and microgrids (MGs).

Autonomous MGs are solutions to supply electricity of islanded and remote/rural areas [1, 2]. MGs supply locally the required demand of customers with the lower transmission, operation, and maintenance costs. On the other hand, their operation has reduced the environmental impact with minimised pollution since they are integrated distributed generation (DG) resources (e.g. photovoltaic panels, wind turbines, fuel cells, batteries, and micro turbines [3].

Optimal operation of MGs is significant to achieve sustainability, reliability, and resilience of these sources of power [4].

Automated network reconfiguration is a smart distribution networks function that could be implemented for optimal operation of MGs using a combination of high-speed communications, smart measuring equipment, smart switching devices, and intelligent controllers. Feeder reconfiguration was firstly introduced by Back and Merlin [5]. Researchers have implemented network reconfiguration on conventional distribution systems (non-MGs) with various objectives such as loss minimisation, voltage profile improvement, power quality improvement etc. [6–11]. Historically, the reconfiguration problem was solved based on constant loads. In reality, loads are variable and time-dependent. Hence, the system configuration must be optimally adjusted according to the load condition to gain the maximum economic benefits. Therefore, recently, variable behaviour of loads and dynamic reconfiguration is considered on conventional distribution systems (non-MGs) [12–18].

As MGs emerge, their reconfiguration is of great interest in the smart grid environment. So far, the feeder reconfiguration of autonomous MGs has been studied with different objectives using various optimisation algorithms [19–22]. However, the loads are assumed to be constant and thus dynamic reconfiguration is not considered in these studies. This is identified to be a poor assumption in this paper since most of MGs operate in the island mode, where interconnectivity between neighbouring networks (loads and generation units) barely exists. Therefore, the variable behaviour of loads has a bold effect on MGs and must be considered in reconfiguration practice to achieve the best economic benefits.

In this paper, reconfiguration of autonomous MGs is presented under the variable behaviour of loads to achieve the best economical and technical benefits. Typical daily load profiles (spring, summer, fall, and winter) with different customers (residential, industrial, and commercial) are taken into account. Moreover, the k-means clustering algorithm is implemented to select a daily load profile that is capable to represent the seasonal load profile statistically. Consequently, the optimal daily, monthly, seasonally configuration of autonomous MGs are calculated. To solve the optimisation problem, the conventional differential evolution algorithm (DEA) [23] is improved with major modifications on the mutation and the crossover operators for better compatibility with non-linear nature of MG's network reconfiguration. The new modifications presented in this study overcome the drawbacks of the conventional version of the DEA. The proposed method is implemented on 33-bus and 69-bus autonomous MGs to evaluate its technical and economic benefits. Overall, the simulation results demonstrate that this approach is less expensive and requires less computational effort. Furthermore, the controlled mutation DEA (CMDEA) is proved to be superior in finding optimum solutions and convergence in performance compared to conventional DEA and invasive weed optimisation algorithm (IWO). The methods of this paper are specifically compatible with the real-time operation of future smart MGs that require fast, high efficient, and low-cost decision-making algorithms.

In summary, this paper is unique in incorporating all the following contributions, simultaneously:

• Despite previously published papers that are focused on conventional distribution networks, this paper aims the long-
term reconfiguration planning of reconfigurable autonomous MGs.

- The scheduling of reconfigurable MGs (RMGs) is accomplished considering both economic and technical aspects including alleviating the power loss, improving voltage stability factor, and reducing switching costs.
- K-means clustering algorithm is utilised to reduce the size of yearly data into daily data which leads to lower computational time throughout the year. This facilitates the data management of long-term operation of distribution networks considering reconfiguration.
- A novel and more efficient CMDEA is developed for the first time to solve the multi-objective reconfiguration problem. The method presents a set of optimum solutions rather than one global solution, from which the fuzzy decision maker selects the ultimate result.

2 Problem formulation

Historically, network reconfiguration is performed based on constant load profiles [6–8, 24, 25]. In practice, daily load demand is variable and time-dependent. Hence, the system configuration must be optimally adjusted according to the load condition to gain the maximum economic benefits. Recently, the significance of time-dependency of load behaviour in such practice is revealed [13, 14, 26, 27]. This effect is more significant in islanded MGs. This is so because the loads are smaller and less congested. Also, there is minimum connectivity between a particular MG and its neighbouring one or the main grid. Therefore, natural fluctuations of loads are more conspicuous from the viewpoint of grid operators.

This paper studies the reconfiguration practice of islanded MGs based on variable load demand. Therefore, time-dependence of load behaviour in such practice is revealed [13, 14, 26, 27]. These problems are addressed in [28]. The active and reactive power is shared among DGs based on droop control, therefore, DGs are modelled as droop buses. The relationships of $P_m$ and $Q_m$ could be used. This depends on the converter (DGs) output impedance. In this research, the output impedance is assumed to be inductive and the relationship of $P_m$ and $Q_m$ is used as shown in the following equations as well as Fig. 2 [28, 30]:

$$\omega = \frac{\sum_{i=1}^{m} (a_i/m_p) - (P_{\text{Load}} + P_{\text{Loss}})}{\sum_{i=1}^{m} (1/m_p)}$$

where $P_{\text{Loss}}$ and $P_{\text{Load}}$ are power losses and real load of MGs, respectively. The bus voltages are calculated as follows:

$$V_i^{t+1} = \frac{1}{Y_n} \left[ \frac{P_i - jQ_i}{V_i^0} - \sum_{j \neq i}^{n} V_j V_i^* \right]$$

An acceleration factor is used to improve the convergence performance of the method:

$$V_i^{t+1} = V_i^t + \alpha(V_i^{t+1} - V_i^t)$$

where $V_i^t$, $V_i^{t+1}$, $P_i$ and $Q_i$ are voltages at bus $i$ at time $t$ and $t+1$, and real and reactive demands at bus $i$, respectively. $\alpha$ is the acceleration coefficient, set to $1.7$ in this paper.

Fig. 1 Main steps of the proposed long-term reconfiguration approach
2.2 Objective function

The objective of the reconfiguration in this paper is to reduce power loss, decrease switching costs, and improve voltage stability index (VSI) as:

\[
\text{OF}_1 = \min \left( \sum_{i=1}^{N_B} R_i |I_i|^2 \right) \quad (9)
\]

\[
\text{OF}_2 = \min \left( \sum_{i} V_{\text{sub}} - \left\{ V_i^2 - 4(P_{i+1}X_i - Q_{i+1}R_i) \right\} \right) \quad (10)
\]

\[
\text{OF}_3 = \min \left( \sum_{i} (\text{PRICE}_{\text{SW,i}} \times (S_i - S_{i-1})) \right) \quad (11)
\]

where \( \text{OF}_1 \) is power loss [31], \( \text{OF}_2 \) is VSI, the indicator of the voltage stability in MG [32], and \( \text{OF}_3 \) is for switching cost minimisation [33]. \( N_B \) is the number of branches of MG, and \( I_i \) is the current at branch \( i \). \( P_{i+1} \) and \( Q_{i+1} \) are active and reactive powers of load at bus \( i+1 \). \( V_i \), \( P_i \), and \( Q_i \) are voltage, real, and reactive power demand at bus \( i \), respectively; and \( R_i \) and \( X_i \) are resistance and reactance of branch \( i \), respectively. \( \text{PRICE}_{\text{SW,i}} \) is the switching cost. \( S_i \) and \( S_{i-1} \) are the new and original states of \( i \)th switch, respectively.

2.3 Long-term reconfiguration

All power system components such as switches are wearable devices. Switches have an effective lifetime and can perform limited switching operations. To minimise the cost of investment on switches, the number of switching actions shall be minimised. To reach this goal, several strategies can be used. For instance, operators may reconfigure the system a few times in a day or a month rather than frequent hourly reconfiguration [27]. They may also consider the switching cost in the objective function. The authors have studied the effect of hourly, daily, weekly, monthly, and seasonally reconfiguration considering the switching cost [14]. The results show that more granular studies result in lower power loss and better voltage profile. However, the switching costs are higher for more frequent reconfiguration studies. This is a trade-off between technical advantages and economic costs. It is concluded that the break-even point is different for different power systems for which it should be investigated individually [14]. Furthermore, the results of such a study can also identify a number of automatic switches required to perform a cost-effective reconfiguration. Although considering the switching in objective function decreases the power loss, hourly reconfiguration brings some technical issues such as electromagnetic transient issues and harmonic distortions [27]. Therefore, it is recommended that reconfiguration be performed for limited times over the study cycle to consider both technical and economic aspects. This paper takes into account both methods outlined above; the cost of switches in the objective function and limiting the topology alterations throughout the time frame to prevent power quality and transient issues.

Long-term reconfiguration (seasonal) is considered, similar to some [34, 35]. For this reason, four typical hourly-sampled load curves which are statistically consistent over a season are extracted using data clustering algorithms. The extracted load profiles corresponding to a specific season are then used to perform reconfiguration.

It is worth mentioning that reconfiguration can be performed several times for a load profile depending on its level of fluctuation. Fig. 3 presents two different load profiles and their impact to identify optimum intervals for reconfiguration. According to a typical load profile (Fig. 3a), there are two specific time intervals to change the topology while for a load profile of Fig. 3b, there are three specific time intervals for reconfiguration. Thus, the frequency of reconfiguration is selected for each day according to the variation of the daily load curve and may be increased several times during a day according to the load profile. Assuming the load profile is similar to Fig. 3a with two intervals, the following relationship is defined:

\[
\begin{align*}
24\text{hour} & \quad \text{OC}_{1,1} \quad \text{OC}_{1,2} \quad \ldots \quad \text{OC}_{1,23} \quad \text{OC}_{1,24} \\
& \quad \text{OC}_{2,1} \quad \text{OC}_{2,2} \quad \ldots \quad \text{OC}_{2,23} \quad \text{OC}_{2,24} \\
& \quad \text{OC}_{3,1} \quad \text{OC}_{3,2} \quad \ldots \quad \text{OC}_{3,23} \quad \text{OC}_{3,24} \\
& \quad \text{OC}_{4,1} \quad \text{OC}_{4,2} \quad \ldots \quad \text{OC}_{4,23} \quad \text{OC}_{4,24}
\end{align*}
\]

where \( \text{OC} \) is optimal configuration of MG at hour \( t \); \( \text{OC}_{1,2,d,sp} \), \( \text{OC}_{1,2,d,Su} \), \( \text{OC}_{1,2,d,Au} \), and \( \text{OC}_{1,2,d,wi} \) are two optimal configurations during a day for spring, summer, fall, and winter, respectively. Therefore, optimal configurations for four typical days of different seasons are obtained.

The same configuration above is considered for the entire corresponding season (3 months). This is shown as follows:

\[
\begin{align*}
\text{Season} & \quad \text{Two configurations} \\
\text{OC}_{\text{Spring}} & \quad \text{OC}_{\text{Winter}} \\
\text{OC}_{\text{Summer}} & \quad \text{OC}_{\text{Spring}} \\
\text{OC}_{\text{Autumn}} & \quad \text{OC}_{\text{Summer}} \\
\end{align*}
\]

where \( \text{OC}_{\text{Spring}}, \text{OC}_{\text{Summer}}, \text{OC}_{\text{Autumn}} \), and \( \text{OC}_{\text{Winter}} \) are optimal configurations during three months in spring, summer, fall, and

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winter, respectively. The energy loss for long term reconfiguration is obtained with the calculation of seasonally energy losses:

\[ EL_{\text{Season}} = C \sum_{t=1}^{N_s} R_{\text{Loss}}(t) \quad t \in \{1, 2, 3, \ldots, N_s\} \]  

(14)

Consequently, the yearly power loss is calculated as:

\[ AEL_{\text{Total}} = \sum_{s=1}^{4} EL_{\text{Season}}(s) \quad s \in \{\text{Spring, Summer, Autumn, Winter}\} \]  

(15)

where \( EL_{\text{Season}} \) is the energy loss for each season, \( C \) is the cost of energy (kWh), and \( N_s \) is the number of days of each season. \( R_{\text{Loss}} \) is real power loss.

This method is completely general and could be easily expanded to more granular studies based on the load profile of the different region, and feeder type (residential, commercial, agricultural, mix load). In some cases, if the oscillation of load has a similar pattern over a year, reconfiguration could be performed only once or twice a year. In the contrary, in some regions where extreme load fluctuations are experienced over each season, more granular studies are required to reach the optimum reconfiguration. Overall, for this paper, we considered four intervals to show the applicability of this concept for most extreme differences in load profiles, which is the seasonal difference.

2.4 Optimisation constraints

The distribution network should remain radial to avoid any complexity in protection settings and coordination. A small example is shown in Fig. 4. This system has four rings (L1–L4) and nine branches (B1–B9). Each ring consists of several branches, L1 = B1, B2, B3; L2 = B3, B4, B5; L3 = B5, B6, B7; L4 = B7, B8, B9. If only one of the branches in each ring is opened, the system changes from ring to radial configuration. Some branches are common between two rings (for example, B3). Therefore, if this switch is selected in one ring, it should be eliminated as a possibility to be selected in the other rings. The penalty factor can be expressed as follows [14]

\[ R_p = \begin{cases} \infty & \text{if open two common branches} \\ 0 & \text{otherwise} \end{cases} \]  

(16)

\( R_p \) is the penalty factor to force a radial system.

The voltage deviation and power line capacity are other constraints that should be limited to the following acceptable ranges:

\[ V_{\min} \leq V_j \leq V_{\max} \quad j = 1, 2, \ldots, N \]  

\[ I_i \leq I_{\max} \quad i = 1, 2, \ldots, N-1 \]  

(17)

where \( V_{\min} \) and \( V_{\max} \) are the lower and upper bounds of voltages, respectively. \( I_i \) and \( I_{\max} \) are the current magnitude and maximum allowable current (thermal limitation) of branch \( i \), respectively. These constraints are modelled using the penalty factor technique as follows [12]:

\[ \Delta V_j = \begin{cases} V_{\min} - |V_j| & \text{if } |V_j| < V_{\min} \\ |V_j| - V_{\max} & \text{if } |V_j| > V_{\max} \\ 0 & \text{if } V_{\min} < |V_j| < V_{\max} \end{cases} \]  

(18)

\[ \Delta I_i = \begin{cases} |I_i| - I_{\max} & \text{if } |I_i| > I_{\max} \\ 0 & \text{if } |I_i| < I_{\max} \end{cases} \]  

(19)

here \( \Delta V_j \) and \( \Delta I_i \) are the voltage and current deviations for each bus and branch, respectively. Then, \( k1.\Delta V \) and \( k2.\Delta I \) are summed into the objective function, \( k1 \) and \( k2 \) are penalty factors.

3 Controlled mutation differential evolution algorithm

Differential evolution (DE) algorithm is a population-based search method [23]. This paper has modified the mutation and crossover operators of the conventional DEA to comply with the non-linear behaviour of the reconfiguration problem. The results in Section 5 demonstrate the effectiveness of CMDEA over conventional DEA.
3.1 Initialisation

Create an initial population according to lower and upper bounds based on the following equation:

$$W^{G, i}_k = \text{LB}_{\text{max}} + \text{rand}[0, 1] \times (\text{UB}_{\text{max}} - \text{LB}_{\text{min}})$$

$$i = [1, NP]; \quad k = [1, D]$$

(20)

where $\text{LB}_{\text{max}}$ and $\text{LB}_{\text{min}}$ are lower and upper bounds, $NP$ is the number of population, respectively, $G$ is the generation number, and $D$ is the number of variables.

3.2 Mutation operator

For each component of population $W^{G, i}_k$, $i = 1, \ldots, NP$, two mutation vectors $X^{G+1}_i = [X^{G+1}_{i1}, X^{G+1}_{i2}, \ldots, X^{G+1}_{iD}]$ and $Y^{G+1}_i = [Y^{G+1}_{i1}, Y^{G+1}_{i2}, \ldots, Y^{G+1}_{iD}]$ are generated as follows:

$$X^{G+1}_i = \left[\psi_i W^{G, i}_i + \psi_k W^{G, i}_k + 2 \times \text{rand} \times (X^{G, i} - W^{G, i})\right]$$

$$Y^{G+1}_i = \left[\psi_i W^{G, i}_i + \psi_k W^{G, i}_k + 2 \times \text{rand} \times (Y^{G, i} - W^{G, i})\right]$$

(21)

where $\psi_i + \psi_k = 1$, $W^{G, i}_k$, $W^{G, i}_k$, $W^{G, i}_k$, $W^{G, i}_k$ are four vectors of population which are randomly selected.

3.3 Crossover operator

$Z^{G+1}_i$ vector is created based on $X^{G+1}_i$ and $Y^{G+1}_i$ vectors:

$$Z^{G+1}_i = \begin{cases} X^{G+1}_i & \text{if } r \leq C_c \\ Y^{G+1}_i & \text{otherwise} \end{cases}$$

(22)

where $C_c$ is crossover rate and is a number between 0 and 1.

3.4 Selection operator

This operator compares vectors and selects the best solution:

$$W^{G+1}_i = \begin{cases} Z^{G+1}_i & \text{if } f(Z^{G+1}_i) < f(W^{G, i}_i) \\ W^{G, i}_i & \text{otherwise} \end{cases}$$

(23)

where $W^{G+1}_i$ is a new population vector which is selected for next generation.

4 Reconfiguration based on CMDEA

In this paper, the CMDEA is employed to find optimal switches for reconfiguration. The steps of the proposed solution are depicted in the flowchart of Fig. 5.

In this paper, the configuration of the network is changed two times a day. As will be shown in simulation results, this is to decrease the switching costs associated with high frequency (hourly) reconfiguration. As such, for each load profile, the optimal time intervals for switching should be identified before running the optimisation routine. These intervals also determine the ‘number of optimal times’ for reconfiguration.

That has translated to the fact that the network reconfiguration could be performed only twice a day to achieve high-quality results that are very close to hourly reconfiguration. The time intervals change for various seasons, but are constant for a specific season. For example, in the daily load curve shown in Fig. 3a, there is one major variation in the load profile, that determines two optimal time intervals (hours [1 16] and [17 24]), and therefore, the ‘number of optimal times’ for reconfiguration is $h = 2$. It is verified via simulations that such load variations lead to two optimal sets of tie switches for daily network reconfiguration. Similarly, the number of optimal times for Fig. 3b is $h = 3$.

The variables are tie switches that must be opened to change the structure of the system. During the initialisation process (20), tie switches (population) are randomly generated as follows:
where \( SW \) is a component of the population (tie switch). In the mutation step, two new vectors are generated based on the mutation operator:

\[
W = \begin{bmatrix}
SW_{1,1} & SW_{1,2} & \ldots & SW_{1,D} \\
SW_{2,1} & SW_{2,2} & \ldots & SW_{2,D} \\
\vdots & \vdots & \ddots & \vdots \\
SW_{i,1} & SW_{i,2} & \ldots & SW_{i,D}
\end{bmatrix}
\]  

(24)

In the crossover step, \( C_i \) is compared with a random number \( r \) in the interval \([0, 1]\). If \( r < C_r \), then \( Y \) is selected. Otherwise, \( W \) is selected:

\[
Z_i = \begin{cases} X_i & \text{if } r \leq C_i \\ Y_i & \text{otherwise} \end{cases}
\]

(26)

Then, the selection operator is utilised to select the best solution, so that, if the fitness of \( Z_i^{G+1} \) is superior than \( W_i^G \), the vector of \( Z_i^{G+1} \) is selected, otherwise \( W_i^G \) is selected.

As there are three objective functions in this research, a multi-objective version of CMDEA can be obtained through the non-dominating sorting mechanism and the final solution is selected by fuzzy decision-maker [36].

In a multi-objective optimisation problem, there are more than one objective function, as well as a set of solutions named Pareto front (instead of a global solution). To obtain the Pareto front, dominance concept is used. For example, if both subsequent equations are satisfied, vector \( Z_i \) dominates the solution \( W_i \):

\[
\forall i \in \{1, 2, \ldots, N\} \quad f(Z_i) \leq f(W_i)
\]

(27)

\[
\exists j \in \{1, 2, \ldots, N\} \quad f(Z_i) < f(W_i)
\]

(28)

here \( Z_i \) and \( W_i \) are vectors of decision variables; \( f \) is the fitness function of \( Z_i \) and \( W_i \); \( N \) is the number of objective functions. A fuzzy approach is then used to normalise the set of solutions into values between \([0, 1]\). The following fuzzy membership functions are utilised:

\[
\mu_{j}(x) = \begin{cases} 1 & f_{\text{min}} \leq f(x) \\ \frac{f(x) - f_{\text{min}}}{f_{\text{max}} - f_{\text{min}}} & f_{\text{min}} < f(x) < f_{\text{max}} \\ 0 & f(x) \geq f_{\text{max}} \end{cases}
\]

(29)

here \( f_{\text{min}} \) and \( f_{\text{max}} \) are the lower and upper limits of the \( j \)th function, respectively. Consequently, a final solution is selected among normalised solutions by utilising:

\[
\gamma_{j}(n) = \frac{\sum_{i=1}^{N_{p}} U_{i} \times \mu_{j}(x_{i})}{\sum_{i=1}^{N_{p}} \sum_{j=1}^{N_{c}} U_{i} \times \mu_{j}(x_{i})}.
\]

(30)

In this equation, \( N_p \) is the number of solutions which have been saved in repository; \( \mu_{j} \) represents the objective functions that have been normalised for the \( n \)th solution; \( U_i \) is the weighting coefficient that are set by operator based on the importance of the sub-objective functions.

5 Data clustering

Clustering algorithms divide large data into several groups. The objects in each group are statistically similar to one another but are dissimilar with other groups. K-means is one of the most popular clustering methods [37]. It is important to find a small data set that effectively represents a large population. This is specifically important in power systems that are full of uncertainties. The nonlinear behaviour of a power system in day-to-day operation, results in a variety of load curves. A challenge when dealing with methods such as reconfiguration is: which load profile should be used? It is not definitely efficient to perform optimisation based on several years of hourly load data. Even if we do so, there is no guarantee that the solution applies to the next day’s load profile that is definitely different from the historical data. Therefore, in this paper, the authors propose to apply k-means clustering technique to obtain a small but efficient data set that statistically represents the majority of load variation cases. K-means is employed to cluster seasonal load profiles into a few groups. Consequently, reconfiguration schedule is performed based on a group which has the majority of members. That means reconfiguration is performed based on a daily load profile that have been statistically repeated more within a season. This helps to reduce the cost and improve the efficiency of planning for the long term. In this paper, k-means [37] is customised to cluster seasonal load profile as follows:

\[
f = \min \sum_{i=1}^{N_p} \sum_{j=1}^{N_{c}} \|X_i - C_j\|^2
\]

(31)

where \( f \) is the objective function, \( N_c \) is the number of clusters (groups), \( N_p \) is the number of members in each cluster, \( X_i \) is the \( i \)th member at each cluster, \( C_k \) is the centre of cluster \( k \)th and calculated as follows:

\[
C_k = \frac{1}{N_p} \sum_{j=1}^{N_p} X_j.
\]

(32)

As can be seen from this equation, this is an optimisation problem with objective function (31). The problem is solved by meta-heuristic algorithms such as DEA. Let the data be a seasonal load profile as follows:

\[
data = \begin{bmatrix}
X_{1,1} & X_{1,2} & \cdots & X_{1,N} \\
X_{2,1} & X_{2,2} & \cdots & X_{2,N} \\
\vdots & \vdots & \ddots & \vdots \\
X_{N,1} & X_{N,2} & \cdots & X_{N,N}
\end{bmatrix}.
\]

(33)

If we assume that the number of clusters is 3 (\( k = 3 \)), a vector of the population for the optimisation algorithm is generated randomly as follows:

\[
\text{vector}_i = [2 \ 1 \ 1 \ 3 \ 2 \ 1 \ \cdots \ N].
\]

(34)

Note that 1, 2, 3 are randomly generated for each vector. The data is then clustered based on these vectors. Consequently, the objective function is calculated based on (31) for these classifications. Each vector that has the smallest objective value is selected as the best class. The above steps are repeated until the maximum generation is reached.

6 Numerical simulation results

In this section, the proposed algorithm is implemented on two MGs, the 33 and 69 bus autonomous systems and the simulation results are analysed in various aspects.

In MG and smart grid environment, measured data will be available from supervisory control and data acquisition and AMI devices. Ideally, reconfiguration should be performed based on measured load profile that is consistently repeated over time (months, season etc.) with measurement devices. This will not only help having optimum planning under load profiles, but it also decreases the investment costs. However, at the time of this study, the authors did not have access to real load data from a power system utility, MG, or a smart network to incorporate in our studies. Smart networks loads, similar to conventional networks, are a mix of different types of loads, such as residential, commercial, industrial, etc.
We have taken a 33-bus and 69-bus system and have modified these networks with typical hourly load profiles that were available publicly to create study cases that are closer to reality than a constant load model.

First, the data clustering algorithm presented in Section 5 is utilised to extract the proper load profile from monthly, seasonally, and yearly loads. Here, we used seasonal data as a reference. The data clustering algorithm is then used for each season to extract daily load profiles that are statistically repeated more within a season. The reconfiguration is then applied on these load profiles and are extended for each season. As such, the variations of three types of loads (residential, industrial, and commercial) for different seasons (spring, summer, fall, and winter) are used as inputs of data clustering algorithm and the extracted load profile for each season are shown in Fig. 6. These load profiles are eventually used for long-term planning strategies. This approach not only reduces the computational burden but also guarantees robust planning against load uncertainty.

### 6.1 Under-study MGs

Different load types are assigned to different buses in each example, and are highlighted in the same colours as defined in Fig. 6 (see Fig. 7). The load value of each bus-bar is taken from the data in reference [38] and is multiplied by the per-unit load variations of Fig. 6. According to the figure, there are two specific time intervals to change the topology. They are [1 9], [10 24]; [1 9], [10 24]; [1 7], [8 24] and [1 9], [10 24], for spring, summer, fall, and winter, respectively. In addition, the cost of switching under load is considered $51 [39]. Three scenarios are considered to show the effectiveness of the proposed method, as follows:

- **Scenario I:** scheduling without reconfiguration.
- **Scenario II:** scheduling with constant reconfiguration.
- **Scenario III:** scheduling with dynamic reconfiguration.

#### 6.1.1 Case study 1: 33-bus autonomous MG

The study has been performed on a MG, the 33-bus autonomous systems. The single-line diagram of the 33-bus autonomous MG is shown in Fig. 7. This MG consists of 33 buses and 37 branches, where 1, 2, …, 32 branches are closed (sectionalising switches) while 33, 34, …, 37 branches are open (tie-lines) [38]. The power is supplied by four DGs (located at buses 8, 22, 25, and 33). The data for DGs are presented in Table 1.

After performing an optimisation algorithm, a Pareto front is obtained. This pattern is also repeated for each scenario and then the results are obtained. Fig. 8 presents an example.

In the first scenario, optimal scheduling of the MG before reconfiguration for a day of each season is performed. This is considered as the base case. The results are presented in Table 2. According to Table 2, the summation of the real power during days of spring, summer, fall, and winter are 0.819, 1.944, 0.841, and 0.926 MW, respectively. The minimum voltages of the bus-bars during days of the different season are 0.959, 0.895, 0.929, and 0.930 per unit (p.u.). Also, the minimum VSIs are 0.848, 0.846, 0.847, 0.847,

### Table 1

Settings of DG units for the 33-Bus MG

| DG | $m_p$  | $n_q$  | $\omega_0$ | $V_0$ | $P_{\text{max}}$ | $Q_{\text{max}}$ |
|----|--------|--------|------------|-------|------------------|------------------|
| 1  | 0.001191 | 0.02758 | 1          | 1.01  | 3                | 3                |
| 2  | 0.005198 | 0.07272 | 1          | 1.01  | 2                | 2                |
| 3  | 0.001446 | 0.02051 | 1          | 1.01  | 3                | 3                |
| 4  | 0.002265 | 0.04000 | 1          | 1.01  | 2                | 2                |

### Table 2

Daily results of scenario I for the 33-Bus MG

| Season | Time | Tie switches | Loss, MW | Min VSI, p.u. | SW cost, $ | Min voltage, p.u. |
|--------|------|--------------|----------|---------------|------------|-----------------|
| spring | [1 24] | 33,34,35,36,37 | 0.819 | 0.848 | 0 | 0.959 |
| summer | [1 24] | 33,34,35,36,37 | 1.944 | 0.643 | 0 | 0.895 |
| fall   | [1 24] | 33,34,35,36,37 | 0.841 | 0.745 | 0 | 0.929 |
| winter | [1 24] | 33,34,35,36,37 | 0.926 | 0.749 | 0 | 0.930 |
As there is no reconfiguration considered in Scenario I, the switching cost is zero.

In the second scenario, the optimal reconfiguration of 33-bus autonomous MG has been carried out based on constant load. According to the results presented in Table 3, the optimal power loss of MG for a 24-h period of spring, summer, fall, and winter are 0.382, 1.091, 0.454, and 0.436 MW, respectively. Minimum voltages of bus-bars for each season are 0.977, 0.918, 0.828, and 0.954 (p.u.). Also, minimum VSIs are 0.907, 0.711, 0.828, and 0.954 (p.u.) for each season. According to Table 3, for each season, only four switches are to be changed. Therefore, there is only one action for each switch per season, which means four switching actions total. This leads to $204 switching costs per season.

In the third scenario, feeder reconfiguration is dynamically applied and results are presented in Table 4. According to Table 4, the total power during a 24-h period for spring, summer, fall, and winter are 0.343, 1.000, 0.370, and 0.407 MW, respectively. Minimum voltages of bus-bars for each season are 0.911, 0.761, 0.872, and 0.874 (p.u.) respectively. Minimum VSIs are 0.907, 0.711, 0.828, and 0.854 (p.u.) for each season. In this case, each switch may change its position 0, 1, or 2 times per day. Therefore, the number of switch performances are much higher than scenario 2, as we have more frequent (daily) operations. The switching costs are presented in Table 4.

Comparing the results of the three scenarios shows that more frequent reconfiguration increase the switching costs. It also increases the chances of power system electromagnetic transients and causes power quality issues. However, the MG may experience lower energy losses and costs. It is eventually evident that this is a tradeoff between technical considerations and economic costs.

The generated real and reactive power of DGs for a day of each season is shown in Figs. 9 and 10. The results show that active power generated by DGs does not change significantly by configuration alterations. The changes were seen in Fig. 10 are due to frequency variations. The power generation increases with a reduction in frequency and it reduces with increments in frequency (see (4)). However, according to Fig. 10, reactive power generation is more sensitive to network reconfiguration. This is so because the reactive power is a function of voltage (see (5)). Since voltage profile is improved significantly after reconfiguration, reactive power is changed.

The frequency of the MG for 24 h of a summer day is demonstrated in Fig. 11. There is no significant change on autonomous MG’s frequency before and after reconfiguration. Only minor variation (3 × 10^-6) is seen for some hours, since system frequency slightly changes the reactance of lines and the loads values. Therefore, it could be concluded that the autonomous MG’s topology has minor impact on frequency. The same results are

| Table 3 Daily results of scenario II for the 33-Bus MG |
|-----------------|-------|--------|----------|----------|----------|
| Season          | Time  | Tie switches | Loss, MW | Min VSI, p.u. | SW cost, $ | Min voltage, p.u. |
| spring          | [1 24] | 35,03,13,15,28 | 0.382    | 0.907      | 204       | 0.977          |
| summer          | [1 24] | 10,02,12,36,27 | 1.091    | 0.711      | 204       | 0.918          |
| fall            | [1 24] | 35,03,14,16,28 | 0.454    | 0.828      | 204       | 0.954          |
| winter          | [1 24] | 35,18,14,15,27 | 0.436    | 0.854      | 204       | 0.961          |

| Table 4 Daily results of scenario III for the 33-Bus MG |
|-----------------|-------|--------|----------|----------|----------|
| Season          | Time  | Tie switches | Loss, MW | Min VSI, p.u. | SW cost, $ | Min voltage, p.u. |
| spring          | [1 9]  | 35,03,13,30,27 | 0.343    | 0.911      | 75,939    | 0.977          |
|                 | [10 24]| 10,02,13,15,22 | 1.000    | 0.761      | 47,583    | 0.934          |
| sumemr          | [1 9]  | 35,03,14,17,27 | 1.000    | 0.761      | 47,583    | 0.934          |
|                 | [10 24]| 35,03,14,15,27 | 0.370    | 0.872      | 46,053    | 0.966          |
| fall            | [1 7]  | 35,02,13,15,27 | 0.370    | 0.872      | 46,053    | 0.966          |
|                 | [8 24] | 35,02,13,15,22 | 0.407    | 0.874      | 64,311    | 0.967          |

Fig. 9 Active power generation for DGs during different days of (a) Spring, (b) Summer, (c) Fall, (d) Winter, for the 33-bus MG

Fig. 10 Reactive power generation for DGs during different days of (a) Spring, (b) Summer, (c) Fall, (d) Winter, for the 33-bus MG
captured for other seasons, but they are not presented because of lack of space.

The frequency of MG is reduced with increments of the load (see Fig. 11). On the other hand, the generation of MGs is increased when the frequency is reduced to supply loads (see (4)). It can be concluded that DGs generate more power to supply the loads when frequency decreases.

6.1.2 Case study 2: 69-bus autonomous MG: In this section, the proposed method is implemented on a 69-bus autonomous MG demonstrated in Fig. 12. This MG consists of 69 buses and 73 branches where branches 1, 2, …, 68 are closed (sectionalising switches) and branches 69, 70, …, 73 are open (tie-lines) [40]. This MG supplies loads through 6 DGs located at buses 5, 14, 27, 30, 46, and 61 (data in Table 5). The results for all scenarios are presented in Tables 6–8.

6.2 Economic analysis

The analysis is performed before and after reconfiguration to show the effectiveness of reconfiguration from the economic point of view. The results for both test systems under three scenarios are presented in Table 9. The cost of energy is considered $85 per MWh. According to Table 9, the yearly energy loss for scenarios I, II, III are 35359.065, 18452.565, 16560.465 MWh for the 33-bus test MG, respectively. This means 47.8 and 53.1% reduction on energy loss for scenarios II and III compared to the base case, respectively. The dynamic reconfiguration (scenario III) shows 5.3% more reduction over scenario II that shows the importance of considering a variable switching schedule. For the 69-bus test system, scenarios II and III show 30.4 and 43.6% reduction compared to scenario I, respectively. This means 13.2% reduction in energy losses when performing dynamic reconfiguration versus regular reconfiguration.

Fig. 11 MG frequency at each hour during different days of summer for the 33-Bus MG

Fig. 12 Single-line diagram of the 69-bus autonomous MG

Table 5 Settings of DG Units for the 69-Bus MG

| DG | $m_p$ | $n_q$ | $\omega_0$ | $V_0$ | $P_{\text{max}}$ | $Q_{\text{max}}$ |
|----|-------|-------|-----------|--------|-----------------|-----------------|
| 1  | 0.0012| 0.0176| 1         | 1.01   | 4.5             | 3               |
| 2  | 0.0022| 0.0176| 1         | 1.01   | 3               | 2               |
| 3  | 0.0044| 0.0784| 1         | 1.01   | 1.5             | 1               |
| 4  | 0.0011| 0.0184| 1         | 1.01   | 4.5             | 2.5             |
| 5  | 0.0044| 0.0760| 1         | 1.01   | 1.5             | 1.5             |
| 6  | 0.0022| 0.0216| 1         | 1.01   | 4.5             | 4.5             |

Table 6 Daily results of scenario I for the 69-Bus MG

| Season | Time | Tie switches | Loss, MW | Min VSI, p.u. | SW cost, $ | Min voltage, p.u. |
|--------|------|--------------|----------|---------------|------------|------------------|
| spring | [1 24] | 69,70,71,72,73 | 1.423 | 0.833 | 0 | 0.955 |
| summer | [1 24] | 69,70,71,72,73 | 3.855 | 0.749 | 0 | 0.931 |
| fall   | [1 24] | 69,70,71,72,73 | 1.923 | 0.753 | 0 | 0.932 |
| winter | [1 24] | 69,70,71,72,73 | 1.344 | 0.783 | 0 | 0.941 |

Table 7 Daily results of scenario II for the 69-Bus MG

| Season | Time | Tie switches | Loss, MW | Min VSI, p.u. | SW cost, $ | Min voltage, p.u. |
|--------|------|--------------|----------|---------------|------------|------------------|
| spring | [1 24] | 11,04,37,21,70 | 0.975 | 0.886 | 204 | 0.971 |
| summer | [1 24] | 12,04,37,21,18 | 2.937 | 0.818 | 255 | 0.951 |
| fall   | [1 24] | 11,08,37,26,18 | 1.055 | 0.878 | 255 | 0.968 |
| winter | [1 24] | 43,08,38,62,18 | 0.971 | 0.881 | 255 | 0.969 |
The objective function is optimized using a developed evolutionary algorithm, with improved mutation and reconfiguration. The power loss reduction is considered as objective-function. The population size and the maximum number of iterations are considered 20 and 50, respectively. The average value of objective-function for ten runs is shown in Fig. 13. This figure demonstrates the superior performance of CMDEA compared to DEA and IWO. The population size and the maximum number of iterations are considered 20 and 50, respectively. The average value of objective-function for ten runs is shown in Fig. 13. This figure demonstrates the superior performance of CMDEA compared to DEA and IWO. CMDEA finds global optimums rather than local minima.

### 6.3 CMDEA evaluation and comparison

The CMDEA performance is compared to conventional DEA and IWO [41] to solve the dynamic network reconfiguration. The power loss reduction is considered as objective-function. The population size and the maximum number of iterations are considered 20 and 50, respectively. The average value of objective-function for ten runs is shown in Fig. 13. This figure demonstrates the superior performance of CMDEA compared to DEA and IWO. CMDEA finds global optimums rather than local minima.

### 7 Conclusion

In this paper, a dynamic long-term reconfiguration is performed to facilitate the optimal operation of autonomous MGs. A new developed evolutionary algorithm, with improved mutation and cross-over operators based on conventional DEA, is proposed with superior performance over conventional DEA. The results demonstrate the significance of this approach considering variable loads from economical points of view. The proposed method also facilitates power loss reduction, switching cost reduction, and VSI improvement. It is revealed that system reconfiguration has minimal impact on the MGs frequency.

The two-stage reconfiguration method presented in this paper along with the application of k-means clustering algorithm effectively reduces the computational burden and the switching costs, which makes the method ideal for real-time operation of future smart distribution grids.

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Table 8: Daily results of scenario III FOR the 69-Bus MG

| Season | Time   | Tie switches | Loss, MW | Min VSI, p.u. | SW cost, $ | Min voltage, p.u. |
|--------|--------|--------------|----------|---------------|------------|------------------|
| spring | [1 9]  | 11,52,35,25,20 | 0.789    | 0.895         | 85,425     | 0.972            |
|        | [10 24]| 14,53,35,61,17 |          |               |            |                  |
| summer | [1 8]  | 14,08,37,61,18 | 2.085    | 0.829         | 85,425     | 0.954            |
|        | [9 24] | 11,52,35,26,18 |          |               |            |                  |
| fall   | [1 7]  | 43,57,36,25,70 | 1.009    | 0.881         | 82,620     | 0.969            |
|        | [8 24] | 13,55,37,63,15 |          |               |            |                  |
| winter | [1 9]  | 44,55,36,62,19 | 0.933    | 0.870         | 82,671     | 0.966            |
|        | [10 24]| 45,55,35,24,16 |          |               |            |                  |

Table 9: Annual energy savings

| MGs | Scenarios | Yearly power loss, MW | Annual energy loss, MWh | Annual energy loss savings, MWh |
|-----|-----------|------------------------|-------------------------|---------------------------------|
| 33 buses | I | 415,989 | 35,359,065 | 0 |
|        | II | 217,089 | 18,452,565 | 16,906,5 |
|        | III | 194,829 | 16,560,465 | 18,798,6 |
| 69 buses | I | 784,884 | 66,715,14 | 0 |
|        | II | 546,156 | 46,423,26 | 20,291,88 |
|        | III | 442,062 | 37,575,27 | 61,787,77 |

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Fig. 13: Average value of fitness for ten runs
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