IET Generation, Transmission & Distribution

Special Issue: Challenges and New Solutions for Enhancing Ancillary Services and Grid Resiliency in Low Inertia Power Systems

Journals
The Institution of Engineering and Technology

Impact study of demand response program on the resilience of dynamic clustered distribution systems

ISSN 1751-8687
Received on 9th January 2020
Revised 15th April 2020
Accepted on 22nd April 2020
E-First on 21st May 2020
doi: 10.1049/iet-gtd.2020.0068
www.ietdl.org

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Abstract: Natural disasters, faults, or the sudden outage of major energy resources can create resilience issues in power systems. Modern distribution systems can reconfigure due to the use of automated protection and control techniques and the proliferation of distributed generators (DGs). If there are several DGs located nearby, distribution systems can be clustered into microgrids in an emergency condition. Clustering of distribution systems offers many benefits to achieve high system resilience. Moreover, demand response (DR) is an efficient way of increasing the operation quality and improving the resilience of the power system. This study discusses the impact of DR on the resilience of dynamically-clustered distribution systems. Accounting for the DR while clustering the distribution system can be beneficial for distribution system customers from the resilience and power quality points-of-view. To this end, the distribution clustering is performed using two different objective functions to improve its resilience and voltage profile. DR is formulated as new constraints applied to the distribution system clustering optimisation problem. This study proposes a multi-objective optimisation function that is solved by using an exchange market algorithm, Pareto efficiency method, and fuzzy satisfying approach. The simulations are performed on IEEE 33-bus test system.

Nomenclature

Indices

d	DGs number index
i	bus index
s	objective function index
t	time index
z	clusters index

Parameters and variables

a, b	weighted coefficients
A_k	incentive rate of the DR at kth hour
A_t	incentive rate of the DR at tth hour
$c_{z_P}, c_{i_p}, c_{p_p}, c_{z_q}, c_{i_q}, c_{p_q}$	ZIP coefficients
$\overline{COF}$	combined objective function
D	total number of DGs in distribution systems
$E_{t,k}$	cross-elasticity of the customers
$E_{t,t}$	self-elasticity of the customers
g_1	risk coefficient of a medium-rank stockholder
g_2	risk coefficient of a low-rank stockholder
k	value of the algorithm's iteration counter
N	number of objective functions
NB	total number of buses in distribution systems
n_j	number of medium-rank stockholders
N_{obj}	number of the objective functions
n_{pop}	total number of market members
n_q	number of top-rank stockholders
n_{t1}	sum of the total number of member's shares before the change
NZ	number of buses in a specific cluster
$OF_s, \bar{OF}_s$	two different results of the sth objective function
$OF_s^{\max}$	maximum results of the sth objective function
$OF_s^{\min}$	minimum results of the sth objective function
OF_s^n	obtained results of the sth objective function
$P_{d,z,t}^{\text{DG}}$	generated active power of the DGs
$P_d^{\text{MAX\_DG}}$	maximum available active power of the DGs
pen_k	penalty rate of the DR at kth hour
pen_t	penalty rate of the DR at tth hour
$P_{i,t}$	demanded active power after ZIP model
$P_{i,t}^D$	amount of the customers' increased or decreased load after the implementation of the DR at ith bus and tth hour
$P_{i,t}^{LD}$	demanded load of the ith bus at tth hour after the implementation of the DR
$P_{i,t}^0$	demanded active power before ZIP model
$pop_k^{\text{group(3)}}$	stock value of the intended member of the third category
$pop_j^{\text{group(2)}}$	stock value of a member of medium-rank stockholders
$pop_{1,q}^{\text{group(1)}}, pop_{2,q}^{\text{group(1)}}$	two randomly selected stocks from the top-rank stockholders
$P_{z,t}^{\text{ENS}}$	active power associated with energy not supplied in the off-grid mode
$P_{z,t}^{\text{loss}}$	distribution systems' active power loss
$Q_{d,z,t}^{\text{DG}}$	generated reactive power of the DGs
$Q_d^{\text{MAX\_DG}}$	maximum possible reactive power of the DGs
$Q_{i,t}^0$	demanded reactive power before ZIP model
$Q_{i,t}$	demanded reactive power after ZIP model
$Q_{z,t}^{\text{loss}}$	distribution systems' reactive power loss
$Q_{z,t}^{\text{VNS}}$	reactive power associated with VArh not supplied in the off-grid mode
r	random number between zero and one
rand	uniformly distributed random number
r_s	random number in the $[-0.5, 0.5]$ range
r_1	random number between zero and one

r_2	random number between zero and one
t_{pop}	rank of the stockholder
$V_{i,t}$	voltage of the customers after ZIP model
$V_{i,t}^0$	voltage of the customers before ZIP model
W_s	sth weighted coefficient
Z	total number of clusters in distribution systems
δ	market characteristic
Δn_{t1}	change of stocks for a medium-rank stockholder
Δn_{t2}	change of stocks for a low-rank stockholder
η_1	risk taken by a medium-rank stockholder
η_2	risk taken by a low-rank stockholder
μ	rank coefficient of the stockholder
ρ_k	price of the energy at kth hour after the implementation of the DR
ρ_t	price of the energy at tth hour after the implementation of the DR
$\rho_{0,k}$	price of the energy at kth hour before the implementation of the DR
$\rho_{0,t}$	price of the energy at tth hour before the implementation of the DR

1 Introduction

With the ever-increasing penetration level of distributed generators (DGs), it is imperative to define solutions for using DGs to increase reliability and resilience of the grid of the future. Of particular importance is developing technologies and operational tools that help power system operators use DGs effectively to help power systems withstand extreme events, such as natural disasters, blackouts, and malicious adversaries [1–3]. According to the U.S. Department of Energy, events resulting from severe weather conditions have caused 58% of the outages since 2002 [4]. The current electric power infrastructure is highly vulnerable to these extreme events. For example, Hurricane Sandy damaged a large portion of the eastern U.S. electric power grid where 7.5 million customers in 15 states experienced power outages [5].

Although using DGs in the distribution system can improve its reliability and resilience [6], the excessive number of DGs increase the distribution system control complexity [7, 8]. To tackle this issue while maximising the benefits from DGs for enhancing power system resilience, clustering of traditional distribution systems into multiple microgrids can be adopted as an efficient solution for operating a highly DG penetrated distribution system. Microgrids, as active structures for distributing electric power, facilitate the effective integration of DGs to help with the enhancement of power system performance [9]. In a clustered distribution system, each clustered section is operated as a microgrid that should supply the required demand of the customers in its area [10]. Clustering of distribution systems into microgrids has recently been investigated in the literature [11, 12]. The energy management of the networked microgrids is investigated in [13, 14]. Furthermore, the voltage of the networked microgrids is studied in [15]. Wang *et al.* [16] surveyed the effect of the networked microgrids on the self-healing characteristic of the power systems. Besides, an approach for the operation of the networked microgrids in the distribution systems is proposed in [17]. In [18], an intentional islanding scheme is presented to prevent the power grid's blackout. A clustering method is proposed in [19] to design a robust and reliable power system. In [20], a method is proposed to enhance the resilience of microgrids' clusters for managing a complex distribution system.

Demand response (DR) is a well-known strategy for addressing the demand-side management's requirements [21, 22]. DR can potentially change load profiles by shifting the peak load to the other periods for improving the reliability, resilience, and economic operation of the system [23]. In [24], the DR's impact on the scheduling of the microgrid's daily generation in the islanded mode has been investigated. The optimal execution of DR for improving the reliability of the power system is proposed in [25]. The impact of the DR on the technical, economic, and reliability issues is surveyed in [26]. The advantages of using the DR in microgrids are surveyed in several papers [27, 28].

In the literature, distribution system clustering and DR have been handled separately. However, accounting for the DR while clustering the distribution system may be beneficial for distribution system customers from the resilience and power quality points-of-view. This paper addresses the simultaneous dynamic implementation of DR and distribution system clustering and investigates its impacts on the operation of the distribution system. To this end, the distribution clustering is performed using two different objective functions to improve its resilience and voltage profile. DR is formulated as new constraints applied to the distribution system clustering optimisation problem. A three-stage optimisation process using the exchange market algorithm (EMA) [29], Pareto efficiency method, and fuzzy satisfying approach is utilised to find the optimal results of the proposed problem. The main contributions of this paper are described as follows:

- DR is integrated into the distribution system clustering optimisation problem.
- Impact of considering DR while clustering distribution systems on the resilience and voltage profile is investigated and analysed using several scenarios and objective functions.
- The simultaneous implementation of DR and dynamic clustering has resulted in 29.1% reduction in the total daily energy not supplied (ENS) compared to the case that DR is not applied.

This paper is structured as follows: Section 2 discusses some preliminaries required to implement the proposed clustering methodology. The proposed clustering methodology and formulations are described in Section 3. Section 4 provides the verification results and discusses the resilience of the distribution system by implementing the newly introduced method. Section 5 concludes this research. A schematic overview of this paper is presented in Fig. 1.

2 Preliminaries

This section discusses the preliminaries required for the proposed clustering methodology including load modelling, EMA, Pareto efficiency approach, fuzzy satisfying method, and DR.

2.1 ZIP model

Customer loads are known to be sensitive to the voltage where a decrease in voltage reduces the amount of real and reactive power consumed by customers. ZIP model [30] is a well-known method for modelling the changes in the customers' demand. To accurately modelling the voltage sensitivity of the customer and the impact of conservation voltage reduction, the ZIP model is used by considering the below constraints

$$P_{i,t} = P_{i,t}^0\left(c_{z_p}\left(\frac{V_{i,t}}{V_{i,t}^0}\right)^2 + c_{i_p}\left(\frac{V_{i,t}}{V_{i,t}^0}\right) + c_{p_p}\right), \quad \forall i, t, \tag{1}$$

$$Q_{i,t} = Q_{i,t}^0\left(c_{z_q}\left(\frac{V_{i,t}}{V_{i,t}^0}\right)^2 + c_{i_q}\left(\frac{V_{i,t}}{V_{i,t}^0}\right) + c_{p_q}\right), \quad \forall i, t. \tag{2}$$

2.2 Introduction to EMA

In this paper, to find the optimal solution of proposed distribution system clustering and DR problem, a three-stage optimisation strategy including EMA, Pareto efficiency approach, and fuzzy satisfying method is used. EMA is applied as the first stage for identifying a set of optimal solutions. EMA is a powerful evolutionary algorithm for solving optimisation problems inspired by the trade's trend in the stock market. EMA has two balanced and unbalanced modes. In each mode, the population members are divided into low, medium, and high rankings. Members' ranking and the risk taken by them to improve their rank have an inverse relationship. Moreover, this algorithm has two powerful operators, namely oscillatory and non-oscillatory, which model the real nature

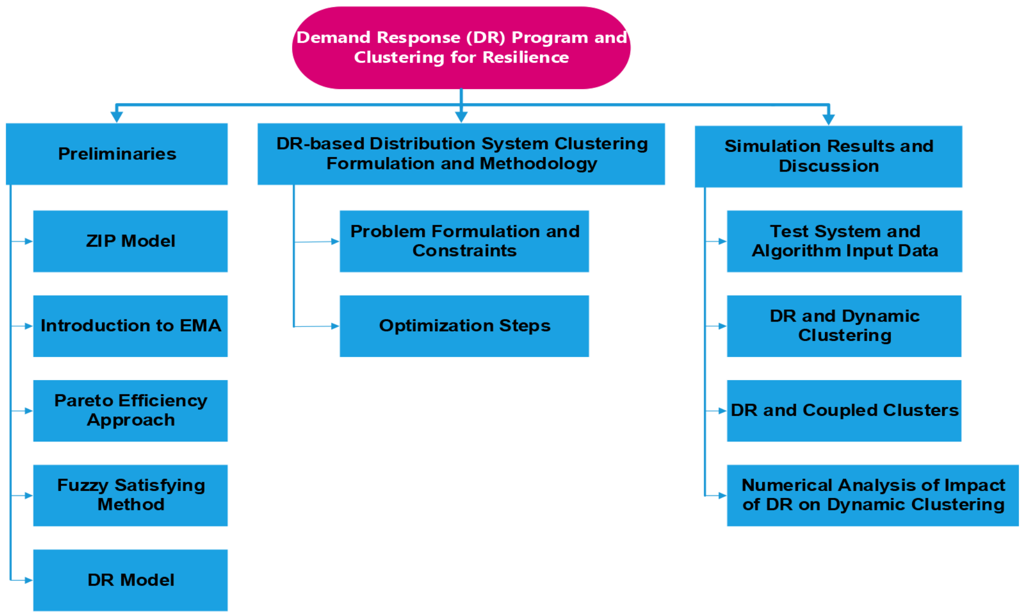

Fig. 1 *Schematic overview of the paper*

of the stock market. EMA has been proven to be an efficient, powerful, accurate, and fast method to find the optimal solutions of the different types of power system's optimisation problems [31–33].

In the balanced mode, stockholders compete with each other to obtain the maximum benefit without taking any risk. Members of the stock market according to their fitness function are classified into three categories:

- Top-rank stockholders form around 10 to 30% of total population members. These stockholders do not change their stocks to maintain their rank in the market. These stockholders represent the most optimal problem answers.
- Medium-rank stockholders from around 20 to 50% of total population members. These stockholders compare their stocks with stocks of top-rank stockholders to achieve a global optimum. Each stockholder selects the value of his/her shares based on the values of stocks of top-rank stockholders using

$$pop_j^{\text{group(2)}} = r \times pop_{1,q}^{\text{group(1)}} + (1-r) \times pop_{2,q}^{\text{group(1)}} \quad q = 1,2,3,\ldots n \quad \text{and} \quad j = 1,2,3,\ldots n_j. \tag{3}$$

- Low-rank stakeholders choose their stock values using the stocks of top-rank stockholders by taking more risk. They adopt a broader search domain compared to the second category as

$$S_k = 2 \times r_1 \times \left(pop_{1,q}^{\text{group(1)}} - pop_k^{\text{group(3)}}\right) + 2 \times r_2 \times \left(pop_{2,q}^{\text{group(1)}} - pop_k^{\text{group(3)}}\right), \tag{4}$$

$$pop_k^{\text{group(3), new}} = pop_k^{\text{group(3)}} + 0.8 \times S_k. \tag{5}$$

- In the fluctuating mode, the stockholders intelligently exchange their stocks by taking risks to achieve a higher rank in the market. Similar to the balanced mode, members of the stock market are divided into three categories:
- Top-rank stockholders (10 to 30% of total members) tend to keep their high rank among the other stockholders and do not exchange their stocks.
- Medium-rank stockholders (20 to 50% of total members) tend to improve their rank by exchanging their stocks. As their rank in the market increases, they take less risk. After exchanging the stocks, the summation of stockholder shares must remain intact. Medium-rank stockholders participate in the market according to

$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1), \tag{6}$$

$$\mu = \frac{t_{pop}}{n_{pop}}, \tag{7}$$

$$n_{t1} = \sum_{y=1}^{n} s_{ty} \quad y = 1,2,3,\cdots,n, \tag{8}$$

$$\eta_1 = n_{t1} \times g_1, \tag{9}$$

$$g_1^k = g_{1,\max} - \frac{g_{1,\max} - g_{1,\min}}{iter_{\max}} \times k. \tag{10}$$

- In the medium-rank category, a portion of Δn_{t1} is randomly added to one of the stocks of a stockholder. This process continues until Δn_{t1} is completely added to all stocks of the corresponding stockholder. In this procedure, the total value of stocks for each stockholder must remain intact. Meanwhile, market information, δ, plays an important role to increase the convergence speed of algorithm to the optimal answer.
- Low-rank stockholders tend to achieve higher ratings by changing their stock values in a broader search domain. Stock changes in this category are based on

$$\Delta n_{t2} = 4 \times r_s \times \mu \times \eta_2, \tag{11}$$

$$r_s = 0.5 - \text{rand}, \tag{12}$$

$$\eta_2 = n_{t1} \times g_2. \tag{13}$$

In the fluctuating mode, the low-rank category members are not required to maintain their total value of stocks at a constant value. In (13), g_2 is between zero and one.

2.3 Pareto efficiency approach

By performing the EMA, several solutions are obtained. The top-ranked solutions of the objective functions are used to find the Pareto solutions. By considering (14) and (15), the non-dominated results are selected as the Pareto solutions. In other words, each selected solution that has at least one better value among the results of the objective functions (abbreviated as OF) is a Pareto solution, i.e.

$$\forall s = \{1,2,\ldots,N_{\text{obj}}\} \quad OF_s \le \bar{OF}_s, \tag{14}$$

$$\exists s = \{1,2,\ldots,N_{\text{obj}}\} \quad \text{OF}_s < \bar{\text{OF}}_s. \tag{15}$$

2.4 Fuzzy satisfying method

After finding the Pareto solutions, the fuzzy satisfying method is executed for obtaining the optimal solutions of the considered multi-objective problem among the Pareto solutions. Because objective functions' dimensions are not the same, the obtained results are normalised by

$$OF_s^n = \begin{cases} 1 & OF_s^n \le OF_s^{\min} \\ OF_s^n - OF_s^{\max} & OF_s^{\min} \le OF_s^n \le OF_s^{\max} \\ 0 & OF_s^{\max} \le OF_s^n \end{cases}. \quad (16)$$

To find the optimal solutions, the combined objective function is used by using the weighted coefficients as

$$\min\,[\overline{COF}] = \sum_{s=1}^{N} W_s\, OF_s, \quad (17)$$

$$\sum_{s=1}^{N} W_s = 1. \quad (18)$$

2.5 DR model

DR could be implemented to increase the quality of the service provided for the customers by asking them to participate in the operation of the distribution systems [9]. In DR, the customers have agreed to decrease or increase their demand according to the operator's request, and in this regard, they may be paid [31]. In this paper, multi-period incentive-based DR is proposed. In the considered DR, the elasticity of the energy price and customer incentives and penalties are taken into consideration. The DR-related constraints are given as

$$P_{i,t}^{LD} = P_{i,t} \times \left\{ \begin{array}{l} 1 + E_{t,t} \times \dfrac{[\rho_t - \rho_{0,t} + A_t + pen_t]}{\rho_{0,t}} \\ + \displaystyle\sum_{\substack{k=1 \\ k \ne t}}^{T} E_{t,k} \times \dfrac{[\rho_k - \rho_{0,k} + A_k + pen_k]}{\rho_{0,k}} \end{array} \right\}, \quad (19)$$

$$-0.16\,P_{i,t} \le P_{i,t}^{D} \le 0.16\,P_{i,t}, \quad (20)$$

$$P_{i,t}^{LD} = P_{i,t} + P_{i,t}^{D}, \quad (21)$$

$$\sum_{t=1}^{24} P_{i,t}^{D} = 0. \quad (22)$$

Equation (19) indicates the multi-period DR's model with elastic loads. Equation (20) represents the acceptable range of the load for DR. Equation (21) shows how the customer's load is calculated after the implementation of the DR. Equation (22) ensures that the total amount of the daily increased and decreased load of the customers are equal.

3 DR-based distribution system clustering formulation and methodology

This section discusses the proposed methodology to use DR for dynamic clustering of distribution systems.

3.1 Problem formulation and constraints

For the proposed dynamic clustering problem along with DR, the following constraints are taken into consideration:

$$0 \le P_{d,z,t}^{\mathrm{DG}} \le P_{d}^{\mathrm{Max\_DG}}, \quad (23)$$

$$0 \le Q_{d,z,t}^{\mathrm{DG}} \le Q_{d}^{\mathrm{MAX\_DG}}, \quad (24)$$

$$0.9 \le V_{i,t} \le 1.05, \quad (25)$$

$$\sum_{d=1}^{D} P_{d,z,t}^{\mathrm{DG}} + \sum_{z=1}^{Z} P_{z,t}^{\mathrm{ENS}} = \sum_{i=1}^{NB} P_{i,t}^{LD} + \sum_{z=1}^{Z} P_{z,t}^{\mathrm{loss}}, \quad (26)$$

$$\sum_{d=1}^{D} Q_{d,z,t}^{\mathrm{DG}} + \sum_{z=1}^{Z} Q_{z,t}^{\mathrm{VNS}} = \sum_{i=1}^{NB} Q_{i,t} + \sum_{z=1}^{Z} Q_{z,t}^{\mathrm{loss}}. \quad (27)$$

Constraints (23) and (24) represent the active and reactive generation constraints of DGs, respectively. The allowable range of the distribution systems' voltage level is formulated in (25). In (26), the active power balance equation of the proposed model is described. ENS denotes the required energy of the customers that is not being supplied by the distribution system. In (27), the reactive power balance equation is provided. VArh not supplied (VNS) denotes the demanded reactive power of customers over time that is not being supplied by the distribution system.

The proposed multi-objective model includes two objectives given as follows:

$$OF_t^1 = a\sum_{z=1}^{Z} P_{z,t}^{\mathrm{ENS}} + b\sum_{z=1}^{Z} Q_{z,t}^{\mathrm{VNS}}, \quad (28)$$

$$OF_t^2 = VDI = \sum_{z=1}^{Z}\sum_{i=1}^{NZ} (V_{z,i,t} - V_{z,i,t}^{0})^2. \quad (29)$$

Equation (28) explains the first objective function in which the minimisation of the ENS and VNS of the clusters are considered. In this paper, active and reactive powers are assumed to have the same level of priority. Thus, both a and b are set as 0.5. In practice, load's reactive power proportionally changes by the variations of loads' active power. Equation (29) describes the second objective function. In this objective function, minimisation of the voltage deviation index (VDI) is considered. Once the multi-objective model and constraints are formulated, the EMA, Pareto efficiency approach, and fuzzy satisfying methods will be applied consecutively to find the optimal solutions.

3.2 Optimisation steps

The clustering process in the distribution systems along with the implementation of DR follows the steps below. The flowchart of the proposed process is shown in Fig. 2.

Step 1: Enter the initial data of the OF^1 or OF^2, e.g. number of the required population and iteration for optimisation, bus data, line data, DGs' data, DR's data etc.
Step 2: Generate the initial population of the selective lines for clustering as well as the output of the DGs considering (23) and (24).
Step 3: Start the first iteration of the first population and determine the end buses' number and location for the selected lines that are used for clustering and initialising the EMA.
Step 4: Identify the buses and lines of each cluster, reorganise the bus and line data of each cluster, and run the power flow.
Step 5: Execute the constraints related to the load in (1) and (2), voltage in (25), and output active and reactive powers of the DGs, (26) and (27), for each of the population members.
Step 6: Calculate the objective functions in (28) and (29), and other variables for all of the clusters.
Step 7: Execute Steps 1 to 6 for all members of population until the algorithm reaches the considered maximum iteration number and the top-ranked members and their results are determined.
Step 8: Apply DR's constraints in (19)–(22) on all the previously obtained results.
Step 9: Apply constraints (14) and (15) to obtain the Pareto solutions. Afterward, the fuzzy satisfying method and weighted coefficients approach are performed by applying (16)–(18) and the final results are obtained.

variable energy price and incentive rate can hide the real impact of the DR. Accounting for the real-time pricing of the energy can only add to the complexity of the proposed model which increases the optimisation time.

Remark 3: The idea of clustering distribution systems into multiple microgrids requires specific regulation and standards from utilities to facilitate this transition. To effectively implement the proposed approach, it is assumed that all DGs are fully controllable. Also, all lines are associated with intelligent electronic devices and measurement and metering infrastructure. Moreover, the distribution system should be equipped with tie switches to accommodate the decoupling and recoupling of the clustered microgrids. In practice, the tie switches are equipped with protection relays that have synchronism check capability. Tie switches should be remotely controllable by the distribution system control centre.

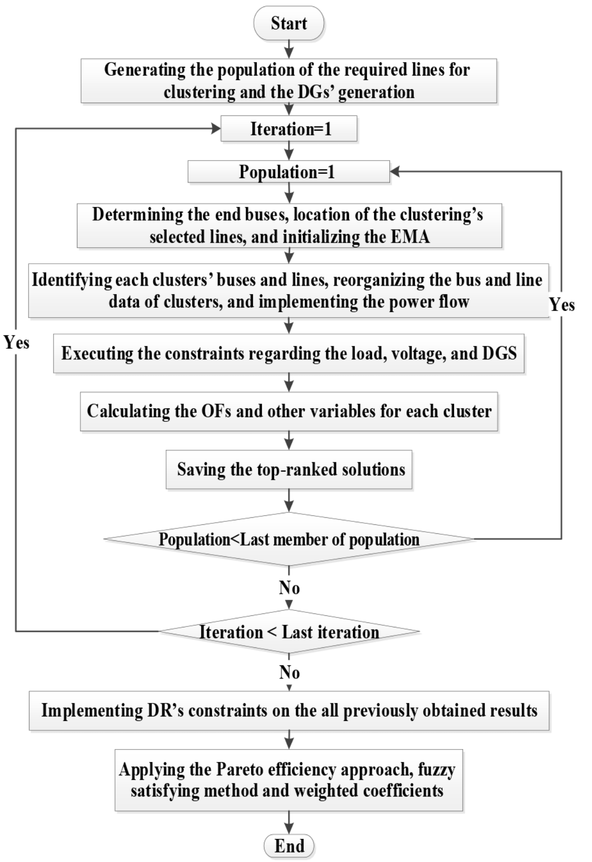

Fig. 2 *Flowchart of the proposed optimisation process*

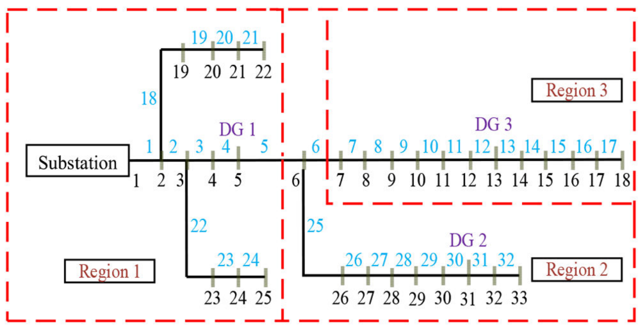

Fig. 3 *Initial regions of distribution system and location of DGs*

Table 1 Selected lines for clustering of 33-bus distribution system considering OF_t^1 with and without DR

Time, h	Selected lines			
	With DR		Without DR	
4	5	26	5	25
6	6	28	5	26
12	6	26	5	26
19	6	28	6	28
21	5	26	6	27
24	5	26	5	27

Remark 1: It should be noted that the proposed optimisation approach is computationally efficient and can be run in <30 s using a conventional computer. The fast nature of proposed approach is of paramount value to accommodate a fast restoration process after natural disasters.

Remark 2: This paper assumes constant energy price and incentive rate to analyse the effect of the proposed method regardless of the energy price and the incentive rate. Considering

4 Simulation results and discussion

In this section, the validity of the proposed clustering methodology is verified through a set of case studies. In the following, the test system data and parameters and assumptions used in the methodology are described. Then, the DR and dynamic clustering methodology are performed for two different objective functions.

4.1 Test system description and assumptions

The proposed methodology is implemented in the IEEE 33-bus test system (shown in Fig. 3) [34]. The test system loading condition is derived from [35]. Moreover, the utilised ZIP model's coefficients are extracted from [36]. The DR penalty is waived to encourage customers to participate in DR. The energy price and the incentive rate are assumed to be constant. The utilised self and cross-elasticities of the incentive-based DR in (19) are provided in [37]. Three DGs are considered as the local demand supplier of the distribution system. Besides, the maximum active and reactive power generation and the optimal location of the DGs are adopted from [38]. For clustering the 33-bus distribution system, three regions are considered based on the available generation and the average demanded load of the customers. Fig. 3 shows the considered regions for clustering and the DGs' location. In Fig. 3, the line numbers are highlighted in blue and bus numbers are in black. The optimisation model is implemented using MATLAB software.

4.2 DR and dynamic clustering

In this section, the results of the proposed model for simultaneous implementation of DR and dynamic clustering of distribution systems are presented for three different scenarios, which are elaborated as follows.

Scenario 1: The objective function in (28) that focuses on the combination of ENS and VNS is considered. To create three clusters within the islanded 33-bus distribution system, two lines must be selected. The selected lines for optimal clustering of the distribution system with and without DR for six different hours are shown in Table 1. In Table 1, because of the dynamic nature of the implemented model, each period has its own specific clusters.

The optimal generations of the DGs are listed in Table 2, showing that optimal schedule of these DGs helps them use their maximum capacity to satisfy the objective function in (28), which in turn results in the minimum ENS and VNS in the distribution system.

Scenario 2: The objective function in (29) that focuses on VDI minimisation is considered. By using the DR and minimising the VDI, new dynamic clusters of the distribution system are determined. Selected lines for clustering the distribution system are illustrated in Table 3. The results of the second objective function with and without DR are different from the first in terms of satisfying the objective functions' requirements.

In addition to finding the optimal lines for clustering the distribution system, the optimal outputs of the DGs that are used to improve the voltage level of the distribution system considering the

Table 2 Optimal output of 33-bus distribution system's DGs considering OF_t^1 with DR

Time, h	Active power, MW			Reactive power, MVAr		
	DG1	DG2	DG3	DG1	DG2	DG3
4	1.5	0.9998	0.7	0.6630	0.4724	0.3452
6	1.5	1	0.7	0.4833	0.4645	0.4505
12	1.5	0.9993	0.7	0.568	0.4976	0.4783
19	1.5	1	0.7	0.4935	0.3130	0.5447
21	1.5	1	0.7	0.689	0.3025	0.4713
24	1.5	1	0.7	0.3751	0.2773	0.3891

Table 3 Selected lines for clustering of 33-Bus distribution system considering OF_t^2 with and without DR

Time, h	Selected lines			
	With DR		Without DR	
4	5	30	10	30
6	5	30	5	30
12	5	30	5	30
19	5	30	11	30
21	5	30	5	30
24	10	30	5	30

Table 4 Optimal output of 33-bus distribution system's DGs considering OF_t^2 with DR

Time, h	Active power, MW			Reactive power, MVAr		
	DG1	DG2	DG3	DG1	DG2	DG3
4	0.05	0.05	0.0507	0.05	0.05	0.05
6	0.05	0.0994	0.05	0.05	0.05	0.05
12	0.05	0.05	0.0594	0.05	0.05	0.05
19	0.0573	0.0517	0.0813	0.05	0.05	0.05
21	0 0644	0.05	0.05	0.05	0.05	0.05
24	0.0674	0.05	0.0538	0.05	0.05	0.05

Table 5 Selected lines for clustering of 33-bus distribution system considering $\overline{COF_t}$ with and without DR

Time, h	Selected lines			
	With DR		Without DR	
4	8	27	7	27
6	11	28	8	28
12	12	29	9	29
19	10	28	8	27
21	7	27	8	28
24	8	27	7	26

Table 6 Optimal output of 33-bus distribution system's DGs considering $\overline{COF_t}$ with DR

Time, h	Active power, MW			Reactive power, MVAr		
	DG1	DG2	DG3	DG1	DG2	DG3
4	1.5	0.4466	0.7	0.506	0.3434	0.5802
6	0.613	0.7023	0.565	0.551	0.1706	0.715
12	0.6409	0.3216	0.644	0.7	0.05	0.6009
19	0.05	0.2868	0.7	0.681	0.081	0.8075
21	0.7326	0.7646	0.565	0.564	0.4544	0.6449
24	1.4358	0.6843	0.681	0.45	0.1359	0.6639

second objective function are shown in Table 4. The DGs' generations in the case of dynamic clustering of distribution systems without DR is provided in [38]. Compared to the results of [38], all of the DGs' generations are affected by the DR. As Table 4 shows, DGs only generate the least possible power to minimise the VDI regardless of the ENS and VNS of the customers which are not the second objective function's targets.

Scenario 3: Both objective functions in (28) and (29) are considered. Optimal lines for determining the dynamic clusters are selected by using the EMA, Pareto efficiency approach, and fuzzy satisfying method. The top-ranked solution is chosen as the optimal solution. Table 5 summarises the optimal dynamic clusters' structure of the proposed multi-objective problem with and without DR. These dynamic clusters are defined to provide the optimal operation of the distribution system from both the voltage and resilience points-of-view.

Table 6 shows the DGs' active and reactive powers when both objective functions are considered. The results in Table 6 show that the multi-objective clustering problem provides a trade-off between ENS/VNS and VDI as the targets. The DGs' active and reactive

Table 7 Values of OF_t^1 and OF_t^2 with and without DR

Time, h	OF_t^1		OF_t^2	
	DR	No DR	DR	No DR
4	0.2384	0.06703	0.000877	0.0009365
6	0.9897	0.26142	0.000331	0.0009420
12	0.8434	0.88451	0.000303	0.00022445
19	1.271	1.28438	0.000110	0.00012547
21	0.6312	1.14965	0.000648	0.00017608
24	0.3016	0.04045	0.000853	0.00110161

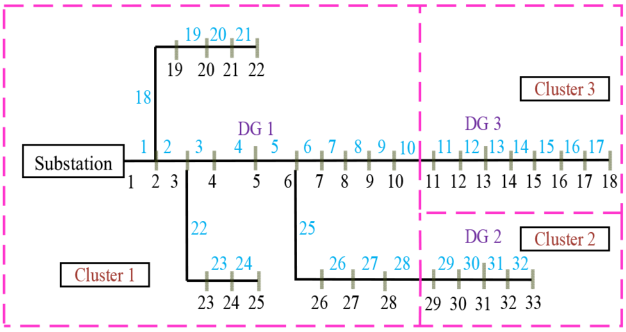

Fig. 4 *New dynamic clusters at hour 19*

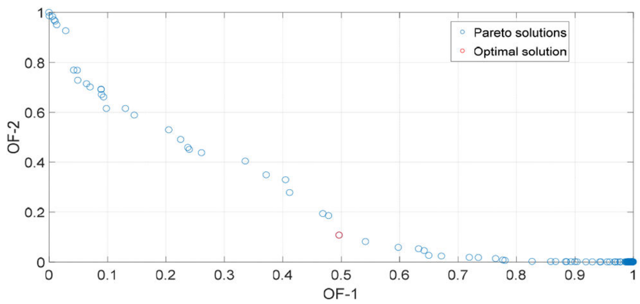

Fig. 5 *Sample of the optimal solution and Pareto front solutions*

Table 8 Not supplied demand of the distribution system before coupling of clusters

Time, h	ENS1, MWh	ENS2, MWh	ENS3, MWh	TENS, MWh
4	0	0	0.0098	0.0098
6	0.2246	0.1054	0.1555	0.4855
12	0	0	0.0189	0.0189
19	0.1590	0.0677	0.1183	0.3451
21	0.0659	0.0115	0.0683	0.1456
24	0.0638	0.0079	0.0695	0.1412

Table 9 Not supplied demand of the distribution system after coupling of clusters

Time, h	ENS, MWh		
	ENS1	ENS2	TENS
4	0	0	0
6	0.2246	0.261	0.4855
12	0	0	0
19	0.1590	0.1861	0.3451
21	0.0659	0.0798	0.1456
24	0.0638	0.0774	0.1412

power generations in Scenario 3 are lower than Scenario 1 when the ENS and VNS are the targets and higher than Scenario 2, which targets VDI.

The values of the first and second objective functions, OF_t^1 and OF_t^2, corresponding to Scenarios 1 and 2 with and without DR are provided in Table 7. As it can be seen, the objective functions' values are significantly improved compared to the without DR mode. In most of the hours, the ENS and VNS of the distribution system are decreased considering the performance of the DR. Also, the VDI of the distribution system is reduced as well. Meanwhile. the daily comparison is presented in the next section. Fig. 4 illustrates a sample structure of the dynamic clusters. Fig. 4 shows the clusters of the 19th period in which lines 10 and 28 are selected for clustering as demonstrated in Table 5. Each cluster has a DG for supplying its demand. Because most Cluster 1 customers have a lower demand than the other clusters, its size is relatively larger. Fig. 5 shows a sample of the Pareto solutions (blue dots) and the optimal solution selected by fuzzy satisfying method (red dot).

4.3 DR and recoupling of microgrid clusters

In a clustered distribution system, microgrid clusters may experience shortage of generation during some periods and require immediate support from their neighbouring microgrids. This section studies the effect of recoupling two clusters and implementing the DR when one of them is in urgent need of power and the other is capable of supporting its neighbour. The goal of cluster recoupling is to increase the reliability and resilience of the distribution system. This approach can decrease the overall ENS of the distribution system which in turn improves its overall reliability and resilience.

The ENS of the three clusters before the coupling are shown in Table 8. ENS1, ENS2, and ENS3 correspond to Cluster 1, Cluster 2, and Cluster 3, respectively. TENS denotes the total ENS of the distribution system. As seen in Table 8, the majority of the ENS is from Cluster 1 due to the structure of the distribution system and its demand. Since the implemented DR has utilised the DGs' capability to supply sufficient reactive power, the VNS for all clusters is equal to zero. ENS of Cluster 1 and the coupled clusters are shown in Table 9. Comparing Tables 8 and 9, one can observe that in some hours (e.g. fourth and twelfth hours) when the dynamic clusters are coupled, the TENS of the distribution system is decreased. Fig. 6 illustrates the distribution system with the coupled clusters at hour 12 with DR.

4.4 Numerical analysis of impact of DR on dynamic clustering in scenario 3

In Fig. 7, TENS of the clustered distribution system is expressed. In this figure, the influence of the DR on the clustered distribution system considering the variation of the TENS during a day is demonstrated. Fig. 7 shows that by implementing the DR, the concentration of TENS is shifted from the peak and middle periods of the day to the initial and final hours of the day. It is noticeable that during these periods, the demand for customers is less than the daily average demand of the customers.

The optimal total daily not supplied demands of the distribution system with DR and without DR are calculated and shown in Table 10. Total daily ENS (TDENS) and Total daily VNS (TDVNS) describe the aggregated amount of the total distribution system's minimum daily ENS and VNS, respectively. Table 10 indicates 29.1% reduction in the TDENS by applying the DR compared to the absence of the DR. Implementing the DR in clustering the distribution systems significantly improves their resilience level by supplying a more demanded load of the customers.

5 Conclusion and future work

In this paper, dynamic clustering of off-grid distribution systems along with DR is performed to improve the resilience and voltage profile in the distribution systems. In the proposed methodology, ENS, VNS, and VDI are considered as the objective functions; by using these objective functions, a comprehensive multi-objective problem is modelled and investigated. This multi-objective problem is solved by using the fuzzy satisfying method, Pareto efficiency approach, and EMA. This dynamic clustering transforms an off-grid distribution system to autonomous clusters where each cluster has the least dependency to the other clusters. Moreover, the execution of the DR improves the reliability and resilience of the

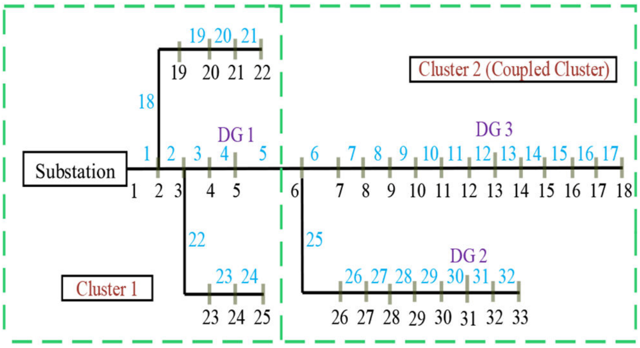

Fig. 6 *New dynamic coupled clusters at hour 12*

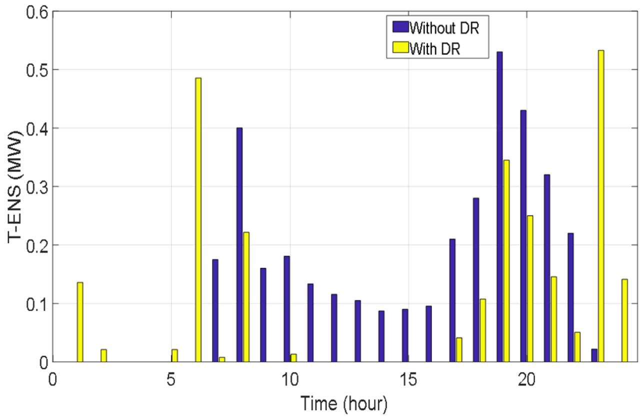

Fig. 7 *Not supplied demand of the clustered with and without DR*

Table 10 Total daily not supplied demand of the clusters

#	TDENS, MWh	TDVNS, MVArh
without DR	3.5557	0
with DR	2.5208	0

distribution system. This proposed method increases the resilience of the distribution system by providing power support among clusters. A total of 29.1% reduction in the TDENS is achieved by applying the DR compared to the absence of the DR. Additionally, the effect of clusters' coupling is also investigated. The obtained results verify the effectiveness of the proposed methodology and impacts of the DR on the reliability, resilience, and voltage of the dynamic clusters of the distribution system. As a potential future work, researchers can consider the financial risk-based scheduling of clustered microgrids in the presence of DR.

6 Acknowledgment

Tohid Khalili and Ali Bidram are supported by the National Science Foundation under the New Mexico SMART Grid Center-EPSCoR cooperative agreement Grant OIA-1757207. Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

7 References

[1] Southwell, P.: 'Disaster recovery within a CIGRE strategic framework: network resilience, trends and areas of future work', *SC C1 CIGRE Tech. Comm.*, 2014

[2] Electric Power Research Institute. Enhancing Distribution Resiliency: Opportunities for Applying Innovative Technologies. [Online]. Available at: http://www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000000001026889. 2013

[3] Li, Z., Shahidehpour, M., Aminifar, F., *et al.*: 'Networked microgrids for enhancing the power system resilience', *Proc. IEEE*, 2017, **105**, (7), pp. 1289–1310

[4] Executive Office of the President.: 'Council of economic advisers, economic benefits of increasing electric grid resilience to weather outages', 2013

[5] Che, L., Khodayar, M., Shahidehpour, M.: 'Only connect: microgrids for distribution system restoration', *IEEE Power Energy Mag.*., 2014, **12**, (1), pp. 70–81

[6] Heidari, A., Agelidis, V.G., Kia, M., *et al.*: 'Reliability optimization of automated distribution networks with probability customer interruption cost model in the presence of DG units', *IEEE Trans. Smart Grid*, 2017, **8**, (1), pp. 305–315

[7] Bidram, A., Davoudi, A., Lewis, F.L.: 'A multiobjective distributed control framework for islanded AC microgrids', *IEEE Trans. Ind. Inf.*, 2014, **10**, (3), pp. 1785–1798

[8] Atwa, Y.M., El-Saadany, E.F., Salama, M.M.A., *et al.*: 'Adequacy evaluation of distribution system including wind/solar DG during different modes of operation', *IEEE Trans. Power Syst.*, 2011, **26**, (4), pp. 1945–1952

[9] Khalili, T., Nojavan, S., Zare, K.: 'Optimal performance of microgrid in the presence of demand response exchange: a stochastic multi-objective model', *Comput. Electr. Eng.*, 2019, **74**, pp. 429–450

[10] Yazdanian, M., Mehrizi-Sani, A.: 'Distributed control techniques in microgrids', *IEEE Trans. Smart Grid*, 2014, **5**, (6), pp. 2901–2909

[11] Jadhav, A.M., Patne, N.R., Guerrero, J.M.: 'A novel approach to neighborhood fair energy trading in a distribution network of multiple microgrid clusters', *IEEE Trans. Ind. Electron.*, 2018, **66**, (2), pp. 1520–1531

[12] Lai, J., Lu, X., Yu, X., *et al.*: 'Cluster-oriented distributed cooperative control for multiple AC microgrids', *IEEE Trans. Ind. Inf.*, 2019, **15**, (11), pp. 5906–5918

[13] Malekpour, A.R., Pahwa, A.: 'Stochastic networked microgrid energy management with correlated wind generators', *IEEE Trans. Power Syst.*, 2017, **32**, (5), pp. 3681–3693

[14] Wang, Z., Chen, B., Wang, J.: 'Decentralized energy management system for networked microgrids in grid-connected and islanded modes', *IEEE Trans. Smart Grid*, 2015, **7**, (2), pp. 1097–1105

[15] Zamora, R., Srivastava, A.K.: 'Multi-layer architecture for voltage and frequency control in networked microgrids', *IEEE Trans. Smart Grid*, 2016, **9**, (3), pp. 2076–2085

[16] Wang, Z., Chen, B., Wang, J., *et al.*: 'Networked microgrids for self-healing power systems', *IEEE Trans. Smart Grid*, 2015, **7**, (1), pp. 310–319

[17] Wang, Z., Chen, B., Wang, J., *et al.*: 'Coordinated energy management of networked microgrids in distribution systems', *IEEE Trans. Smart Grid*, 2014, **6**, (1), pp. 45–53

[18] Esmaeilian, A., Kezunovic, M.: 'Prevention of power grid blackouts using intentional islanding scheme', *IEEE Trans. Ind. Appl.*, 2017, **53**, (1), pp. 622–629

[19] Hasanvand, S., Nayeripour, M., Arefifar, S.A., *et al.*: 'Spectral clustering for designing robust and reliable multi-MG smart distribution systems', *IET Gener. Transm. Distrib.*, 2018, **12**, (16), pp. 1359–1365

[20] Khederzadeh, M.: 'Multi-agent system design for automation of a cluster of microgrids', *CIRED-Open Access Proc. J.*, 2017, **2017**, (1), pp. 1304–1307

[21] Bahrami, S., Amini, M.H., Shafie-Khah, M., *et al.*: 'A decentralized renewable generation management and demand response in power distribution networks', *IEEE Trans. Sustain. Energy*, 2018, **9**, (4), pp. 1783–1797

[22] Bahrami, S., Wong, V.W.S., Huang, J.: 'Data center demand response in deregulated electricity markets', *IEEE Trans. Smart Grid*, 2019, **10**, (3), pp. 2820–2832

[23] Kopsidas, K., Abogaleela, M.: 'Utilizing demand response to improve network reliability and ageing resilience', *IEEE Trans. Power Syst.*, 2019, **34**, (3), pp. 2216–2227

[24] Eghbal, M., Saha, T.K., Mahmoudi-Kohan, N.: 'Utilizing demand response programs in day ahead generation scheduling for micro-grids with renewable sources'. 2011 IEEE PES Innovative Smart Grid Technologies, ISGT Asia 2011 Conf.: Smarter Grid for Sustainable and Affordable Energy Future, Perth, WA, Australia, 2012

[25] Kopsidas, K., Kapetanaki, A., Levi, V.: 'Optimal demand response scheduling with real-time thermal ratings of overhead lines for improved network reliability', *IEEE Trans. Smart Grid*, 2017, **8**, (6), pp. 2813–2825

[26] Dadkhah, A., Vahidi, B.: 'On the network economic, technical and reliability characteristics improvement through demand-response implementation considering consumers' behaviour', *IET Gener. Transm. Distrib.*, 2018, **12**, (2), pp. 431–440

[27] Aderibole, A., Zeineldin, H.H., Al Hosani, M., *et al.*: 'Demand Side management strategy for droop-based autonomous microgrids through voltage reduction', *IEEE Trans. Energy Convers.*, 2018, **34**, (2), pp. 878–888

[28] Haddadian, H., Noroozian, R.: 'Multi-microgrid-based operation of active distribution networks considering demand response programs', *IEEE Trans. Sustain. Energy*, 2018, **10**, (4), pp. 1804–1812

[29] Ghorbani, N., Babaei, E.: 'Exchange market algorithm', *Appl. Soft Comput. J.*, 2014, **19**, pp. 177–187

[30] Wang, C., Wang, Z., Wang, J., *et al.*: 'Robust time-varying parameter identification for composite load modeling', *IEEE Trans. Smart Grid*, 2017, **10**, (1), pp. 967–979

[31] Khalili, T., Jafari, A., Abapour, M., *et al.*: 'Optimal battery technology selection and incentive-based demand response program utilization for reliability improvement of an insular microgrid', *Energy*, 2019, **169**, pp. 92–104

[32] Jafari, A., Ganjeh Ganjehlou, H., Khalili, T., *et al.*: 'A two-loop hybrid method for optimal placement and scheduling of switched capacitors in distribution networks', *IEEE Access*, 2020, **8**, pp. 38892–38906

[33] Jafari, A., Khalili, T., Babaei, E., *et al.*: 'A hybrid optimization technique using exchange market and genetic algorithms', *IEEE Access*, 2020, **8**, pp. 2417–2427

[34] Parasher, R.: 'Load flow analysis of radial distribution network using linear data structure', arXiv Prepr. arXiv1403.4702. 2014

[35] Gharebaghi, S., Safdarian, A.: 'Voltage regulation in private environment: opportunity or threat', *IEEE Trans. Power Deliv.*, 2018, **33**, (6), pp. 3218–3219
[36] Diaz-Aguiló, M., Sandraz, J., Macwan, R., *et al.*: 'Field-validated load model for the analysis of CVR in distribution secondary networks: energy conservation', *IEEE Trans. Power Deliv.*, 2013, **28**, (4), pp. 2428–2436
[37] Aalami, H.A., Moghaddam, M.P., Yousefi, G.R.: 'Demand response modeling considering interruptible/curtailable loads and capacity market programs', *Appl. Energy*, 2010, **87**, (1), pp. 243–250
[38] Khalili, T., Hagh, M.T., Zadeh, S.G., *et al.*: 'Optimal reliable and resilient construction of dynamic self-adequate multi-microgrids under large-scale events', *IET Renew. Power Gener.*, 2019, **13**, (10), pp. 1750–1760