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Optimum electricity purchase scheduling for aggregator storage in a reliability framework for rural distribution networks

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ABSTRACT

The inclusion of Renewable Energy Resources (RER) and Electric Energy Storage (EES) can significantly improve the reliability of rural feeder customers with no cross connect switches to alternative supply. In such setups, there can be a financial incentive for aggregators to facilitate bulk storage to deal electricity with energy supplier and customers by using optimal scheduling strategy. Within this context, this paper proposes a framework for network reliability assessment to include bulk storage scheduling strategy in the evaluation. In this technique, seasonal effects on load demand and RER output, electricity market price, islanding provisions and EES state of charge (SOC) are taken into consideration. Finally, a case study is presented to illustrate the application of this approach and to evaluate the results.

1. Introduction

In rural networks with long feeders, cross connect switches to alternative supply feeders may not be economically viable, or even be practically possible. In such cases often poor reliability is reported, for instance; as noted in a utility Distribution Annual Planning Report (DAPR) [1]. Inclusion of EES facilities in these networks not only reduces energy and peak network costs for the customer, it can significantly improve customers' reliability by making some islanding operation possible. Generally, customers are reluctant to invest and manage such expensive devices, therefore aggregator owned bulk storage is recommended in literature [2–6]. But, in addition to EES, the inclusion of customers' RER in rural distribution networks can also complement financial benefits to both aggregators and customers. Nonetheless, such network arrangements can introduce complications in terms of reliability assessment. Commonly, reliability evaluation methods are categorized into two main techniques; simulation and analytical methods. Both techniques are based on failure mode and effect analysis (FMEA) for evaluating load points and system reliability indices [7]. With the integration of Photovoltaic (PV) resources and EES into the distribution system new evaluation approaches are required to assess the reliability, with different modes of operation. As part of maximizing the cost benefit operation of storage, an economic charge/discharge scheduling strategy is required for bulk storage devices to take advantage of market price changes. This scheme needs to be coupled with probabilistic network outage events for long term economic viability and network planning purposes.

The reliability assessment methods and various storage scheduling strategies cited in the literature are briefly discussed in the following. In [8] the reliability improvement of a distribution system which incorporates energy storage and renewable energy generation is investigated. A Model Predictive Control (MPC) based operation strategy for the energy storage considering wind turbine as the renewable energy source, and a framework for reliability assessment has also been proposed. In [3] an intelligent operation strategy for energy storage that can improve reliability and be integrated with renewable energy is presented. This approach uses smart grid communication and centralized network control to implement the proposed energy storage operation. A sequential Monte Carlo method has been used for reliability evaluation. This requires a long convergence time and uses a type of data which may not easily be available.

Researches on strategies to evaluate smart grid reliability have also been proposed in the literature. In [9] a scenario based technique has been proposed to assess distribution system reliability with renewable distributed generators. Related analytical methods are taken into account including islanding operation, load shedding and curtailment policies in this approach. The proposed procedures for reliability evaluation in the foregoing research work can notably be reduced by using a segmentation based strategy proposed in [10]. Normally, a long rural feeder with its radial branches can be formed into segments. A segment is part of distribution network that starts with a protective device such as an automatic

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Nomenclature

b	number of segments
c	case index
c_{ch}	price of extra PV energy to charge EES ($/kWh)
c_t	tariff price ($/kWh)
c_g	electricity locational marginal price ($/kWh)
CB	circuit breaker
d	number of load points in the network
d_{MPP}	DC power output drop above STC temperature (25°)
E_{ch1}	energy to charge EES from utility (kWh)
E_{ch2}	energy to charge EES from PV surplus generation (kWh)
E_{chmax}	maximum charging power limit (kW)
E_{dis}	energy discharged from EES (kWh)
E_{dismax}	maximum discharging power limit (kW)
E_g	total purchased energy from utility (kWh)
E_{pv}	total generated RER (PV) energy (kWh)
E_L	total load energy demand (kWh)
η_c	charging efficiency including inverter losses
η_d	discharging efficiency including inverter losses
η_{inv}	inverter efficiency
h	number of load points inside the segment
i	segment index where fault occurs
j	segment index where the load points locate
k	line index
LS	lower shoulder price ($)
$L_{soiling}$	soiling loss
LMP	locational marginal price ($)
LP	load point
$\lambda_k^{s,i}$	failure rate of kth line inside segment i
λ^s	segment failure rate matrix
$\lambda^{LP,s}$	load point failure rate affecting by fault in other segments
λ^{LP}	load point failure rate affecting by fault in the same segment
λ_k	failure rate of line k inside a segment
m	number of lines in network
$M1$	segments' interconnection relationship matrix
$M2$	segments and CBs' interconnection relationship matrix
MP	mean price ($)
N	number of time periods (e.g. 24 for one day)
n	number of lines inside the segment
nc	number of cases
$NOTC$	nominal operation cell temperature (manufacturer)
p	load point index
P_{ac}	AC power output
P_{dc}	DC power output
$P_{PVarray}$	nominal cell output power
ρ	probability of available cases
S	insolation in mW/cm^2
SOC	state of charge of EES at the end of period t
S^p	segment number that includes load point p
SSE	sum of squared errors
t	time period
T_{amb}	ambient temperature
T_{cell}	cell temperature
t_{sr}	alternative supply restoration time
t_{sw1}	island formation time for a fault outside the segment
t_{sw2}	fault isolation time for a fault inside the segment
t_r^k	repair time of line k
U^{LP}	load point outage time affecting by fault in the same segment
$U^{LP,s}$	load point outage time affecting by fault in other segments
U^s	segment outage time matrix
US	upper shoulder price ($)

switch/recloser, as the only protective switch in this segment [8]. In such modeling [11] if a failure occurs downstream of a switch in the segment, all the customers in that segment and the downstream segments will be disconnected from the grid supply [8]. In such events, even with possible islanding operation, some loads in the affected segments may still experience a limited outage immediately after a fault. The reliability evaluation method based on segmentation, proposed in [10], considers distributed generators, where the reliability has been evaluated considering load curtailment for some of the islanding situations.

With the emerging distribution networks and the corresponding solutions offered as discussed above, an opportunity is recognized for aggregators to invest and manage segment based bulk storage. This opportunity occurs as a result of hourly (as modeled in this paper) or half-hourly change in grid electricity market price, customers' load demand, and surplus PV generation. In this context, an aggregator can buy and store customers' surplus PV generation and/or grid electricity during daily low price periods and sell it in the peak load demand period. This dealing arrangement can benefit both customers and aggregator.

The research work in this paper proposes an optimum economic strategy for purchase of electric energy in a framework where an aggregator operates existing bulk storage in dealing with both retailer and customers. In this context, a systematic approach is developed to evaluate network reliability while considering the planned scheduled storage. The main contribution of this paper is establishing a systematic reliability evaluation method suitable for large and complex networks as in this method a large network is broken into a number of small networks for simplifying the reliability assessment. Moreover, scheduled EESs and hourly PV generation in normal and islanding situations are considered in the reliability assessment. This approach can also include power exchange between electrically linked island segments with different levels of PV and EES. In fact, this work provides a systematic link between long term assessment and short term operation in order to minimize energy cost and improve system reliability. This work also contributes aggregators and retailers to manage their storage to get financial benefit while improving the reliability of their customers.

The remaining sections of the paper are organized as follows. Section 2 provides problem formulation and methodology. Section 3 presents a case study following with the conclusions in Section 4.

2. Problem formulation and methodology

In a distribution network, aggregator is responsible to provide power to its customers. It also operates EESs in the distribution network. The aggregator aims to minimize the energy costs of the network by using flexible operation of EESs to store low cost energy and dispatch in peak load hours. The other objective of aggregator is to use EESs as an alternative supply in islanding operation mode to supply loads independently and improve the reliability of the system. In this section a scheduling strategy for the aggregator to minimize the energy costs using k-means clustering technique to minimize computation time is proposed. A reliability evaluation framework to consider storage state of charge is also developed in this section. The framework of the proposed reliability evaluation can be summarized as follows:

(1) Obtain the annual normalized value of hourly load and grid supply price data from historical data, and PV generated energy from weather forecast as is explained in Section 2.1.
(2) Form a data set matrix of the hourly load, PV generation, and grid supply price; arrange a matrix with 365 rows and 72 columns. 72 columns include 24 h' data of load, price, and PV generation. Hence, each row of the matrix includes one-day data of load, price, and PV generation.
(3) Apply elbow method to find the optimal number of clusters k1 for the data set formed in step 2. Then, apply k-means clustering technique to find k1 centroid cases with their associated probabilities. The reason for this clustering is to find similar days in a year to reduce scheduling computation time.
(4) Apply the scheduling strategy to all clustered days' data found in step 3, to obtain hourly SOC of EESs for the respective days.
(5) From a data set matrix of hourly load, PV generation, and the SOC of EESs that are obtained in step 4; form a matrix with k1 rows and 72 columns.
(6) Apply elbow method to find the optimal number of clusters k2 for the data set found in step 5. Then apply k-means clustering technique to find k2 centroid cases with the probability of each case (associated with hours in a year), forming the final clustered data. The reason for this clustering is to reduce the number of representing hours in a year, to decrease the computation time of reliability evaluation.
(7) Use the data calculated in step 6 to evaluate network reliability.

In all evaluations, the following assumptions are considered in this paper:

(1) The bulk energy storage exists and only its scheduling is considered.
(2) The distribution network is radial and there are no cross-connect switches in the network.
(3) A segment is a portion of distribution network that starts with a switching device. It includes customer loads that are near in one area; loads that are geographically close. The main supply lines feeding a segment have isolators to isolate a fault manually.
(4) All switching and protection devices are 100% reliable.
(5) Energy storage devices are 100% reliable.
(6) A fuse is installed at the beginning of each lateral feeder, where component failure in this section has no effect on other feeder loads.
(7) The auto protection switches operate instantaneously, so their operation time is neglected.
(8) The transient effects are not considered in this paper.
(9) Once a switching device operates, PVs inside the relevant segment are disconnected automatically and following the island formation, PVs are restored automatically after a defined time.
(10) It is assumed that EESs are selected such that maximum charging and discharging capability satisfy the line capacity limitations in the network.
(11) The aggregator is responsible for the investment and maintenance costs of the bulk EESs.
(12) The aggregator purchases electric energy from wholesaler/retailer to serve its customers.
(13) The aggregator can purchase customers excess PV generation with a certain price; $\boldsymbol{c}_{ch}$.
(14) The aggregator sells electricity to customers at the prevailing retail tariff price (tariff 12 Queensland) irrespective of whether that energy is sourced from the utility or EES discharge.
(15) The aggregator can sell electricity to the utility (wholesaler/retailer) at any time at the locational marginal price (LMP).
(16) The aggregator can charge or discharge EESs at any time, choosing any of the EESs for this purpose considering the technical constraints.
(17) The islanding operation is allowed and distributed PVs and storage's operation in islands is stable.

2.1. EES scheduling strategy

The purpose of utilizing scheduling strategy is to manage a segment's EES charge and discharge in order to minimize the total energy cost. This is evaluated while reserving a minimum level of EES state of charge to provide an alternative source of supply in the event of islanded operation mode in the network.

The total purchased energy by the aggregator at the end of each time period t can be calculated as follows [12]:

$$\boldsymbol{E}_g(t) = \boldsymbol{E}_L(t) - \boldsymbol{E}_{pv}(t) + \boldsymbol{E}_{ch1}(t) - \boldsymbol{E}_{dis}(t) \tag{1}$$

The energy delivered to the storage at each time interval t can be purchased from utility ($\boldsymbol{E}_{Ch1}$) or from PV surplus generation ($\boldsymbol{E}_{Ch2}$). The objective function for total cost optimization is:

$$M = \min(C) \tag{2}$$

where

$$C = \sum_{t=1}^{N} \hat{\boldsymbol{E}}_g(t) \times \hat{\boldsymbol{c}}_g(t) + \boldsymbol{E}_{ch2}(t) \times \boldsymbol{c}_{ch}(t) - \boldsymbol{E}_{dis}(t) \times \boldsymbol{c}_t(t) \tag{3}$$

$$\hat{\boldsymbol{E}}_g(t) = \hat{\boldsymbol{E}}_L(t) - \hat{\boldsymbol{E}}_{pv}(t) + \boldsymbol{E}_{ch1}(t) - \boldsymbol{E}_{dis}(t) \tag{4}$$

where the hat symbol (^) represents the forecast values and N is the number of time periods (e.g. 24 for one day).

By optimizing the total cost of energy for a period of 24 h in advance, the aggregator is able to decide on purchasing electricity based on charging EES during the lowest price and highest PV generation periods, and discharging EES during peak load and high price periods. The EES in this paper is modeled as its state of charge, charge, and discharge in each time period t. The SOC at the end of period t can be calculated as follows [13].

$$\boldsymbol{SOC}(t) = \begin{cases} \boldsymbol{SOC}(t-1) + \eta_c \times (\boldsymbol{E}_{ch1}(t) + \boldsymbol{E}_{ch2}(t)) & \text{charging period} \\ \boldsymbol{SOC}(t-1) - (1/\eta_d) \times \boldsymbol{E}_{dis}(t) & \text{discharging period} \end{cases} \tag{5}$$

All variables should be within their operating limits. Minimum state of charge should be considered to ensure a defined amount of electricity for peak load provision:

$$\boldsymbol{SOC}_{\min}(t) \leqslant \boldsymbol{SOC}(t) \leqslant \boldsymbol{SOC}_{\max}(t) \tag{6}$$

$$0 \leqslant \boldsymbol{E}_{ch1}(t) + \boldsymbol{E}_{ch2}(t) \leqslant \boldsymbol{E}_{chmax} \tag{7}$$

$$0 \leqslant \boldsymbol{E}_{dis}(t) \leqslant \boldsymbol{E}_{dismax} \tag{8}$$

The "fmincon" function with interior point solver in MATLAB is used for this optimization.

Methods have been developed for load, price, and PV generation forecasting [14–22]. These approaches can be used to obtain load demand and energy price for a variety of applications. As forecasting methods are not the focus of this paper, it is assumed that the forecast load and price data are given. The PV generation in this paper; P_{ac} is obtained from annual hourly weather forecasted data using the following equations [23]:

$$T_{cell} = T_{amb} + \left(\frac{NOCT - 20^{\circ}}{0.8}\right) \cdot S \tag{9}$$

$$P_{dc} = P_{PVarray} \times [1 - d_{MPP} \times (T_{cell} - 25^{\circ})] \tag{10}$$

$$P_{ac} = P_{dc} \times L_{soiling} \times \eta_{inv} \tag{11}$$

The basic procedure of the proposed method is that; a cost optimization problem determining the EES operation for the next 24 h (24 periods) is solved in advance. The estimated energy price is divided into four price bands between minimum to maximum for that day. The more number of price bands require substantially more computations, while four price bands using trial and error proved to be adequate in retaining good accuracy in results. Optimization is based on the electricity price, available PV generation and load consumption in the next period (hourly periods are considered). The scheduling strategy determines whether to charge or discharge the EESs and import or export power from the utility. The steps of the proposed strategy are as follows:

(a) Obtain the predicted load, price and available PV generation for the 24 h ahead.
(b) For each period, assess the load demand compared with available PV generation. Select one of the two different choices based on PV output; less than load or greater than load.
(c) Allocate the price of electricity from four available choices among the five following limits, based on forecasted electricity price:
  (a) Minimum price
  (b) Lower shoulder (LS)
  (c) Mean price (MP)
  (d) Upper shoulder (US)
  (e) Maximum price
(d) Classify daily loads in two parts; equal to or greater than 80% of the peak load, and the remaining. This is to consider maximum discharge from storage in peak load times.
(e) Assign the constraints for optimization according to the flowchart in Fig. 1 that includes upper and lower limits for EES charge and discharge based on load amount, electricity price, and PV generation. Margins for EES state of charge should be considered in all periods based on forecasted load.
(f) Solve the optimization problem for the next period considering previous SOC of the storage and future periods to obtain the energy charge (import) and discharge (export) in current period.
(g) Continue for the next period, starting from step b.

2.2. K-means data clustering

Clustering techniques can be used to generate substantially reduced multiple states from that of hourly historical data of load and renewable resources. In this paper, the k-means clustering technique is used to find non-overlapping clusters which represent a multiple states model for PV and load. The main advantage of this technique is that with a large number of variables, k-means may be computationally faster than hierarchical clustering. Moreover, k-means may produce tighter clusters than hierarchical clustering, especially if the clusters are globular. In addition, this technique is simple, easy to implement and easy to interpret the clustering results. In general, k-means is a prototype-based, simple partitioned clustering algorithm that attempts to find k non-overlapping clusters. These clusters are represented by their centroids (a cluster centroid is typically the mean of the points in that cluster) [24]. The steps of the k-means clustering technique used in this paper are as follows;

1. The data set to be clustered can be expressed as $\boldsymbol{D} = \{x_1, \ldots, x_n\}$. The Parameter x_i is a vector, consisting of data points for each period. In general, the probability of each cluster is ρ_x.
2. k initial centroids (m) [24] are selected, where k is specified by the user and indicates the desired number of clusters. Methods for obtaining optimal k are presented in literature [25–27]. In this paper the elbow method is used [25] to find optimal number of clusters. The idea of the elbow method is to run k-means clustering for a range of values of k and calculate the sum of squared errors (SSE) for each value of k. Then, plot a line chart of the SSE as a function of k. If the line chart looks like an arm, then the "elbow" on the arm is the value of k that is the optimum one. In fact, the smaller SSE is desired but the SSE decreases towards zero when k increases. The SSE is equal to zero when k is equal to the number of data points in the dataset. In this case, each data point is its own cluster and there is no error between it and the center of its cluster. So our goal is to choose a small value of k that still has a low SSE. The elbow point usually represents where the SSE starts to decrease by increasing k.
3. Compute the squared Euclidean distance that is $||\boldsymbol{x}–\mathrm{m}||^2$ for each data set. Every point in the data set is then assigned to the closest centroid, and each collection of points assigned to a centroid forms a cluster. The k-means can be expressed by an objective function that depends on the proximities of the data points to the cluster centroids in (12), as follows:

$$\min \sum_{k=1}^{K} \sum_{x \in C_k} \rho_x \times dist(x, m_k) \tag{12}$$

4. The centroid of each cluster is then updated based on the points assigned to that cluster. This process is repeated until no point changes clusters.

The aim of using k-means data clustering is to substantially reduce computations while retaining good accuracy by applying the clustering technique to the annual hourly data. In this paper, the first clustering is to find similar days in term of load, PV generation and grid supply price in a year, in order to apply a daily scheduling strategy. The second clustering is to find similar possible hourly data cases of the first similar daily clusters, to be used for the proposed reliability assessment scheme.

2.3. Analytical reliability evaluation

This section provides a suitable reliability assessment for the ESS scheduling method proposed in this paper, based on the segmentation structure given in [10]. This approach is based on contingency scenario enumeration, where seasonal load and PV generation clustered data, together with the storage state of charge is incorporated into the framework for network reliability evaluation.

Briefly; in this strategy, the three matrices of $\boldsymbol{U}^{LP,s}$, $\boldsymbol{U}^{s}$, and $\boldsymbol{U}^{LP}$ for outage times and three matrices $\lambda^{LP,s}$, λ^{s}, and λ^{LP} for failure rates are formed in two stages. The total load point outage time and failure rate are obtained from these matrices. The process of the proposed reliability approach includes two stages. The first stage is explained in steps 1 and 2. The second stage is presented in steps 3–5 as followings.

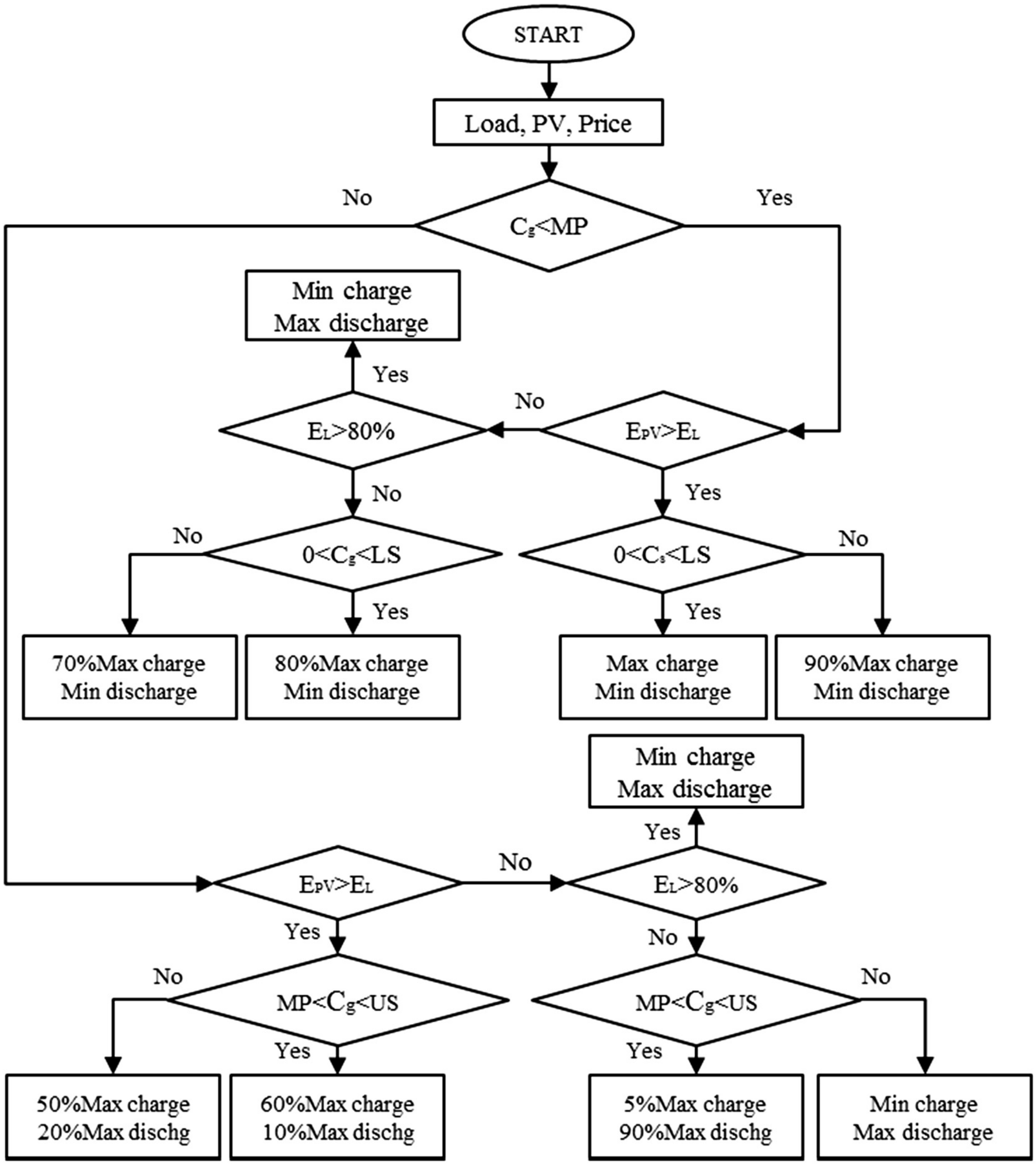

Fig. 1. Flowchart for optimization constraint determination.

Stage one:

- In the first stage of the process, in order to simplify the network, aggregate all loads and PVs in each segment separately, at the storage node in the same segment. This will form a simple network of lumped loads and sources as shown in Fig. 2a and b.
- Evaluate outage time, as shown in the flowchart of Fig. 3. For all possible contingencies in the newly formed network use the segment based evaluation method presented in [10]. In this step, two b by b matrices of outage time $\boldsymbol{U}^s$ and failure rate λ^s for affected segments, and two b by d matrices $\boldsymbol{U}^{LP,s}$ and $\lambda^{LP,s}$ for load points affected by internal segment faults are evaluated. This process is explained using an example as follows:

  2.1. Consider the network of Fig. 2a divided into 5 segments as shown. The Segment interconnection relationship matrix $\boldsymbol{M}_1$ can be defined for this network as in [10]. $\boldsymbol{M}_1$ (i, j) describes the interconnection relationships of segment i (S_i) and segment j (S_j) as follows:

$\boldsymbol{M}_1$ (i, j) = 0 if S_i and S_j are the same
$\boldsymbol{M}_1$ (i, j) = 1 if S_i is upstream of S_j
$\boldsymbol{M}_1$ (i, j) = 2 if S_i is downstream of S_j
$\boldsymbol{M}_1$ (i, j) = 3 for other cases

For the network of Fig. 2a, the ***M1*** matrix is:

$$\boldsymbol{M}_1 = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 \\ 2 & 0 & 1 & 3 & 1 \\ 2 & 2 & 0 & 3 & 3 \\ 2 & 3 & 3 & 0 & 3 \\ 2 & 2 & 3 & 3 & 0 \end{bmatrix}$$

2.2. $\boldsymbol{M}_2$ (i, j) describes the interconnection relationship between S_j and the CBi which is tripped by the fault in S_i [10]. In practice, the value of $\boldsymbol{M}_2$ (i, j) is equal to $\boldsymbol{M}_1(CB_i, j)$. For network of Fig. 2a:

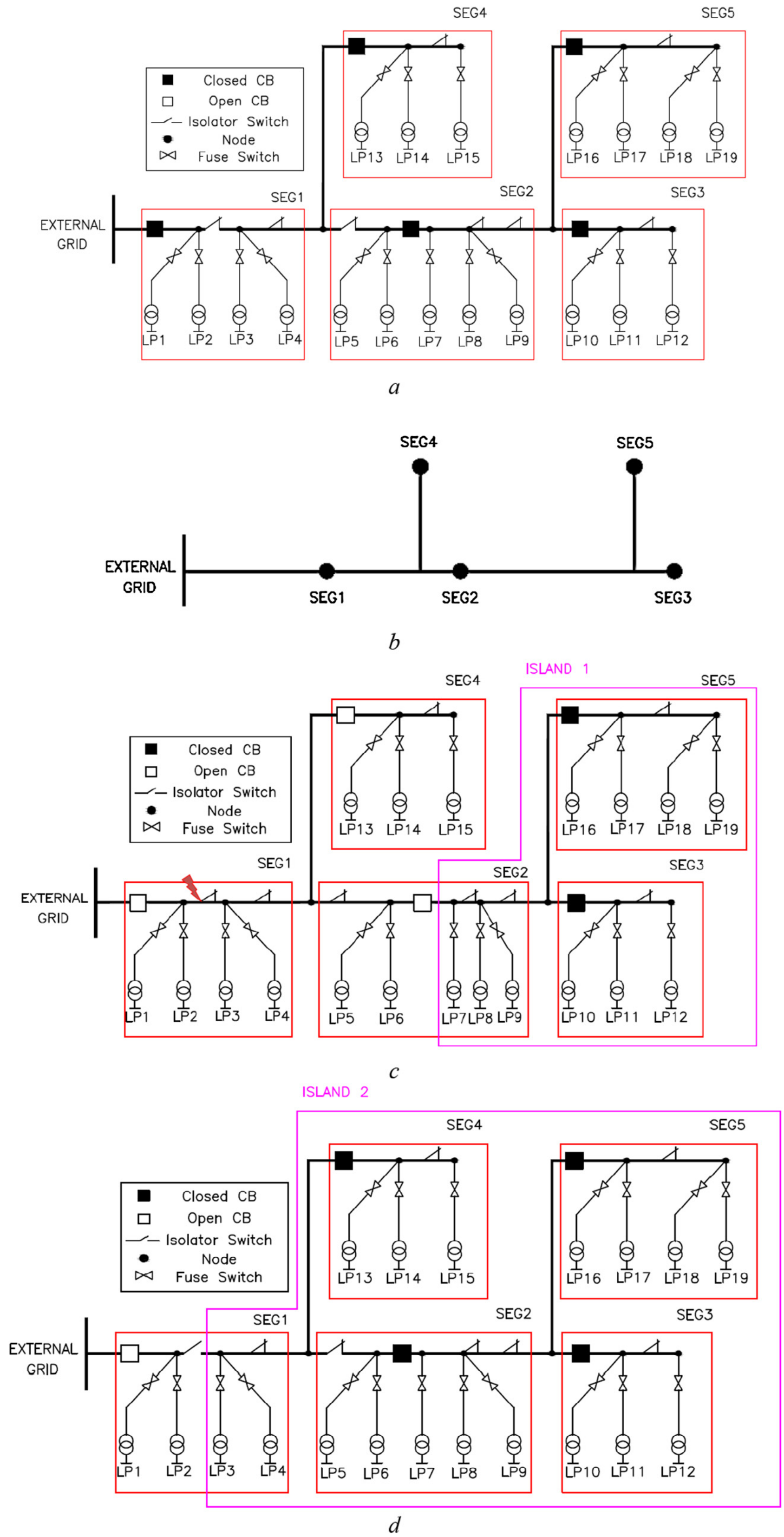

Fig. 2. Distribution network single line diagram. (a) Distribution network divided into segments. (b) Aggregated load and PV in each segment to simplify the network. (c) Island 1 formation immediately after fault occurrence in segment 1. (d) Island 2 formation after fault is isolated manually in segment 1.

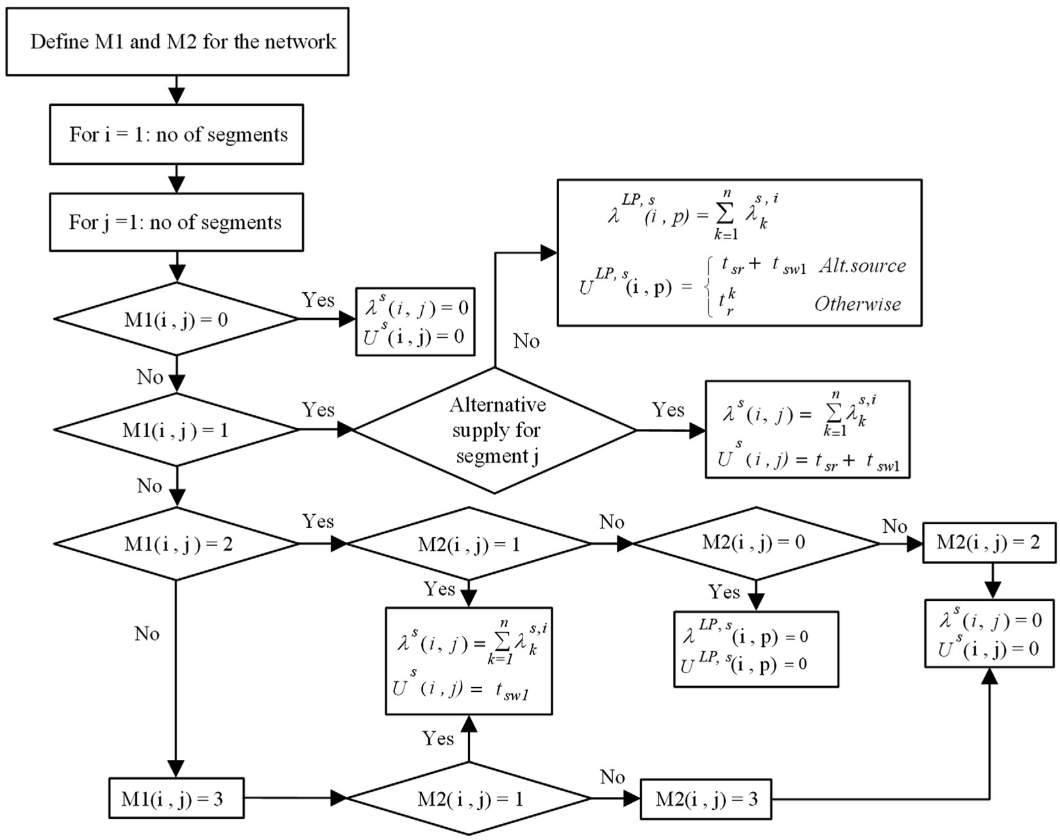

Fig. 3. Segment based failure modes and effects evaluation by looking at segments as single load points.

$$
\boldsymbol{M}_2 = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 \\ 2 & 0 & 1 & 3 & 1 \\ 2 & 0 & 1 & 3 & 1 \\ 2 & 3 & 3 & 0 & 3 \\ 2 & 2 & 3 & 3 & 0 \end{bmatrix}
$$

For different fault scenarios, considering that fault is inside *Si* and load point *p* is in *Sj*. The following cases can be expressed:

2.2.1. $\boldsymbol{M}_1(i,j) = 0$

In such case, fault *i* is inside segment *j*. So the fault impact on load points within this segment should be evaluated in the second stage of the process where each segment is treated as an independent network. In this first stage of assessment, the failure rate and outage time of segment *j* are considered equal to zero. The actual values are evaluated during the second stage of the assessment.

$$\boldsymbol{U}^s(i,j) = 0 \tag{13}$$

$$\boldsymbol{\lambda}^s(i,j) = 0 \tag{14}$$

2.2.2. $\boldsymbol{M}_1(i,j) = 1$

Segment *j* in this case is downstream of the faulted segment. Based on CB operation, $\boldsymbol{M}_2(i,j)$ can be 0 or 1 meaning that the operating CB is inside or upstream of segment *j*. In such situation:

$$\boldsymbol{\lambda}^s(i,j) = \sum_{k=1}^{n}\lambda_k^{s,i} \tag{15}$$

In the case of sufficient alternative supply for all load points inside segment *j*:

$$\boldsymbol{U}^s(i,j) = t_{sr} + t_{sw1} \tag{16}$$

Otherwise, the outage time $\boldsymbol{U}^{LP,s}$ and failure rate $\boldsymbol{\lambda}^{LP,s}$ matrices should be calculated for the load point *p* inside segment *j* affected by a fault in segment *i*, as follows:

$$\lambda^{LP,s}(i,p) = \sum_{k=1}^{n}\lambda_k^{s,i} \tag{17}$$

$$\boldsymbol{U}^{LP,s}(i,p) = \begin{cases} t_{sr} + t_{sw1} & \textit{alternative source} \\ t_r^k & \textit{otherwise} \end{cases} \tag{18}$$

This case can be explained using Fig. 2c and d, for example, when $i = 1$, $j = 2$; island 1 forms immediately after fault is detected and CBs in segment 1, 2, and 4 tripped. After the time t_{sw1} fault is isolated manually and island 2 forms. Then after the time t_{sr}, PVs and storage in island 2 will be restored and supply the loads inside the island. If there is sufficient alternative source for load points inside the island, the time to repair is not included in the outage time. In order to evaluate the sufficiency of alternative supply in the segment, the load points with the higher priority are supplied first based on the available SOC and PVs in the segment. Then the rest of the loads that remains unsupplied will shed.

2.2.3. $\boldsymbol{M}_1(i,j) = 2$

Segment *j* in this case is upstream of faulted segment. Based on CB operation, two subcases occur:

- $\boldsymbol{M}_2(i,j) = 1$, when the operated CB is upstream segment *j*:

$$\boldsymbol{\lambda}^s(i,j) = \sum_{k=1}^{n}\lambda_k^{s,i} \tag{19}$$

$$\boldsymbol{U}^s(i,j) = t_{sw1} \tag{20}$$

- $\boldsymbol{M_2}(i, j) = 0$, when the operated CB is inside segment j:

For loads inside segment j that are located upstream of operated CB:

$$\lambda^{LP,s}(i,p) = 0 \tag{21}$$

$$\boldsymbol{U}^{LP,s}(i,p) = 0 \tag{22}$$

For loads in segment j that are located downstream of operated CB:

$$\lambda^{LP,s}(i,p) = \sum_{k=1}^{n} \lambda_k^{s,i} \tag{23}$$

$$\boldsymbol{U}^{LP,s}(i,p) = t_{sw1} \tag{24}$$

- $\boldsymbol{M_2}(i, j) = 2$, when the operated CB is downstream segment j:

$$\lambda^{s}(i,j) = 0 \tag{25}$$

$$\boldsymbol{U}^{s}(i,j) = 0 \tag{26}$$

2.2.4. ***Or*** $\boldsymbol{M_1}(i, j) = 3$

In such case, segment j is neither upstream nor downstream of the faulted segment i. So two subcases are possible:

- $\boldsymbol{M2}(i, j) = 1$, when operated CB is upstream segment j:

$$\lambda^{s}(i,j) = \sum_{k=1}^{n} \lambda_k^{s,i} \tag{27}$$

$$\boldsymbol{U}^{s}(i,j) = t_{sw1} \tag{28}$$

- $\boldsymbol{M2}(i, j) = 3$, when operated CB is neither upstream nor downstream segment j:

$$\lambda^{s}(i,j) = 0 \tag{29}$$

$$\boldsymbol{U}^{s}(i,j) = 0 \tag{30}$$

After finalizing this step, the outage time and failure rate matrices for segments and load points affected by segment failures are obtained.

Stage two:

- Now (second stage) in this step, consider each segment as an independent network and form new small networks. Evaluate load points' outage time within new formed networks. So, two m by d matrices of load point failure rate λ^{LP} and load point outage time $\boldsymbol{U}^{LP}$ are obtained by arranging n by h matrices of $\boldsymbol{U}$ and λ for each segment diagonally in one matrix. The existing scenarios can be given in the following steps for fault on line k:

3.1. For LP^p connected to the grid:

$$\boldsymbol{\lambda}^{LP}(k,p) = \lambda_k \tag{31}$$

$$\boldsymbol{U}^{LP}(k,p) = t_{sw2} \tag{32}$$

3.2. For LP^p in islanded mode:

$$\boldsymbol{\lambda}^{LP}(k,p) = \lambda_k \tag{33}$$

$$\boldsymbol{U}^{LP}(k,p) = \begin{cases} t_{sr} + t_{sw1} + t_{sw2} & \textit{alternative source} \\ t_r^k & \textit{otherwise} \end{cases} \tag{34}$$

3.3. For LP^p on outage:

$$\boldsymbol{\lambda}^{LP}(k,p) = \lambda_k \tag{35}$$

$$\boldsymbol{U}^{LP}(k,p) = t_r^k \tag{36}$$

4. The overall outage time $\boldsymbol{U}^{LP}$ and failure rate λ^{LP} for load point p of the main network can be calculated as follows:

$$\lambda^{LP}(p) = \sum_{i=1}^{b} \boldsymbol{\lambda}^{LP,s}(i,p) + \sum_{k=1}^{m} \boldsymbol{\lambda}^{LP}(k,p) + \sum_{i=1}^{b} \boldsymbol{\lambda}^{s}(i,s^p) \tag{37}$$

$$\boldsymbol{U}^{LP}(p) = \sum_{i=1}^{b} \boldsymbol{\lambda}^{LP,s}(i,p) \times \boldsymbol{U}^{LP,s}(i,p) + \sum_{k=1}^{m} \boldsymbol{\lambda}^{LP}(k,p) \times \boldsymbol{U}^{LP}(k,p) + \sum_{i=1}^{b} \boldsymbol{\lambda}^{s}(i,s^p) \times \boldsymbol{U}^{s}(i,s^p) \tag{38}$$

5. The network reliability indices then can be calculated, using load points' unavailability and failure rates, considering probability of each case. For example, the *SAIDI* index for each cluster is determined by (39) and annual *SAIDI* can be obtained by considering the probability of each cluster in a year using (40):

$$\boldsymbol{SAIDI} = \frac{\text{sum of customer interruption duration}}{\text{total number of customer}} = \frac{\sum U_i N_i}{\sum N_i} \tag{39}$$

$$ANNUALSAIDI = \sum_{c=1}^{nc} \boldsymbol{SAIDI}(c) \times \boldsymbol{\rho}(c) \tag{40}$$

In the proposed reliability assessment strategy, all possible scenarios are taken into account.

3. Case study

The proposed method in this paper is applied to the modified feeder 4 at bus 6 of the RBTS network [28], as illustrated in Fig. 4.

The reliability data can be found in [28]. The PV's power output is calculated using actual annual sun radiation data collected on hourly basis from Australian Climate Data Bank (ACDB). The load data of the network is based on hourly load of South East Queensland distribution network, Australia. The price of electricity is obtained from real data in Australian Energy Market Operator (AEMO).

At the first step, k-means clustering technique is applied to the data in order to cluster 365 days (8760 h) into 40 representative days. The number 40 is obtained from elbow method which finds the optimum number of clusters. The reliability assessment technique given in this paper is applied to evaluate the described network for three different cases.

The defined cases are listed as follows:

Case I: There is no EES in the network. PVs are the only alternative supply in this case.

Case II: In this case aggregator adds EES to each segment; however, no scheduling strategy is applied. The no scheduling strategy means that; EES stores surplus PV energy and delivers during peak hours, without applying any optimization.

Case III: In this case EES scheduling optimization strategy is applied to the network.

EES scheduling strategy is then applied to each segment in the network using the load, electricity price, and PVs' output cluster days. This is followed by the second k-means clustering of load, PV, and SOC data for each segment. In order to maximize the correlation of the clusters, normalized values of PV generation, load and SOC of the EESs are used in the clustering. The second clustering procedure resulted in 10 representative hours that are used for reliability evaluation. The number of clusters 10 is obtained from elbow method. Fig. 5 shows the graph of SSE as a function of k for this case study to find the elbow point which represents the optimum number of clusters for our data set. As the figure shows, the optimum k in the elbow point is equal to 4. However, in order

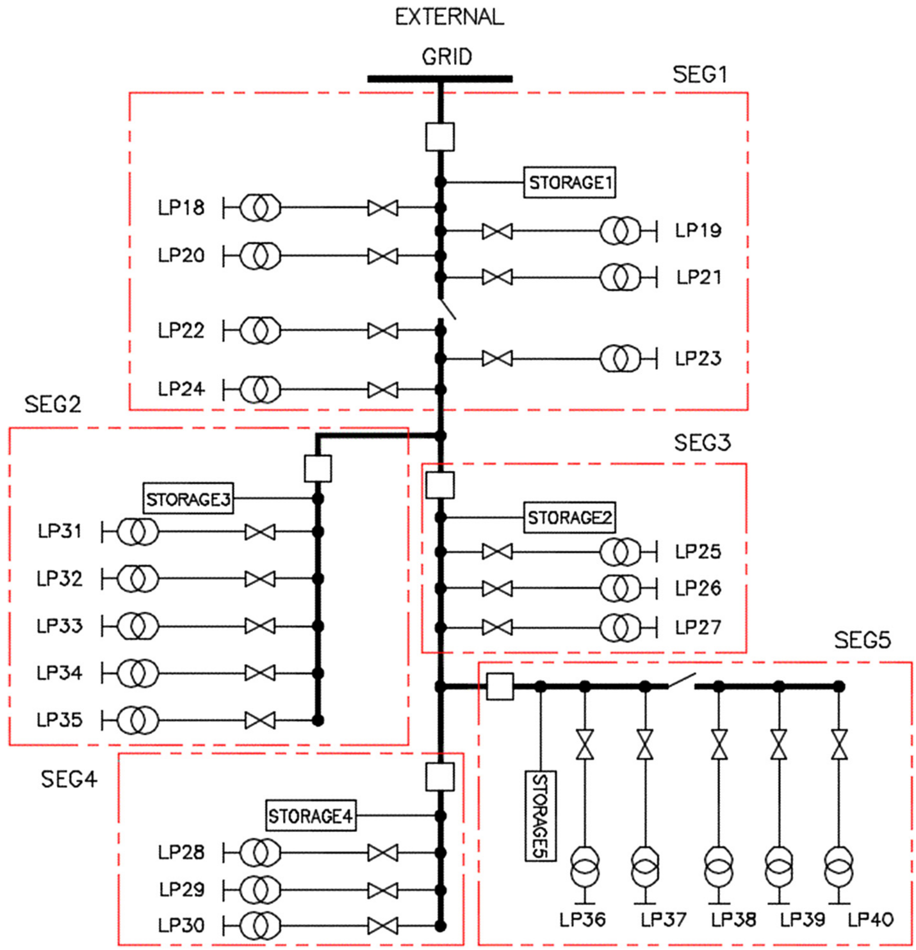

Fig. 4. Modified feeder 4 at bus 6 of the RBTS network [28].

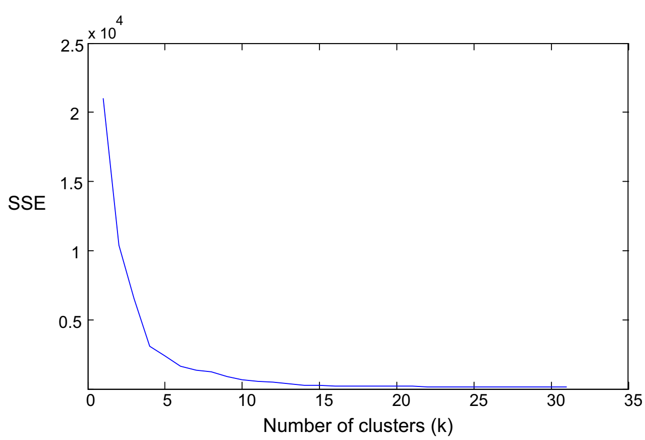

Fig. 5. Sum of squared errors (SSE) as a function of number of clusters in elbow method.

to consider a safety margin, k is considered equal to10 for our clustering calculation at this stage.

Fig. 6 provides stacked bar chart of 10 clusters for segment 1. The values of load and PV generation in kW and SOC in kWh with the corresponding cluster probabilities are given separately in Table 1. As the figure shows, the various possible mix of load, PV's power and SOC is obtained from the clustering which represent the data of a year considering the probability of each data mix happening in the year.

The data associated with storage devices are as shown in Table 2. The minimum and maximum energy storage level in this table represents SOC_{min} and SOC_{max} which is defined by the storage manufacturer. In this work, a minimum SOC of 500 kWh is considered as the provision of alternative supply in islanding situation. Maximum charge/discharge power limit in the table represents E_{chmax} and E_{dismax} defined by the storage manufacturer.

The EESs' capacity for the network of Fig. 2 is selected based on the excess PV generation capability of a day represented by a cluster belonging to days with highly excess PV generation in each segment. Also it is assumed that the charge/discharge power limits comply with the lines current capacity in each period.

After applying the proposed method of this work to the three case studies, the reliability indices and total cost of purchased energy for all cases are obtained as presented in Table 3. As the results show, installation of the EES offers a saving in the cost of purchased energy, in addition to a significant improvement in the reliability indices. By considering storage as an alternative supply in addition to PVs in the islands, an increase of about one hour in a year for SAIDI is achieved. In terms of CAIDI the improvement is about 1.5 h per year. The reason for the outage time reduction is that islanding operation is allowed in the third case considering storage SOC for supplying loads in island. ENS has also a significant improvement due to reducing the number of interrupted customers. The improvement of SAIFI is also significant in the third case due to lower number of customers affecting by the fault. The improvements in reliability indices from case one to case

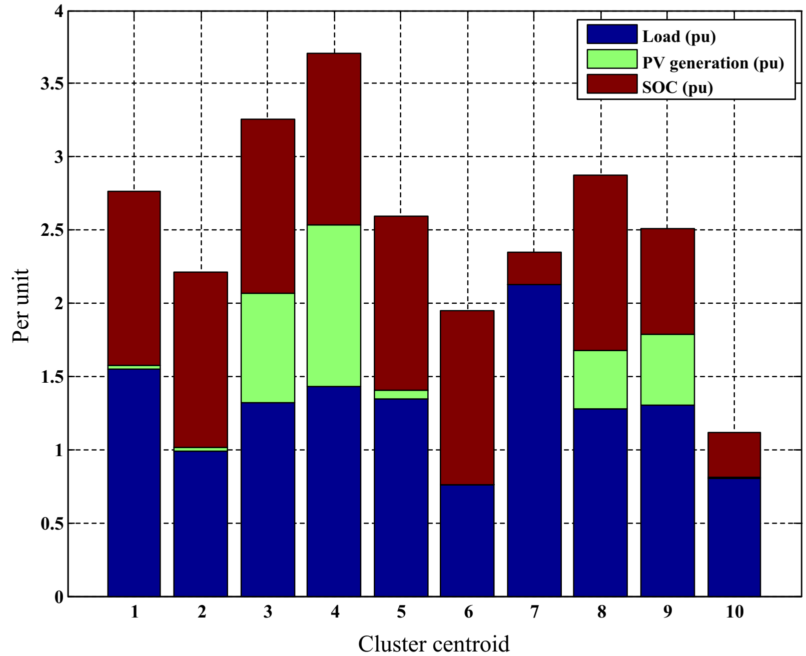

Fig. 6. Normalized values of Load, PV, and SOC for 10 clusters.

Table 1
The 10 cases of clustered Load, PV generation, and SOC for segment 1.

Case	Load (kWh)	PV (kWh)	SOC (kWh)	Probability
1	5859.87	77.25	4403.22	0.0738
2	5627.12	4394.97	4326.67	0.249
3	4711.97	1988.36	4436.62	0.0433
4	5317.08	1216.78	4361.58	0.1222
5	5471.83	2951.18	4328.34	0.1891
6	8495.84	0.00	824.31	0.1074
7	3442.06	57.46	4428.58	0.0878
8	2826.80	1.24	4397.26	0.1034
9	4340.00	73.22	4432.06	0.017
10	3385.05	126.22	1285.31	0.0071

two is not notable since in the second case there is no strategy for alternative supply provision in islands. Consequently, the probability of supplying loads by the storage in islands is very low. In terms of cost of purchased energy, the decrease in cost of energy can be counted as an economic justification for the aggregators/retailers for central storage installation in their network.

4. Conclusion

In this paper, a new strategy for aggregator owned bulk EES scheduling is proposed to optimize the cost of purchasing energy from retailer by the aggregator in rural distribution networks. In this set-up, a systematic approach is devised to evaluate reliability indices for rural distribution networks efficiently, including the impact of scheduling bulk EES in islanding situations. The seasonal effects on PV output, load demand, and consequently on scheduling process are also considered in the proposed framework. The results for different case studies in this paper show the effectiveness of this approach in reliability evaluation of complicated networks with PVs and EESs, while reducing the total aggregator purchasing energy costs. As for the future research recommendation; investment and maintenance costs of EESs for achieving

Table 2
EES technical data.

Segment number	1	2	3	4	5
Minimum energy storage level (kWh)	200	200	200	200	200
Maximum energy storage level (kWh)	5000	3000	4000	3000	4000
Maximum charging/discharging power limit (kW)	1000	1000	1000	1000	1000
Charging/discharging efficiency including inverter losses	0.75	0.75	0.75	0.75	0.75

Table 3
Reliability assessment results for the three cases.

Indices	SAIDI (h/cust-yr)	CAIDI (h/cust-int)	ENS (MWh/yr)	SAIFI (Interruptions/Customer)	Total cost of purchased energy ($/yr)
Case I	2.6314	2.7450	43.44	0.9586	28,895,001
Case II	2.5201	2.6289	41.01	0.9586	24,000,520
Case III	1.8532	1.9332	31.19	0.9586	16,124,010

specific reliability target for the network is suggested to be included as part of the optimum storage sizing and siting.

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