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Clustering-Based Penalty Signal Design for Flexibility Utilization

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ABSTRACT As the penetration level of renewable energy sources (RES) increases, the associated technical challenges in the power systems rise. Enhancing the utilization of energy flexibility is known to be the main key to overcome the load-supply balance challenge caused by RES. In this regard, the trend is toward the utilization of demand-side flexibility. Meanwhile, individual penalty signals positively affect the utilization of available flexibility from the demand-side. Previous studies in this field are based on designing penalty signals according to electricity price and regardless of the demand situation. However, designing and implementing a proper penalty signal with finite amplitude requires analyzing large datasets of load, storage and generation. Therefore, to fill this gap in designing a proper penalty signal we have proposed a novel approach in which, clustering is used to overcome the complexity of analyzing large datasets. The main goal of the proposed method is to utilize energy flexibility from responsive batteries according to a request from the aggregator without violating the consumers' privacy and comfort level. Therefore, aggregator's attainable load and generation datasets are used in the case studies to maintain the practicality of the proposed method. Simulation results show the proposed penalty signal designing method effectively increases the available flexibility of microgrids.

INDEX TERMS Demand-side flexibility, microgrid clusters, individual penalty signal, clustering.

NOMENCLATURE

α	Ratio of illumination intensity to the standard one
$\delta^i_{MG}(p(t))$	Response of the i^{th} pinning battery to the penalty signal (kA)
η_c	Battery's charge coefficient
η_d	Battery's discharge coefficient
$\hat{V}^c_{DC_k}$	Average voltage estimate in c^{th} microgrid for the kth agent (V)
Φ	Set of edges in the global layer
ρ_0	Normal operation current signal (kA)
ρ_c	The accumulated penalty-based current signal (kA)
a^c_{kj}	Element of the adjacency matrix
c_i	Cluster ith centroid
d_i	Positive coupling gain
$d_{i+j,k}$	Merging cost of combining the clusters i + j and k
d_{ik}, d_{jk}, d_{ij}	Pairwise distances between the clusters i/k, j/k, and i/j
FI	Flexibility index
$g(t)$	Power generation at time t (kW)
$i,\ j,\ ,k$	Index of cluster

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I_{MG}^{i}	Baseline current (kA)
k	Power temperature coefficient
$L(t)$	Load at the time (kW)
l_i	Margins of level i of SOC of the battery (%)
$Level_G(t)$	Defined generation level at time t
$Level_L(t)$	Defined load level at time t
$Level_{SOC}$	Defined SOC level at time t
M_{lin}	Margin of linear behavior of batteries (%)
$N^C \in R$	N^{th} agents in C^{th} microgrid
n_i	Number of members in cluster i
$num_{i,j,k}$	Number of members of clusters i, j and k respectively
$P(t)$	Generated penalty signal
$P_b(t)$	Power of the battery at time t (kW)
$P_{b,c}$	Charging power of a battery (kW)
$P_{b,d}$	Discharging power of a battery (kW)
$P_{PV}(t)$	PV generation power at time t (kW)
$S(t)$	Defined situation in the microgrid at time t
$SOC(t)$	State of charge of the battery (%)
SOC_{max}	Upper bound of SOC (%)
SOC_{min}	Lower bound of SOC (%)
T_c	Surface temperature of the PV cells (°C)
T_s	Temperature under the standard condition (°C)
x_i	Sample in cluster i
$y^i(p(t))$	Current of each cluster (responsive battery of each cluster) considering Penalty signal (kA)

I. INTRODUCTION

Flexibility is a recent concept in power systems, which has been officially recognized by organizations like IEA [1], NERC [2], and IRENA [3]. Flexibility can be defined as the power system's (PS's) ability to respond to both expected and unexpected changes in demand and supply [4]. However, there is no universal definition of flexibility. This concept can contribute to an increase in the stability of the grid and the integration of renewable energy sources (RES). Intuitively, the increasing share of RES in PS is escalating the need for flexibility [5]. Traditionally, balancing system responsible parties rely on the flexibility of bulk generation units to maintain the supply-demand balance of the grid. However, the trend in this area is toward planning, scheduling, and exploitation of flexibility mostly seen from the demand-side [6] and low voltage grid, while later research has investigated generation units and large-scale energy storage systems (ESS) [7].

Recently, residential-scale battery energy storage systems (BESS) have gained significant interest in both academia and industry under the new paradigm of renewable energy and demand response. This interest has been driven by the rapid increase in the integration of variable renewable generation to the grid, which eventually results in flexible resource requirements in power systems. Another contributing factor is the declining capital costs for ESS technologies, which made them an economical choice. With the increasing installed capacity of ESS, it becomes an urgent problem about how to best operate BESS to meet different stakeholders' needs [8].

Demand-side flexibility (DSF) is defined as the capability of consumption modification in response to control signals. Possible sources of those control signals are external market signals (or penalty signals [9]) to smart meters or internal control signals from the home energy management system (HEMS). Two trends continue to drive the growth of demand-side flexibility. First, there is growing customer interest in smart home appliances, residential-scale BESS, and electric vehicle charging, all of which can contribute significantly to energy flexibility. Second, regulation is evolving to enable flexibility beyond traditional demand response programs, and new policy and market frameworks are poised to emerge as grid-connected devices become widespread [7].

Designing proper penalty signals is a fundamental step in increasing the utilization of flexibility and it is one of the main challenges in this field. Time-varying price based penalty signals are normally utilized for increasing the flexibility of different sectors in recent studies [10]–[13]. In the majority of these studies, the main goal is reducing the cost and increasing the balance between load and generation. However, the main drawback of these studies is eliminating the the comfort of users, and the need for high capacity storage systems [14].

Forecasting the available flexibility, especially in the demand-side, depends on several parameters, including electricity generation and consumption forecast as well as grid constraints and market prices and the behavior of the occupants and their willingness to change their consumption pattern [16]. However, the presence of the uncertain factors influencing electricity generation and load, makes forecasting energy flexibility very hard to be mathematically formulated. Meanwhile, due to the huge volume of these datasets, conventional approaches like computing the average of the data are not efficient in analyzing this volume of data [10]. Therefore, machine learning (ML) approaches are considered as a powerful tool to deal with huge datasets. There are different ML methods such as classification, clustering, neural network (NN), and so on, which were used in this field [17], [18]. Since clustering extracts useful information and reduces the dimension, it is one of the common algorithms which is used in this field [19]. Furthermore, clustering reduces the complexity of analysis while ensuring the optimal results.

Microgrids can potentially be utilized in a low voltage grid to mitigate the ramping and variability of both load and generation [20]. Therefore, they are considered to be a promising solution to increase the integration of RES. There are three main types of microgrids, AC, DC, and Hybrid (AC/DC). Due to the increasing utilization of DC power sources, such as solar photovoltaic and DC loads like motor drive systems, and the fact that there is no need for multiple conversion stages of AC-DC and DC-AC, DC microgrids gain increasing attention in power systems. Furthermore, in contrast with AC microgrids, they do not have the challenges of synchronization, reactive power flow, and harmonics. In other

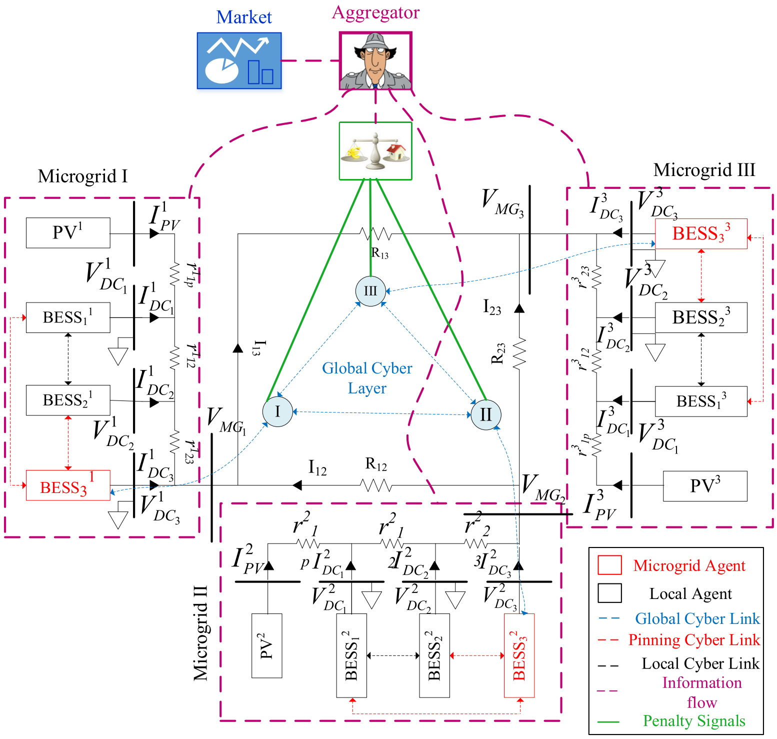

FIGURE 1. Single line diagram of the DC microgrid clusters in [15] with the proposed information flow to generate individual penalty signal.

words, in comparison with AC microgrids, DC microgrids have clear advantages of higher efficiency and reliability, better compatibility with DC sources and loads, and simpler control structure [21], [22]. Therefore, we have focused on DC microgrids in this paper. Despite extensive research, load forecasting and flexibility estimation remain to be a difficult problem. More than that, effective utilization of the forecasted flexibility and delivering it to the grid is also an unsolved problem. Although the existing research has successfully demonstrated the superior performance of deep learning on forecasting tasks, inherently, most of the studies are actually based on deterministic models, which lack the ability to capture uncertainty.

The main contribution of this paper is designing a novel individual penalty signal generator for utilization of the available flexibility from responsive batteries based on a request from the aggregator without violating the consumers' privacy and comfort level. To overcome the computational complexity and time, Linkage-Ward (LW) clustering algorithm, as the most suitable method for quantitative variables, has been used in the proposed method. In addition to filling a gap in designing the proper penalty signal for flexibility utilization in the microgrids, the proposed method offers the following advantages over conventional price-based approaches:

- Based on the authors' knowledge, this is the first paper that penalty-signal design considers all three main factors, i) load, ii) generation, iii) SOC level of batteries and the trade-off between them. Therefore, the proposed method is more practical and realistic.
- Since clustering is utilized for analyzing the huge volume of the datasets, the complexity and time of computation decrease. Moreover, it can be used for different datasets which makes the proposed method scalable.
- The proposed design method utilizes aggregator's attainable data and there is no need for the training dataset of each consumer. More than that, this approach protects the privacy and comfort of consumers.

The rest of the paper is organized as follows. Section II describes the cyber-physical dc microgrid cluster considered in this paper. Section III is about the proposed level extraction, including the proposed information flow to design an individual penalty signal. Section IV develops the proposed machine learning-based individual penalty signals generating method. Section V presents numerical simulations to show the merits and effectiveness of the proposed method. Section VI discusses the future works, and finally, Section VII concludes the paper.

II. CYBER-PHYSICAL DC MICROGRID CLUSTERS

Fig. 1 shows the DC microgrid clusters in [15] with the proposed information flow in this paper to generate individual penalty signals. Each microgrid includes a BESS, PV generation unit, and loads. Each BESS is connected to the DC bus through a DC/DC bidirectional converter with voltage regulation ability. In the cyber layer, each BESS is considered as an agent. A distributed fixed-time-based dual-layer secondary controller is designed in [15] to improve inter and intra-microgrid dynamic performance within a fixed

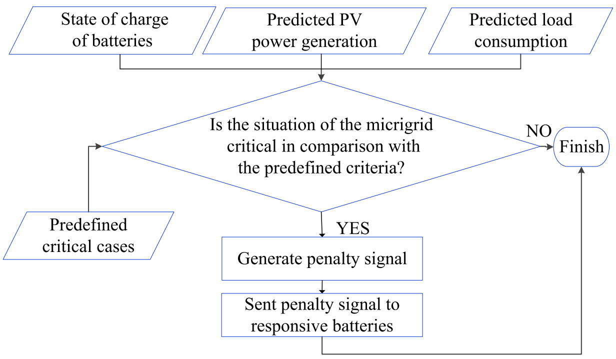

FIGURE 2. General underlying proposed penalty signal design for the microgrid.

settling time. The local layer in [15] is for voltage and current regulation and using the following equations:

$$\hat{\dot{V}}^c_{DC_k}(t) = \dot{V}^c_{DC_k}(t) + \sum_{j\in N^c_k} a^c_{kj}\dot{V}^c_{DC_j}(t) - \dot{V}^c_{DC_j}(t) \quad (1)$$

$$\dot{I}^c_{DC_k}(t)) = d_i \sum_{j\in N^c_k} a^c_{kj}\left(\frac{I^c_{DC_j}(t)}{I^{c,max}_{DC_j}} - \frac{I^c_{DC_k}(t)}{I^{c,max}_{DC_k}}\right) = 0 \quad (2)$$

$a_k j^c$ is the element of the adjacency matrix in microgrid c and defined as:

$$a_{kj} = \begin{cases} > 0, & \text{if } (x^k, x^j) \in \Phi \\ 0, & \text{otherwise} \end{cases}$$

The global layer is responsible for loss minimization and loads mismatch mitigation as:

$$\dot{I}^i_{MG}(t) = \sum_{m\in N^c} I^m_{MG}(T) - I^i_{MG}(T) = 0 \quad (3)$$

In designing individual penalty signals, the following assumptions have been made:

Assumption 1: The pinning batteries in the clusters are assumed penalty-responsive.

Assumption 2: Regarding [23], the output response of the batteries to the penalty signal is a first-order linear function.

Assumption 3: BESS are operating in local control level and cost-effectively mode.

III. PROPOSED PRE-PROCESSING PHASE

The presence of fluctuations and uncertainties in PV power generation and load consumption patterns, time-varying market price, and the varying stored energy in batteries caused complexity in defining an effective penalty signal. In other words, all these factors and the trade-off between them should be considered as constraints for generating a proper penalty signal. Therefore, in this research, we have proposed a novel approach to design a realistic, state-aware penalty signal for each specific state of the microgrid. The proposed method considers all the aforementioned factors, measures the operational criticalness of the microgrid, and generates the proper penalty signal accordingly. Fig. 2 illustrates the general flowchart of the proposed method.

However, considering all factors as continuous parameters increases the computational complexity. To reduce the computational complexity and increase the calculation speed, we have proposed a new data-driven algorithm which defines different levels for each factor by analyzing the measured dataset and quantize them. Due to the high volume of these datasets, clustering, as a recent method of reducing the volume of data, is utilized in this paper. Clustering is applied to the data of each hour separately and representatives of clusters are extracted [24]. The discrete levels are defined based on the representatives of clusters. The proposed level-extraction approach can be categorized into three main phases:

A. QUANTIFYING SOC LEVELS

It is an undeniable fact that the high-energy storage capacity of batteries plays an important role in increasing the flexibility of microgrid [25], [26]. This stored energy in batteries is indicated with the state of charge (SOC) which is computed as [10]:

$$SOC(t+1) = SOC(t) + \eta_c P_{b,c}(t) - \eta_d P_{b,d}(t) \quad (4)$$

$$SOC^{min} < SOC(t) < SOC^{max} \quad (5)$$

It should be noted that, if the SOC of a battery gets out of its limits, the behavior of the battery would be non-linear. Therefore, it is important to consider this as a constraint in the proper management of the microgrid. In this work, to consider this constraint in generating penalty signal, 4 different levels of SOC based on the margin of the linear behavior of the battery (M_{lin}) are defined. The margin of these levels are computed based on (7).

$$M_{lin} = (SOC^{max} - SOC^{min})/4 \quad (6)$$

$$l_i = [(SOC^{min} + (i-1)M_{lin}), (SOC^{min} + iM_{lin})]$$

$$i = 1, 2, 3, 4 \quad (7)$$

To quantify these levels a new parameter ($Level_{SOC}$) is defined as (8) and entitled as "Very low", "Low" and "Normal" and "High". As shown in Fig. 3, the lowest $Level_{SoC}$ shows that the SOC of the battery is in a critical situation and the highest one shows that the battery is fully charged, and by implementing a penalty signal the stored energy can be used in the microgrid.

$$Level_{SOC}(t) = \begin{cases} 1, & \text{if } SOC(t) \in l_1, \; \textit{Very low} \\ 2, & \text{if } SOC(t) \in l_2, \; \textit{Low} \\ 3, & \text{if } SOC(t) \in l_3, \; \textit{Normal} \\ 4, & \text{if } SOC(t) \in l_4, \; \textit{High} \end{cases} \quad (8)$$

B. QUANTIFYING GENERATION AND CONSUMPTION LEVELS

To decrease the computation complexity and volume of data, clustering is utilized to segment the load and generation datasets. Generally speaking, clustering methods aim to group given data points into the optimal number of classes

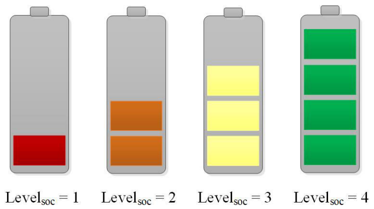

FIGURE 3. Graphical representation of the SOC levels.

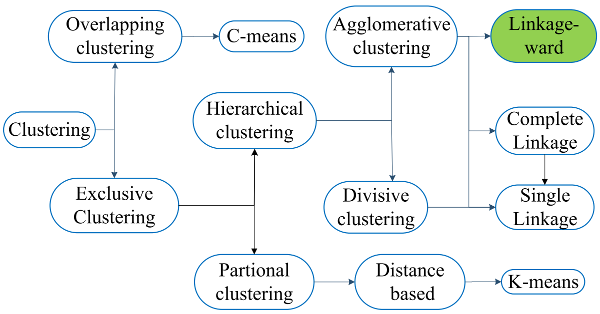

FIGURE 4. Different algorithms of clustering.

based on their similarity and define a centroid for each cluster [24]. These centroids are representatives of the whole data and researchers can analyze these to extract information about the whole dataset. Analyzing representatives not only decreases the complexity of calculation but also reduces the computation time.

As shown in Fig. 4, clustering algorithms can be categorized into two main classes, exclusive ones, where a data point just belongs to one cluster, and overlapping ones, that a data point belongs to different clusters. The main algorithms of exclusive clustering are partitional and hierarchical clustering [24]. K-means is a famous method of partitional clustering and defines the similarity of data points based on the distance of data points. This method is sensitive to initial values. Therefore, its main drawback is different results in each iteration. Hierarchical methods are more common in analyzing the huge volume of datasets. Hierarchical methods are divided into two main groups, i) divisive algorithms (top-down) and ii) agglomerative algorithms (bottom-up). In divisive algorithms, at first all data points belong to a single cluster, then based on the diversity this cluster is divided into different numbers of clusters. Agglomerative algorithms treat each data point as a single cluster and then these clusters merge based on their similarity until all data points belong to one cluster [24]. In this paper, the Linkage-Ward (LW) clustering algorithm, the most suitable method for quantitative variables, has been used for segmenting given data into the predefined number of clusters. The merging policy analyzes the dissimilarity between the existing clusters and chooses the two clusters to be merged by guaranteeing the minimum increase in the merging cost function in each iteration. The merging cost is the dissimilarity and defined as [10]:

$$d_{i+j,k} = ad_{ik} + ad_{jk} + bd_{ij} + c|d_{ik} - d_{jk}| \tag{9}$$

where

$$\begin{aligned} a &= \frac{num_i + num_j}{num_i + num_j + num_k}, \\ b &= -\frac{num_k}{num_i + num_j + num_k}, \\ c &= 0 \end{aligned}$$

c_i is the mean of the members of each cluster and chosen as the centroid of the cluster:

$$c_i = \frac{1}{n_i} \sum_{i=1}^{n_i} x_i \tag{10}$$

One of the main challenges of clustering methods in determining the optimal number of clusters. In this research, an elbow method is used for extracting this number. The main idea of the elbow method is computing the dissimilarity between the members of each cluster and its centroid for the different number of clusters based on (11). The number in which adding another cluster does not minimize this error as much, considered as the optimal number of clusters [10].

$$e_c = \sum_{i=1}^{k} \sum_{j=1}^{N_i} (x_j - c_i)^2 \tag{11}$$

In the following, the LW algorithm is used to cluster the load and generation datasets.

1) PV LEVEL EXTRACTION

Since, the generated power of PV units, P_pv, is affected by the temperature as formulated in (12), it is not constant during the day. Therefore, it is important to analyze the data at each hour of the day and find the upper and lower levels of generation at each hour [10].

$$P_{PV}(t) = \alpha[1 + k(T_c - T_S)] \tag{12}$$

Due to the high volume of the measured generation dataset, clustering is used for segmenting these data points and defining a few representatives for it. Considering the optimal number of clusters (k_g) based on (11), LW is applied to the data of PV generation power at each hour of the day. The centroid of each cluster is computed based on (10). Then, centroids are sorted from the highest to the lowest one, and labels of centroids are assigned as:

$$Centroids\ \ set = \{c_1, \ldots, c_{k_g}\}, c_i > c_{i+1} \tag{13}$$

$$Level_{G(t)} = \begin{cases} 1, & \text{if } g(t) \in c_1 \\ 2, & \text{if } g(t) \in c_2 \\ \vdots & \\ k_g, & \text{if } g(t) \in c_{k_g} \end{cases} \tag{14}$$

2) LOAD LEVEL EXTRACTION

Applying a penalty signal at each hour to the microgrids may jeopardize the comfort level of customers. To maintain the comfort of the customers, the level of consumption power at each hour must be taken into consideration while generating a penalty signal. To do this, the measured load dataset is considered. To overcome the complexity of computation, after applying LW on data for reducing the volume, considering the optimal number of clusters extracted from (11), the centroid of clusters are computed based on (10) and sorted from the highest to the lowest one (15). To show the importance of applying the penalty signal a new parameter, entitled as $Level_L$, is defined as (16) based on the sorted centroids.

$$Centroids\ \ set = \{c_1, \ldots, c_{K_L}\}, c_i > c_{i+1} \tag{15}$$

$$Level_{L(t)} = \begin{cases} 1, & \text{if } g(t) \in c_1 \\ 2, & \text{if } g(t) \in c_2 \\ \vdots & \\ k_g, & \text{if } g(t) \in c_{k_g} \end{cases} \tag{16}$$

C. OPERATIONAL STATE EVALUATION

To evaluate the criticalness the microgrid'operational state, a new decision-making parameter, called S(t), is defined as explained in (17). This parameter evaluates the microgrid's condition by considering the trade-off between the load, generation, and SOC level of batteries, and decides if the penalty signal should be generated or not. In other words, this parameter measures the properness of the operational state in the microgrid to generate the penalty signal.

$$S(t) = \begin{cases} 1, & \text{if } \dfrac{Level_{SOC}(t)}{Level_G(t)} \geq 1.2 \ \& \ Level_{SOC}(t) > 1 \\ 0, & \text{if } g(t) \in C_{k_g} \end{cases} \tag{17}$$

As it is shown in (17), two main constraints should be satisfied for generating the penalty signal. The first one is the ratio of SOC level to the generation level and the second one is about the SOC level of the batteries. If this ratio is very high (more than 1.2) and the SOC is not at its lowest level, the penalty signal will be generated and the load should be feed by the stored energy in the batteries.

IV. PROPOSED PENALTY SIGNAL DESIGN METHOD

Suppose that the microgrid is in a critical operational state and a penalty signal should be generated. The amplitude of this signal must be defined considering the SOC level of batteries, the load level, the predicted power generation. Considering all the above-mentioned factors, the proposed penalty signal is formulated as:

$$P(t) = S(t)\frac{Level_{SOC}(t) + Level_L(t)}{Level_{SOC}(t) + Level_L(t)} \tag{18}$$

Fig. 5 summarizes the proposed individual machine learning-based penalty signal design method. This control signal is generated in the cyber-security layer of the microgrid. It is implemented to responsive batteries and their response is added to the IMG in the global layer of the microgrid and increases that. The effect of implementing penalty signals to the responsive batteries is added to the current of each

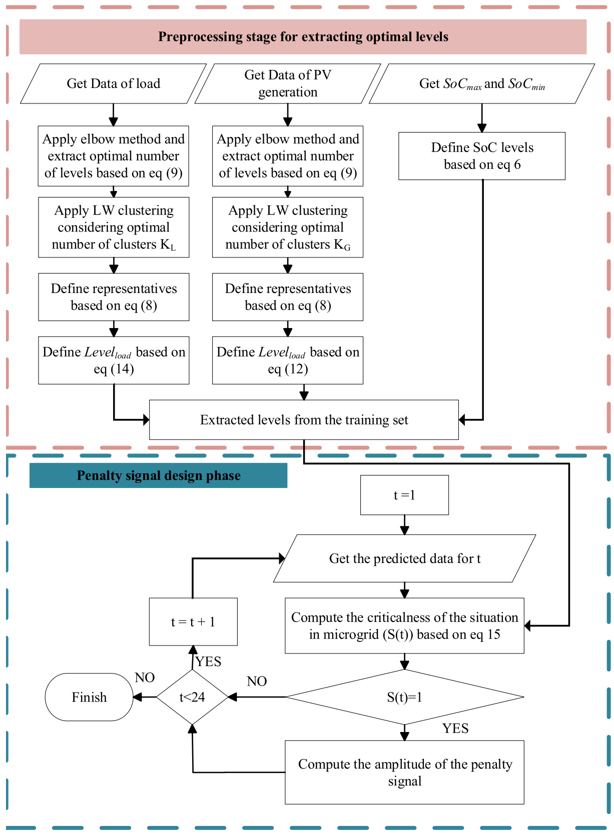

FIGURE 5. Flowchart of the proposed clustering-based penalty signal design method.

microgrid in the global layer as [23],

$$y^i(P(t)) = I^i_{MG}(t) + \delta^i_{MG}(P(t)) \tag{19}$$

Index of flexibility [23] has been used to quantify the utilized flexibility:

$$FI_i = 1 - \frac{\rho_c}{\rho_0} \tag{20}$$

where ρ_0 is the accumulated penalty and ρ_0 is the normal operation and are calculated as [23]:

$$\rho_c = \sum_{t=0}^{T} P(t) y^i(P(t)) \tag{21}$$

$$\rho_0 = \sum_{t=0}^{T} I_{MG_i}(t) \tag{22}$$

Furthermore, as shown in (23), (24), the SOC of a battery has a direct relation with the I_{dc} of it. Therefore, by decreasing the I_{dc} of battery, the SOC of the battery decreases. As it is mentioned in [25], I_{dc} of a battery has an inverse relation with the IMG in the global layer. Therefore, by implementing a penalty signal, I_{MG} increases, and consequently, I_{dc} and SOC of the battery decreases.

$$SOC(t) \propto P_b(t) \tag{23}$$

$$P_b(t) = V_{dc}(t) I_{dc}(t) \tag{24}$$

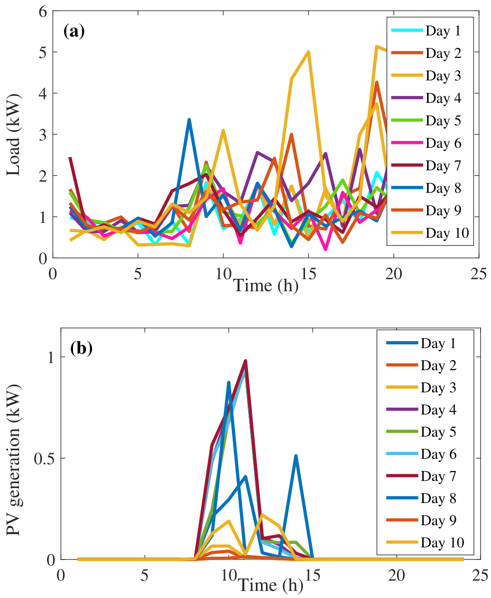

FIGURE 6. a: Load and b: PV generation patterns of 10 typical days.

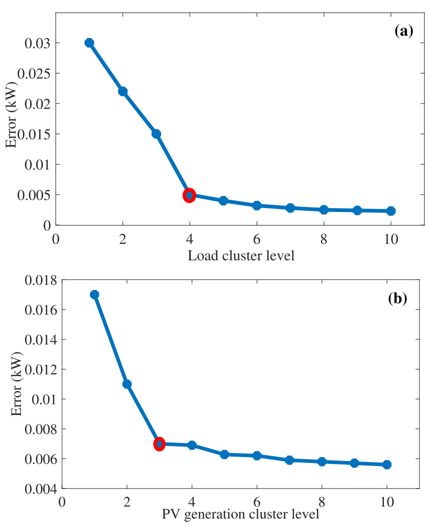

FIGURE 7. Optimal cluster level for: a. load, b. PV.

V. SIMULATION RESULTS

To evaluate the performance of the proposed method, one year datasets of PV generation, and load consumption [25] are used. Fig. 6 shows the daily profiles of 10 randomly chosen days of these datasets. To extract the optimal level of load and PV generation for clustering, the elbow method is applied to these datasets. As shown in Fig. 7, the optimal cluster level is 4 and 3 for load and PV generation, respectively. Considering these optimal cluster levels, the LW is applied to these datasets, and centroids of each cluster are computed. Accordingly, $Level_L$ and $Level_g$ are assigned to each centroid. Fig. 8 illustrates the centroids of load/power generation and their labels, respectively. Extracting 4 and 3 different levels for load and PV generation based on the proposed clustering algorithm and defining 4 different levels for SOC of batteries, 48 different states may occur at each hour of the day.

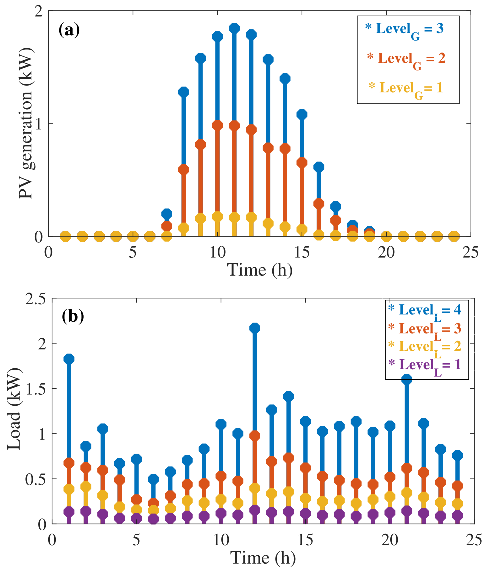

FIGURE 8. The centroid of a: generation and b: load patterns at each hour and their levels' label.

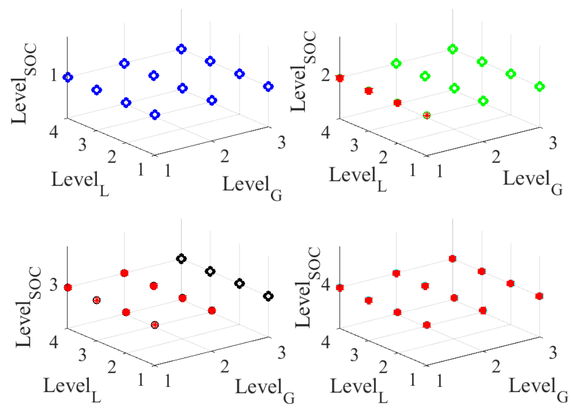

FIGURE 9. The state of microgrid considering different levels of load, generation, and SOC of batteries (red circles display critical situation in a microgrid in which a penalty signal should be generated).

All these probable states are shown in Fig. 9. Among all these conditions for microgrid, comparing to the pre-defined threshold, in 24 cases the penalty signal should be generated, which are shown with red dots in Fig. 9. As shown, we have the most critical states when the SOC of battery is minimum ($\alpha = 1$) and so is the PV generation. Because in this situation, if the battery is used for feeding the load, the SOC of the battery will get out of the safe band and will show nonlinear behavior. Therefore, in this case, the microgrid should feed the load from the main grid. Table 1, shows ten randomly chosen scenarios of states in the microgrid and the amount of designed penalty signal. The effect of the penalty signal on the SOC of the battery in two typical days is shown in Fig. 10. As it is shown in these case studies when the microgrid is in a critical state, the penalty signal is implemented to the battery and the stored energy of the battery feeds the load, and SOC decreases. Table 2, shows the calculated flexibility index for each microgrid after applying the penalty signal

TABLE 1. Operational state criticalness of microgrid for generating penalty signal in 10 random scenarios.

Scenario	$Level_L$	$Level_G$	$Level_{SOC}$	S	P(t)
1	1	2	1	0	0
2	3	1	3	1	0.66
3	1	3	1	0	0
4	4	1	5	1	1
5	4	2	5	0	1
6	4	3	1	0	0
7	1	3	2	0	0
8	2	1	3	0	0.55
9	3	1	2	1	0.55
10	4	3	4	0	0

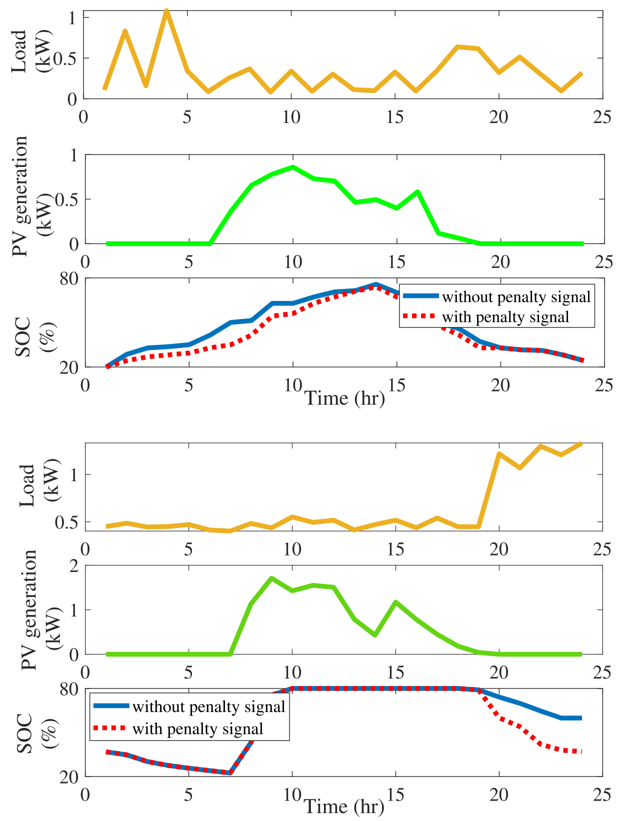

FIGURE 10. Effect of the designed penalty signal on the SOC in two different typical days.

based on (20). As it is shown in this table, implementing the penalty signal increases the flexibility of each microgrid.

VI. DISCUSSIONS

A. COMPARATIVE ANALYSIS

Clustering is a powerful unsupervised method of data mining that does not require any parameter tuning which is utilized in this paper to generate the penalty signal. Therefore, in comparison with the fuzzy logic controller (FLC) for generating the penalty signal in [25], the proposed approach does not require any tuning of parameters for various datasets and is scalable for applying to the different number of microgrids. However, FLC is tedious to develop fuzzy rules and membership functions of each dataset.

TABLE 2. Calculated FI in case of implementing individual penalty signal for each cluster.

Cluster	C1	C2	C3
FI	1.92	2.60	1.52

TABLE 3. Comparison of the proposed clustering-based and FLC-based method.

	Proposed Clustering-based method	FCL_based method [25]
Human expertice	Not required	Required for defining rules
Pre-information	Number of clusters extracted from the dataset	Membership functions and rules
Required memory	Low	High
Computation Time	Low	High
Computation complexity	Low	High
Scalibility	Scalable	Not scalable

Furthermore, our proposed method requires less memory and it has less computation time and complexity. In addition to these, to get accurate results, various rules should be defined for FLC. On the other hand, increasing the number of rules increases the computational complexity and requires much human expertise to define the rules and regularly updating them [25]. Table 3 presents a comparison of these two methods.

B. FUTURE WORK

Future works will address several issues like implementing a real-time series of penalty signals, exploiting the flexibility from all loads, not only the ESS, through disaggregation and forecasting the flexibility in the load patterns. In particular, we would like to deeply investigate the following subjects:

Cyber Security; Modern power systems (MPSs) have now gradually transitioned into a complex cyber-physical energy system (CPES). The cyber layer has not only made it possible for MPSs to become more responsive to faults and other systemic problems but also to co-ordinate production and load energy by reacting faster and smarter to changes. Moreover, individual households are empowered to install energy management systems to manage their production and load as well as interactions with the power system. The efficient transformation of an MPS into a CPES is doubly important today because global climate-change issues have made it necessary to integrate large amounts of RES. However, this transformation comes with a price: vulnerability to cyberattacks [15].

Moreover, aggregated power electronic converters in microgrids, which are key enablers for integrating RES into MPSs, are typically controlled by employing a hierarchical three-stage structure, namely, primary, secondary and tertiary layers. This leaves behind additional vulnerabilities and possible attack points in different layers of the system. In the context of this paper, the penalty signals could be a potential target by a cyber attacker to influence the optimal operation. These cyber-attacks could also affect the flexible usage of

RESs and hamper the system objectives. Hence, advanced and resilient technologies and mitigation measures will be developed as future scope of work and implemented at every level to ensure the secure energy flexibility of microgrids. Co-simulation Platform; Simulation packages for assessing system integration of components typically cover only one sub-domain, while simplifying the others. Co-simulation overcomes this by coupling sub-domain models that are described and solved within their native environments, using specialized solvers and validated libraries [27]. Besides, it is possible to solve a problem that consists of subproblems with different time steps through co-simulations.

In the case of utilizing flexibility from demand-side through generation penalty signals, in practice, one issue would be different time steps of flexibility resources, their control systems (most likely power electronic devices), forecast data, and market signals. Our future focus will be on developing a co-simulation platform capable of integrating models of the electrical ESS and flexibility resources, their control system, the grid constraints (developed in the RTDS [28], MATLAB or Python,) and forecasting models and algorithms (MATLAB or Python) as well as energy market, to achieve realistic, accurate and optimize scheduling and operation plan for flexibility resources. Currently, developed co-simulation platforms [29]–[31] have not considered these cases and capabilities. Thereafter, it will be possible to develop a real-time tool to provide flexibility feedbacks for different stakeholders.

VII. CONCLUSION

Designing a practical penalty signal relies on two main factors, (i) energy consumption behavior (consumer's load, generation, and the SOC level of the batteries) and (ii) analyzing a large volume of data. Since conventional methods are inefficient to handle the mentioned factors properly, this paper proposed a new clustering-based method to analyze these datasets and extract different levels for load and PV generation and quantify them. Based on the defined levels a novel method is proposed to design the proper state-aware penalty signal in each time step.

Simulation results showed that the aggregator will be able to effectively leverage the flexibility of responsive batteries in the microgrid clusters without jeopardizing the customer's comfort level while removing the need for new investments in the generation and distribution measurement facilities.Implementing the designed penalty signal increases the flexibility index of each microgrid at least by 50 percent.

Since the proposed method is based on the data that the aggregator or utility already has access to, it will not violate customer's privacy or raise any security concerns. Moreover, analyzing the datasets with the clustering method decreases the computation time and complexity and makes it more scalable and applicable to other kinds of microgrids too.

REFERENCES

[1] H. Chandler, *Harnessing Variable Renewables: A Guide to the Balancing Challenge*. Paris, France: International Energy Agency, 2011.

[2] *Accomodating High Levels of Variable Generation*, North Amer. Electr. Rel. Corp., Princeton, NJ, USA, 2009.

[3] E. Taibi, T. Nikolakakis, L. Gutierrez, C. Fernandez, J. Kiviluoma, S. Rissanen, and T. J. Lindroos, "Power system flexibility for the energy transition: Part 1, overview for policy makers," IRENA, Abu Dhabi, U.A.E., Tech. Rep., 2018.

[4] J. Cochran, "Flexibility in 21st century power systems," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-6A20-61721, 2014.

[5] A. Fernández-Guillamón, E. Gómez-Lázaro, E. Muljadi, and Á. Molina-García, "Power systems with high renewable energy sources: A review of inertia and frequency control strategies over time," *Renew. Sustain. Energy Rev.*, vol. 115, Nov. 2019, Art. no. 109369.

[6] R. Ahmadiahangar, A. Rosin, I. Palu, and A. Azizi, "New approaches for increasing demand-side flexibility," in *Proc. Demand-side Flexibility Smart Grid*, 2020, pp. 51–62.

[7] J. Hu, M. R. Sarker, J. Wang, F. Wen, and W. Liu, "Provision of flexible ramping product by battery energy storage in day-ahead energy and reserve markets," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 10, pp. 2256–2264, May 2018.

[8] Y. Xu and X. Shen, "Optimal control based energy management of multiple energy storage systems in a microgrid," *IEEE Access*, vol. 6, pp. 32925–32934, 2018.

[9] C. Dang, X. Wang, X. Wang, F. Li, and B. Zhou, "DG planning incorporating demand flexibility to promote renewable integration," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 20, pp. 4419–4425, Nov. 2018.

[10] M. Babaei, E. Azizi, M. T. Beheshti, and M. Hadian, "Data-driven load management of stand-alone residential buildings including renewable resources, energy storage system, and electric vehicle," *J. Energy Storage*, vol. 28, Apr. 2020, Art. no. 101221.

[11] G. Xu, C. Shang, S. Fan, X. Hu, and H. Cheng, "A hierarchical energy scheduling framework of microgrids with hybrid energy storage systems," *IEEE Access*, vol. 6, pp. 2472–2483, 2018.

[12] R. Ahmadiahangar, T. Haring, A. Rosin, T. Korotko, and J. Martins, "Residential load forecasting for flexibility prediction using machine learning-based regression model," in *Proc. IEEE Int. Conf. Environ. Electr. Eng.*, Jun. 2019, pp. 1–4.

[13] X. Liu, "Research on flexibility evaluation method of distribution system based on renewable energy and electric vehicles," *IEEE Access*, vol. 8, pp. 109249–109265, 2020.

[14] D. Prudhviraj, P. B. S. Kiran, and N. M. Pindoriya, "Stochastic energy management of microgrid with nodal pricing," *J. Mod. Power Syst. Clean Energy*, vol. 8, no. 1, pp. 102–110, 2020.

[15] S. Sahoo, S. Mishra, S. M. Fazeli, F. Li, and T. Dragicevic, "A distributed fixed-time secondary controller for DC microgrid clusters," *IEEE Trans. Energy Convers.*, vol. 34, no. 4, pp. 1997–2007, Dec. 2019.

[16] S. Shafiee, M. Fotuhi-Firuzabad, and M. Rastegar, "Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1351–1360, Sep. 2013.

[17] T. Haring, R. Ahmadiahangar, A. Rosin, and H. Biechl, "Impact of load matching algorithms on the battery capacity with different household occupancies," in *Proc. 45th Annu. Conf. IEEE Ind. Electron. Soc.*, Oct. 2019, pp. 2541–2547.

[18] N. Shabbir, R. Ahmadiahangar, L. Kutt, and A. Rosin, "Comparison of machine learning based methods for residential load forecasting," in *Proc. Electr. Power Qual. Supply Rel. Conf. (PQ) Symp. Electr. Eng. Mechatronics (SEEM)*, Jun. 2019, pp. 1–4.

[19] E. Azizi, H. KHARRATI-SHISHAVAN, B. MOHAMMADI-IVATLOO, and A. Mohammadpour Shotorbani, "Wind speed clustering using linkage-ward method: A case study of Khaaf, Iran," *GAZI Univ. J. Sci.*, vol. 32, no. 3, pp. 945–954, Sep. 2019.

[20] A. Majzoobi and A. Khodaei, "Application of microgrids in supporting distribution grid flexibility," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3660–3669, Sep. 2017.

[21] S. Mudaliyar and S. Mishra, "Coordinated voltage control of a grid connected ring DC microgrid with energy hub," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1939–1948, Mar. 2019.

[22] Y. Li, L. He, F. Liu, C. Li, Y. Cao, and M. Shahidehpour, "Flexible voltage control strategy considering distributed energy storages for DC distribution network," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 163–172, Jan. 2019.

[23] R. G. Junker, R. Relan, and H. Madsen, "Designing individual penalty signals for improved energy flexibility utilisation," *IFAC-Papers Line*, vol. 52, no. 4, pp. 123–128, 2019.

[24] E. Azizi, S. Ghaemi, B. Mohammadi-Ivatloo, and M. J. Piran, "Application of comparative strainer clustering as a novel method of high volume of data clustering to optimal power flow problem," *Int. J. Electr. Power Energy Syst.*, vol. 113, pp. 362–371, Dec. 2019.
[25] R. Ahmadiahangar, E. Azizi, S. Sahoo, T. Haring, A. Rosin, D. Vinnikov, T. Dragicevic, M. T. Hamidi Beheshti, and F. Blaabjerg, "Flexibility investigation of price-responsive batteries in the microgrids cluster," in *Proc. IEEE 14th Int. Conf. Compat., Power Electron. Power Eng. (CPE-POWERENG)*, Jul. 2020, pp. 456–461.
[26] X. Hou, J. Wang, T. Huang, T. Wang, and P. Wang, "Smart home energy management optimization method considering energy storage and electric vehicle," *IEEE Access*, vol. 7, pp. 144010–144020, 2019.
[27] S. Sahoo, T. Dragicevic, and F. Blaabjerg, "Cyber security in control of grid-tied power electronic Converters–Challenges and vulnerabilities," *IEEE J. Emerg. Sel. Topics Power Electron.*, early access, Nov. 14, 2020, doi: 10.1109/JESTPE.2019.2953480.
[28] P. Palensky, A. A. Van Der Meer, C. D. Lopez, A. Joseph, and K. Pan, "Cosimulation of intelligent power systems: Fundamentals, software architecture, numerics, and coupling," *IEEE Ind. Electron. Mag.*, vol. 11, no. 1, pp. 34–50, Mar. 2017.
[29] R. AhmadiAhangar, A. Rosin, A. N. Niaki, I. Palu, and T. Korøtko, "A review on real-time simulation and analysis methods of microgrids," *Int. Trans. Electr. Energy Syst.*, vol. 29, no. 11, 2019, Art. no. e12106.
[30] B. P. Bhattarai, M. Levesque, B. Bak-Jensen, J. R. Pillai, M. Maier, D. Tipper, and K. S. Myers, "Design and cosimulation of hierarchical architecture for demand response control and coordination," *IEEE Trans. Ind. Informat.*, vol. 13, no. 4, pp. 1806–1816, Aug. 2017.
[31] P. Palensky, A. van der Meer, C. Lopez, A. Joseph, and K. Pan, "Applied cosimulation of intelligent power systems: Implementing hybrid simulators for complex power systems," *IEEE Ind. Electron. Mag.*, vol. 11, no. 2, pp. 6–21, Jun. 2017.

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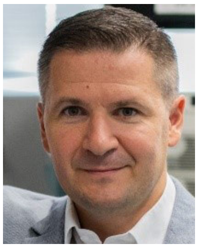

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