Adaptive Under-Frequency Load Shedding in Power Systems with Socio-Technical Criticality Functions

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***Abstract*—We consider the problem of adaptive load shedding in power systems experiencing sudden frequency variations due to imbalances in power generation and load consumption. While existing research has primarily focused on load-shedding schemes using voltage-stability indices or predefined weighting factors, our approach integrates a new type of criticality function. These functions consider diverse shedding priorities across the system's loads, incorporating both technical and societal data. This inclusion allows the decision-making algorithms used by the load-shedding scheme to incorporate demographic and technical information, mitigating unintended second-order adversarial effects within system subsets. Our proposed methodology represents an initial step towards systematically incorporating societal factors into power system load shedding schemes. We present numerical simulations that demonstrate the efficacy of the proposed under-frequency load-shedding scheme in achieving an equitable rearrangement of the shed load without compromising the scheme's effectiveness.**

***Index Terms*—Adaptive Under-Frequency Load Shedding, Socio-Technical Systems, Decision-Making.**

I. Introduction

A. Motivation and Literature Review

Under-Frequency Load Shedding (UFLS) entails strategically coordinating control strategies to reduce electrical loads in a power system. This strategy is activated when the system frequency drops below a predetermined set point due to disturbances or faults [1]. The primary objective of UFLS is to restore equilibrium by establishing a new balance between load and generation, ensuring that the system frequency remains within the nominal range. This is achieved through selectively disconnecting loads from the grid, guided by a combination of technical and economic criteria.

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Generally, UFLS can be categorized into three main types: 1) traditional stage-by-stage schemes; 2) adaptive schemes; and 3) semi-adaptive schemes [2]. The stage-by-stage scheme establishes a priori a certain number of load shedding stages that are triggered when the frequency goes below a pre-defined threshold. This approach sheds loads based on local frequency measurements and, in general, is the most used UFLS scheme nowadays. Despite the flexibility in configuring the number of steps and frequency thresholds, the main challenge of this scheme is to create a solution suitable that fits every operational scenario. Furthermore, the risk of over-shedding or under-shedding has persisted as an issue within the stage-by-stage scheme [3].

Adaptive load-shedding schemes, utilizing the Rate of Change of Frequency (ROCOF) at the Center Of Inertia (COI), have been extensively studied. The frequency at the COI is the average frequency measured on all electric machines and weighted by their respective inertia constants. In [4], the "Takagi-Sugeno (TS) fuzzy inference" method estimates optimal load shedding, successfully tested on a 102-bus distribution network. High-wind penetration energy systems are addressed in [5], estimating the equivalent inertia constant (EIC) for optimal load shedding.Various adaptive models are presented, such as a bi-level linear programming model in [6], optimizing load shedding with distributed architecture and Phasor Measurement Units (PMUs). Model predictive control and Monte Carlo methods [7], along with recursive convex optimization [8], further contribute to the exploration of optimal load-shedding profiles.

Finally, the semi-adaptive scheme combines elements of both the stage-by-stage approach and the adaptive approach [9]. Despite its intermediate nature, the semi-adaptive scheme is not immune to the pitfalls of over-shedding or under-shedding due to its comparably limited stages, reminiscent of the stage-by-stage scheme's challenges.

B. Contributions

While several works have recently studied adaptive and semi-adaptive load-shedding strategies in power systems, most existing schemes compute and execute load-shedding based solely on safety and technical considerations, which could potentially overlook unintended second-order impacts on users and consumers. For example, as discussed in [10], [11], in power grids with heterogeneous loads across complex societal systems, different economic and societal factors could also influence the outputs of load-shedding schemes. To incorporate such factors, load-shedding schemes that integrate priority-based rules have been recently explored during the last years [10]–[12]. For example, recursive approaches with prioritization for large-scale networks have been recently studied in [8] via convex optimization techniques. These methods can complement standard and adaptive load-shedding schemes by incorporating priority-based rules that seek to minimize potential negative unintended outcomes that result from purely technical load-shedding mechanisms. However, existing approaches have mostly focused on prioritizing load-shedding based on the economic nature of the load, e.g., residential, industrial, etc. Such approaches rely on classifying the loads as critical, non-critical, and semi-critical [12], which are disconnected from the grid only after an optimization problem with weighted cost functions has been solved. Yet, in grids with highly heterogeneous users, load-shedding mechanisms could benefit from prioritization-based rules with a higher granularity that allows to accommodate different types of loads with different types of "criticality" factors. Motivated by this need, in this paper, we study the systematic incorporation of *criticality functions* into adaptive load-shedding mechanisms for power systems. By considering such types of functions in the system, the load-shedding schemes can efficiently disconnect highly heterogeneous loads based not only on critical and safety considerations but also on pre-defined priority values that are encoded on functions that can be systematically constructed in a data-driven way. We present numerical results illustrating the approach in the Quebec 29-bus system model.

C. Organization

The rest of the paper is organized as follows: In Section II-C, we review the standard adaptive UFLS methodology, and we introduce the proposed scheme with criticality functions. Section III contains a description of the Quebec 29-bus system. In Section IV, we present numerical results of the methodology tested on the modeled system using MATLAB/Simulink. Finally, Section V ends with the conclusions.

II. Adaptive UFLS with Criticality Functions

The main idea behind adaptive load shedding is to curtail load at each stage by taking into consideration the *real-time* magnitude of the disturbance, voltage, and frequency characteristics at each stage. In this way, dynamic load shedding allows to shedding larger loads under larger system imbalances, and also smaller loads under smaller system imbalances [13].

In most adaptive schemes, the strategy computes *online* load shedding based on the ROCOF at the COI. This strategy is founded on the notion that the initial ROCOF at the COI correlates with the system-wide power imbalance [14]. Since this approach relies on frequent measurements of signals of interest from the system, i.e., real-time feedback, it is the most robust, precise, and reliable UFLS approach. However, its sensing and computational requirements are higher compared to traditional stage-based UFLS schemes. Adaptive UFLS is also sometimes called *dynamic* UFLS [1], as it takes into account the size of the disturbances and the voltage and frequency characteristics. Since adaptive UFLS strategies take into account not only the value of the frequency but also its rate of change, they are more effective at managing large disturbances that may cause rapid sudden deviations in the frequency of the grid. In particular, load shedding should take into account how fast the system responds to disconnections of loads before proceeding to disconnect other loads.

A. The Swing-Equation-Based Approach

The most common technique used in adaptive UFLS is based on the swing equations of the generators, which are used to compute the generation-load imbalance ΔP (equal to the amount of load to shed) based on the following expression:

$$\Delta P = \sum_{i=1}^{N_G} 2 \frac{H_i S_i}{f_n} \frac{df_i}{dt} \tag{1}$$

where N_G is the total number of generators, H_i is the constant of inertia of the i^{th} generator, S_i is its rated capacity, $f_n = 60$ Hz, and $\frac{df_i}{dt}$ is ROCOF at that location. Load shedding is initiated only if the frequency, or the ROCOF, crosses their corresponding acceptable thresholds. Such events would usually occur shortly after the occurrence of a disturbance in the system, or a sudden unbalance in the generation and consumption in the grid. In the meantime, the primary frequency controller would act to prevent the frequency from rapidly dropping. Typically, a pre-defined percentage $k\%$ of ΔP is initially shed at the first step to prevent the system from further degradation. The load shedding share corresponding to ΔP_i at the i^{th} bus is decided based on the vulnerability of that bus to voltage instability, quantified via Voltage Stability Index (VSI) [12]. By using these indices, an optimization or decision-making algorithm selects which loads to shed in order to recover from the calculated generation-load imbalance ΔP.

B. Advantages and Limitations of Standard Adaptive UFLS

UFLS has been shown to enhance the grid's effectiveness in responding to disturbances and faults. Moreover, by factoring in voltage drop within the network, UFLS can avert voltage collapse through the recursive shedding of load. Adaptive UFLS further integrates more effective shedding parameters in terms of precision and frequency of updates. This is achieved by leveraging constant monitoring of the frequency derivative, providing real-time feedback to prevent overshooting [15]. This bears resemblance to the impact of Proportional-Integral-Derivative (PID) controllers in regulation problems in standard dynamical systems [5], [16].

On the other hand, even in scenarios where the frequency and its derivative can be accurately obtained via direct measurement or estimation, adaptive UFLS schemes that rely solely on safety and technical considerations can lead to sub-optimal solutions once other socio-technical factors are taken into consideration. For example, this situation can emerge when two different load-shedding profiles lead to the same voltage stability indices but have substantially different impacts on the communities they impact. Such types of non-unique solutions frequently emerge in combinatorial problems and are usually solved via randomization methods. Yet, for power systems with heterogeneous users, randomization methods can be highly sub-optimal when considering the socio-economic impact that load-shedding can have in the system. To address this issue, in this paper, we introduce *criticality functions* in adaptive UFLS schemes with highly heterogeneous users. By incorporating these functions into the decision-making process, the power systems operator can effectively control (via load-shedding) energy systems whose users (i.e., loads) have a high degree of heterogeneity in terms of "criticality" values.

C. Incorporating Criticality Functions

To prioritize the shedding of non-critical loads in the system, we assume that each load ℓ has a criticality value $C(\ell)$, assigned by the so-called *criticality function* $C : \mathbb{R}_{\geq 0} \to [0, 1]$. The following definitions will be instrumental in our results:

Definition 1 (Criticality Functions): A function $C : \mathbb{R}_{\geq 0} \to [0, 1]$ is said to be a *criticality function* if it is a non-decreasing function of the loads, and it satisfies $\lim_{\ell \to \infty} C(\ell) = 1$.

Our goal is to incorporate the criticality functions into the adaptive UFLS scheme to stabilize the system whenever there is a sudden generation-consumption imbalance, while simultaneously prioritizing the shedding of non-critical loads $i \in \{1, 2, \ldots, m\}$ characterized by a low value of $C(\ell_i)$. Fig. 1 shows two different criticality functions for the Montreal (MTL) and Quebec City (QUE) regions in the Quebec 29-bus system. We note that, in general, characterizing these functions for a given geographical area might require feedback from local authorities, energy utilities, and system operators, as well as the incorporation of data analyzing the impact of outages on different demographics in a population. For example, as noted in [17], demographic features such as age or level of income, can determine the level of preparedness of a user before an outage, and their adaptability to an emergency. Moreover, we note that the criticality of the loads may change over time if the length of the outage is extended.

To incorporate criticality functions into adaptive UFLS schemes, we will leverage the following definition:

Definition 2 (Priority-based Set): A set of loads $A \subset \{1, 2, \ldots, m\}$ is said to be a priority-based set if for all $i \in A$ and $j \in \{1, 2, \ldots, m\} \setminus A$, we have $C(\ell_i) < C(\ell_j)$.

Based on the previous definitions, we incorporate the following optimization problem into the UFLS mechanism:

$$\arg \min_{\substack{A \text{ is a priority-based set} \\ \sum_{i \in A} \ell_i \geq \mathbb{L}_s}} \sum_{i \in A} \ell_i - \mathbb{L}_s, \tag{2}$$

where $\mathbb{L}_s = -\Delta P$ is the amount of load that needs to be shed to stabilize the system. In this way, if $C(\ell) > C(\ell')$, then ℓ' should be shed before ℓ. With this formulation, the main goal is to find a subset A of m loads $\ell_1, \ldots, \ell_m$ whose total amount is equal to $\mathbb{L}_s$ in (1), while simultaneously satisfying the Priority-based Condition, which is defined in Definition 1. While priority-based load shedding has recently been studied in the literature using pre-computed weights in assignment and/or optimization problems [8], [12], the use of criticality functions seems to be mostly unexplored, and it provides flexibility in problems where the loads are highly heterogeneous and cannot be classified into a small number of subsets, e.g., industrial, commercial, residential. Moreover, criticality functions can be obtained in a data-driven way using publicly available socio-technical information from the demographics in the system.

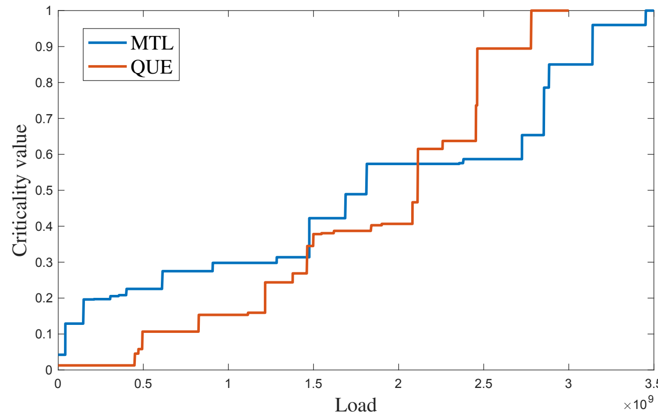

Fig. 1. Examples of criticality functions for the aggregated loads in the Montreal and Quebec cities in the numerical example.

To solve (2), we first assume that the total load shedding amount $\mathbb{L}_s$ needed to stabilize the system is known a priori. However, in practice, we will estimate $\mathbb{L}_s$ using real-time frequency measurements. Additionally, we assume, without loss of generality, that $C(\ell_i) < C(\ell_{i+1})$ for $i \in [m]$. It follows that the solution A^* to problem (2) can be written as:

$$A^* = \{1, \ldots, i^*\} \quad \text{s.t.} \quad \sum_{i=1}^{i^*} \ell_i \geq \mathbb{L}_s \text{ and } \sum_{i=1}^{i^*-1} \ell_i < \mathbb{L}_s \tag{3}$$

To implement this solution, we consider two different cases depending on the scale of the system:

(a) *Small-Scale Power Networks:* When m is a small or moderate number (i.e., of order $\mathcal{O}(10^1)$), the cardinality of the range of the mapping $C(\cdot)$ is small. In this case, the prioritized solution A^* that incorporates the information of the criticality function can be pre-computed and stored in a look-up table accessed by the A-UFLS scheme whenever load-shedding needs to be executed and the safety voltage indices have been pre-computed;

(b) *Large-Scale Power Networks:* For large networks (i.e., of order $\mathcal{O}(10^k)$, $k > 2$), a binary-search method that leverages the monotonic structure of the functions C can be implemented. In particular, in this case, we execute Algorithm 1. The inputs are the set of loads $\{\ell_1, \ldots, \ell_m\}$, which are sorted by ascending criticality, and the amount of load shedding $\mathbb{L}_s$. The goal of Algorithm 1 is to find the optimal set of loads A^* to shed, or equivalently i^*, which is defined in (3).

Therefore, the output of the algorithm is i^*. To do so, we use the auxiliary load indexes a, b, and r.

Algorithm 1 Adaptive Load Shedding with Priority-based Sets Criticality Functions

Input: $\mathbb{L}_s, \{\ell_1, \ldots, \ell_m\}$
Output: i^*
$a \leftarrow 1$
$b \leftarrow m$
while $b > a + 1$ **do**
  $r \leftarrow \lfloor (a+b)/2 \rfloor$
  if $\mathbb{L}_s > \sum_{i=1}^{r} \ell_i$ **then**
    $a \leftarrow r$
  else
    $b \leftarrow r$
  end if
end while
$i^* \leftarrow r$

III. Use Case

The aforementioned adaptive UFLS algorithm that incorporates problem (2) is tested on the Quebec 29-bus system, modeled in MATLAB/Simulink. The base model is publicly available on the MATLAB examples website. This power system is a simplified representation of the transmission power grid in the Canadian province of Quebec. The model has two main power generation areas in the North and two large power consumption regions in the South, MTL and QUE [18]. In this model, power is transported from North to South through several 735 kV hundreds of kilometers long. The generation is made up of large hydropower plants. There are 8 generating units in the system. The approximate generation capacity is 26.2 GW. Fig. 2 shows the system diagram. The

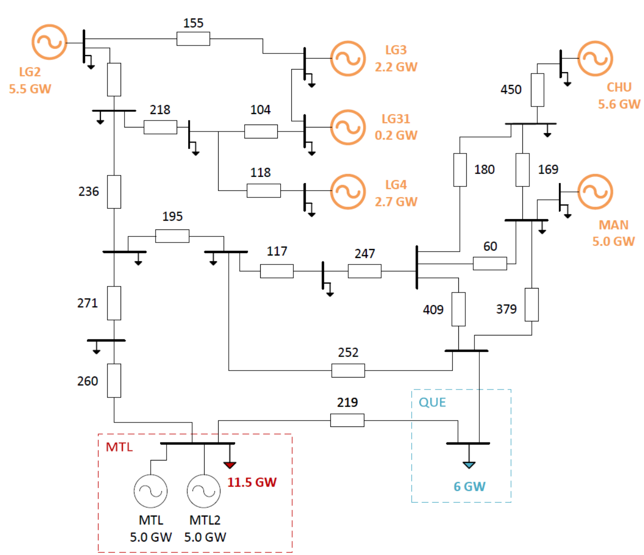

Fig. 2. Quebec 29-bus system diagram

generators that are disconnected to test the proposed adaptive UFLS are highlighted in orange. The annotations next to the generators indicate the generator name and power rating. The aggregated loads for MTL and QUE are highlighted in red and blue, respectively, and their capacity is specified. Other black arrows symbolize smaller loads that are not available for shedding. The number next to the power lines indicates the line length in kilometers. Given that the system is dominated by large hydro-power plants, Quebec's frequency requirements are slightly more flexible than their counterparts in the US. Specifically, the operational requirements for generators during low-frequency events can be found in the NERC's PRC-024-3 standard [19].

To analyze the role of criticality functions in the adaptive UFLS scheme, the large majority of the system load is aggregated into two primary locations, MTL and QUE. Their respective load-shedding capacity is as follows: 3.5 GW in MTL, and 3 GW in QUE. Each region is comprised of 20 smaller load components (a criticality value has been assigned to each of them), as seen in Fig. 1. In this way, it is considered that the criticality values of specific substations (or groups of substations) are summarized on larger load shedding blocks.

IV. Experimental Results

The proposed adaptive UFLS scheme with socio-technical criticality functions (named as "ST" is tables and figures below) is implemented for 6 generation disconnection cases. Generators are tripped at $t = 4$ seconds. This section gathers the results for the frequency response and the load-shedding effect according to the regional criticality profiles.

In order to compare the effectiveness of the proposed scheme, two other methods have been simulated to establish a baseline: the 1) Proportional method (Prop.) and the 2) Equally Distributed method (ED). In the Prop. method, each region (MTL and QUE) sheds an amount of load proportional to the total load amount in that region. While in the ED method, both regions shed the same amount of load (if possible). For example, if the shedding of 3.25 GW is needed, using the Prop. method, we shed $3.25 \times \frac{3.5}{6.5} = 1.75$ GW and $3.25 \times \frac{3}{6.5} = 1.5$ GW in MTL and QUE, respectively. While using ED, 1.625 GW is shed in each region.

A. Frequency Response

The associated frequency response at the system's COI is presented in Table I. As can be seen, the proposed ST method can successfully contain the unexpected frequency declines. For all the approaches, in general, the frequency at the COI at $t = 250$ seconds is above 59 Hz for every scenario. When comparing the performance of the proposed ST approach with the Prop. and ED methods, it can be seen that in most cases (when LG2, LG3, and LG4 are disconnected) frequency response is slightly worse using the ST approach by roughly a tenth of an Hz. This can be explained by how the load-shedding is arranged across the system. Fig. 3 shows the frequency at the system's COI following the tripping of generator LG4 across various methods. Compared to Prop.

and ED methods, the ST approach achieves a slightly lower frequency nadir and steady-state frequency.

It is important to note that UFLS schemes are the last resort to stabilize frequency when a large disturbance occurs. However, UFLS schemes do not necessarily need to bring the frequency back to nominal. In general, other system-wide frequency regulation mechanisms, whose effect becomes noticeable after a few dozen of seconds following the event, are in charge of restoring the frequency.

TABLE I
FREQUENCY RESPONSE RESULTS (Hz)

Method	Time stamp	LG2	LG3	LG31	LG4	CHU5	MAN5
ST	nadir	55.81	59.44	59.70	57.72	56.09	55.99
	$t = 250$s	59.67	60.03	59.98	59.82	59.48	59.12
Prop.	nadir	55.82	59.43	59.70	57.77	55.89	56.01
	$t = 250$s	59.67	60.05	59.98	59.85	59.12	59.12
ED	nadir	55.85	59.43	59.70	57.85	55.9	55.25
	$t = 250$s	59.67	60.07	59.98	59.85	59.16	57.96

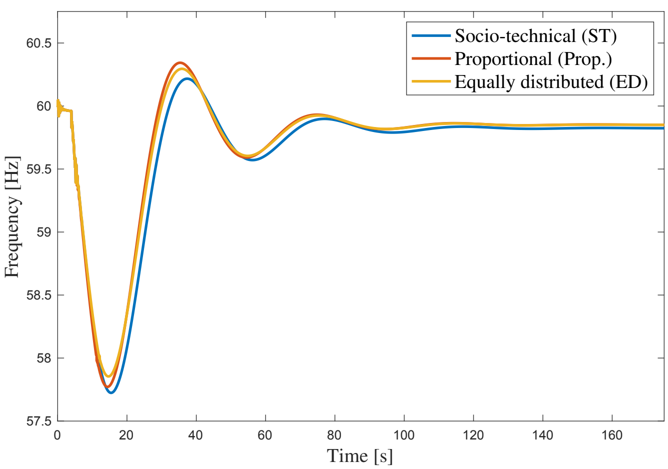

Fig. 3. Frequency at the system's COI after disconnecting the generator LG4.

B. Load-Shedding Effects

The amount of load-shedding in each region, either MTL or QUE, for each of the approaches and for each scenario, is shown in Table II[1]. In general, the ST approach estimates a very similar amount of total load shedding in the system. Differences in load-shedding are due to the small differences in the specific frequency responses for each method and their implications to the generation-load mismatch estimations. It is important to note that the load shedding blocks are discrete, which means that very small differences in the load-shedding estimation can lead to a more noticeable amount of shed load due to the triggering of the next load shedding block.

Considering the load shedding quantities outlined in Table II, each method (ST, Prop., and ED) allocated some load shedding in both the MTL and QUE regions, leading to the

[1]As LG31 generates a relatively small amount of power, there is no need for load shedding following its disconnection.

TABLE II
LOAD-SHEDDING RESULTS (GW)

Method	Region	LG2	LG3	LG4	CHU5	MAN5
ST	MTL	3.5	1.69	1.48	3.45	3.5
	QUE	3	2.11	1.46	2.78	3
	Total	6.5	3.80	2.94	6.23	6.5
Prop.	MTL	3.5	2.36	1.81	3.14	3.5
	QUE	3	1.9	1.46	2.78	3
	Total	6.5	4.26	3.27	5.92	6.5
ED	MTL	3.5	2.36	1.69	2.88	2.72
	QUE	3	2.08	1.55	3	2.78
	Total	6.5	4.44	3.24	5.88	6.5

TABLE III
SOCIO-TECHNICAL CRITICALITY RESULTS

Method	Criticality	LG2	LG3	LG4	CHU5	MAN5
ST	c^*_{MTL}	1	0.49	0.42	0.96	1
	c^*_{QUE}	1	0.47	0.27	0.89	1
	Σ	2.86	0.94	0.62	2.6	2.86
Prop.	c^*_{MTL}	1	0.58	0.49	0.85	1
	c^*_{QUE}	1	0.4	0.27	0.89	1
	Σ	2.86	1.18	0.68	2.3	2.86
ED	c^*_{MTL}	1	0.58	0.49	0.79	0.65
	c^*_{QUE}	1	0.41	0.38	1	0.89
	Σ	2.86	1.25	0.74	2.3	2.06

computation of the regional marginal criticality c^* as presented in Table III. The values of c^*_{MTL} and c^*_{QUE} represent the maximum criticality value associated with a load that is shed in the MTL and QUE regions, respectively. Also, in Table III, Σ is the criticality aggregation, i.e.,

$$\Sigma \triangleq \sum_{\ell \text{ is shed}} C(\ell)\ell.$$

The LG3 tripping scenario better shows the implication of load-shedding when socio-technical factors are considered. In this case, using the ST approach, more load-shedding is assigned to QUE while the load-shedding in MTL is smaller, compared to the Prop. and ED methods. It can be deduced that some load-shedding was transferred from MTL to QUE due to socio-technical reasons. However, this action did not have a significant negative impact on the UFLS performance as the overall frequency response is similar among the three methods, as can be seen in Table I.

Regarding the load criticality, the LG3 example again shows the benefits of considering socio-technical values. Using the ST approach, the load-shedding is rearranged to divide the socio-technical impacts among MTL and QUE in a more equitable way. For the Prop. and ED approaches, one of the regions tends to absorb a larger impact (MTL in both cases). The proposed ST method assigns the load-shedding in a more fair manner taking into account the socio-technical criticality profiles of each load.

V. CONCLUSIONS

In this paper, we introduced the usage of socio-technical criticality functions for adaptive Under-Frequency Load-Shedding (UFLS) schemes in power systems. The approach generalizes existing methods based on weight prioritization, and it is suitable for power systems with highly heterogeneous loads where multiple solutions can exist for standard safety and technical considerations with vastly different outcomes at the socio-technical level. The criticality functions can be constructed in a data-driven way for each system of interest, and they can be fed directly into the proposed methodology. Extensions to stochastic models are also possible. A numerical example in the Quebec 29-bus system illustrating the priority-based load-shedding approach was also presented. The proposed socio-technical approach for adaptive load shedding rearranges the load shedding across the system to achieve a more equitable impact on the system without compromising the UFLS scheme performance.

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