Learning-based load control to support resilient networked microgrid operations

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Abstract: Networked and interconnected microgrids can improve resilience of critical end-use loads during extreme events. However, the frequency deviations in microgrids during transient events are significantly larger than those typically seen in bulk transmission systems. The larger frequency deviations can cause a loss of inverter-connected assets, resulting in a loss of power to critical end-use loads. Grid Friendly Appliance™ (GFA) controllers can mitigate the transient event effects by engaging end-use loads. This paper presents a method to select set-points for end-use loads equipped with GFA controllers, while minimizing the interruptions to end-use customers. An online (i.e. real-time), device-level algorithm adjusts individual GFA controller frequency setpoints based on the operational characteristics of each end-use load and on the changing grid dynamic characteristics to selectively engage the load for mitigating the switching transients. The adaptive gradient-descent-based algorithm does not require control or coordination amongst end-use devices for adapting frequency setpoints. The method is validated using dynamic simulations on a modified version of the IEEE 123-node test system with three microgrids using the GridLAB-D™ simulation environment. The improved dynamic stability achieved through the engagement of GFAs support the switching operations necessary for networked microgrid operations.

Nomenclature

- $\alpha$: learning rate
- $\beta$: GFA tier coefficient
- $\delta$: TCL thermal distance
- $\epsilon$: smoothing term
- $\Phi$: GFA tier
- $\sigma$: system frequency standard deviation
- $\tau$: TCL temperature
- $\tau_{\text{min}}$: minimum value of temperature deadband for TCL
- $\tau_{\text{max}}$: maximum value of temperature deadband for TCL
- $f_{\text{sp}}$: GFA UF set-point
- $f_{\text{max}}$: maximum GFA UF set-point
- $f_{\text{sys}}$: system frequency
- $f_{\text{nadir}}$: UF event frequency nadir
- $f_{\text{peak}}$: highest frequency during overshoot
- $G$: diagonal element with sum of gradient squares
- $J$: objective function
- $k$: event index
- $P$: real-time power consumption

1 Introduction

Extreme event occurrences like cascading technical failures, natural disasters, and cyberattacks are increasingly affecting the power delivery system [1, 2]. Isolated microgrids have shown the ability to support critical end-use loads when there is a loss of the bulk power system [3]. During past extreme weather events, the ability of microgrids to integrate local distributed energy resources (DERs) supported their ability to maintain service to critical end-use loads [4]. Further, microgrids positioned geographically close to each other have the potential to be networked, providing additional resilience [5]. However, the combination of low inertia due to grid-following inverter-connected DERs and the switching operations necessary to support networked microgrid operations can cause frequency deviations that lead to a loss of short-term frequency stability [6, 7]. Further, the frequency deviations experienced during switching transients in networked microgrids are significantly larger than those typically seen in bulk transmission systems [8]. Effects that increase the magnitude and duration of frequency deviations include: (i) inrush currents arising from energising portions of de-energised conductors and the associated loads; (ii) low-inertia inverter-connected DERs; and (iii) operation outside ranges prescribed in the IEEE Standard for Interconnecting Distributed Resources with Electric Power Systems, Amendment 1, such as IEEE Std. 1547a for inverter-connected generation assets [9]. This paper’s work is relevant for arresting both under-frequency (UF) (frequency transients below the desired 60 Hz) and over-frequency (frequency transients above the desired 60 Hz) events. However, the focus will be on UF events for brevity.

1.1 Status quo and related work

Conventional methods for arresting frequency deviations focus on using generation assets. This can be through automated generation controls [10], which offer a slow response (5–15 min) or using the spinning reserves capabilities for frequency regulation, which is often cost-prohibitive [11]. Arresting frequency deviation occurs within 1–2 s and the recovery of frequency back to desired levels can take longer [12]. The most common methodology used for primary frequency control in microgrids is droop-type controllers implemented on the individual generators that respond to frequency deviations without the need for communications [13–15]. A cost-effective alternative is to take advantage of the large flexibility potential of end-use loads, which can respond to stability events within seconds or even milliseconds. Typically, end-use loads are only engaged in load-shedding schemes in extreme cases, at the substation level, to arrest deviations in frequency during primary frequency response [16, 17]. However, they can be a much more flexible resource.

Investigations into the potential of device-level load-shedding controls, as opposed to traditional substation-level load shedding, is gaining momentum. Previous works established its benefits to improved system stability and frequency control [16–19]. One way to facilitate end-use load control is through Grid Friendly Appliance™ (GFA) controllers. The GFA controllers are housed in

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an appliance (such as a clothes dryer or electric water heater) and equipped with sensors to detect the local frequency and voltage [20–23]. GFAs autonomously respond to frequency deviations and can respond and operate in 80 ms [24]. To this regard, considerations for GFA controllers are increasing in recent years [20–23, 25–31].

GFAs were studied in loads that have a thermal mass or duty cycle, so the customer will not immediately notice the operation of the GFA. For example, a GFA on an electric clothes dryer turns off the heating elements, but not the motor. The result is a 90% reduction in load and the clothes continue to dry for several minutes. In a field demonstration using GFA controllers as a form of distributed UF load shedding, appliance owners reported that GFA operations caused little to no inconvenience [24]. Design considerations for using GFAs for frequency response were studied in [20]. Locally measured frequency influenced the selection of the various control parameters. The results of the field demonstration and usage for frequency response further increased research in GFA deployment. Additional work was conducted on the fundamental design, applications, and control logic [23, 25–28] of the controllers.

An investigation into the use of GFAs to facilitate the switching operations of multiple low-inertia microgrids was first conducted in [20]. The work showed that GFAs can support the switching operations necessary for networked microgrids. It provided a proof of concept but did not address the details in implementing GFAs to support networked microgrid operations. In particular, the GFA set points were suboptimal and shed excessive load to maintain short-term frequency stability. At present, two crucial technical challenges in the deployment of GFAs include: (i) characteristics of end-use loads and their importance and (ii) selection of the individual controller frequency/voltage set points.

A hierarchical control strategy for the selection of frequency setpoints for load shedding during over- or UF events was proposed in [30, 31]. The hierarchical control systems benefit from the coordination of information at multiple levels, but they require a communications infrastructure. However, end-use loads typically do not have connections with utility-operated industrial control systems. Also, Lian et al. [30] provided no theoretical or practical foundation for the selection of various parameters required for the algorithm. An initial, but an incomplete, investigation of a completely decentralised frequency set-point selection algorithm was introduced in [32].

1.2 Main contributions

This paper presents a method for determining the individual set points of GFA controllers attached to end-use loads for participation in primary frequency control to support the operations of networked microgrids; specifically, the UF setpoints for each GFA. Each GFA continuously calculates a tier indicative of the criticality of the load based on its real-time power consumption. An adaptive gradient descent algorithm uses the continuously updated tier value and the grid frequency trends to calculate the frequency at which the particular GFA should automatically curtail its power consumption for a preset duration, called the under-frequency set point. Determining set points does not require a communications infrastructure, and set points are continuously updated as the grid dynamics change over time. The specific contributions of this paper are:

(i) The mathematical framework to determine the participation of each GFA controller so that networked microgrid switching operations are supported, with a minimal effect on the end-use loads.
(ii) A decentralised, communication-less algorithm for determining the frequency setpoints for GFA controllers, based on the end-use load operations.
(iii) A set-point adaptation technique that autonomously adjusts to changing system dynamics and end-use load participation.

The rest of this paper is organised as follows. Section 2 describes the selection and prioritisation of the end-use loads and Section 3 details the set-point selection algorithm. Section 4 presents the simulations that evaluate the method. Section 5 contains concluding comments and presents possible future research directions.

2 Selection and prioritisation of GFAs

Each of the end-use loads supported by a resilience-based microgrid is considered important. However, within a building or facility, not all loads are equally critical for its operations. Depending on the type of building, the most critical end-use loads may include those that permit safe traversal (e.g. lighting), preserve food (e.g. refrigeration), and/or regulate ambient temperature and air quality (e.g. heating, air conditioning). Identifying which end-use loads have the highest priority for a given demand-response scenario depends on several criteria, such as the building function, its hours of operation, the time of day, weather conditions, correlations between loads, and priorities of loads among building types. Generally, any device that has a thermal mass is suitable for control by a GFA controller because the controller can minimise effects on the end-user while it is engaged. For example, an electric water heater has a thermal mass, and a short interruption of power will not noticeably change the temperature of the water supplied.

Furthermore, an interruption of the process should not result in damage to a consumer product or unsatisfactory performance of the process and consumers should not be required to notice a change in their behaviour. Based on these considerations, the following sections examine which end-use loads should be selected for inclusion in a load-shedding scheme, and for the loads selected, what their priority of operation should be.

2.1 Criteria for prioritisation

The selection and prioritisation of end-use loads to participate in primary frequency control are dictated by their criticality and flexibility. In past works, end-use loads have been classified based on their ability to move operations in time without affecting end-use service, and further classified by their ability to curtail power consumption or be interrupted [33]. The ability to control end-use loads typically requires more hardware and/or communications, but technologies such as the Smart Power Strips allow consumers to choose which loads are controllable or uncontrollable [34].

Typically, life-safety services, monitoring, and security systems are excluded from consideration. Additionally, the engagement of end-use loads should start gradually, but accelerate quickly to ensure that stability is maintained. As a result, Schneider et al. [29] proposed biasing the distribution of GFA set points to obtain a non-linear droop response, with coefficients of the non-linearity selected by the microgrid operator. However, it is not practical for a microgrid operator to continually update the biased distribution of all end-use loads; this should be done autonomously by the load controller itself.

This work assumes that the individual building operators have selected the end-use loads for frequency response during switching transients. To minimise the end-use load disruptions, and to develop a frequency-biased population of GFA controller setpoints, a tier is assigned to each end-use load, representative of its operational capacity and flexibility for grid response. The lower the value of the tier, the sooner it will be engaged for primary frequency response. For each of the GFA controllers that control an end-use load, the tier value is assigned based on real-time active power consumption and thermal distance, as detailed below.

2.1.1 Real-time active power consumption: When operating GFAs for large switching transients, a strategy that engages end-use loads that consume more power after those that consume less is beneficial [29]. Ideally, the aggregate GFA response would approximate a non-linear droop-like response, which would prevent GFA operations during minor frequency deviations. One option for prioritising load participation is to base it on the loads’ active power rating [35]. Though the rating carries useful information, end-use loads do not always operate at the rated conditions. This can be seen in multi-state time-variant load
models, which use more than one state to describe the power consumption of an end-use load [36, 37]. To this effect, this work uses the real-time active power consumption as one of the parameters for prioritising the end-use loads for the load-shedding schemes. Hence, the GFA controller must track the real-time active power consumption \( P \) of the load to be used for the prioritisation calculations. This assumption can be altered based on the load composition of a specific microgrid, and the presented algorithm could still be used.

2.1.2 Thermal distance: A second factor for prioritising load participation is the distance between the current operating point(s) and the boundaries of the operational dead bands. For example, the current operating points of thermostatically controlled loads (TCLs), such as HVAC units and electric water heaters, cycle within the limits of a dead band, which is centred around the desired operating point (temperature setpoint). Because TCLs have thermal mass, the power consumption can be interrupted without having a noticeable effect on the end-user(s) [38]. When prioritising TCLs for participation in primary frequency response, one option is to interrupt units that will most imminently turn off to reduce power consumption according to their thermal distance from the switching boundary [38]. Additionally, interrupting units that cycle and operate within a dead band before dropping continual loads such as lighting, is less likely to have an immediate effect on end-users.

A TCL currently at temperature \( r \), operating in the cooling mode within a deadband specified by a minimum value of \( \tau_{\text{min}} \) and a maximum value of \( \tau_{\text{max}} \), has a normalised thermal distance \( \delta \) for UF events calculated as

\[
\delta = \begin{cases} 
\frac{r - \tau_{\text{min}}}{\tau_{\text{max}} - \tau_{\text{min}}} & \text{in cooling mode} \\
\frac{\tau_{\text{max}} - r}{\tau_{\text{max}} - \tau_{\text{min}}} & \text{in heating mode}
\end{cases}
\] (1)

It can be seen in Fig. 1 that, as the temperature cycles through time, its distance from the upper and lower deadband limits varies. This distance can be used as a basis for prioritising the participation of TCLs in primary frequency response.

2.2 Tier calculation

The real-time active power consumption and thermal distance factors are accessible locally to the GFA controllers and are used in this work for assigning the tier for primary frequency response. The controller continuously updates its tier \( \Phi \) through the following equation:

\[
\Phi = P \times \delta \tag{2}
\]

The tier is indicative of the load priority, with large loads or larger thermal distances reflected in a higher tier. The proposed ranking system not only takes into account criticality, but it also prioritises end-user thermal comfort and minimises disturbances to end users.

3 Set-point adaptation algorithm

The previous subsections provided a basis on which end-use loads should be included in a load-shedding scheme and a basis for prioritising them. This section will explain how the GFA controller autonomously adapts UF set points for improved frequency response in networked microgrids. The GFA controller uses a Microchip Technology 16F88 microprocessor with 256 bytes of data memory and 368 bytes of RAM. Due to its limited processing power, it cannot be equipped with complex computations for selecting UF set points; instead, a simple, but effective, gradient-based algorithm that makes decisions based on observed system frequency is presented.

Each GFA uses the following equation to calculate its UF set point, \( f^{fp} \):

\[
f^{fp} = f_{\text{max}} - \beta \Phi, \tag{3}
\]

where \( f_{\text{max}} \) is the highest frequency to which the GFA would respond in a UF event and the tier coefficient \( \beta \) influences how close the set point is to the maximum value, depending on its real-time rank \( \Phi \). The following sections will explain how the values of \( f_{\text{max}} \) and \( \beta \) are calculated and present the objective function of the set-point adaptation algorithm.

3.1 Maximum frequency

Contemporary inverter-connected solar photovoltaic (PV) generation is typically IEEE Std. 1547 compliant, with future units expected to be IEEE Std. 1547a compliant [9]. For systems with a large number of inverter-connected resources, the frequency should be regulated within the ranges in IEEE Std. 1547a [9]. To support this, the GFAs participate in primary frequency control to arrest frequency transients before the inverter-based generation trips off, preventing a loss of short-term frequency stability. With a nominal system frequency of 60 Hz, end-use load shedding at frequencies significantly lower than 60 Hz may not produce any desired effects in a microgrid. Similarly, set points very close to 60 Hz could cause frequency overshoots. Due to the lack of existing guidance on specific set-point values, [24] conducts an extensive study of the frequency deviations on a bulk power system during normal operations and selects a range of 59.75–59.95 Hz. Schneider et al. [29] propose using a set-point range of 57.5–59.95 Hz for microgrids but acknowledges that these values are heuristically selected. The work also emphasises that setpoints may need to change over the lifetime of the controller due to gradual, long-term changes in the system’s transient response.

This work assumes that each GFA controller is capable of tracking the standard deviation, \( \sigma_t \), of the system frequency, \( f_{\text{sys}} \). Dynamic processes within three standard deviations are statistically considered to be operating efficiently [39], and this metric is used to calculate the maximum frequency for the GFA response \( f_{\text{max}} \), as shown in (4):

\[
f_{\text{max}} = 60 - 3\sigma_f \tag{4}
\]

The choice of the metric is motivated by its use established in transactive controls and real-time demand-response applications [40].

3.2 Objective function

The goal of GFAs participating in primary frequency response is to reduce the deviation of system frequency \( f_{\text{sys}} \) from the nominal value of 60 Hz. While autonomously adjusting UF set points, too many GFA-controlled loads may be shed at higher frequencies, resulting in a frequency overshoot following the initial frequency deviation. Hence, the goal of the algorithm is to reduce the
magnitude of frequency deviations in both positive and negative directions; i.e. both over- and UF. At every UF event trigger, the GFA controller monitors system frequency, \( f_{\text{sys}} \), from the start of the UF event \( t = 0.00 \), until a set reconnect time \( t = \text{end} \), and records the frequency nadir \( f_{\text{sys}}^{\text{adir}} \) during the UF transient and the frequency peak \( f_{\text{sys}}^{\text{peak}} \) during any frequency overshoot that may follow:

\[
\begin{align*}
    f_{\text{sys}}^{\text{adir}} &= \begin{cases} 
        60 - \min (f_{\text{sys}}(t)), & \text{if } f_{\text{sys}}(t) < 60 \\
        0, & \text{otherwise}
    \end{cases} \\
    f_{\text{sys}}^{\text{peak}} &= \begin{cases} 
        \max (f_{\text{sys}}(t)) - 60, & \text{if } f_{\text{sys}}(t) > 60 \\
        0, & \text{otherwise}
    \end{cases}
\end{align*}
\]

(5) \( (6) \)

The overall adaptive set-point algorithm minimises the difference between the highest and lowest system frequencies following a UF event observed by the GFA, i.e. minimise the objective function \( J \):

\[
J = (f_{\text{sys}}^{\text{peak}} - f_{\text{sys}}^{\text{adir}})
\]

(7)

### 3.3 Tier coefficient adaptation

Gradient descent is a first-order iterative optimisation algorithm used to find the parameters of a function that minimises an objective function as far as possible [41]. It is a simple, intuitive, and robust solution that measures how much the output of a function or process is influenced by a change in the input signals. For a system as highly non-convex as a microgrid, gradient descent may halt or significantly slow down near a stationary point. A common solution is to normalise the function gradient and continuously adapt learning rates.

The adaptive gradient descent method adapts the learning rate to the parameters, performing smaller updates (i.e. low learning rates) for parameters associated with frequently occurring features, and more significant updates (i.e. high learning rates) for parameters associated with infrequent features [42]. One of the main benefits of adaptive gradient descent is that it eliminates the need to manually tune the learning rates, which is essential for the autonomous operation of GFA controllers. Another advantage is that the algorithm also works for sparse data; UF setpoints are updated only in response to UF events and these do not occur frequently, even on microgrids.

This work uses adaptive gradient descent [42] as part of the online algorithm for actively adapting UF set points to changing system dynamics. The specific details of the workings of adaptive gradient descent are widely available in the literature and are not discussed in this paper. However, the equations involved in the process, which will be incorporated into the GFA controllers, are presented in (8)–(10):

\[
G(k + 1) = G(k) + \nabla J(k)\beta
\]

(8)

\[
\alpha_{\text{adapt}} = \frac{\alpha}{\sqrt{G(k + 1) + \epsilon}}
\]

(9)

\[
\beta(k + 1) = \beta(k) - \alpha_{\text{adapt}} \nabla J(k)
\]

(10)

where \( \nabla J(k) \) is the partial derivative of the objective function \( J(k) \) with respect to the tier coefficient \( \beta \), \( G(k) = \nabla J(k - 1)^2 + \nabla J(k - 2)^2 + \cdots \) keeps track of the sum of squares of the past gradients, \( \alpha \) is the initial learning rate, \( \alpha_{\text{adapt}} \) modifies the learning rate after each event \( k \) with respect to the past gradients, and \( \epsilon \) is a smoothing term that avoids division by zero.

### 3.4 Process flow

Fig. 2 depicts the process flow for the online adaptation algorithm described in this section. Each GFA controller continuously measures local power consumption and thermal distance from the appliance operations. The measurements are used to continually update the tier of the appliance using (2), accounting for flexibility and criticality. The lower the value of the tier, the lower its priority and the higher the frequency at which the controller will actuate. Concurrently, the GFA controller monitors the system frequency \( f_{\text{sys}} \), maintains an up-to-date standard deviation value \( \sigma_t \), and updates the maximum frequency at which the GFA is required to respond \( f_{\text{max}} \) through (4). The two parameters are then used to continuously calculate the relative UF set points from (3), controlled by the tier coefficient \( \beta \), which continuously learns from the grid frequency, and adjusts with every occurrence of a UF event. If at any time a GFA is tripped due to a UF event, the learning algorithm is triggered and \( f_{\text{sys}} \) is recorded until the GFA reconnects. The objective function is calculated through (5)–(7), and the adaptive gradient descent algorithm updates \( \beta \) through (8)–(10).

The autonomous frequency set-point adaptation can adjust to changing system dynamics and any increase or decrease of end-use load participation without the need for communication networks or a central-control authority. It should be noted that with the proposed learning algorithm, the expectation is not to achieve the absolutely ‘optimal’ load-shedding sequence for UF events. The high complexity and shifting dynamics of an operational microgrid make it impractical to equip GFAs with enough computational and communication power to find the globally optimal primary frequency response. The goal is to deploy controllers that can adapt to changing conditions and maintain their ability to participate in primary frequency response. Specifically, the aim is to avoid inverter trip-off during switching transients in networked microgrids and further enable the controllers to adapt to changing system dynamics such that a manual reset of frequency set points of each GFA controller is not required.

### 4 Simulation studies

To verify the performance of the method presented in the previous sections, dynamic simulations of networked microgrid operations are conducted using the GridLAB-D\textsuperscript{TM} simulation environment [43, 44]. A modified version of the IEEE 123-node test system with three microgrids [45, 46] is simulated to examine the incorporation of end-use loads equipped with GFA controllers for mitigating switching operation transients.

Each of the microgrids has a combination of diesel generators and inverter-connected solar PV generation, as detailed in Table 1. For each of the seven generation sources, Table 1 indicates which microgrid they are located in, which node they are connected to, the generator type, the rated apparent power, and the controller type(s) installed on the unit. The diesel generators are represented using the classical machine representation. The speed control governors use the GGOV1 model with SEXT-type voltage regulator control [47]. The PI controllers on the PV units use a standard grid-following representation. Grid-following PI controllers do not regulate frequency or voltage. Only grid-following inverters are considered here because they are more commonly deployed for cost reasons.

The inverters are assumed to be compliant with the IEEE standard 1547a [9] replicated in Table 2. A 1547a compliant inverter is required to trip off line if the frequency exceeds certain
Table 1 Distributed Energy Resource Data

| DER (#) | Node, # | DER type     | Rating, kVA | DER Controller type |
|---------|---------|--------------|-------------|---------------------|
| G1      | 1       | 50           | Diesel      | 1250                |
| G2      | 1       | 51           | PV          | 750                 |
| G3      | 1       | 151          | PV          | 500                 |
| G4      | 2       | 300          | Diesel      | 300                 |
| G5      | 2       | 101          | PV          | 120                 |
| G6      | 2       | 105          | PV          | 60                  |
| G7      | 3       | 97           | Diesel      | 600                 |

Table 2 IEEE Std. 1547a frequency ranges

| Function | Default settings | Range of adjustability | |
|----------|------------------|------------------------|---|
|          | Frequency, Hz    | Clearing time, s       | Clearing time, s |
| UF1      | <57.0            | 0.16                   | 56–60             | 10 |
| UF2      | <59.5            | 2.00                   | 56–60             | 300 |
| OF1      | >60.5            | 2.00                   | 60–64             | 300 |
| OF2      | >62.0            | 0.16                   | 60–64             | 10 |

Fig. 3 IEEE 123-node test system with three microgrids highlighted

Fig. 4 Case 1: Microgrid 1 frequency and total generator active power output when the substation is lost. In this case, end-use loads do not participate in primary frequency control

values for a given period of time. There are four functions, two for UF and two for over-frequency. IEEE std. 1547a provides ranges for frequency and clearing times, with recommended default settings for each of the four functions. By default, function UF1 requires an inverter to trip off line for larger magnitude short duration transients; specifically, if the frequency drops below 57.0 Hz for longer than 0.16 s. By default, function UF2 requires an inverter to trip off line for smaller magnitude longer duration transients; specifically, if the frequency drops below 59.5 Hz for longer than 2 s. The two over frequency functions, OF1 and OF2, operate similarly to UF1 and UF2 except that they operate on frequencies above the 60.0 Hz nominal.

Consistent with the IEEE 123-Node Test System, the end-use loads are represented by a composition of constant impedance, constant current, and constant power element. The shading in Fig. 3 illustrates the boundaries of the three microgrids overlaid on the IEEE 123-node test system.

A detailed description of the system is provided in [29]. Four use cases are examined in the following subsections. The simulations represent how GFA setpoints would be autonomously adjusted after deployment and how the GFAs would affect the system for events other than switching transients.

4.1 Baseline operating conditions

In the baseline case, it is assumed that due to storm activity, the utility anticipates a high probability of losing the single transmission line supplying the distribution substation. Hence, the utility operates the microgrids and the DERs to support critical loads. Initially, the three microgrids shown in Fig. 3 are interconnected to each other and the substation, with 3490 kW of load. Similar to the basic IEEE 123-node system, the switches between nodes 151 and 300 and nodes 54 and 94 are normally open. At $t = 1.00$ s, the utility operates the switch between nodes 60 and 160 to island the combination of Microgrids 2 and 3, designed to operate as a single community microgrid for resource sharing [8]. The isolation of Microgrids 2 and 3 leaves only Microgrid 1 interconnected with the substation. At $t = 3.00$ s, storm events cause loss of the substation voltage, isolating Microgrid 1. The transient caused by the loss of the substation is typical of the type of transients seen during networked microgrid operations.

4.2 Case 1: response without GFA participation

Case 1 assumes that Microgrid 1 does not have any GFA controllers, and only the DER controls participate in primary frequency response. Fig. 4 illustrates the frequency response and the total active power output of Microgrid 1. Despite the nameplate capacity of the generation being greater than the end-use load, the frequency transient experienced by Microgrid 1 is extreme enough that all inverters trip off-line at $t = 3.15$ s on function UF2. The loss of nearly 1200 kW of PV results in a generation deficiency, which causes a loss of short-term frequency stability, as defined in [7].

4.3 Case 2: response with GFA participation through the proposed learning algorithm

In Case 2, 170 end-use loads incorporate GFA controllers using the set-point adaptation algorithm presented in Section III; the 170 units control ~2100 kW of end-use load. Each GFA controller locally runs the set-point adaptation algorithm for UF events, continuously tracking the real-time active power consumption and thermal distance. The initial values of the tier coefficient $\beta$ and the learning rate $\alpha$ are 0.050 and 0.015, respectively, with $f_{\text{max}} = 59.95$. These initial values were selected for their heuristic performance, and do not have a formal analytic basis. The intent is that the initial setpoints are selected to provide an acceptable level of performance during the first UF event and that the setpoints automatically adjust through the adaptive algorithm for improved
Fig. 5 Case 2: Changing frequency profile of Microgrid 1 as GFA controllers iterate adaptive UF set points

Fig. 6 Case 2: Microgrid 1 frequency and total generator active power output when the substation is lost. End-use loads participate in primary frequency control via GFA controllers

Fig. 7 Case 3: Comparison of frequency trends with and without end-use loads participating in primary frequency control via GFA controllers with (a) 80% load, (b) 70% load on the system

performance over time. The goal is to achieve set points that will support stability and the smallest frequency drop during the transient with minimal interruptions to end-use load operations. Fig. 5 shows how the frequency response of the system improves from the baseline operating conditions over iterations 1–5 of the switching transient when the GAs are equipped with the set-point adaptation algorithm. While this paper shows how the algorithm adapts to simulation results, deployed GFAs would adjust setpoints based on local events without any simulation. With the initially selected GFA set points, i.e. iteration 1 in Fig. 5, the GFAs operate to successfully prevent the inverters from tripping. The algorithm adjusts the frequency setpoints according to the measured response, through iterations 2 to 5, and modifies the value of β to reduce the frequency deviation even further during the next UF event.

The corresponding non-linear, cumulative frequency response for the same iterations is on the right side of Fig. 5 and shows that the biased distribution of GFA setpoints are such that the end-use loads consuming less power engage first and larger loads engage only during larger transients. The exact responses during iterations 4 and 5 are very similar to each other, and the differences in setpoints cannot be viewed. The fifth and final iteration presents results in a 0.7 Hz frequency deviation, as shown in Fig. 6, and requires the participation of only 6% of the end-use loads. After the fifth iteration, the response is the same for subsequent iterations because the adaptive gradient descent algorithm has converged.

The initial values of the tier coefficient β and learning rate α influence the exact iterative response of the GFAs. A very small learning rate would mean that the response does not significantly improve with each iteration, and a large number of iterations are needed to reach a stable value. On the other hand, a very large learning rate could lead to a response where too many GFAs are operated, leading to large overshoots following the UF event. This is a property of the adaptive gradient algorithm, and is still widely studied in the field of machine learning and controls engineering. The adaptive gradient descent algorithm is well suited for adapting the learning rate to an application with sparse data, such as the UF set-point selection, and a suitable range for assigning the initial values can be selected through a predereffect simulation analysis without requiring a rigorous tuning process during field deployment. With no changes to the system loading or topology, the adaptive gradient descent algorithm will adjust the tier coefficient β to a stable value for each GFA controller, and the corresponding setpoints will change only with the specific load’s tier value at any time.

4.4 Case 3: response with GFA participation in a system with reduced load

The operating conditions of a typical microgrid with DERs are constantly in flux with varying load levels. Case 3 examines the frequency response with GFA participation when the overall load on the system is reduced to 80 and 70% of the baseline operating conditions of the IEEE 123-node system. The purpose of this use case is to establish that the participation of GFAs does not cause instability when the network is less loaded and end-use load participation may not be necessary during switching transients. All the cases studied delivered a frequency response that stabilised after the switching transient, with the GFAs contributing to improved frequency response at different scales. Greater system inertia and lower load demand than the baseline operating condition mean a more favorable network condition for frequency stability, and the GFA controller responses led to less improvement in frequency response than was attained in Case 2. Fig. 7 shows results for this case. Both results show more favorable network conditions than the baseline operating condition and neither leads to system collapse without the participation of GFAs. However, even with the GFAs participating, the system avoids adverse effects and experiences better frequency response in both cases. The improvement in response is smaller with the more reduced load because the network conditions make it less prone to instability.

4.5 Case 4: response with GFA participation in a system with high inertia

Typical microgrid with DERs experience varying production portfolios along with varying load levels. Case 4 examines the frequency response with GFA participation when diesel generation contributes 80% of capacity (rather than the standard 50% of the IEEE 123-node system), which increases the system inertia. The purpose of this use case is to establish that the participation of
Networked microgrids have the potential to increase the resilience of critical end-use loads beyond what can be achieved with traditional stand-alone backup generators or isolated microgrids. However, the frequency deviations experienced during the required switching transients can result in dynamic instabilities that lead to a loss of service.

This paper builds on past work using GFA controllers for end-use loads and presents an adaptive frequency set-point selection algorithm to support primary frequency response during switching transients. In determining the individual time-varying UF set points, the presented method prioritises the end-use loads based on real-time power consumption and the current thermal distance from temperature set points. The determined priority level influences the UF set-point selection employing a tier coefficient that adapts to changing system dynamics. The setpoints are selected using an adaptive gradient descent based algorithm. The setpoints adaptively update over time as more power system transients are experienced, so they are based on recent system conditions.

The simulation results validate the approach through extensive testing over various operational scenarios. The adoption of the learning-based load control algorithm reduces frequency transients. This avoids the baseline inverter trip-off conditions. Further, the algorithm improves over time consistently improving the effectivenes of the primary frequency control. The algorithm is completely decentralised and autonomous, which obviates the need for a communications infrastructure and the need to manually tune individual GFA controllers.

Additional simulations test how the adoption of the algorithm affects normal operational conditions. Separate cases explore the frequency response during changing generation portfolios, varying load levels, and a sudden step increase in system load. In all cases, the algorithm improves the frequency response and also limits the end-use load engagement to a minimal amount.

Future work will develop the theoretical basis of the bounds for the selection of control parameters associated with the adaptation algorithm and analyse the system dynamics with varying levels of GFA penetration and inclusion of energy storage technologies in networked microgrid operations.

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