Median-Consensus-Based Deception-Tolerant Secondary Frequency Control for Distributed Generators

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***Abstract*—With the increasing penetration of renewable energy, modern power systems are evolving into cyber-physical systems, where secondary frequency regulation becomes vulnerable to communication disturbances such as false data injection and outliers. To address this issue, this paper proposes a resilient distributed secondary frequency control strategy based on median consensus and local-global coordination. Different from conventional weighted-average-based methods, the proposed approach employs a median filtering mechanism based on order statistics to reduce the influence of corrupted data. Each distributed generator updates its control input using only local and neighboring frequency information. By incorporating the reachability of the global reference frequency, a median-based local reference is constructed for each node, based on which an iterative distributed control law is developed. Simulation results demonstrate the effectiveness of the proposed method in maintaining stable frequency regulation and reference tracking under communication disturbances.**

Keywords—Microgrid, secondary frequency control, resilient control, median consensus, cyber-physical systems, distributed control.

I. INTRODUCTION

With the increasing penetration of renewable energy, modern power systems are evolving into low-inertia cyber-physical systems (CPSs) [1]. Although distributed generation and energy storage improve operational flexibility, they also reduce physical inertia and damping, making system frequency more sensitive to disturbances. Recent studies on renewable-energy-based interconnected power systems and load frequency control have shown that robust frequency stabilization becomes increasingly important under high renewable penetration [2]. Meanwhile, the growing dependence of secondary frequency regulation on communication networks introduces new vulnerabilities, such as false data injection, outliers, delays, and packet loss [3]. In particular, false data injection attacks have been widely recognized as a critical security threat in cyber–physical power systems [4]. As a result, resilient secondary frequency control under non-ideal communication conditions has become an important issue in microgrids.

Distributed secondary frequency regulation has been widely studied because of its scalability and its ability to avoid the single-point-of-failure problem of centralized schemes [5]. Related studies on microgrid control and multi-energy microgrid optimization indicate that distributed or decentralized coordination mechanisms are effective for improving system flexibility and scalability [6], [7]. Existing methods usually rely on average-consensus-based protocols to coordinate distributed generators for frequency restoration and power sharing. However, their performance may deteriorate significantly under communication disturbances or cyberattacks [8], [9]. Robust control provides an effective framework for handling uncertainties and disturbances, and recent frequency regulation studies have demonstrated the effectiveness of optimized MPC-based control, fuzzy-PID control, and disturbance-observer-based control in improving frequency stability under renewable energy fluctuations [10], [11]. Nevertheless, conventional average-consensus mechanisms remain sensitive to corrupted data.

As a robust alternative to average consensus, median consensus can suppress the influence of outliers and malicious data by replacing weighted averaging with median-based updates [12], [13]. However, median-based methods have never been studied in the distributed secondary control problem. To address these issues, this paper proposes a resilient distributed secondary frequency control strategy based on median consensus. A nonlinear order statistic filter is introduced to mitigate corrupted communication data, while a pinning-based leader-follower mechanism is incorporated to improve convergence and guarantee accurate frequency restoration [14], [15].

The remainder of this paper is organized as follows. Section II presents the system model and problem formulation. Section III develops the proposed control strategy. Section IV provides simulation results. Section V concludes the paper.

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II. Problem Formulation

A. System Model

Consider a microgrid composed of N distributed generators (DGs), indexed by the node set $\mathcal{V} = \{1,2,\dots,N\}$. The information exchange among DGs is described by a directed communication graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$, where $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ denotes the set of communication links, and $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N\times N}$ is the weighted adjacency matrix. An edge $(j,i) \in \mathcal{E}$ indicates that DG i can receive information from DG j, and $a_{ij} = 1$ represents the corresponding communication weight; otherwise, $a_{ij} = 0$. We assume that there is no self-loop, i.e., $a_{ii} = 0$ for all $i \in \mathcal{V}$. A directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ is said to be $(2f+1)$-connected if, for any nonempty proper subset $\mathcal{S} \subset \mathcal{V}$, there exists at least one node $i \in \mathcal{S}$ that has no fewer than $(2f+1)$ in-neighbors outside $\mathcal{S}$, i.e.,

$$|\mathcal{N}_i \backslash \mathcal{S}| \geq 2f+1.$$

The neighbor set of DG i is defined as $\mathcal{N}_i = \{j \in \mathcal{V} \mid (j,i) \in \mathcal{E}\}$. A path from node i to node j is defined as a sequence of nodes $(i = v_0, v_1, \dots, v_\ell = j)$ such that $(v_{k-1}, v_k) \in \mathcal{E}$ for all $k = 1, \dots, \ell$. The graph $\mathcal{G}$ is said to be strongly connected if there exists a directed path between any pair of nodes.

Assumption 1: The communication graph $\mathcal{G}$ is $(2f+1)$-connected, and each normal DG can receive at least $2f+1$ values at each update instant.

The reference frequency is denoted by ω^{ref}, which is assumed to be constant. If the ith node can access to the reference frequency, then $b_i = 1$. Otherwise, $b_i = 0$.

Each DG is assumed to operate under primary droop control, while a distributed secondary controller is employed to restore the system frequency. The frequency dynamics of DG i are described by

$$M_i \dot{\omega}_i(t) = -D_i \omega_i(t) + P_i^m(t) - P_i^e(t) + v_i(t),$$

where $\omega_i(t)$ is the frequency deviation, $M_i > 0$ and $D_i > 0$ denote the inertia and damping coefficients, $P_i^m(t)$ and $P_i^e(t)$ are the mechanical input and electrical output power, respectively, and $v_i(t)$ is the secondary frequency control input.

Define the net power imbalance as

$$P_i(t) = P_i^m(t) - P_i^e(t).$$

Then, the dynamics can be rewritten as

$$M_i \dot{\omega}_i(t) = -D_i \omega_i(t) + P_i(t) + v_i(t).$$

Since the proposed control strategy is implemented digitally, the system is discretized with a sampling period $T_s > 0$. Let

$$\omega_i[k] = \omega_i(kT_s), \quad x_i[k] = x_i(kT_s),$$
$$P_i[k] = P_i(kT_s), \quad v_i[k] = v_i(kT_s).$$

Using the forward Euler method, the discrete-time dynamics of DG i are obtained as

$$\omega_i[k+1] = \omega_i[k] + \frac{T_s}{M_i}(-D_i \omega_i[k] + P_i[k] + v_i[k]).$$

Equivalently,

$$\omega_i[k+1] = \left(1 - \frac{D_i T_s}{M_i}\right)\omega_i[k] + \frac{T_s}{M_i} P_i[k] + \frac{T_s}{M_i} v_i[k].$$

Since T_s is usually chosen to be sufficiently small, it is reasonable in the subsequent analysis and controller design to take $\left(1 - \frac{D_i T_s}{M_i}\right) \approx 1$.

Moreover, to compensate for the power imbalance, the secondary control input is designed to include a feedforward term $-P_i[k]$, i.e.,

$$v_i[k] = u_i[k] - P_i[k],$$

where $u_i[k]$ is the distributed feedback control to be designed. Substituting the above expression into the discrete-time model yields

$$\omega_i[k+1] = \omega_i[k] + \frac{T_s}{M_i} u_i[k].$$

Define $\beta_i = \frac{T_s}{M_i}$. Then, the resulting discrete-time model can be compactly expressed as

$$\omega_i[k+1] = \omega_i[k] + \beta_i u_i[k]. \tag{1}$$

B. Information Corruption Model

In practical communication networks, the information transmitted by DGs may be corrupted due to communication failures, faulty devices, or deceptive behaviors. In this paper, such abnormal data are modeled at the node level, namely, some DGs may transmit corrupted state values to their neighbors.

Let $\mathcal{F} \subset \mathcal{V}$ denote the set of corrupted DGs, which is unknown a priori. It is assumed that the total number of corrupted DGs in the network is upper bounded by a nonnegative integer f, i.e.,

$$|\mathcal{F}| \leq f.$$

For a normal DG $i \in \mathcal{V}\backslash\mathcal{F}$, the exact number of corrupted neighbors is unknown, but cannot exceed f. The value received by DG i from its neighbor $j \in \mathcal{N}_i$ is denoted by $\widetilde{\omega}_j[k]$. If DG j is normal, then the transmitted value is its true state, i.e.,

$$\widetilde{\omega}_j[k] = \omega_j[k], \qquad j \in \mathcal{V}\backslash\mathcal{F}.$$

If DG j is corrupted, then the transmitted value $\widetilde{\omega}_j[k]$ may be arbitrary.

Hence, the set of neighboring values received by DG i is given by

$$\{\widetilde{\omega}_j[k] : j \in \mathcal{N}_i\},$$

among which at most f values may be corrupted.

To ensure that the correct neighboring information dominates the corrupted one, it is further assumed that each normal DG has at least $2f+1$ neighbors, i.e.,

$$|\mathcal{N}_i| \geq 2f+1, \qquad \forall i \in \mathcal{V}\backslash\mathcal{F}.$$

Under this condition, each normal DG receives at least $f+1$ correct neighboring values, which is strictly greater than the maximum possible number of corrupted values. This condition is necessary; otherwise, if the number of corrupted values is not smaller than that of the correct ones, then based solely on the

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received neighboring data, no algorithm can reliably distinguish the correct information from the corrupted information.

C. Problem Descriptionl

Under the system model and the information corruption model described above, the objective is to design a distributed secondary frequency control law $u_i[k]$, using only locally received neighboring information, such that

$$\lim_{k\to\infty}\omega_i[k]=\omega^{ref},\qquad \forall i\in\mathcal{V}, \tag{2}$$

for the closed-loop system, even when the information transmitted by the corrupted DGs is arbitrary.

III. Resilient Distributed Secondary Frequency Control

Building upon the problem formulation, this section details the design of the nonlinear median-based secondary controller and mathematically analyzes its stability and convergence properties.

A. Median-Consensus-Based Control Law Design

The traditional control law updates the secondary command $u_i(t)$ by algebraically aggregating the differences between the local state and all neighbor states:

$$\begin{aligned}u_i^{av}[k]=-K_i(&\sum_{j\in\mathcal{N}_i}a_{ij}\,(\omega_i[k]-\widetilde{\omega}_j[k])\\&+b_i(\omega_i[k]-\omega^{ref})),i\in\mathcal{N}.\end{aligned} \tag{3}$$

where K_i is the integral gain, and a_{ij}, b_i represent the communication weights. The fundamental flaw of this traditional architecture lies in its reliance on a linear algebraic summation. If even a single neighbor $j\in\mathcal{C}_i$ transmits severely corrupted data (e.g., an extremely large value $\widetilde{\omega}_j^c[k]\to\infty$), the entire summation term diverges. This unbounded error is directly integrated into $u_i^{av}[k]$ and injected into the physical primary droop layer, causing severe frequency oscillations and eventual system collapse. Thus, conventional average-consensus fails entirely under the information corruption model.

To overcome the inherent fragility of linear aggregation, we introduce a nonlinear filtering mechanism based on order statistics. Rather than algebraically summing the data, DG_i collects the incoming frequencies and forms a local dataset $\Omega_i[k]$ alongside its own state

$$\Omega_i[k]=\{\,\widetilde{\omega}_j[k]\mid j\in\mathcal{N}_i\,\}\cup\{\omega^{ref}\big|b_i=1\}. \tag{4}$$

The filter sorts $\Omega_i[k]$ in ascending order to obtain the ordered sequence

$$\widetilde{\omega}_{i,1}[k]\le\widetilde{\omega}_{i,2}[k]\le\cdots\le\widetilde{\omega}_{i,|\Omega_i|}[k] \tag{5}$$

The robust reference state, $\omega_i^r[k]$, is extracted via a median mapping function

$$\omega_i^r[k]=\begin{cases}\widetilde{\omega}_{i,\left(\frac{||\Omega_i||+1}{2}\right)}[k], & \text{if } |\Omega_i| \text{ is odd}\\ \frac{1}{2}\left(\widetilde{\omega}_{i,\left(\frac{|\Omega_i|}{2}\right)}[k]+\widetilde{\omega}_{i,\left(\frac{|\Omega_i|}{2}+1\right)}[k]\right), & \text{if } |\Omega_i| \text{ is even}\end{cases} \tag{6}$$

By replacing the vulnerable summation term with the robust reference, the proposed resilient discrete-time control law is formulated as

$$u_i[k]=-K_i\big((\omega_i[k]-\omega_i^r[k])\big) \tag{7}$$

where $K_i>0$ is the integral gain that determines the speed of frequency restoration.

Substituting (7) into the discretized physical layer dynamics (1), the closed-loop frequency update equation becomes

$$\omega_i[k+1]=\omega_i[k]-K_i\beta_i(\omega_i[k]-\omega_i^r[k]),i\in\mathcal{N}. \tag{8}$$

B. Convergence Analysis

We aim to show that $e_i[k]=\omega_i[k]-\omega^{ref}$ converges to zero, and hence the frequencies of all DGs asymptotically track the reference frequency ω^{ref}.

Define

$$e_{\max}[k]=\max_{i\in\mathcal{V}}e_i[k],\qquad e_{\min}[k]=\min_{i\in\mathcal{V}}e_i[k].$$

The error dynamics of each DG are given by

$$e_i[k+1]=e_i[k]-K_i\beta_i(e_i[k]-e_i^r[k]),$$

where

$$e_i^r[k]=\omega_i^r[k]-\omega^{ref}.$$

Equivalently,

$$e_i[k+1]=(1-K_i\beta_i)e_i[k]+K_i\beta_ie_i^r[k].$$

Since the ith node collects at least $2f+1$ values, among which at least $f+1$ are correct, the median-based reference satisfies

$$e_{\min}[k]\le e_i^r[k]\le e_{\max}[k],\qquad \forall i\in\mathcal{V}. \tag{9}$$

Assume that the control gain satisfies

$$0<K_i\beta_i<1. \tag{10}$$

Then

$$\begin{aligned}(1-K_i\beta_i)e_i[k]+K_i\beta_ie_{\min}[k]&\le e_i[k+1]\\&\le(1-K_i\beta_i)e_i[k]+K_i\beta_ie_{\max}[k].\end{aligned} \tag{11}$$

Since $e_i[k]\ge e_{\min}[k]$, it follows that

$$e_i[k+1]\ge e_{\min}[k],$$

where the equality holds if and only if $e_i[k]=e_{\min}[k]$ and $e_i^r[k]=e_{\min}[k]$, namely, node i attains the minimum error at time k.

Similarly, since $e_i[k]\le e_{\max}[k]$, one has

$$e_i[k+1]\le e_{\max}[k],$$

where the equality holds if and only if $e_i[k]=e_{\max}[k]$ and $e_i^r[k]=e_{\max}[k]$, namely, node i attains the maximum error at time k.

Therefore,

$$e_{\min}[k]\le e_i[k+1]\le e_{\max}[k],\qquad \forall i\in\mathcal{V}.$$

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That is, the interval $[e_{\min}[k], e_{\max}[k]]$ is forward invariant.

Theorem 1: Consider the system (1) under Assumption 1. If the control is designed as (7) with gain K_i satisfying (10), then it holds (2).

Proof: From the previous analysis, the interval $[e_{\min}[k], e_{\max}[k]]$ is forward invariant, and

$$e_{\max}[k+1] \le e_{\max}[k], \qquad e_{\min}[k+1] \ge e_{\min}[k].$$

Hence, $\{e_{\max}[k]\}$ and $\{e_{\min}[k]\}$ are both convergent. Denote

$$\bar{e}_{\max} = \lim_{k\to\infty} e_{\max}[k], \qquad \bar{e}_{\min} = \lim_{k\to\infty} e_{\min}[k].$$

We first show that $\bar{e}_{\max} = \bar{e}_{\min}$. Suppose, on the contrary, that

$$\bar{e}_{\max} > \bar{e}_{\min}.$$

Consider the set

$$\mathcal{S} = \left\{ i \in \mathcal{V} : \lim_{k\to+\infty} e_i[k] \le \bar{e}_{\min} + \varepsilon \right\}, \tag{12}$$

where $\varepsilon < \min_{i\in\mathcal{V}} \frac{K_i\beta_i}{K_i\beta_i+1}(\bar{e}_{\max} - \bar{e}_{\min})$ is a given small constant. Since the network is $(2f+1)$-connected, there exists at least one node $i_k \in \mathcal{S}$ that has at least $2f+1$ neighbors outside $\mathcal{S}$. It holds

$$e_{i_k}[k+1] = (1 - K_{i_k}\beta_{i_k})e_{i_k}[k] + K_{i_k}\beta_{i_k}e^r_{i_k}[k],$$

and $e^r_{i_k}[k]$ is outside of $\mathcal{S}$, which means $e^r_{i_k}[k] \ge \bar{e}_{\max} - \varepsilon$ for sufficiently large k. Hence,

$$\begin{aligned} e_{i_k}[k+1] &\ge (1 - K_{i_k}\beta_{i_k})\bar{e}_{\min} + K_{i_k}\beta_{i_k}(\bar{e}_{\max} - \varepsilon) \\ &\ge \bar{e}_{\min} + K_{i_k}\beta_{i_k}(\bar{e}_{\max} - \bar{e}_{\min} - \epsilon) \\ &> \bar{e}_{\min} + \epsilon \end{aligned}$$

which is a contradiction to the definition of $\mathcal{S}$. Therefore, one must have

$$\bar{e}_{\max} = \bar{e}_{\min} =: \bar{e}.$$

It remains to show that $\bar{e} = 0$. Since the leader reference ω^{ref} is included in the local dataset of each pinned node i with $b_i = 1$, the corresponding median-based reference $e^r_i[k]$ is directly affected by the value 0. If $\bar{e} > 0$, then for sufficiently large k, all node errors satisfy $e_i[k] > 0$. In this case, for every pinned node, the presence of the reference value 0 in its local dataset makes the median reference satisfy

$$e^r_i[k] < e_i[k]$$

whenever the node error stays at the positive consensus value. Consequently,

$$e_i[k+1] = (1 - K_i\beta_i)e_i[k] + K_i\beta_i e^r_i[k] < e_i[k],$$

which contradicts the assumption that $e_i[k] \to \bar{e} > 0$. Similarly, if $\bar{e} < 0$, then for sufficiently large k, all node errors satisfy $e_i[k] < 0$, and the inclusion of the reference value 0 yields

$$e^r_i[k] > e_i[k]$$

for pinned nodes, implying

$$e_i[k+1] > e_i[k],$$

which contradicts the assumption that $e_i[k] \to \bar{e} < 0$. Therefore, the only possible common limit is

$$\bar{e} = 0.$$

Hence,

$$\lim_{k\to\infty} e_i[k] = 0, \qquad \forall i \in \mathcal{V},$$

or equivalently,

$$\lim_{k\to\infty} \omega_i[k] = \omega^{ref}, \qquad \forall i \in \mathcal{V}.$$

The proof is complete.

IV. Simulation

To evaluate the effectiveness of the proposed resilient secondary frequency control, we utilize the IEEE 33-bus distribution system as the testing benchmark. The physical testbed consists of 33 buses and 32 lines. For the purpose of microgrid secondary control, we select $N = 6$ buses (e.g., buses 1, 6, 12, 18, 22, and 25) to be equipped with Distributed Generators (DGs). The communication graph $\mathcal{G}$ among the 6 DGs is designed to satisfy the $(2f+1)$ **-connectivity** requirement with $f = 1$. This implies that each normal DG is connected to at least 3 neighbors to ensure the median filter can isolate one corrupted node. The specific communication topology is illustrated in Fig. 1.

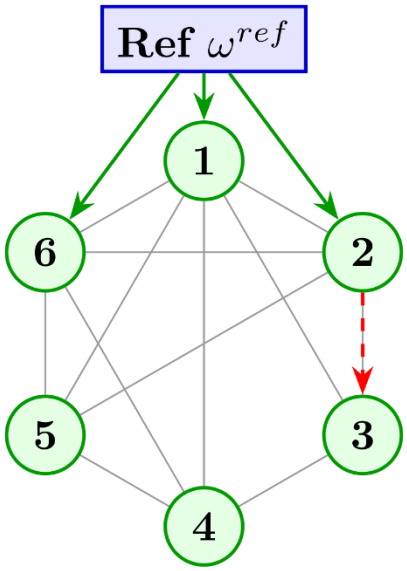

Fig. 1. Communication topology of the six-DG system with pinned reference information.

The system frequency dynamic is modelled as

$$\omega_i[k+1] = \omega_i[k] - \beta_i u_i[k], \quad i = 1,2,3,4,5,6, \tag{13}$$

where u_i is the control, and β_i is the control coefficient.

The reference frequency is set to $\omega^{ref} = 50$ Hz. The initial frequencies of the 6 DGs are randomly generated within the range of [49.5,50.5] Hz to simulate realistic operating conditions. The control gain is set to $K_i = 0.1$ for all DGs, and the control coefficient β_i is set to 0.05.

In the simulation, we consider a scenario where DG 2 is compromised and transmits corrupted frequency data to its neighboring DG 3. Specifically, the value received by DG 3 from DG 2 is modeled as

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$$\widetilde{\omega}_2[k] = \omega_2[k] + \xi[k],$$

where $\xi[k]$ denotes a Gaussian random disturbance.

Existing methods generally design the controller as

$$u_i[k] = -K_i\left(\sum_{j\in\mathcal{N}_i}(\omega_i[k] - \widetilde{\omega}_j[k]) + b_i(\omega_i[k] - \omega^{ref})\right). \quad (14)$$

By contrast, the proposed method employs a median-based controller given by

$$u_i[k] = -K_i(\omega_i[k] - \omega_i^r[k]), \quad (15)$$

where $\omega_i^r[k]$ is the median of the neighboring frequency values together with the reference frequency when $b_i = 1$.

The sampling period is chosen as $T_s = 0.01$ s, and the simulation results are shown in Fig. 2, Fig. 3, and Fig. 4. It can be observed that, under the proposed median-based control law (15), the frequency trajectories of all DGs converge smoothly to the reference frequency, which demonstrates the robustness of the proposed method against corrupted information. In contrast, under the conventional control law (14), the frequency trajectories exhibit severe oscillations and fail to converge to the reference frequency due to the corrupted data transmitted from DG 2. For comparison, the frequency trajectories under the conventional consensus-based controller without corrupted communication data are shown in Fig. 4, which further highlights the adverse effect of the attack and the superiority of the proposed median-based method.

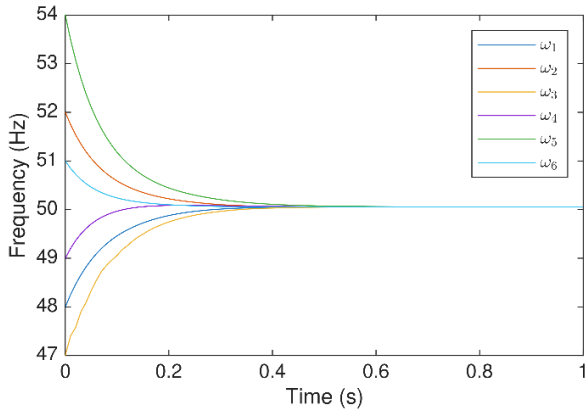

Fig. 2. Frequency trajectories under the proposed median-based control law (14) with corrupted communication data.

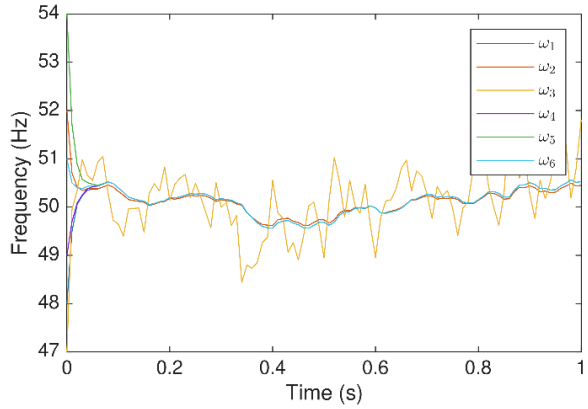

Fig. 3. Frequency trajectories under the conventional consensus-based control law (14) with corrupted communication data.

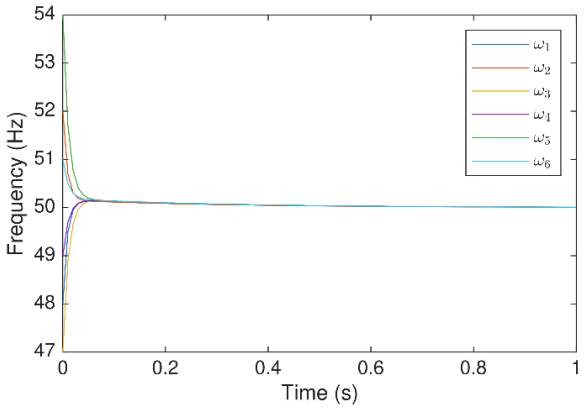

Fig. 4. Frequency trajectories under the conventional consensus-based control law (14) without corrupted communication data.

V. Conclusion

This paper addresses the critical issue of frequency regulation in microgrids under non-ideal communication conditions, where some distributed generators may transmit corrupted state information. We propose a resilient distributed secondary frequency control strategy based on a median-consensus algorithm, which inherently suppresses the influence of outliers and malicious data. The control law is designed to utilize the median of neighboring states, ensuring that the system can achieve frequency restoration even when up to f neighboring nodes are compromised, provided that the communication graph is $(2f + 1)$ -connected. Theoretical analysis confirms the convergence of the proposed control strategy, and simulation results on the IEEE 33-bus system demonstrate its effectiveness in maintaining frequency stability under adversarial conditions. Future work will explore the extension of this approach to more complex scenarios, including time-varying communication topologies, multi-agent systems with heterogeneous dynamics, and the integration of machine learning techniques for adaptive control gain tuning.

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