Impact of Open Communication Networks on Load Frequency Control with Plug-In Electric Vehicles by Cyber-Physical Dynamic Co-Simulation

Preprint

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Impact of Open Communication Networks on Load Frequency Control with Plug-In Electric Vehicles By Cyber-Physical Dynamic Co-simulation

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***Abstract*—With the increasing electrification of the transportation sector to achieve the carbon neutrality objective, despite the challenges of charging electric vehicles (EV), there are also opportunities through smart charging EVs to improve system frequency stability; however, EV control technologies might require nontraditional communication support. This paper investigates the impacts of communication variations of EV on power system load frequency control through a cyber-physical dynamic system (CPDS) co-simulation. Here, the CPDS is built upon our previously developed transmission-and-distribution dynamic co-simulation model with the added communication variation functions (i.e., delay and packet loss). The case studies consider multiple communication variation scenarios when the system experiences an N-1 generation trip contingency. The scenarios include communication delays and packet loss using both homogeneous and heterogeneous assumptions. The outcomes of this work can help improve EV frequency regulation services and provide robust and effective tests for different load frequency control algorithms of the future power systems.**

***Index Terms*—Communication, electric vehicle, frequency regulation, transmission-and-distribution-and-communication dynamic co-simulation, smart charging**

I. INTRODUCTION

To maintain a stable frequency, power systems normally have three layers of frequency regulation: primary, secondary, and tertiary frequency control [1]. With the increasing electrification of the transportation sector to reach the carbon neutrality objective by the middle of this century, despite the challenges of charging a large number of electric vehicles (EVs), there are also opportunities via smart charging plug-in electric vehicles (PEVs) to provide reliable grid ancillary services, such as load frequency control (LFC), realized by automatic generation control (AGC) [2]. To enable smart charging, EVs need: 1) a stable connection with the electric grid (i.e., PEVs), 2) high quality communications with the grid control center through aggregators using open communication networks [3] (i.e., cellular services used by mobile devices, internet of things technology), and 3) controls and metering onboard the vehicle [4]. With these in place, the vehicle can adjust its charging power with remote control signal. Although PEVs can also provide other grid services for local distribution systems [5], here, we focus on PEVs providing LFC to transmission system. Therefore, it is urgent to analyze the cyber-physical dynamic interactions between PEVs and the grid considering PEVs' potential communication variations such as extended latency and signal packet loss.

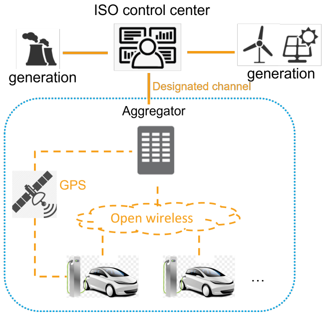

Fig. 1. Typical LFC system with EV aggregators

Ref. [6] used the state-space linear equation model to investigate the delay margin and the stability criterion of LFC with a time delay by PEVs. Ref. [7] developed an LFC method considering the time delay based on sliding mode control with EVs. Our previous work investigated the homogeneous delay margin by T&D dynamic co-simulation [8]. The advantages of the cosimulaion over the traditional state-space model include: 1) easily scalable because of the parallel computing structure; 2) provides a natural description of the overall cyber-physical system so that it is flexible to model communication impacts. (Cyber-physical systems are integrations of computation, communication, and physical processes [9].) However, past literature including our previous work did not analyze the impacts of the heterogeneous delay or packet loss, i.e., the delay times and the packet loss rate of different channels and at different time might not be the same, which could result in compromised control performance.

In this paper, we focus on the communication variation impacts, such as delays and packet loss, on the system frequency recovery after the N-1 generation contingency. The

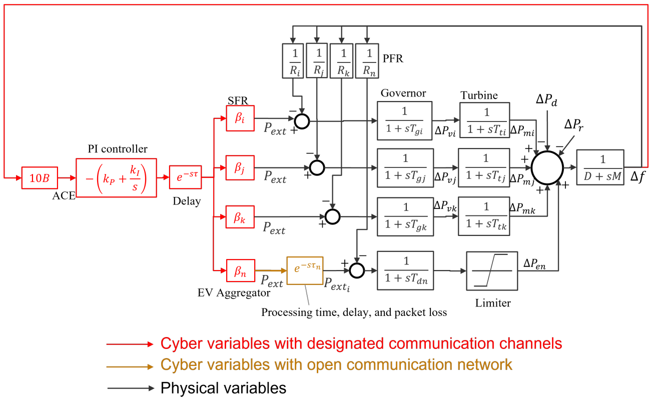

Fig. 2. LFC with communication considerations

main contributions of this paper can be summarized as follows:

- Our previously developed T&D dynamic co-simulation model [10] is extended with communication variation functionalities to simulate randomized communication delays and packet loss, thus an new transmission-distribution-communication (TDC, here also called cyber-physical dynamic system, CPDS) co-simulation model is designed.
- Multiple scenarios of communication variations are investigated, including homogeneous and heterogeneous delays and packet loss in AGC provided by EVs. To the best of our knowledge, these impacts—especially heterogeneous impacts for delays and packet loss—have not been investigated in existing LFC with PEVs.

II. EV AGGREGATORS AND LFC COMMUNICATIONS

A. *Aggregators for LFC*

Fig. 1 shows a typical LFC system with EV aggregators. The transmission control center sends control signals (generation set points) using the designated communications to the registered generation units for the LFC. For PEVs to provide this service, they likely need to have communications with the control center through aggregators [3] because transmission system operators typically have a minimum capacity requirement for a provider of ancillary services, e.g., 500 kw in PJM [11]. In addition, the aggregators might need to know the locations of the PEVs if there are different control areas. The aggregators can be in the form of remote terminal units that control the PEVs within a certain distance. Certain charging stations, smart buildings (e.g., EVs charge while the EV owners are at work), and multiunit apartments or houses with PEVs can also be considered aggregators [12].

B. *LFC*

Fig. 2 shows a dynamic model of LFC, enabled by an AGC model [1]. The model includes an area-level (assuming one area) estimation of the area control error (ACE) and a plant-level control that receives the secondary frequency response (SFR) reference power, P_{ext}, for each plant [13]. When there are aggregators in the system, after the aggregator receives the control signals, there is an additional layer to allocate the control signals to individual PEVs. The communication-related considerations are described in the next subsection.

C. *Communication Considerations*

Conventional LFC is transmitted through designated private communication channels from the system control center to generation plants. It is relatively reliable, and the time delay normally ranges from 80–200 milliseconds [14]; however, to enable grid services from EVs, aggregators of numerous EVs might send power dispatch commands wirelessly to the vehicles, therefore the wireless open communication networks are likely used instead of the designated private communication network. This method also avoids the high cost of connecting a large number of EVs using the private channels. In addition, because of the mobility of EVs, it's impractical to have static communication infrastructures from aggregators to EVs.

The smart charging demonstration project in [15] used Cellular Digital Packet Data[1] (CDPD, i.e., 2G family) to communicate between the aggregator and EVs. The project also showed that there was a latency of 400–2000 milliseconds among all packets being transmitted; note that these values include battery response time. A different test in [11] did not use wireless communications but leveraged the communication link inside the connector (the charging cable of EVs) and thus required plugging in; then, with the help of a specially designed board mounted on the vehicle, this formed a communication connection between the charging station and the vehicle. Under the assumption that charging stations or buildings can be aggregators, the authors in [12] discussed different wireless communication techniques to be considered between the aggregator and individual EVs: Zigbee, Near-Field Communication, Bluetooth, IEEE 802.11p, and WiMAX; however, these technologies cover a limited distance, from 10 m to 5 km. The project in [16] used the cloud to host aggregators for controlling home energy management systems: Once the home energy management system is connected with the internet, the communication is formed. It is promising that cellular network technologies (i.e., 4G, 5G) can fulfill the needs of smart charging—they are fast, mobile, inclusive, etc. Statistical data[2] show that 4G and 5G are fast, have high reliability, and the median latency of both is approximately 33 milliseconds.

When receiving an AGC signal, the EV aggregator (e.g., hosted in the cloud) will allocate and send the signal to each participating vehicle through open communications; a representative block is highlighted in yellow in Fig. 2. This process might include multiple communication delays of different communication and measurement channels, processing times of the aggregator, response rates of the PEV batteries, and packet loss caused by imperfect network reliability. In open communication networks, the time delays and data packet loss are somewhat random, and their average behaviors depend on many factors, such as communication network capacity and transmitted distance.

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[1] https://en.wikipedia.org/wiki/Cellular_digital_packet_data

[2] https://www.speedtest.net/global-index/united-states#mobile

III. CPDS Co-simulation Platform

A. *CPDS Co-simulation Introduction*

The CPDS co-simulation model in this paper is based on our previously developed T&D dynamic co-simulation framework [10]. In this paper, we add communication variation functions, i.e., random homogeneous/heterogeneous communication delays and packet loss. The overall CPDS model is based on the Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) [17] and the open-source power system simulators ANDES (for transmission dynamics) and OpenDSS [18] (for distribution). HELICS enables different simulators to perform time-based simulations together and maintains synchronizations among them. The communication variations are enabled by the filter functions in HELICS.

To investigate EV LFC service, assume that the overall system comprises a transmission system, a control center, many distribution systems, and many EV aggregators with PEV loads that are hosted in distribution systems. The transmission system sends the system frequency measurement to the transmission control center every 0.5 second, where the ACE signals and the AGC signals are calculated with the PI controller and sent to the EV aggregators every 4 seconds, and the aggregator will then allocate control signals to each PEV.

B. *Communication Layer Model*

Assume that the communication variations can happen each time whenever transmitting data are needed. In the developed mode, we add two filter functions in HELICS to each communication channel: delay filter and packet loss filter functions.

A delay filter function can keep a sending end point from sending the data until a preconfigured time is past and then pass on the data to the destination end point; this preconfigured time (read by a HELICS broker[3] internally) can be a constant or generated randomly from a distribution, i.e., normal distribution. The normal distribution assumption is based on the information in [14]. This setup can model a constant or time-varying delay for different communication channels.

In addition, each transmit of data packet has a chance of losing the packet (e.g., caused by hardware failure), resulting in the data packet either passing successfully or failing to pass. These events are naturally modeled as Bernoulli distributions and are parameterized by a single variable, p, the probability of packet loss, with $p \in [0, 1]$. Inside HELICS, the added packet loss filter function can remove the packet data problematically and not send it to the destination end point. Note that we allow different values of p for different communication channels.

IV. Case Studies

This section illustrates the impacts of smart charging with communication variations on the frequency response by a CPDS co-simulation. The co-simulation is performed on a 2,000-bus transmission network model covering most of the Electric Reliability Council of Texas region [19]. Two sets of cases are studied for the communication variations in the AGC signals. Case 1 explores the impact of the communication delay; Case 2 tests the packet loss effects. Note that there is a difference between the unidirectional smart charging and the bidirectional vehicle-to-grid (V2G), which can involve discharging EV batteries. To accentuate the effect of communication variations, in this section, we consider V2G, but it is important to recognize that very similar results would apply for smart charging for twice the number of vehicles in terms of the same amount of power provided to the grid.

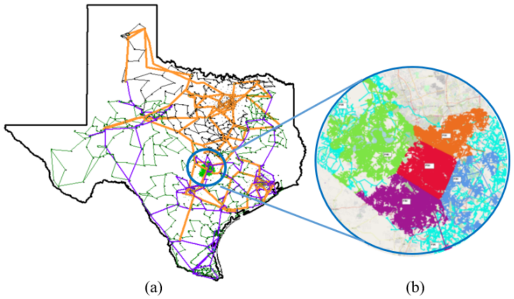

Fig. 3. (a) One-line diagram of the 2,000-bus case [19], with Austin area circled, and (b) five urban subregions in the distribution Austin data set [20]

A. *Large-Scale Test System and Setup*

Fig. 3 (a) shows a one-line diagram of the 2,000-bus transmission system. Fig. 3 (b) shows synthetic distribution feeders [20] that are used to attach to transmission load buses to form the overall T&D networks. The detailed overall system information can be found in [21]. There are 243 distribution feeders connected (modeled in detail), with an adjustment of load to match the transmission load, which represents approximately 2.83 GW. The overall distribution system contains a total of more than 1 million electrical nodes. Assume there are 8,400 distributed photovoltaic (DPV) units and 42,000 EVs connected to the distribution feeders Each EV is assumed to have a rated power of 7 kW and a rated energy capacity of 50 kWh. The total DPV power output is 222.7 MW, and the total installed DPV capacity is 2.1 GW, assuming a low PV power production time of the day, e.g., in the late afternoon. All 42,000 EVs consume 294 MW (charging at rated power) of power, and the total frequency regulation headroom is 588 MW (from rated charging to discharging).

The assumptions for the types of generation providing primary frequency response (PFR) and SFR are summarized in Table I; Each connected EV can provide support ranging from 100% charging to 100% discharging of rated power. The simulations assume that at the 5th second, a generator in the Austin area, with 477 MW of real power output, is dropped.

B. *Impacts of Homogeneous and Heterogeneous Delays*

1) Homogeneous: Fig. 4 shows the homogeneous delay with different delay times: i.e., 0, 2, 4, 10, and 20 seconds. It shows that longer delay times result in longer system frequency recovery. It is straightforward that with a large delay the system needs a long time to restore frequency to

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[3] https://docs.helics.org/en/latest/user-guide/fundamental_topics/helics_terminology.html

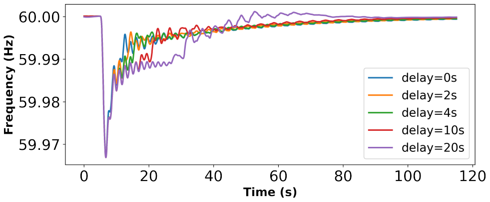

Fig. 4. Homogeneous delay with different delay times

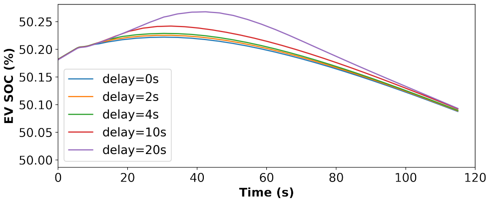

Fig. 5. EV SOC example

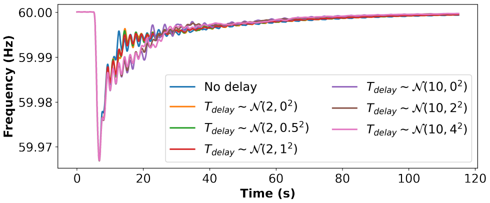

Fig. 6. Heterogeneous delay with different delay times

TABLE I

TYPES OF GENERATION

Generation Type	PFR	SFR
EV	Yes	Yes
DPV	Yes	No
Traditional unit	Yes	No

the nominal value. Accordingly, this will result in a change in its state of charge (SOC), as shown in Fig. 5. When a PEV is providing frequency regulation, its SOC can change from increasing to decreasing, which might slightly increase the PEV's charging time. Despite its insignificant impact, this should still be considered by PEV owners when a PEV is enabled to provide frequency regulation.

2) Heterogeneous: To simulate the time-varying and heterogeneous delay cases (i.e., different channels of AGC signals have different delays), it is assumed that each EV channel transmitting data each time has a delay time that follows a normal distribution, i.e., $T_{delay} \sim \mathcal{N}(\mu, \delta^2)$, with mean μ and standard deviation δ. Fig. 6 shows the comparison of the system frequency response under different normally distributed delay time assumptions. It shows that the impacts of the standard deviation of the delay time are not as significant as its mean value. This is because the control signals affected by the dispersed delay times (random delay times deviate from the mean) compensate each other; thus, compared to the standard deviation of the communication delay, the mean values of the communication delay have a more noticeable impact on the system frequency recovery.

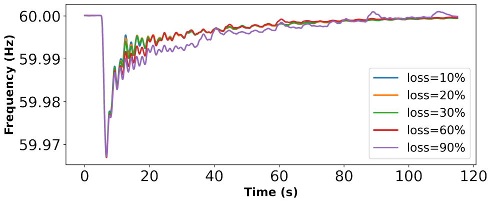

Fig. 7. Homogeneous packet loss with different loss rates

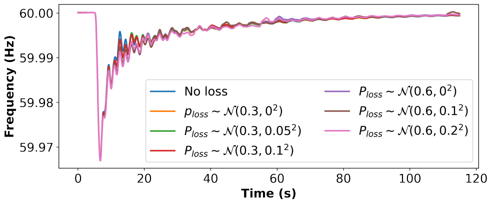

Fig. 8. Heterogeneous loss with different loss rates

C. Impacts of Homogeneous and Heterogeneous Packet Loss

Packet loss occurs when one or more packets of data traveling across a communication network fail to reach their destination. Packet loss is caused by either errors in data transmission, typically across wireless networks, or network congestion. Packet loss measures whether a packet sent is successful or fails each time, i.e., $X \sim Bernoulli(p_{loss})$, where $X \in \{0, 1\}$, and the loss rate $p_{loss} \in [0, 1]$. For example, if a transmission channel has a loss rate of 0.2, it means that there is a 20% chance the transmitting packet is lost each time the transmission channel is used.

1) Homogeneous: Fig. 7 shows the comparison of the homogeneous packet loss with different loss rates. It shows that the packet drop impacts are not as significant as the communication delays. This is because the packet drop is random and the packet drops of different channels can offset the impacts of each other.

2) Heterogeneous: The loss rates of different communication channels can be different and are assumed to be different this time. To represent the diversity of the loss rate, they are randomly generated for each communication channel from a normal distribution, i.e., $p_{loss} \sim \mathcal{N}(\mu, \delta^2)$, with mean μ and standard deviation δ. The simulated cases in Fig. 8 do not show significant different impacts on the system frequency recovery times. It is also observed that compared to the homogeneous packet drop in Fig. 7, the heterogeneous packet drop has a smaller impact on the system frequency recovery. This can be explained by the random packet drop compensating the effects of each other.

All the simulation results demonstrate the impact of the communication variations on the LFC by EVs using open communication networks. The results show that as the delay and packet loss rates increase, the system frequency tends to recover more slowly and thus the increasing impact to AGC performance. In extreme cases, the system frequency might oscillate (e.g., 20-second delay case, it seems a rather extreme case, but it is useful information for cyber-resilient research). The heterogeneous cases show a smooth effect in AGC [22].

Furthermore, the deviations of the communication variations among different channels are less significant compared with the mean values. In addition, the scalability of the proposed model has been proved by the size of the test system.

V. CONCLUSION

With the increasing electrification of the transportation sector, smart charging technologies are promising solutions to improve system flexibility. This paper studies the impacts of PEVs on the system frequency regulation considering communication variations. The simulation results demonstrate that the mean values of the communication delay have a higher impact on the frequency recovery than the standard deviation of the delay. Meanwhile, the packet drop impacts on the frequency restoration are not significant in both the homogeneous and heterogeneous packet drop rates. The quantitative analysis and modeling scheme in this paper can provide insights into designing future LFC algorithms and communication infrastructure planning for LFC with PEVs. Future work includes improvement of the communication modeling by using network simulator NS-3.

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