



Deposited via The University of Sheffield.

White Rose Research Online URL for this paper:

<https://eprints.whiterose.ac.uk/id/eprint/239656/>

Version: Accepted Version

Article:

Qiu, D., Zhang, S., Luo, T. et al. (2026) Global sensitivity analysis for cyber-physical power distribution network. IEEE Transactions on Industrial Cyber-Physical Systems, 4. pp. 213-224. ISSN: 2832-7004

<https://doi.org/10.1109/ticps.2026.3674974>

© 2026 The Authors. Except as otherwise noted, this author-accepted version of a journal article published in IEEE Transactions on Industrial Cyber-Physical Systems is made available via the University of Sheffield Research Publications and Copyright Policy under the terms of the Creative Commons Attribution 4.0 International License (CC-BY 4.0), which permits unrestricted use, distribution and reproduction in any medium, provided the original work is properly cited. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>

Reuse

Items deposited in White Rose Research Online are protected by copyright, with all rights reserved unless indicated otherwise. They may be downloaded and/or printed for private study, or other acts as permitted by national copyright laws. The publisher or other rights holders may allow further reproduction and re-use of the full text version. This is indicated by the licence information on the White Rose Research Online record for the item.

Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

Global Sensitivity Analysis for Cyber-Physical Power Distribution Network

Dongmeng Qiu, Suhan Zhang, Tianyu Luo and Xin Zhang

Abstract—Cyber-physical power systems (CPPS) operate under uncertainties from both the power and communication layers, yet there are limited systematic methods to evaluate uncertain cyber-physical impacts. To address this gap, we build a CPPS model by coupling a power distribution network represented by differential–algebraic equations (DAEs) and a discrete-event communication network with node-specific communication delays. On this basis, global sensitivity analysis (GSA) is introduced to quantify the impact of cyber-physical uncertainties on the power distribution network, thereby identifying the most critical factors that affect CPPS operation. Probabilistic models are used to simulate load, photovoltaic (PV) generation, and communication delays, and a Monte Carlo framework is built to estimate Sobol’ sensitivity indices. Finally, a CPPS digital co-simulation platform is developed which integrates OPAL-RT power system simulator and OMNeT++ communication network simulator via shared memory mechanism to validate the CPPS framework. Case studies demonstrate the quantitative relationship between the sources of uncertainty and their impacts within the CPPS, indicating that PV generation dominates the variance of bus voltages, whereas communication node delays mainly affect local voltage stability in the test system.

Index Terms—Cyber-physical power systems, global sensitivity analysis, uncertainty, digital co-simulation.

NOMENCLATURE

τ	Communication delay vector
$I(t)$	Injected current vector
$V(t)$	Bus voltage vector
δ_i	Stochastic delay deviation
η	Communication network state
κ, ε	Beta distribution shape parameters
λ_i	Delay uncertainty bound at node i
$\mathbf{u}^{\text{ps}}(t)$	Coupling inputs to the power system vector
$\mathbf{X}$	Uncertain input vector
$\mathcal{M}(\mathbf{X})$	Model output
$\mu_{\psi^{\text{lp}}}, \sigma_{\psi^{\text{lp}}}$	Mean and standard deviation of load active power
ν	System input signal
ζ	System output signal

d	PWM duty ratio
$G_C(\cdot)$	Communication state update map
$K(\cdot)$	Communication output map
N_x	Dimension of the uncertain inputs
$q_\ell(\cdot)$	Output extraction function
$S_i^{(\ell)}$	First-order Sobol’ index
$S_{T_i}^{(\ell)}$	Total-effect Sobol’ index
SR	Solar radiation
$SR_{\max}$	Maximum solar radiation
T_s	Synchronisation step
$t_{0,i}$	Nominal communication delay at node i
U_x, U_y	Real and imaginary parts of bus voltage
Y_N	Network admittance matrix
Y_ℓ	Scalar output

I. INTRODUCTION

THE increasing integration of advanced information and communication technologies (ICTs) into modern power grids has evolved into cyber-physical power systems. This integration brings significant benefits, including real-time monitoring, wide-area control, demand-side participation, and promoting renewable energy sources (RES) integration, all of which are critical to achieving the Net Zero target in the United Kingdom [1]. However, new vulnerabilities of the coupling CPPS structure have been created. For example, cyberattacks such as false data injection [2], denial-of-service attacks [3], or cross-layer hybrid attacks [4] can bypass traditional defense mechanisms, directly disrupting measurement and control processes between physical and cyber layers and triggering large-scale disturbance. In 2023, a hacker accessed power grid control systems and cut off power supply in Russia. In 2022, Sandworm caused an unplanned power outage in Ukraine. As a result, the cybersecurity and resilience of CPPS have become an urgent challenge that requires more attention.

The power distribution networks play an important role in CPPS, since they are developing towards active distribution networks that integrate active RES such as photovoltaics (PVs). Distribution networks are characterised by dispersed structures, bidirectional power flows, and high uncertainties due to stochastic demand and renewable generation [5]. In addition, power distribution networks connect directly to end users, where flexible resources are deployed, including electric vehicles, energy storage, and demand-side management. These unique features make distribution networks more sensitive to communication quality, providing significant challenges to the stability, security, and resilience of CPPS.

This work was supported by the U.K. Research and Innovation Future Leaders Fellowship entitled ‘Digitalisation of Electrical Power and Energy Systems Operation’ under Grant MR/W011360/2. (Corresponding author: Xin Zhang, Suhan Zhang).

D. Qiu, S. Zhang, and X. Zhang are with the School of Electrical and Electronic Engineering, the University of Sheffield, Sheffield, United Kingdom (e-mails: dqiu4@sheffield.ac.uk, suhan.zhang@sheffield.ac.uk, xin.zhang1@sheffield.ac.uk).

T. Luo is with the SSE Renewables, Glasgow City, Scotland, United Kingdom (e-mail: tianyu.luo@sse.com).

In recent years, significant progress has been made in analysing the uncertainties in the distribution network. Reference [6] identified several causes of uncertainty within communication networks, including both technical and economic factors. In [7], the uncertainties in communication performance (e.g., communication delay) can affect the reliability and operational quality of distribution. Reference [8] took the operator performance into account to present a human-in-the-loop uncertainty analysis. However, both [7], [8] have limited investigation on uncertainties in coupling systems. Reference [9] proposed quantitative indices with 5G-based recovery strategies to mitigate the effect of communication uncertainties. However, it lacked the validation provided by the CPPS digital co-simulation platform.

Despite these advancements, some limitations remain to be resolved. Many studies were still based on static or simplified models [10], [11], which lacked insight into power system dynamics and multi-source uncertainties. Communication delay analysis often relied on fixed or simple stochastic models [12], [13], failing to capture real network congestion, packet loss, and dynamic variations. Furthermore, most studies did not systematically quantify uncertainties or provide holistic assessments of CPPS resilience. Some studies relied on Monte Carlo simulations for security assessment or critical-component identification; however, high computational cost and data-quality limitations constrained their practical applicability, given the fact that these methods were purely theoretical [14].

To fill these research gaps, this paper proposes a global sensitivity analysis (GSA) method for CPPS based on a real-time digital co-simulation framework, which offers a systematic and quantitative approach to assess the influence of various uncertainties in the CPPS model. The main contributions are as follows:

- A probabilistic CPPS modelling framework is developed to establish coupling between a DAE-based power distribution network model and a discrete-event communication network, incorporating both physical and functional coupling. This enables bidirectional interaction and accurately captures cross-domain dependencies in CPPS.
- The GSA method is applied for the first time to CPPS to quantitatively assess the impact of system states and cyber variables on overall system performance. Both first-order and total-effect Sobol' indices are employed to distinguish the main effects from interaction effects of uncertainty, allowing a systematic ranking of uncertain inputs, and providing valuable information for uncertainty quantification.
- A digital co-simulation platform is proposed that employs a shared memory mechanism for efficient data exchange between the OPAL-RT power system simulator and the OMNeT++ communication network simulator. The real-time digital co-simulation platform is implemented to demonstrate the capability for CPPS digital co-simulation and validate the effectiveness of the proposed GSA method.

The rest of this paper is organised as follows: Section

II presents the probabilistic modelling of CPPS; Section III presents the GSA method with independent random inputs; Section IV describes the proposed real-time digital co-simulation platform; Section V reports simulation results on the IEEE 33-bus system; Section VI concludes the paper.

II. PROBABILISTIC MODELLING OF CYBER-PHYSICAL POWER SYSTEMS

A. Formulations of Power and Communication Systems

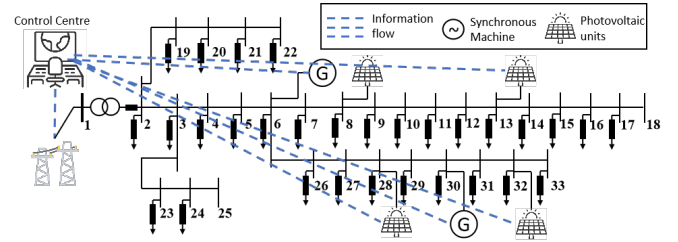


Fig. 1: IEEE 33-bus power distribution network with communication structure.

1) *Power System Model*: This paper focusses on a typical IEEE 33-bus power distribution network as shown in Fig. 1. The power distribution network includes both physical and cyber components, such as a main grid feeder, control centre, radial distribution lines, information flow, synchronous machines, distributed RES such as PV generation, and various loads connected at the buses. The physical components are typically modelled by DAEs,

$$\dot{x} = f(x, V), \quad (1)$$

$$0 = I(x, V) - Y_N V, \quad (2)$$

where x collects the states of the power system devices (machines, converters, controllers), V denotes the real and imaginary parts of the bus voltage vector, I denotes injected current vector from the power system devices, and Y_N is the network admittance matrix. The DAEs capture the system dynamics and couple the state variables with the network constraints, which are the basis for physical simulations in this work.

Synchronous machines are modelled with the classical rotor motion and stator voltage equations (rotor angle δ and speed deviation $\Delta\omega$), interfaced to the network through an internal transient electromotive force behind x'_d [15]. PV units are represented by a concise two-stage model of a PV array with DC/DC converter and a grid-tied inverter equipped with an L_f filter, where L_f denotes the inverter filter inductance. The array current-voltage relation feeds a DC-DC conversion stage that regulates DC-link voltage u_{dc} , while outer (DC-voltage and reactive power) and inner (current) PI loops set the inverter output; the resulting inverter and filter currents provide the PV contribution to I in (2). Detailed formulations of the full two-stage model can be found in [16].

2) *Communication Network Model*: Communication networks, including TCP/IP, VoIP and cellular technologies, are packet-switched systems and are commonly simulated as

discrete-event systems [17]. The state variables of communication components are updated according to discrete-events and are defined over discrete sets, rather than being derived from continuous dynamics. Mathematically, the communication system is formulated as follows: let $\eta \in \Upsilon$ represent the communication network state, where $\Upsilon \subset \mathbb{R}^{n_c}$ denotes the corresponding Euclidean state space. The condition of η is governed by a difference inclusion, with its right-hand side characterised by a set-valued communication state update map G_C . The system receives a system input signal $\nu \in \mathcal{V} \subset \mathbb{R}^{m_c}$, and the system output signal $\zeta \in \mathbb{R}^{r_c}$ is determined by a communication output map K that depends on both the state and the input:

$$\eta^+ \in G_C(\nu, \eta), \quad \zeta = K(\nu, \eta). \quad (3)$$

B. The Coupling Mechanism of Cyber-Physical Power Systems

In the proposed CPPS framework, the interaction between the power system and the communication network is represented by node-specific communication delays. These node-specific communication delays model the effective time shift between measurements, communication, and control actions at the system level, while the physical data-transfer delay of the digital co-simulation platform is assumed to be negligible and handled separately by the synchronisation mechanism [18].

Let $\mathbf{u}^{\text{ps}}(t)$ denote the coupling inputs to the power system vector and $\mathbf{u}^{\text{cn}}(t)$ denote the coupling inputs to the communication network vector, respectively. The coupling between the cyber and physical layers is formulated as

$$\mathbf{u}^{\text{ps}}(t) = f_{\text{cn} \rightarrow \text{ps}}(\mathbf{y}^{\text{cn}}(t - \boldsymbol{\tau})), \quad (4)$$

$$\mathbf{u}^{\text{cn}}(t) = f_{\text{ps} \rightarrow \text{cn}}(\mathbf{y}^{\text{ps}}(t - \boldsymbol{\tau})), \quad (5)$$

where $\mathbf{y}^{\text{ps}}(t)$ and $\mathbf{y}^{\text{cn}}(t)$ denote the measurement outputs and control signals, respectively. $\boldsymbol{\tau}$ denotes communication delay vector and $\boldsymbol{\tau} = [\tau_1, \dots, \tau_N]^\top$ represents the vector of node-specific communication delays.

The communication delay τ_i characterises the effective delay of the closed-loop information exchange associated with node i , including communication, scheduling, and control execution within the CPPS. It represents a model-level delay of the cyber-physical interaction, rather than the physical transmission or synchronisation latency of the HIL or digital co-simulation platform.

In this work, each node-specific communication delay is modelled as

$$\tau_i = t_{0,i} + \delta_i, \quad (6)$$

where $t_{0,i}$ denotes the nominal communication delay at node i , and δ_i is a stochastic delay deviation capturing the uncertainty in the cyber-physical coupling at that node.

C. Uncertainties in Cyber-Physical Power Systems

The uncertainties in CPPS arise from two main aspects: power system and communication network. In this paper, we focus on three types of uncertainties during the CPPS normal operation: load, PV generation and communication delay.

1) *Load Uncertainty*: In CPPS, we assume loads have constant power factors and the active power of loads follows a Gaussian distribution as [19]:

$$p(\psi^{\text{lp}}) = \frac{1}{\sqrt{2\pi}\sigma_{\psi^{\text{lp}}}} \exp \left[-\frac{(\psi^{\text{lp}} - \mu_{\psi^{\text{lp}}})^2}{2\sigma_{\psi^{\text{lp}}}^2} \right], \quad (7)$$

where p denotes the probability density function; ψ^{lp} represents the active power of loads; $\mu_{\psi^{\text{lp}}}$ and $\sigma_{\psi^{\text{lp}}}$ denote the mean and standard deviation of load active power. Although the stochastic loads enter the power system model as algebraic parameters, the system states remain continuous due to network dynamics and inverter-based generation control.

2) *Solar Generation Uncertainty*: In this paper, PV generation uncertainty is represented through uncertain solar radiation, modelled by a Beta distribution [20].

$$p(SR) = \frac{\Gamma(\kappa + \varepsilon)}{\Gamma(\kappa)\Gamma(\varepsilon)} \left(\frac{SR}{SR_{\max}} \right)^{\kappa-1} \left(1 - \frac{SR}{SR_{\max}} \right)^{\varepsilon-1}, \quad (8)$$

where Γ is the gamma function, κ and ε are Beta distribution shape parameters, SR and $SR_{\max}$ are the actual and maximum solar radiation, respectively.

3) *Time Delay Uncertainty*: The uncertainty of the node-specific communication delay is modelled by a uniform distribution centred on its nominal value $t_{0,i}$ [21]:

$$p(\tau_i) = \begin{cases} \frac{1}{2\lambda_i}, & t_{0,i} - \lambda_i \leq \tau_i \leq t_{0,i} + \lambda_i, \\ 0, & \text{otherwise,} \end{cases} \quad (9)$$

where τ_i denotes the communication delay associated with node i , and λ_i denotes the delay uncertainty bound at node i , in other words, it specifies the maximum deviation that captures the uncertainty of the cyber-physical information exchange at that node.

For each Monte Carlo realisation, τ_i is sampled once from the above distribution and kept constant during the entire transient simulation, representing a quasi-static but uncertain communication condition in the CPPS. Moreover, τ_i is different in different Monte Carlo realisations.

III. GLOBAL SENSITIVITY ANALYSIS WITH INDEPENDENT RANDOM INPUTS

A. Variance Decomposition

A deterministic model whose outputs depend on an uncertain input vector $\mathbf{X} \in \mathbb{R}^{N_x}$ is considered in this paper, where $\mathbf{X}$ collects all uncertain parameters from both the power and communication layers, and the inputs are assumed to be independent and N_x represents the dimension of the uncertain inputs. Furthermore, an isoprobabilistic transform is applied to map the marginal distributions to make the analysis performed on $[0, 1]^{N_x}$.

1) *Input $\mathbf{X}$* : The input vector can be written as

$$\mathbf{X} = (X_1, \dots, X_{N_x}), \quad N_x \in \mathbb{N}. \quad (10)$$

The components X_i represent the model parameters, initial or boundary conditions, and external parameters. In this paper,

the uncertain inputs, including load, PV generation, and node-specific communication delay, are treated as statistically independent random variables. Only marginal probability distributions are considered. The uncertain inputs X_i include: load of each bus, which is represented by the operation of injected current and voltage at each bus; communication delay (τ_i) on each bus i ; stochastic fluctuation of solar radiation.

2) *Output Y_ℓ* : Let $\mathcal{M}(\mathbf{X})$ denote the model output (for example, a state vector or trajectory). The scalar observable analysis at the index ℓ is obtained by an output extraction function q_ℓ :

$$Y_\ell = q_\ell(\mathcal{M}(\mathbf{X})), \quad (11)$$

which can be regarded as a scalar function of the input vector $\mathbf{X}$. The following analysis is conducted for each system state and component individually, i.e., for any fixed index ℓ . In this paper, the scalar output Y_ℓ includes synchronous machine states: rotor angles and angular speeds; PV unit states: inverter currents, terminal voltages, DC-link voltages, and duty ratios. Bus voltages: real and imaginary parts of bus voltages U_x, U_y . Bus currents: real and imaginary parts of injected currents I_x, I_y .

3) *Functional of Hoeffding–Sobol’ decomposition*: To quantify how individual uncertainties contribute to the variability of Y_ℓ , a variance-based decomposition is adopted. For a fixed ℓ and square-integrable Y_ℓ on $[0, 1]^{N_x}$ with independent inputs,

$$Y_\ell = f_0^{(\ell)} + \sum_{i=1}^{N_x} f_i^{(\ell)}(X_i) + \sum_{i < j} f_{ij}^{(\ell)}(X_i, X_j) + \cdots + f_{1\dots N_x}^{(\ell)}(\mathbf{X}), \quad (12)$$

where the component functions are mutually orthogonal (zero mean with respect to each of their arguments). They are identified via

$$\begin{aligned} f_0^{(\ell)} &= \mathbb{E}[Y_\ell], \\ f_i^{(\ell)}(X_i) &= \mathbb{E}[Y_\ell | X_i] - f_0^{(\ell)}, \\ f_{ij}^{(\ell)}(X_i, X_j) &= \mathbb{E}[Y_\ell | X_i, X_j] - f_0^{(\ell)} - f_i^{(\ell)} - f_j^{(\ell)}, \end{aligned} \quad (13)$$

with analogous expressions for higher orders.

According to Eqs. 11, 12 and 13, the variance decomposes as

$$\text{Var}(Y_\ell) = \sum_{i=1}^{N_x} V_i^{(\ell)} + \sum_{i < j} V_{ij}^{(\ell)} + \cdots + V_{1\dots N_x}^{(\ell)}, \quad (14)$$

with

$$\begin{aligned} V_i^{(\ell)} &= \text{Var}_{X_i}(\mathbb{E}[Y_\ell | X_i]), \\ V_{ij}^{(\ell)} &= \text{Var}_{X_i, X_j}(\mathbb{E}[Y_\ell | X_i, X_j]) - V_i^{(\ell)} - V_j^{(\ell)}. \end{aligned} \quad (15)$$

Here, each term $V_i^{(\ell)}$ represents the variance contribution caused solely by the uncertainty of input X_i , while higher-order terms capture interaction effects among multiple uncertain inputs. Repeating the analysis with different indices ℓ yields sensitivity profiles by spatial, temporal, or component sensitivity in a model-agnostic manner.

From a physical perspective, the variance terms $V_i^{(\ell)}$ quantify the extent to which the uncertainty of input X_i alone

contributes to the variability of the output Y_ℓ , while higher-order terms represent interaction effects among multiple inputs. This interpretation is particularly relevant for CPPS, where uncertainties from the power and communication layers may interact in complex ways.

B. First-order and Total-Effect Sobol’ Indices

In this work, first-order and total-effect Sobol’ indices are adopted to achieve a practical and physically balance between computational feasibility and sensitivity interpretability in CPPS. From a computational perspective, the proposed CPPS framework involves more than one hundred uncertain inputs (including stochastic loads, solar radiation, and node-specific communication delay), for which the explicit computation of higher-order indices can result in a high computational cost in the digital co-simulation procedure.

From a physical perspective, first-order indices capture the dominant contributions of individual uncertainty states, while the difference between total-effect and first-order indices reflects aggregated interaction effects. In the investigated scenarios, output uncertainties are primarily dominated by first-order contributions, indicating limited multi-way coupling. Therefore, first-order and total-effect indices provide effective sensitivity characterisation with significantly reduced computational burden.

Given the input vector $\mathbf{X}$ in Eq. 10 and the scalar observable Y_ℓ in Eq. 11, and using the functional decomposition in Eq. 12, the first-order Sobol’ index $S_i^{(\ell)}$ quantifies the main (additive) contribution of the uncertain input X_i to the variance of Y_ℓ . The total-effect Sobol’ index $S_{Ti}^{(\ell)}$ measures the overall influence of X_i , including both its direct effect and all interaction effects with the remaining inputs.

1) *First-order index*:

$$S_i^{(\ell)} = \frac{V_i^{(\ell)}}{\text{Var}(Y_\ell)}, \quad (16)$$

where $V_i^{(\ell)} = \text{Var}_{X_i}(\mathbb{E}[Y_\ell | X_i])$. This measures the fraction of the variance of Y_ℓ attributable solely to the variability of X_i , with the remaining inputs $\mathbf{X}_{\sim i}$ averaged out.

2) *Total-effect index*:

$$\begin{aligned} S_{Ti}^{(\ell)} &= \frac{\mathbb{E}_{\mathbf{X}_{\sim i}}[\text{Var}_{X_i}(Y_\ell | \mathbf{X}_{\sim i})]}{\text{Var}(Y_\ell)} \\ &= 1 - \frac{\text{Var}_{\mathbf{X}_{\sim i}}(\mathbb{E}_{X_i}[Y_\ell | \mathbf{X}_{\sim i}])}{\text{Var}(Y_\ell)}. \end{aligned} \quad (17)$$

Here, $\mathbf{X}_{\sim i}$ denotes all inputs except X_i ; therefore, $S_{Ti}^{(\ell)}$ accounts for both the main effect of X_i and all its interaction effects. The use of the first-order and total-effect indices allows dominant uncertainty sources and interaction effects in CPPS to be systematically distinguished without computing higher-order Sobol’ indices.

C. Indices Calculation

For analytically tractable models, Sobol’ indices can be obtained in closed form by evaluating the integrals implied

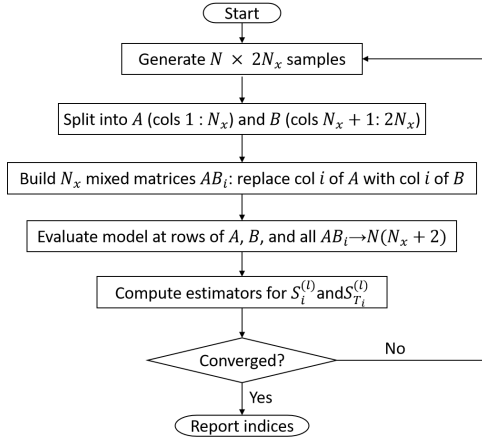


Fig. 2: Process of Sobol' indices computation using Monte Carlo sampling.

by the Hoeffding–Sobol' decomposition. In most practical sensitivity analysis cases, these integrals are intractable and the indices are estimated numerically via Monte Carlo sampling over the unit hypercube. The Monte Carlo method draws random points uniformly in $[0, 1]^{N_x}$ and evaluates the model at these points to construct variance-based estimators.

The iterative process for computing Sobol's indices using Monte Carlo sampling method is presented in Fig. 2. Starting from an $N \times 2N_x$ sample, the columns are split into two base designs A and B . For each input i , a mixed matrix AB_i is formed by replacing column i of A with column i of B . Evaluating the model at all rows of the A , B , and AB_i matrices requires $N(N_x + 2)$ runs and produces estimates of $S_i^{(\ell)}$ and $S_{T_i}^{(\ell)}$ according to Eqs. 16 and 17. Finally, the sample size N increases until the estimates stabilise.

There are several Monte Carlo estimators available for both indices. The approaches used in this paper are inspired by the following indices estimation method in [22]:

$$\text{Var}_{X_{\sim i}}(\mathbb{E}_{X_i}(Y|X_{\sim i})) \approx \frac{1}{N} \sum_{j=1}^N \mathcal{M}(\mathbf{B}_j) (\mathcal{M}(\mathbf{A}_{B,j}^{(i)}) - \mathcal{M}(\mathbf{A}_j)), \quad (18)$$

and

$$\mathbb{E}_{X_i}(\text{Var}_{X_{\sim i}}(Y|X_i)) \approx \frac{1}{2N} \sum_{j=1}^N (\mathcal{M}(\mathbf{A}_j) - \mathcal{M}(\mathbf{A}_{B,j}^{(i)}))^2, \quad (19)$$

for the estimation of the S_i and the S_{T_i} indices, respectively.

IV. CYBER-PHYSICAL POWER SYSTEMS DIGITAL CO-SIMULATION PLATFORM

As mentioned in Section I, the Monte Carlo method requires substantial data of the input and output state vectors, and previous research mainly focused on the theory and had limited insight in realistic scenarios. Therefore, it is essential to establish a CPPS digital co-simulation platform and use it to generate large-scale, high-fidelity input–output datasets under realistic cyber–physical operating conditions, which are subsequently used in the Monte Carlo framework to estimate

Sobol' sensitivity indices. This paper provides the Ethernet-based implementation framework for cyber-physical digital co-simulation, thereby providing essential data for GSA. As shown in Fig. 3, the CPPS digital co-simulation platform consists of an OPAL-RT power system simulator and an OMNeT++ communication network simulator, and a time-stepped digital co-simulation scheme is used to exchange data.

A. Power Distribution Network Simulation in OPAL-RT

The OPAL-RT is a powerful simulator for real-time digital power system simulation. Featuring an Intel Xeon processor with a maximum of 44 cores, the OP 5033XG simulator is a powerful master system for setups that expanded with FPGA and I/O expansion modules. In addition, it offers a suitable platform for real-time cybersecurity applications, where hardware integration supports network protocols such as C37.118 and IEC61850.

This study develops a power system digital simulation model based on the IEEE 33-bus power distribution network implemented on the proposed simulation platform. The power distribution system topology is presented in Fig. 1. The original 12.66 kV and 60 Hz IEEE 33-bus system is modified by integrating four distributed PV units at buses 8, 13, 28, and 32, operating in parallel with existing loads, and two distributed machines based on synchronous machines at buses 6 and 30. The main grid is represented by a slack bus with a fixed voltage magnitude of 1 p.u. and a phase angle of 0° , which provides the reference operating point during the simulation.

The PV units are modelled using a detailed PV array model with double-loop vector control and DC link voltage regulation, while the synchronous machine-based distributed generators are represented by a classical generator model with rotor angle and speed dynamics, augmented with transient EMF states. The system load is represented as a stochastic, time-varying demand following a Gaussian distribution and centres at $5084.26 + j2547.32$ kVA, with active and reactive power updated at each simulation step to emulate realistic load fluctuations ($\mu = 1, \sigma = 0.05$ in p.u.). The installed rated PV power corresponds to 40% of the nominal system load under baseline operating conditions. During simulation, stochastic load variations are introduced independently, and the instantaneous PV penetration is allowed to vary naturally without dynamic rescaling. To ensure numerical stability during real-time execution, the detailed PV and synchronous machine models are executed within the OPAL-RT real-time simulation environment, which is designed to handle stiff DAE-based power system models under fixed-step real-time constraints. The main dynamic parameters of PVs and synchronous machines are provided in Tables I and II.

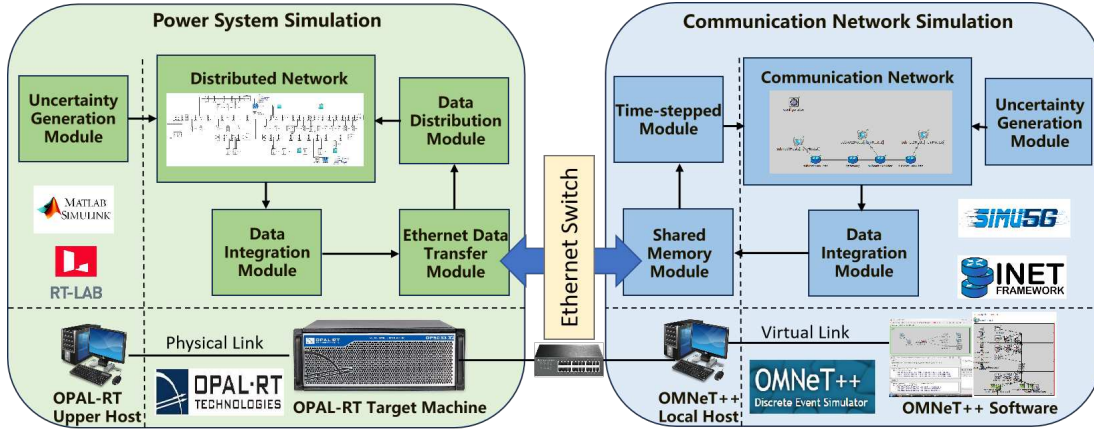


Fig. 3: Cyber-physical digital co-simulation structure.

TABLE I: Main Dynamic and Control Parameters of PV Units

C_{pv} (F)	L_{dc} (H)	C_{dc} (F)	L_f (H)	$u_{dc,ref}$ (V)	T (°C)
1.0×10^{-4}	5.0×10^{-2}	5.0×10^{-3}	5.0×10^{-3}	800	25
k_p (DCV)	k_i (DCV)	k_{op}	k_{oi}	k_{ip}	k_{ii}
-0.1	-0.01	-0.05	10	2	9

In the PV model, C_{pv} denotes the equivalent capacitance of the PV array, L_{dc} and C_{dc} represent the inductance and capacitance of the DC-link circuit, respectively, and L_f is the inverter filter inductance. $u_{dc,ref}$ denotes the reference DC-link voltage, and T represents the operating temperature of the PV units. The parameters k_p and k_i correspond to the proportional and integral gains of the DC-voltage control loop, while k_{op} and k_{oi} denote the proportional and integral gains of the outer control loop. The parameters k_{ip} and k_{ii} represent the proportional and integral gains of the inner current control loop.

TABLE II: Main Dynamic Parameters of Synchronous Machines

P_m (p.u.)	T_j (s)	D_{sg} —	r_a (p.u.)	x'_d (p.u.)	x'_q (p.u.)	f (Hz)
0.58665	47.28	100	0	0.0608	0.0969	60
0.37923	47.28	100	0	0.0608	0.0969	60

In the synchronous machine model, P_m denotes the mechanical input power, T_j is the inertia time constant, and D_{sg} represents the damping coefficient of the machine. The parameter r_a denotes the armature resistance, while x'_d and x'_q represent the transient reactances along the d -axis and q -axis, respectively. Finally, f denotes the nominal operating frequency of the synchronous machine.

B. Communication Network Simulation in OMNeT++

OMNeT++ is an open source discrete-event simulator, which provides a modular simulation framework written in

C++, along with various extensions that support the development of network simulation models based on a component-based architecture.

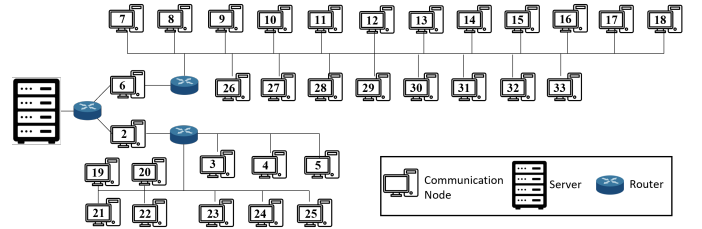


Fig. 4: The OMNeT++ model of the IEEE 33-bus communication network.

As shown in Fig. 4, each bus in the power distribution system and each distributed power source corresponds to a communication node in the communication network, which is modelled by the INET model StandardHost. Since OMNeT++ is a discrete-event simulator, most of the simulation is non-real-time. To implement OMNeT++ with OPAL-RT to conduct CPPS digital co-simulation, the OMNeT++ model should not only communicate with the OPAL-RT target machine, but also operate in a real-time manner. The communication network adopts a double-star topology, where node 2 and node 6 are two data transfer nodes, and node 1 acts as the server. The node-specific communication delay τ_i in the CPPS model follows a uniform distribution as shown in Eq. 9.

There are multiple methods to implement the data transfer interface for digital co-simulation between OPAL-RT and OMNeT++, such as virtual Ethernet(veth) pairs and shared memory. The veth method can better simulate Internet protocols, since it creates virtual Ethernet peers to transfer data from the OMNeT++ host machine to the OMNeT++ model. Compared with the veth method, the shared memory method does not rely on virtual links. Instead, external input data are assigned to the corresponding memory space using the Boost::interprocess library from which the OMNeT++ model can directly access and process the data. In OMNeT++, the network configuration in the omnetpp.ini file should be configured with the RealTimeScheduler to ensure that the simulated time is

consistent with real time. This method enhances execution speed and improves data processing efficiency, thus reducing transmission delays in real-time simulation and increasing the overall accuracy of CPPS digital co-simulation.

C. Time-Stepped Synchronisation Scheme Using Shared Memory

The digital co-simulation mechanism between the power distribution network in the OPAL-RT and communication network in the OMNeT++ is carried out using a time-stepped synchronisation scheme. In this approach, both simulators are simulated in discrete time steps to improve the data consistency between the physical and cyber dynamics and to ensure accurate temporal alignment between the continuous-time DAE-based power system model and the discrete-event communication network.

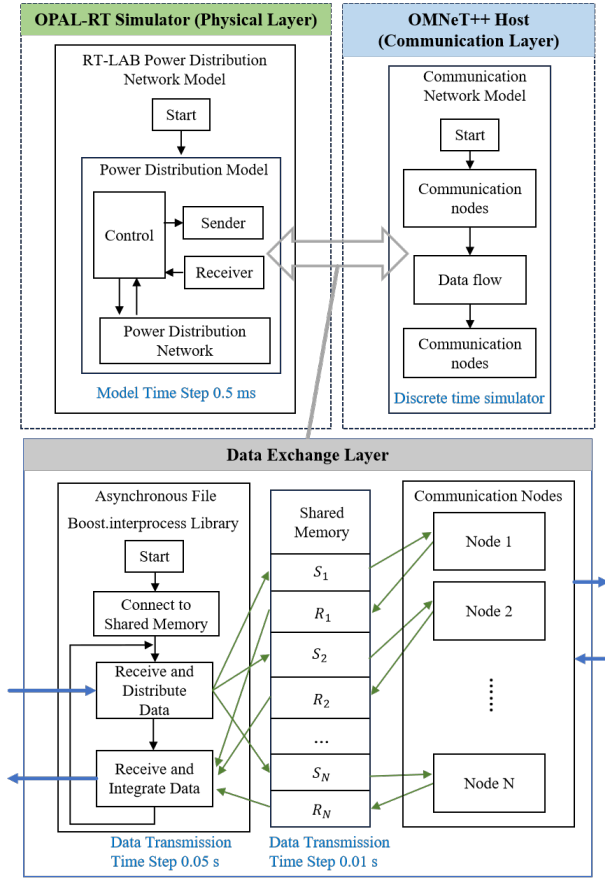


Fig. 5: Mechanism of shared memory time-stepped synchronisation scheme.

Compared to the conventional time-stepped method [23] and existing shared-memory-based implementations [24], the proposed scheme provides an improved experimental integration framework for cyber-physical digital co-simulation. As shown in Fig. 5, at the beginning of each digital co-simulation step, the power distribution network model running in OPAL-RT's RT-LAB computes the electrical states (e.g., bus voltages, branch currents, generator outputs) based on the most recent control and measurement data received from the communication network. These outputs are exchanged

with OMNeT++ via the UDP protocol using the sender and receiver in the Ethernet communication interface. The *Boost.Interprocess* function is used in the Asynchronous File in OMNeT++ host to ensure data is received and distributed to the shared memory. The communication network simulation delivers the updated control messages or network status information between nodes and sends back to the power distribution network simulation at the end of the simulation loop. This synchronisation scheme ensures deterministic data exchange and mitigates errors caused by asynchronous event scheduling.

To characterise the timing behaviour of the proposed digital co-simulation platform, key synchronisation and data-exchange metrics are summarised in Table III. Furthermore, cycle-to-cycle synchronisation skew and scheduler-induced jitter are negligible under the fixed-step RealTimeScheduler configuration and are therefore omitted.

TABLE III: Timing Metrics of the Proposed CPPS Digital Co-Simulation Platform

Metrics	Value
Synchronisation step T_s	0.5 s
Data-exchange latency (RTT)	0.156/0.234/0.257 ms (min/avg/max)
Latency jitter (mdev)	0.018 ms
Packet loss rate	0 %
Node-specific communication delay τ_i^{cn}	[0.3, 0.5] s

Monte Carlo samples are generated offline prior to the CPPS digital co-simulation, and each Monte Carlo realisation is executed as an independent digital co-simulation loop. This execution strategy prevents platform-level nondeterministic latency and jitter from accumulating across runs, while time synchronisation within each loop is preserved by the fixed-step synchronisation scheme.

Moreover, fast PV dynamics and physical transients are resolved within the DAE solver of the OPAL-RT power system simulator. Node-specific communication delay and packet losses are handled exclusively at the digital co-simulation boundary as delayed or held inputs applied at fixed synchronisation time-step. As a result, time-step violations between continuous-time and discrete-event simulations can be prevented.

V. SIMULATION RESULTS

As shown in Fig. 6, the proposed CPPS digital co-simulation platform is constructed based on the facilities in the Control and Power Systems laboratory at the University of Sheffield.

In this paper, as mentioned in Section III-A, a total of 119 parameters are considered in the input X , mainly including the voltage and current of the PV units, the load on each bus, and node-specific communication delay. The output Y consists of several system states of the power distribution network. The GSA is conducted using the output Y , and the following section presents key simulation results.

A. IEEE 33-bus System Normal Operation Results

The CPPS digital co-simulation results of four buses in the IEEE 33-bus power distribution network are presented in Fig.

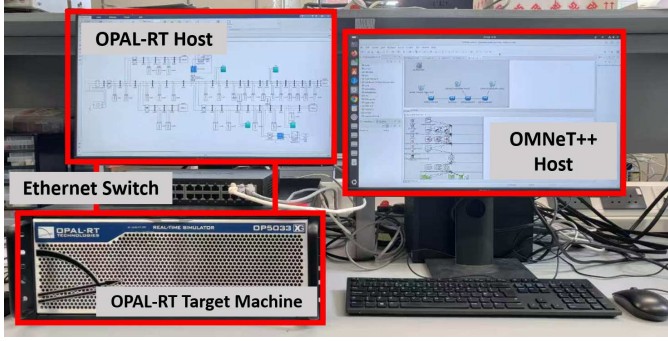


Fig. 6: Implementation of cyber-physical power systems digital co-simulation platform.

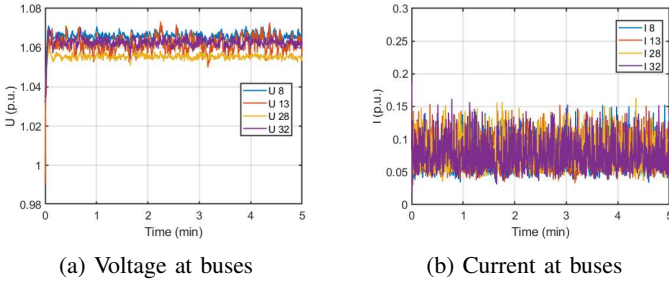


Fig. 7: CPPS digital co-simulation results of voltage and current at buses 8, 13, 28 and 32.

7. The voltage and current of the buses are shown in Fig. 7a and Fig. 7b, respectively.

The results show that both voltage and current responses of the buses exhibit noticeable fluctuations when the uncertainties are considered in the system. As shown in Fig. 7a, the bus voltages stabilise around their nominal values but present continuous oscillations. These oscillations are mainly due to three sources: (i) PV generation variations due to solar radiation dynamics, (ii) load fluctuations in the power distribution network, and (iii) the effect of node-specific communication delay. The currents in Fig. 7b also display noticeable fluctuations under input uncertainties and follow very similar patterns across all four units. The quantified analysis of the sensitivity to the three sources of uncertainties is discussed in the following sections.

B. Global Sensitivity Analysis Results on Node-specific Communication Delays

The sensitivity of outputs to node-specific communication delay is analysed in this section, which is one of the key parameters in the cyber-physical coupling system. The data for GSA are obtained from the proposed CPPS digital co-simulation platform, containing the input vector and output state vector from the CPPS simulation. Table IV presents the most and the least sensitive output states to node-specific communication delays, respectively. The synchronous machine speeds ω_1 (0.862) and ω_2 (0.534) are the most delay-sensitive, showing that node-specific communication delays strongly affect the frequency response and electromechanical dynamics. Therefore, the frequency of the system is mainly affected by the node-specific communication delay. By contrast, the

sensitivity of rotor angle δ_1 (0.000) is the lowest in response to node-specific communication delay, as angle changes slower than speed. Similarly, PV currents and certain controller references, e.g. PV3 i_y (sensitivity of 3.7×10^{-4}), reference voltage u_{rd1} at PV4, and reference current $i_{d,ref1}$ at PV1, remain almost unaffected by communication delay, since they are dominated by fast local control loops and electrical constraints rather than delayed communication.

TABLE IV: Most and Least Sensitive Output States to Node-Specific Communication Delays

Most sensitive output states			
Output Index	Group	Parameter	Sensitivity
3	SG state	Generator speed ω_1	0.862
4	SG state	Generator speed ω_2	0.534
40	PWM duty	PV4 duty ratio d	0.378
79	Bus voltage U_y	Bus 6 U_y	0.213
72	Bus voltage U_x	Bus 32 U_x	0.210
Least sensitive output states			
Output Index	Group	Parameter	Sensitivity
1	SG state	Generator rotor angle δ_1	0.00000
18	Controller	PV2 reference voltage u_{rd1}	0.00001
11	PV grid current	PV3 grid current i_y	0.00037
20	Controller	PV4 reference voltage u_{rd1}	0.00052
13	Controller	PV1 reference current $i_{d,ref1}$	0.00053

To facilitate physical interpretation of the Sobol' sensitivity results, a set of aggregated metrics is introduced to characterise (i) the robustness of dominant delay locations, (ii) the spatial locality of delay impacts, (iii) the relative contribution of delays to different state groups. These metrics are derived directly from the Sobol' indices.

TABLE V: Cross-Scenario Comparison of Communication Delay Sensitivity Characteristics

Metric	Scenario A	Scenario B
Top-5 delay overlap (mean)	2.19 / 5	
Jaccard similarity (Top-5 delays)	0.419	
Mean voltage locality ratio (U_x)	0.38	6.11
Mean voltage locality ratio (U_y)	0.11	1.99
Delay-energy ratio (current / voltage)	0.014	0.366

Table V summarises a comparison between two scenarios, a baseline configuration (Scenario A) and a targeted delay perturbation case (Scenario B), in which additional delays of +0.5 s and +1 s are introduced at node 10 and 24, respectively. The Top-5 delay overlap and the corresponding Jaccard similarity quantify the consistency of the most influential delay nodes across scenarios. The Jaccard similarity measures the degree of overlap between the sets of dominant delay nodes identified under different scenarios, with values closer to one indicating higher consistency. An average overlap of 2.19 and a Jaccard similarity of 0.419 indicate a moderate but non-random robustness of the dominant delay structure under perturbation.

For voltage-related states, the locality ratio provides a direct measure of spatial dominance, where values exceeding unity indicate local influence and values above three imply strong

locality. The markedly increased locality ratios observed in Scenario B therefore demonstrate that delay-induced voltage sensitivities become strongly localised when targeted perturbations are applied. By contrast, the delay-energy ratio between current and voltage states remains below 1, confirming that communication delays predominantly affect algebraic voltage states through local measurement and control paths, while current sharing is largely preserved by network impedance constraints and inverter inner-loop regulation.

C. Global Sensitivity Analysis Results on Solar Radiation

TABLE VI: Top-Ranked Input States and Their Rank Shifts Between Different Scenarios

Index	Type	Rank ₁	Rank ₂	$\Delta Rank$
9	PV terminal voltage (PV state)	8	1	-7
72	Bus 32 U_x	5	2	-3
13	Controller $i_{d,ref1}$ (PV1)	116	3	-113
15	Controller $i_{d,ref3}$ (PV3)	86	4	-82
14	Controller $i_{d,ref2}$ (PV2)	94	5	-89
16	Controller $i_{d,ref4}$ (PV4)	107	6	-101
90	Communication delay at node 8	17	7	-10

The GSA results in Table VI show input importance between the two scenarios. In scenario 1 ($Rank_1$), all PV units operate under a uniform distribution corresponding to 40% solar radiation, with communication delays at baseline values. Scenario 2 ($Rank_2$) increases the solar radiation of the PV units from 40% to 90%, and introduces additional communication delays of 1 s at Bus 24 and 0.5 s at Bus 10. This setting represents a realistic stressed operating condition combining high solar radiation and cyber-layer congestion.

It can be seen that the uncertainty ranking in scenario 1, sensitivity ranking is dominated by electrical and control states on PV units, reflecting the prevalence of local inverter dynamics under moderate and simultaneous penetration. In contrast, the stressed scenario ($Rank_2$) leads to substantial rank shifts, with several less sensitive inputs becoming dominant. In particular, the PV terminal voltage becomes one of the most sensitive variables, indicating heightened sensitivity to local voltage regulation under higher PV generation output. In the power distribution network layer, the voltage component U_x at Bus 32 also becomes highly sensitive, indicating the remote buses are sensitive to the asymmetric power injections. In addition, multiple inverter current reference signals $i_{d,ref}$ exhibit rank increases, reflecting the increased sensitivities on converter control actions to maintain power balance. Moreover, the rank of communication delay at node 8 rises as well, demonstrating that communication network layer disturbances can significantly affect system dynamics under high PV penetration.

Overall, the results show that sensitivity rankings depend on the system operation conditions. The proposed GSA-based comparison between nominal and stressed scenarios therefore provides an effective assessment of external validity beyond fixed penetration and normal cyber conditions.

D. Global Sensitivity Analysis Results on Fixed-Time Uncertainties

In the following section, typical results of the GSA according to Section III are reported to quantify the sensitivity contribution of uncertain inputs to the system states of the CPPS.

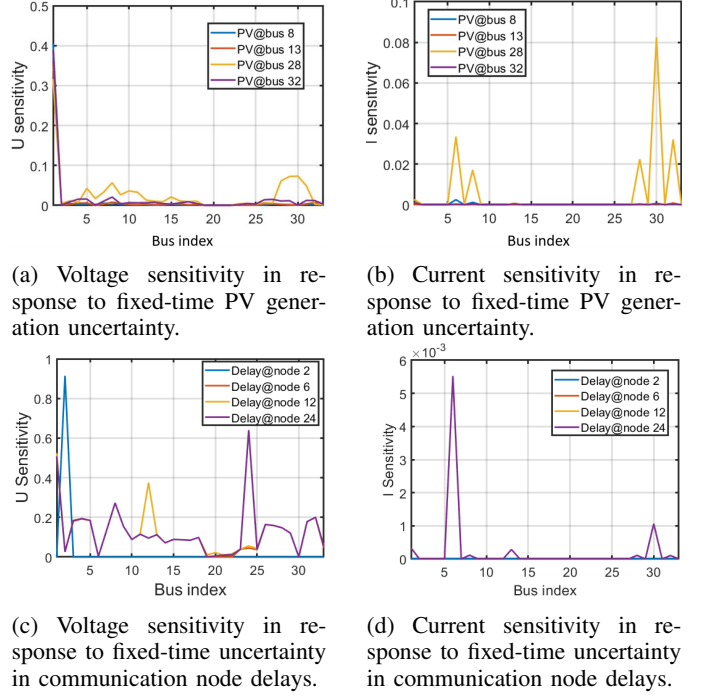


Fig. 8: Sensitivity analysis on fixed-time uncertainties at 10th minute of CPPS simulation.

1) *Sensitivity Contribution of Uncertain PV Generation:* Fig. 8a shows that the voltage sensitivity at bus 1 (slack bus) is relatively high (ranging from 0.3 to 0.4) in response to all four uncertain PV units, while the sensitivities at most other buses remain close to zero. This can be explained by the role of the slack bus, which serves as the system reference and balances active and reactive power. Therefore, any uncertainty that leads to PV output variation will be reflected in the voltage sensitivity of the slack bus. In addition, Bus 28 exhibits higher voltage sensitivity because it is a PV connection point and is located at the end of the power distribution network, making its voltage more sensitive to variations in PV generation. These results verify that PV output influences bus voltages both globally, through the slack bus, and locally, near the PV connection points.

Fig. 8b illustrates that only the uncertain PV unit located at bus 28 exhibits noticeable contributions to the current sensitivity, particularly at buses 6, 8, 28, 30, and 32, whereas the other PV units show little influence. This is mainly attributed to the control characteristics of the PV inverters. PV units typically operate in a current-controlled mode, directly modulating current injection to track active power references. Since PV unit at bus 28 contributes more significantly to generation at this time (10th minute), its uncertain variations affect the current distribution, and subsequently affect neigh-

bouring generation nodes. This phenomenon indicates that the sensitivity of PV current states is primarily governed by the employed PV control mode, in which active power regulation is achieved through direct current control, rather than by any global reference effect.

The sensitivity of voltages is higher than that of currents. This indicates that the uncertainties of PV generation have a greater impact on bus voltages, while their influence on current distribution is relatively limited. As a result, in the CPPS framework, PV-related uncertainties are expected to play a more critical role in voltage dynamics than in current sensitivity.

2) *Sensitivity Contribution of Uncertain Node-Specific Communication Delays:* In Fig. 8c, at the 10th minute, the communication delay at each node mainly affects the voltage sensitivity of its own bus, while its influence on other buses is limited. For example, the communication delays at nodes 2 and 6, which serve as data transfer nodes in the communication network as shown in Fig. 4, do not significantly affect the voltage sensitivities at nodes 12 and 24, even though the latter rely on them to reach the data centre. Similarly, communication delays at nodes 12 and 24 do not affect neighbouring buses through the communication paths. This is because communication delays enter the control loop as node-specific measurement or actuation delays, rather than as cumulative hop-by-hop delays along the communication routes. This indicates that the effect of the uncertainty in communication delays on bus voltages is highly localised and is not influenced by the topology of the communication network.

As shown in Fig. 8d, the sensitivities of bus currents with respect to communication delays are extremely low, with the maximum value below 5×10^{-3} . This is because PV-injected currents are primarily determined by local measurements and control, such as solar radiation and local voltage feedback in droop or dq control. This suggests that communication delays have almost no observable impact on current distribution, while their effects tend to be highly localised at their own delayed nodes. The results highlight that communication delay uncertainties play a more critical role in shaping voltage dynamics than in affecting current flows in the CPPS framework.

E. Global Sensitivity Analysis Results on Time-Varying Uncertainties

1) *Voltage Sensitivity in Response to Time-Varying Uncertainties of PV Generation:* Fig. 9a shows the time-varying sensitivity of bus 8 voltage with respect to the four uncertain PV units. It can be observed that PV units at buses 8 and 13 exhibit similar sensitivity variations, while PV units at buses 28 and 32 have negligible impact on bus 8 voltage. This corresponds to the network topology as in Fig. 1, since buses 8 and 13 are located on the same power distribution line, resulting in a stronger correlation between their outputs. These results indicate that voltage fluctuations are strongly related to time-varying uncertainties of PV generation outputs only on the same power distribution line, verifying the influences of both local PV units and network topology on voltage control in the power distribution network.

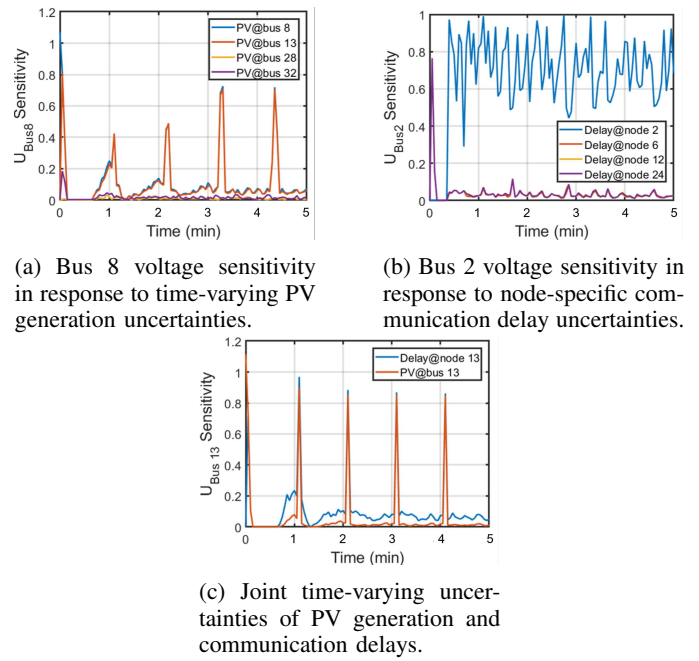


Fig. 9: Sensitivity analysis of bus voltages in response to time-varying uncertainties.

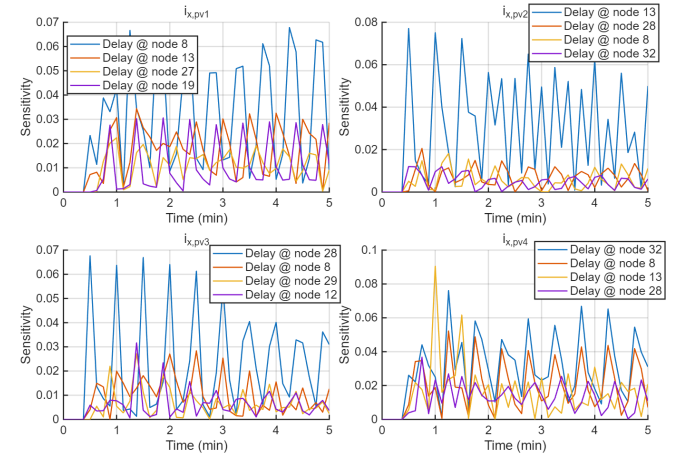


Fig. 10: Sensitivity analysis of PV inverter currents in response to communication delays.

2) *Voltage Sensitivity in Response to Time-Varying Uncertainties of Communication Delays:* Fig. 9b illustrates the sensitivity of bus 2 voltage with respect to the communication delays at nodes 2, 6, 12, and 24. The results show that only the delay at node 2 maintains a consistently high influence on the voltage of its own bus, while the other three nodes exhibit little contribution. This indicates that the impact of communication delay is highly localised: the delay of a communication node primarily affects its corresponding power bus.

3) *PV Inverter Current Dynamics in Response to Time-Varying Uncertainties of Communication Delays:* Fig. 10 shows the time-varying sensitivity of PV inverter currents in response to communication delays. For each PV unit, the delay at its locally connected communication node consistently exhibits the highest sensitivity, indicating that inverter current

dynamics are most affected by local measurement and communication delays. Moreover, communication delays associated with other PV buses also appear in the dominant delays in the figure. Delays at nodes 8 and 13 are also among the most sensitive variables in inverter currents of PV unit on bus 32. These effects are because delay-induced voltage and current perturbations propagate through network impedances and influence neighbouring inverter operating points. Overall, the results demonstrate that communication delays impact PV inverter current dynamics through a combination of local control-loop variation and network interactions among multiple power system devices.

4) *Joint Time-Varying Uncertainties of PV Generation and Communication Delays*: Fig. 9c compares the sensitivity of bus 13 voltage with respect to the joint uncertainties of PV generation and communication delays located at both bus 13 and node 13. It can be seen that the effect of communication delay remains higher than that of PV generation throughout the entire CPPS simulation time steps, indicating that communication delay uncertainty plays a more dominant role than local PV generation uncertainty at the same bus. However, at the time of data exchange in the CPPS synchronisation scheme, the sensitivity contribution of PV generation increases significantly and combines with the effect of communication delay, so that the voltage fluctuations at bus 13 are more determined by the joint influence of local PV generation and communication delay. This demonstrates a significant coupling effect between power and communication uncertainties in the CPPS framework.

VI. CONCLUSION

In this paper, a GSA-based method is proposed to investigate the impacts of multiple uncertainties in CPPS with respect to the power distribution network. The uncertainties of load, PV generation, and node-specific communication delays in the CPPS framework are quantified using probabilistic models, and Monte Carlo-based Sobol' indices are used to quantify the sensitivity. A CPPS digital co-simulation platform integrating an OPAL-RT power system simulator and an OMNeT++ communication network simulator is developed using shared memory and a time-stepped synchronisation scheme. The global sensitivity indices on the IEEE 33-bus system show that PV generation has a dominant effect on bus voltages, while communication delays mainly influence local voltage but have a limited impact on bus currents. It is worth noting that communication node delays, as a key parameter of the communication network, present a non-negligible influence on the frequency of the power distribution network.

Future work will focus on the scalability of the proposed GSA framework and a more realistic assessment of delay-induced frequency disturbances. Potential solutions include model order reduction for higher dimensional CPPS framework and hierarchical or staged GSA strategies.

ACKNOWLEDGMENT

The authors acknowledge OPAL-RT for collaboration with the University of Sheffield and for providing real-time simulation solutions and software support.

REFERENCES

- [1] SSE plc, "From Targets to Action – SSE's Net Zero Transition Plan," SSE plc, Tech. Rep., Jun. 2025, accessed: Sep. 8, 2025. [Online]. Available: <https://www.sse.com/media/iwoduslk/net-zero-transition-report-2025.pdf>
- [2] M. Du, X. Liu, Z. Li, and H. Lin, "Robust mitigation strategy against dummy data attacks in power systems," *IEEE Transactions on Smart Grid*, vol. 14, DOI 10.1109/TSG.2022.3225469, no. 4, pp. 3102–3113, 2023.
- [3] Y. Jiang, S. Wu, R. Ma, M. Liu, H. Luo, and O. Kaynak, "Monitoring and defense of industrial cyber-physical systems under typical attacks: From a systems and control perspective," *IEEE Transactions on Industrial Cyber-Physical Systems*, vol. 1, DOI 10.1109/TICPS.2023.3317237, pp. 192–207, 2023.
- [4] R. Zeng, Y. Li, S. Hu, X. Shao, Y. Xu, X. Yang, and Y. Cao, "Edge resilient control for feeder automation system under hybrid attacks: A hybrid physical model-driven and data-driven approach," *IEEE Transactions on Smart Grid*, DOI 10.1109/TSG.2025.3581370, pp. 1–1, 2025.
- [5] M. Khalaf, A. Ayad, M. H. K. Tushar, M. Kassouf, and D. Kundur, "A survey on cyber-physical security of active distribution networks in smart grids," *IEEE Access*, vol. 12, DOI 10.1109/ACCESS.2024.3364362, pp. 29 414–29 444, 2024.
- [6] A. Ehsan and Q. Yang, "State-of-the-art techniques for modelling of uncertainties in active distribution network planning: A review," *Applied Energy*, vol. 239, DOI <https://doi.org/10.1016/j.apenergy.2019.01.211>, pp. 1509–1523, 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0306261919302247>
- [7] D. Bian, M. Kuzlu, M. Pipattanasomporn, S. Rahman, and D. Shi, "Performance evaluation of communication technologies and network structure for smart grid applications," *IET Communications*, vol. 13, DOI 10.1049/iet-com.2018.5408, no. 8, pp. 1025–1033, 2019.
- [8] M. Bessani, R. Z. Fanucchi, A. C. C. Delbem, and C. D. Maciel, "Impact of operators' performance in the reliability of cyber-physical power distribution systems," *IET Generation, Transmission & Distribution*, vol. 10, DOI <https://doi.org/10.1049/iet-gtd.2015.1062>, no. 11, pp. 2640–2646, 2016. [Online]. Available: <https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-gtd.2015.1062>
- [9] X. Wang, Q. Kang, X. Wei, L. Guo, and Z. Liang, "Resilience assessment and recovery of distribution network considering the influence of communication network," *International Journal of Electrical Power Energy Systems*, vol. 152, DOI <https://doi.org/10.1016/j.ijepes.2023.109280>, p. 109280, 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S014206152300337X>
- [10] S. Blasi and F. Capitanescu, "Hierarchical optimization for active distribution networks with der and microgrids," in *Proceedings of the IEEE PES General Meeting (PESGM)*, DOI 10.1109/PESGM48719.2022.9917071, pp. 1–5, 2022.
- [11] F. Gao, J. Wang, and G. Li, "Integrated planning of active distribution networks considering cyber-physical coupling," *IET Generation, Transmission & Distribution*, vol. 16, DOI 10.1049/gtd.1.22277, no. 5, pp. 887–897, 2022.
- [12] P. Delcourt, M. Tushar, and A. K. Srivastava, "Time synchronization attack detection in unbalanced distribution systems," *IEEE Transactions on Smart Grid*, vol. 12, DOI 10.1109/TSG.2021.3054159, no. 4, pp. 3052–3062, 2021.
- [13] S. Weng, Y. Liu, M. Zhou, and G. Li, "Distributed resilient self-triggered control for multi-pv systems against denial-of-service attacks," *IEEE Transactions on Smart Grid*, vol. 14, DOI 10.1109/TSG.2022.3201184, no. 1, pp. 505–516, 2023.
- [14] T. Ding, C. Li, C. Yan, F. Li, and Z. Bie, "A bilevel optimization model for risk assessment and contingency ranking in distribution system reliability evaluation," *IEEE Transactions on Power Systems*, vol. 35, DOI 10.1109/TPWRS.2020.2965294, no. 5, pp. 3803–3813, 2020.
- [15] R. Yu, W. Gu, W. Liu, P. Li, and W. Liu, "Dynamic simulation of distribution networks using multi-stage discontinuous galerkin method," *CSEE Journal of Power and Energy Systems*, vol. 10, DOI 10.17775/CSEEJPES.2020.00930, no. 1, pp. 185–196, 2024.
- [16] W. Liu, W. Gu, P. Li, G. Cao, W. Shi, and W. Liu, "Non-iterative semi-implicit integration method for active distribution networks with a high penetration of distributed generations," *IEEE Transactions on Power Systems*, vol. 36, DOI 10.1109/TPWRS.2020.3003367, no. 1, pp. 438–450, 2021.
- [17] D. Qiu, M. Liu, R. Zhang, T. Luo, A. Griffo, and X. Zhang, "Cyber-physical real-time digital simulation for cybersecurity analysis in micro-

grids,” *IEEE Transactions on Industrial Cyber-Physical Systems*, vol. 3, DOI 10.1109/TICPS.2025.3569640, pp. 429–441, 2025.

- [18] R. V. Yohanandhan, R. M. Elavarasan, P. Manoharan, and L. Mihet-Popa, “Cyber-physical power system (cpps): A review on modeling, simulation, and analysis with cyber security applications,” *IEEE Access*, vol. 8, DOI 10.1109/ACCESS.2020.3016826, pp. 151 019–151 064, 2020.
- [19] H. Sheng and X. Wang, “Probabilistic power flow calculation using non-intrusive low-rank approximation method,” *IEEE Transactions on Power Systems*, vol. 34, DOI 10.1109/TPWRS.2019.2896219, no. 4, pp. 3014–3025, 2019.
- [20] M. Aien, M. Fotuhi-Firuzabad, and M. Rashidinejad, “Probabilistic optimal power flow in correlated hybrid wind–photovoltaic power systems,” *IEEE Transactions on Smart Grid*, vol. 5, DOI 10.1109/TSG.2013.2293352, no. 1, pp. 130–138, 2014.
- [21] Y. Xia and D. Tse, “Inference of link delay in communication networks,” *IEEE Journal on Selected Areas in Communications*, vol. 24, DOI 10.1109/JSAC.2006.884022, no. 12, pp. 2235–2248, 2006.
- [22] I. Sobol, “Global sensitivity indices for nonlinear mathematical models and their monte carlo estimates,” *Mathematics and Computers in Simulation*, vol. 55, DOI [https://doi.org/10.1016/S0378-4754\(00\)00270-](https://doi.org/10.1016/S0378-4754(00)00270-6)



nerability assessment.

Dongmeng Qiu (Student Member, IEEE) received the B.Sc. degree in Electrical Engineering from North China Electric Power University, Beijing, China, in 2020 and the M.Sc. degree from the School of Mechanical Engineering, University of Manchester, U.K., in 2021. He is currently pursuing the Ph.D. degree with the School of Electrical and Electronic Engineering, University of Sheffield, U.K. His research interests include cyber-physical power systems, power system and communication system modelling, and vul-



cyber-physical energy systems.

Suhan Zhang (Member, IEEE) received his B.S. and Ph.D. degrees in electrical engineering from North China Electric Power University, China, in 2018 and Southeast University, China, 2023. He was a visiting scholar at the University of Birmingham and postdoctoral fellow at the Hong Kong Polytechnic University. He currently works as a postdoc research associate at the School of Electrical and Electronic Engineering, The University of Sheffield. His research interests include modelling, simulation and operation of

6, no. 1, pp. 271–280, 2001, the Second IMACS Seminar on Monte Carlo Methods. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0378475400002706>

- [23] W. Li, M. Ferdowsi, M. Stevic, A. Monti, and F. Ponci, “Cosimulation for smart grid communications,” *IEEE Transactions on Industrial Informatics*, vol. 10, DOI 10.1109/TII.2014.2338740, no. 4, pp. 2374–2384, 2014.
- [24] L. Ren, Y. Qin, B. Wang, P. Zhang, P. B. Luh, and R. Jin, “Enabling resilient microgrid through programmable network,” *IEEE Transactions on Smart Grid*, vol. 8, DOI 10.1109/TSG.2016.2589903, no. 6, pp. 2826–2836, 2017.



and smart grid.

Tianyu Luo received the Ph.D. degree in Dept. of Electronic and Electrical Engineering from University of Strathclyde in 2015. He is currently a Grid Manager and Technical Authority in multiple offshore wind projects with SSE Renewables plc. He worked as a senior power system engineer with National Grid Electricity System Operator from 2016 to 2023. With strong background and experience in renewable industry and power system operation, his research interests encompass decentralised energy control



Xin Zhang (Senior Member, IEEE) received the B.Eng. degree in automation from Shandong University, China, in 2007, and the M.Sc. and Ph.D. degrees in electrical power engineering from The University of Manchester, U.K., in 2007 and 2010, respectively. He is currently a Professor of control and power systems with the School of Electrical and Electronic Engineering, University of Sheffield, U.K. He was with National Grid Electricity System Operator, where he worked on the real-time power system operation at the Electricity National Control Centre, Wokingham, U.K. His research interests include cyber-physical power systems modelling and simulation, smart grid security and resilience, and renewable energy integration and control. He was the recipient of the U.K. Research and Innovation Future Leaders Fellowship in 2022. He serves as an Associate Editor for *IEEE Transactions on Smart Grid*, *IEEE Transactions on Sustainable Energy*, *IEEE Transactions on Industrial Cyber-Physical Systems*, and *IEEE Power Engineering Letters*.