# Robust Scenario Modeling of Distributed Energy Resources Adoption

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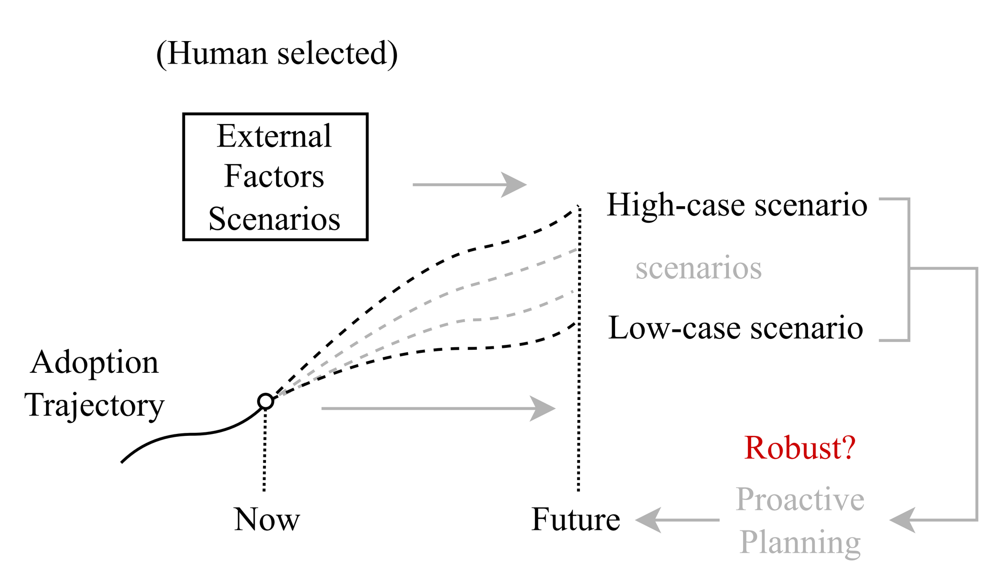
## Intro: Green & Sustainable Energies

Distributed Energy Resources (DERs):

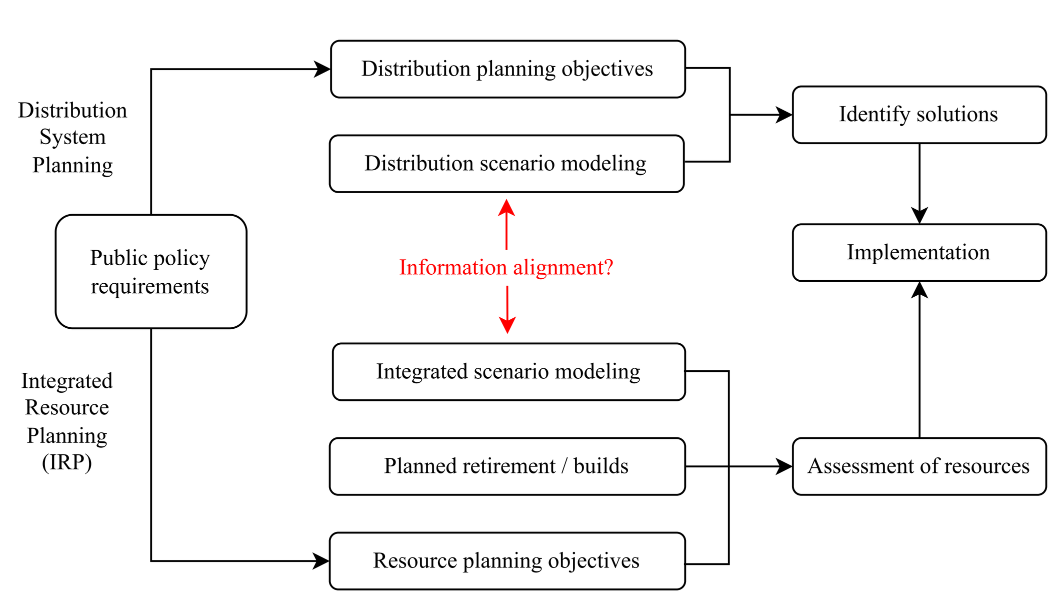
- Decentralized, demand-side power generation
- Aggregation and coordination for market participation

## Two Operational Challenges

**C1: Towards "Robust" Scenario Modeling** Scenarios are sets of hypothetical futures intended to be used as the basis for strategic discussions.




**C2: Planning Alignment** Harmonization between distributed system planning and integrated resource planning is key to effective distributed resource management.




## A Novel Framework

**Overview:** An end-to-end scenario modeling framework for DER adoption through the lens of uncertainty quantification,

1. **Base scenarios** modeled by Hawkes process model with intensity function
$$\lambda_i^*(t) = \gamma_t \left[ \mu_i + \sum_{t'<t} \sum_{i'} \alpha_{i,i'} \underbrace{\mathcal{K}(t,t')}_{\text{excitation effect}} \right],$$
where $\gamma_t$ is the inhibition effect, $\mu_i$ is a linear function of all external covariates, $\alpha_{i,i'}$ is the spillover effect.
2. **Low-case and high-case scenarios** are calibrated from historic data using a novel distributed non-conformity score:
$$\hat{e}_{it} = \min_{1\le k\le K} \left\| \left[\mathbf{C}\mathbf{C}^\top\right]_i \odot \left(y_t - \hat{y}_t^{(k)}\right)\right\|_\infty,$$
where $\mathbf{C}$ is the network topology matrix.

**Robustness Guarantees:** We prove that under **minimal** assumptions, our algorithm guarantees that:

- The low-case and high-case are conservative enough to reflect the worst-case distributed uncertainty,
$$\mathbb{P}\left([\mathbf{C}^\top \hat{L}]_j \le [\mathbf{C}^\top Y_{T+1}]_j \le [\mathbf{C}^\top \hat{U}]_j\right).$$
- The low-case and high-case scenarios are tight.

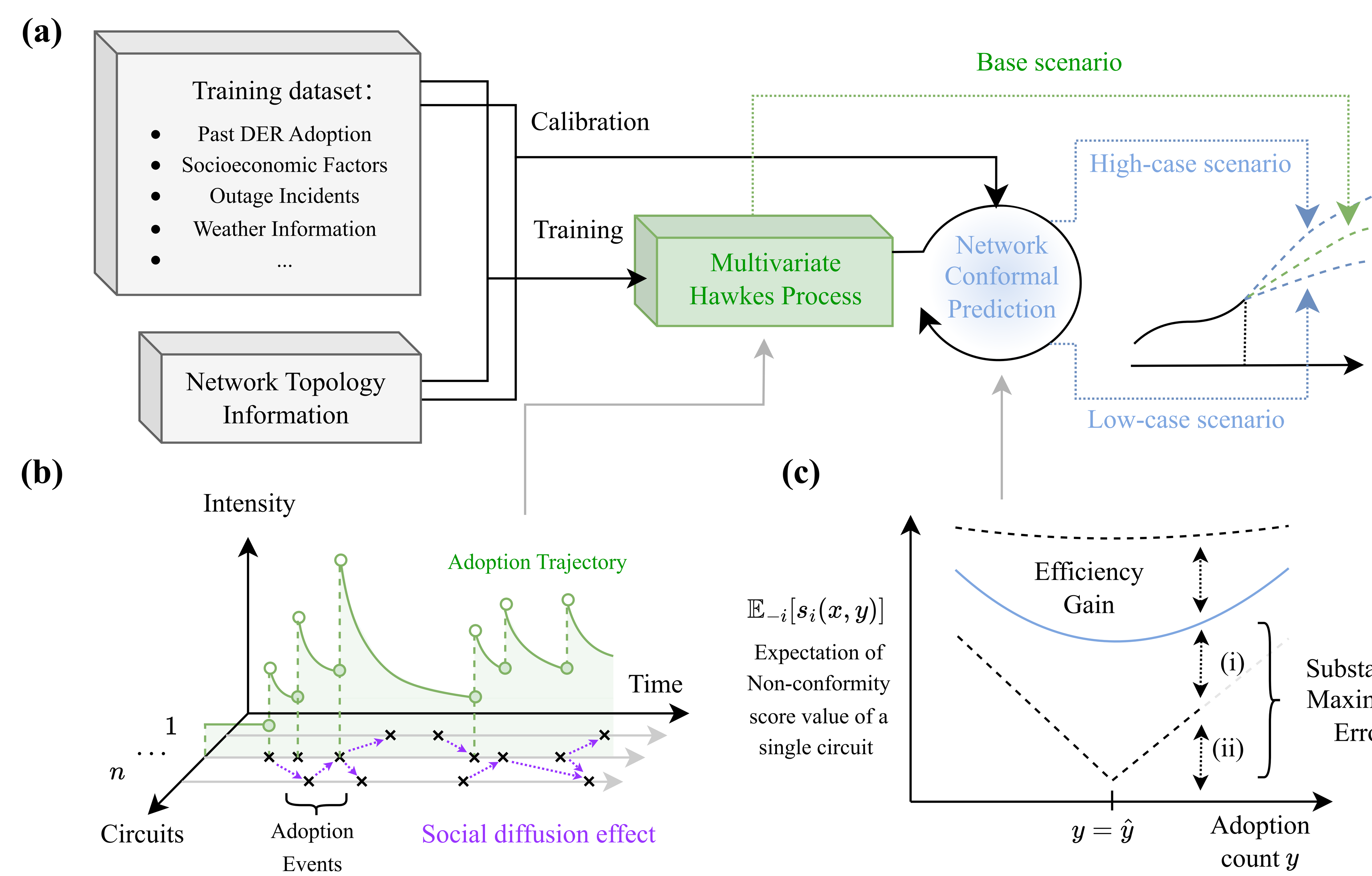



Figure: High-level illustration of the proposed framework: (a) algorithmic pipeline; (b) multivariate Hawkes process for base-scenario DER adoption modeling & simulation; (c) A decomposition of the mechanism of the proposed distributed non-conformity score.

## Simulations & Evaluations

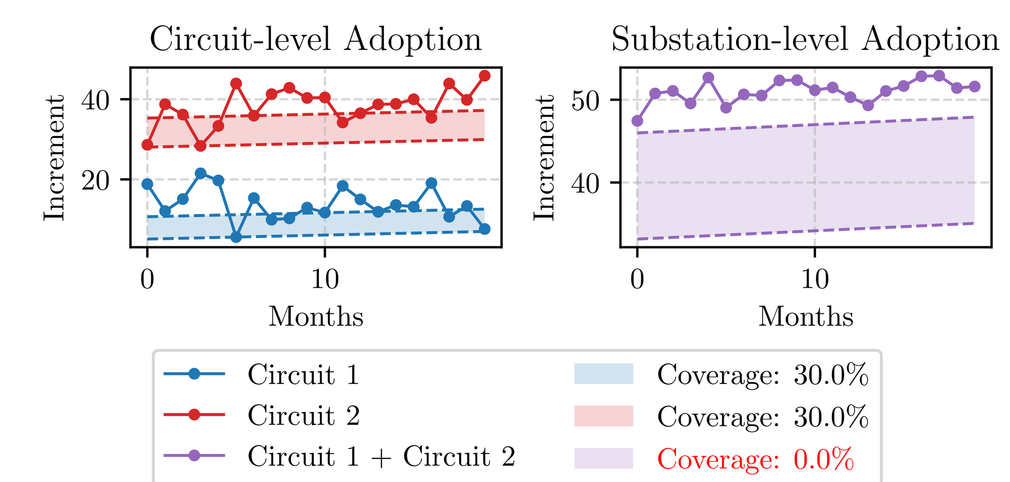



Figure: The vanishing uncertainty problem, illustrating the necessity for robust scenario modeling

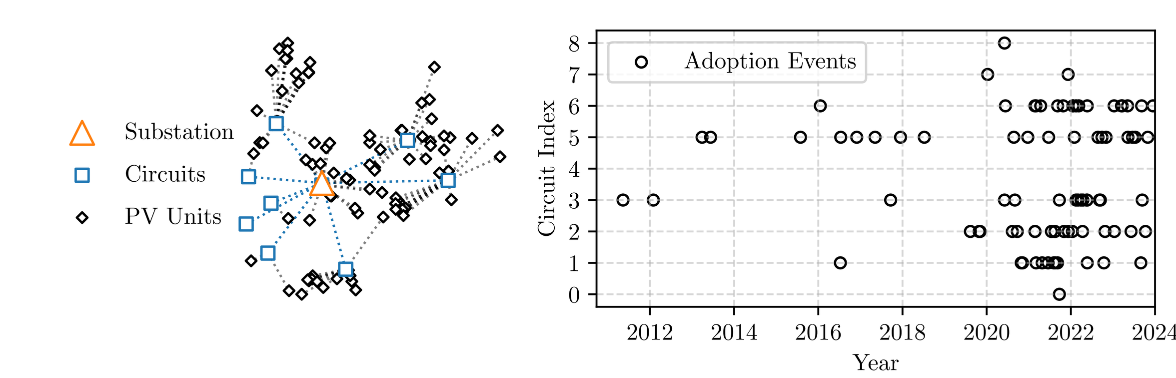
| MAE | Time Resolution (Month) | | |
|---|---|---|---|
| | 1 (Monthly) | 3 (Seasonal) | 12 (Annual) |
| RNN | 0.20 ± 0.03 | 0.38 ± 0.08 | 0.93 ± 0.09 |
| LSTM | 0.16 ± 0.03 | 0.37 ± 0.10 | 0.96 ± 0.09 |
| VAR | 0.12 ± 0.04 | 0.29 ± 0.10 | 0.92 ± 0.12 |
| GP | 0.12 ± 0.03 | 0.30 ± 0.10 | 0.94 ± 0.15 |
| DeepAR | **0.06 ± 0.02** | **0.21 ± 0.08** | 0.99 ± 0.17 |
| Discrete Hawkes | 0.08 ± 0.02 | 0.24 ± 0.07 | **0.91 ± 0.12** |
| Multivariate Hawkes | **0.06 ± 0.02** | **0.21 ± 0.08** | 0.97 ± 0.15 |

## Case Study: Indianapolis, IN

**Data description:** In collaboration with AES Indiana, we collected

- 1,742 customer-level rooftop solar panel installation records within AES Indiana territory.
- Network topology information (circuits, substations, *etc.*).
- Load time series and outage records

From external sources, we referred to weather data, socioeconomic data, and incentives (compensation, net metering tariffs, *etc.*) The data spans from 2010 to mid-June 2024.




**Long-term Forecast:** We generate scenarios using our model through 2050. The first figure below shows the distribution level temporal trajectories and the second figure shows the distribution level spatial trajectories.