Structural Modeling of Annual Hourly Load Considered Coupled Dynamics

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Background

- ☐ Mid-term Load Forecasting (MTLF) is critical for power system **maintenance, fuel planning, and electricity procurement.**
- ☐ Forecasting requirements transition from monthly forecast to **annual hourly forecast**, and generate realistic 8760-hours scenarios.
- ☐ Auto-regressive methods fail at long horizons; traditional conditional modeling methods overlook structural evolution and complex holidays.

Challenges and Contribution

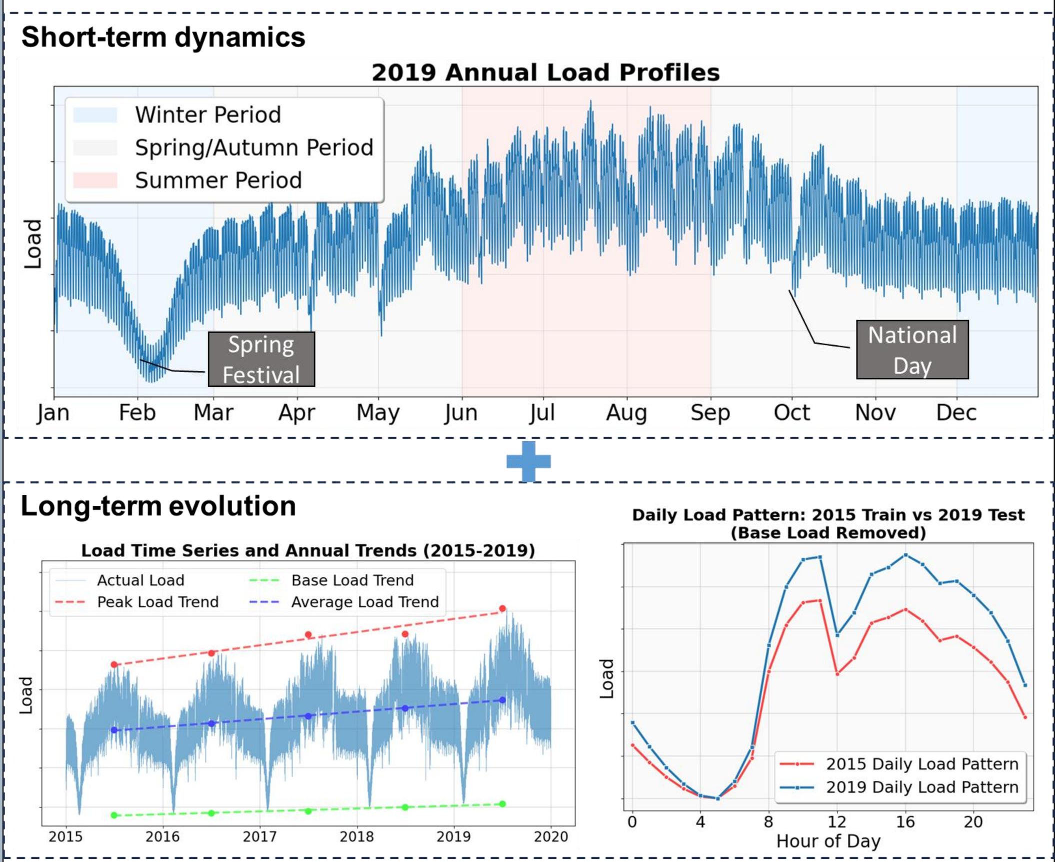

Fig. 1. Illustration of annual hourly load modeling challenges

➤ Challenges

- ☐ Complex Dynamics: **Short-term patterns** coupled with **long-term year-over-year evolution**.
- ☐ China's Unique Holidays: Lunar Calendar shifts and "Time-off in-lieu" system (weekend adjustments make load patterns irregular).
- ☐ Structural Uncertainty: Need to quantify annual hourly load uncertainties and build **long-term temporal dependencies** to generate realistic scenarios.

➤ Our Contribution

- ☐ Propose a novel structural GAM, explicitly model the **coupled dynamics and long-term structural evolution** of load profile.
- ☐ Propose a robust pattern-based holiday modeling approach within the GAM.
- ☐ Scenario Generation: A two-stage method (Mixture Distribution + Decoupled Residuals) for **probabilistically consistent and realistic 8760-load scenarios**.

Methodology

➤ Structural GAM for Annual Hourly Load Modeling

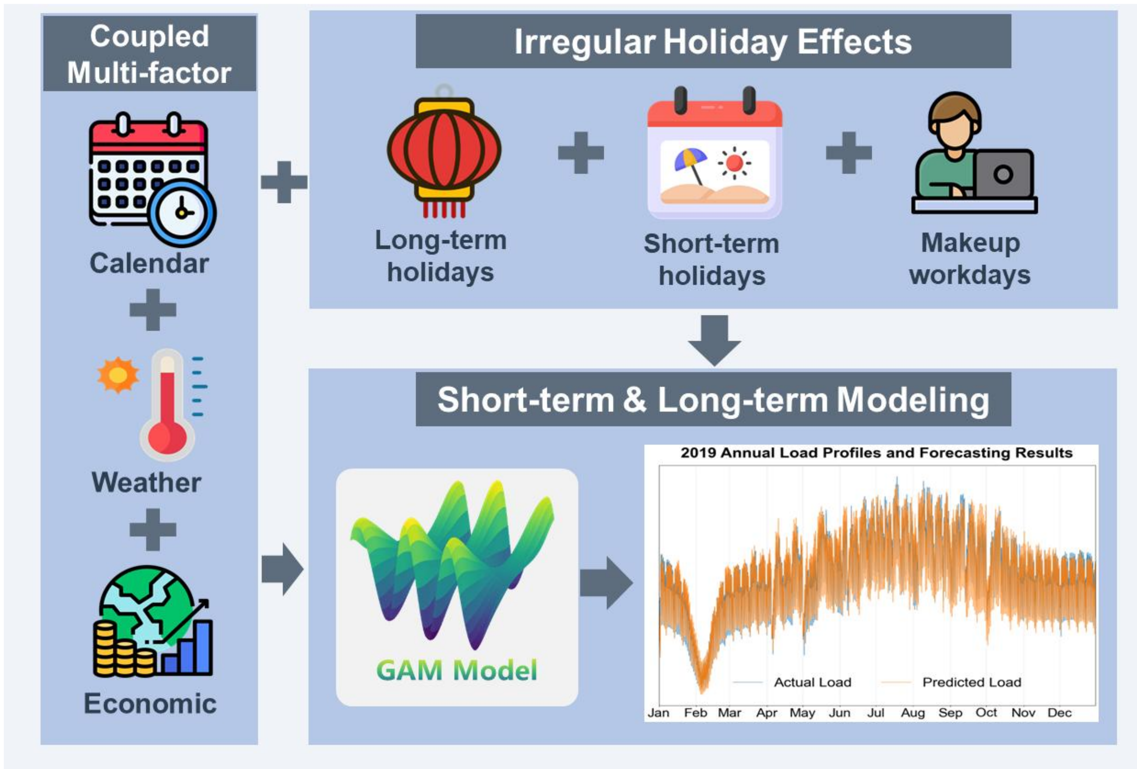

Fig. 2. GAM for annual load modeling

$$l_t = \beta + f_{cal} + f_{wea} + f_{holi} + f_{eco} + \epsilon_t$$

Calendar

$$f_{\text{cal,t}} = \underbrace{s(\text{HoD}_t) + w_{\text{HoW},t} \cdot (\text{HoW}_t) + s(\text{HoY}_t)}_{\text{main cyclical patterns}} \\ + \underbrace{te(\text{HoD}_t, \text{HoW}_t) + te(\text{HoD}_t, \text{HoY}_t) + te(\text{HoW}_t, \text{HoY}_t)}_{\text{cyclical patterns interactions}} \\ + \underbrace{te(\text{Year}_t, \text{HoD}_t) + te(\text{Year}_t, \text{HoW}_t)}_{\text{long-term evolution}}$$

Weather

$$f_{\text{wea,t}} = \underbrace{m_{T,t} \cdot te(T_t,\ \text{HoD}_t)}_{\text{evolving daily effect}} + \underbrace{te(T_t,\ \text{HoW}_t)}_{\text{weekly temperature effect}} + \underbrace{te(T_t,\ \text{HoY}_t)}_{\text{seasonal temperature effect}}$$

Economic

$$f_{\text{eco,t}} = \beta_{\text{GDP}} \cdot \text{GDP}_t, \quad \text{where } \beta_{\text{GDP}} \geq 0$$

Holidays

$$f_{\text{holi,t}} = f_{\text{3-days,t}} + \underbrace{f_{\text{SF,t}} + f_{\text{ND,t}}}_{\text{Long-term holidays}} + f_{\text{TOIL,t}}$$

$$\begin{cases} f_{\text{SF},t} = m_{h,t} \cdot s(\text{SF}_t) + te(\text{HoD}_t, \text{SF}_t) \\ f_{\text{ND},t} = m_{h,t} \cdot s(ND_t) + te(\text{HoD}_t, ND_t) \\ f_{\text{3-days}}(t) = \sum_{\text{type}=1}^{7} m_{h,t} \cdot s(h_{\text{type},t}) \\ f_{\text{TOIL,t}} = s(M_{6,t}) + s(M_{7,t}) \end{cases}$$

- ☐ Structural GAM: Explicitly decomposes load into **Calendar, Weather, Economy, and Holiday** components.
- ☐ Decomposition Strategy: Using smooths $s(\cdot)$ and tensor product smooths $te(\cdot)$ to capture non-linear interactions; Explicitly modeling year-over-year changes in patterns.

➤ Two-Stage Load Scenario Modeling

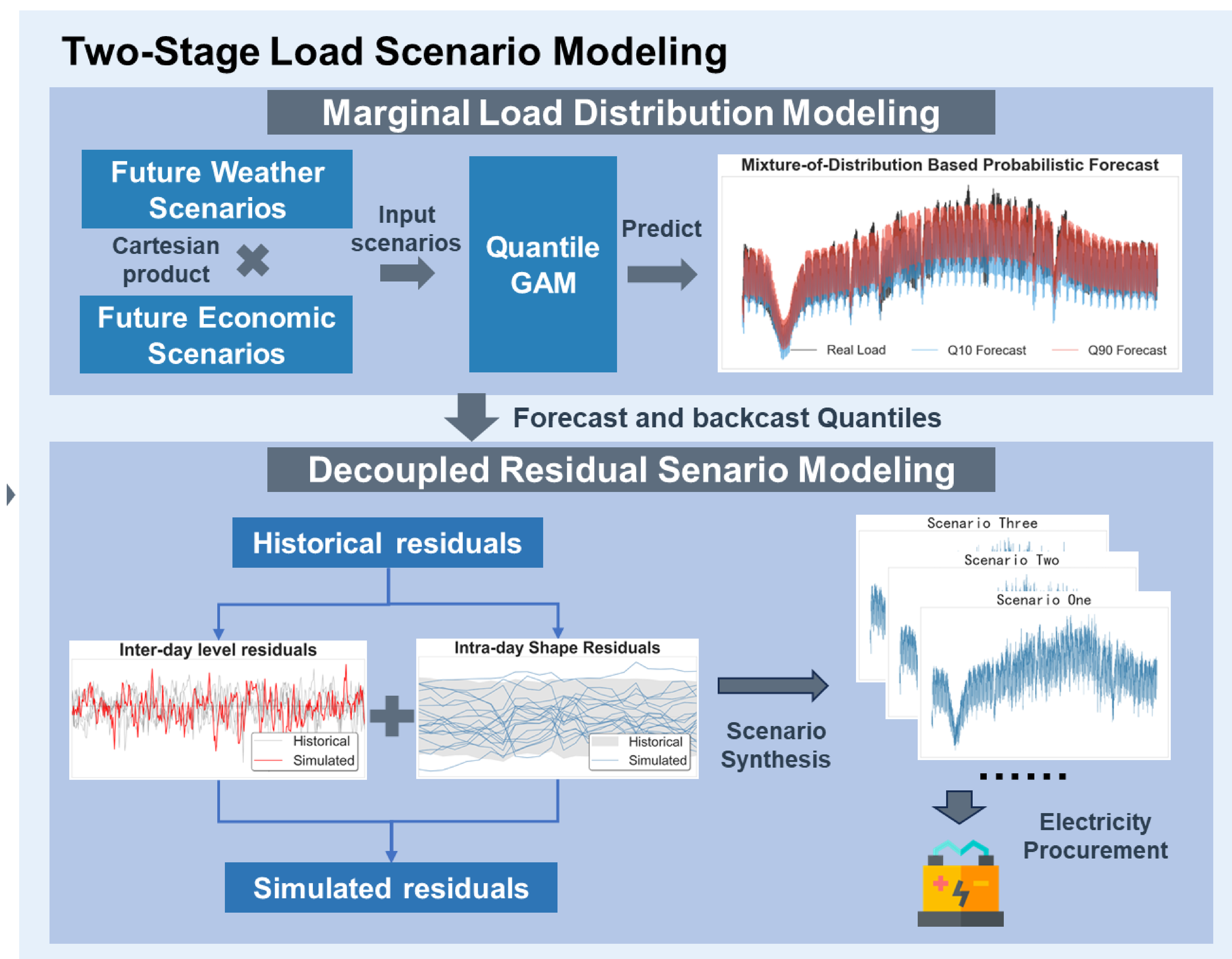

Fig. 3. The sketch of end-to-end modeling.

- ☐ Mixture-of-distributions probabilistic forecasting: simultaneously considered **the input uncertainty** and **load inherent randomness**.
- ☐ Scenario generation: 8760-hour scenario generation need to build long-term temporal dependencies; we generate realistic scenarios using a decoupled residual modeling strategy.

Case study

➤ Experiment results

Part A: input actual weather and GDP data

Metric	MLR	Prophet	MLP	LGBM	Proposed
Overall MAPE	7.65	8.88	5.17	5.74	**3.97**
Spring Festival	27.42	25.95	8.21	6.86	**5.63**
National Day	12.09	13.30	7.87	7.79	**5.86**
3-Day Holidays	11.78	12.05	11.20	9.82	**5.54**
Normal Days	4.69	6.34	4.25	5.24	**3.59**

Part B: input forecast weather and GDP data

Metric	MLR	Prophet	MLP	LGBM	Proposed
Overall MAPE	8.37	8.88	6.84	6.27	**5.20**
Spring Festival	27.10	25.95	10.57	7.15	**6.52**
National Day	13.18	13.30	10.62	9.58	**8.76**
3-Day Holidays	11.92	12.05	11.66	9.67	**7.15**
Normal Days	5.57	6.34	5.90	5.81	**4.78**

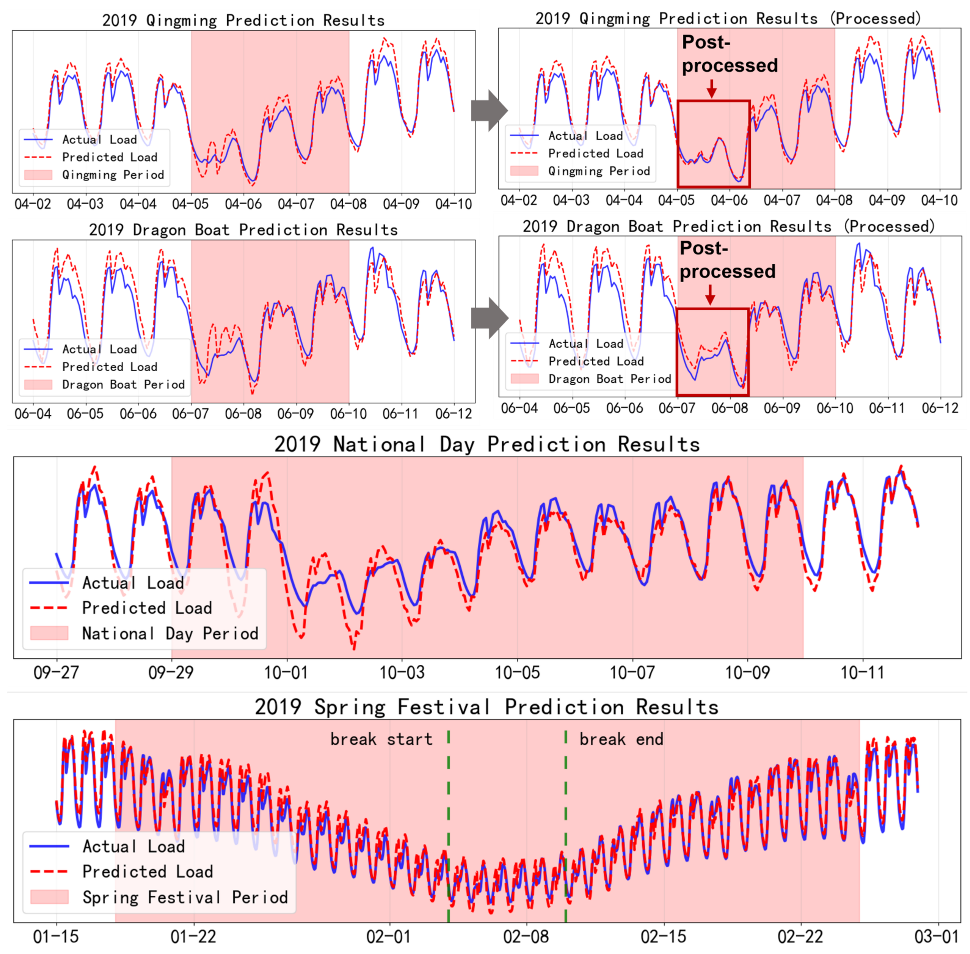

Fig.4. Holidays load forecasting results.

- ☐ 12 years of Guangdong load dataset.
- ☐ Consistently outperforms all, reducing the overall MAPE to **3.97% (ideal) and 5.20% (realistic).**
- ☐ Holiday components are effectively captured

➤ Model Interpretability Analysis

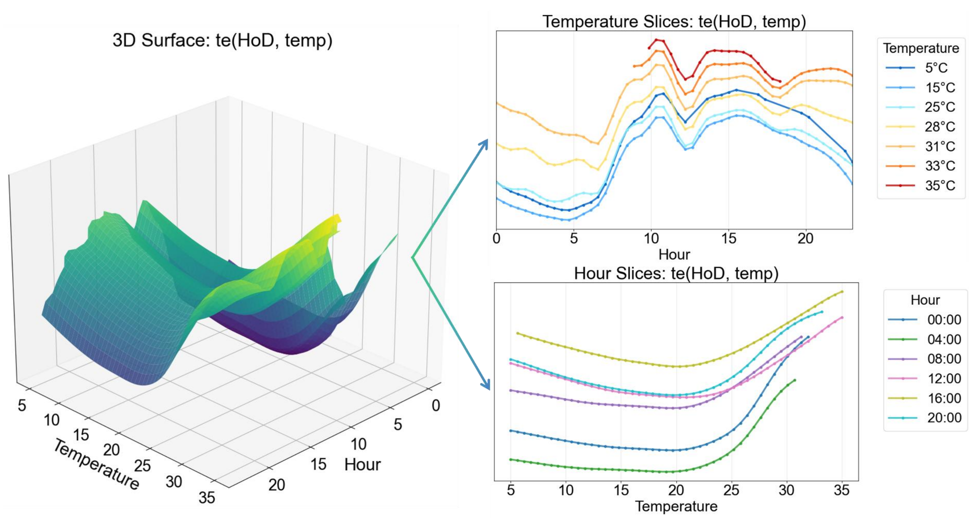

Fig.5. Temp. hours interaction term.

- ☐ The model is capable to **quantify the impact of specific drivers**. Enable deeper understanding of load patterns

➤ Load Scenario generation and application

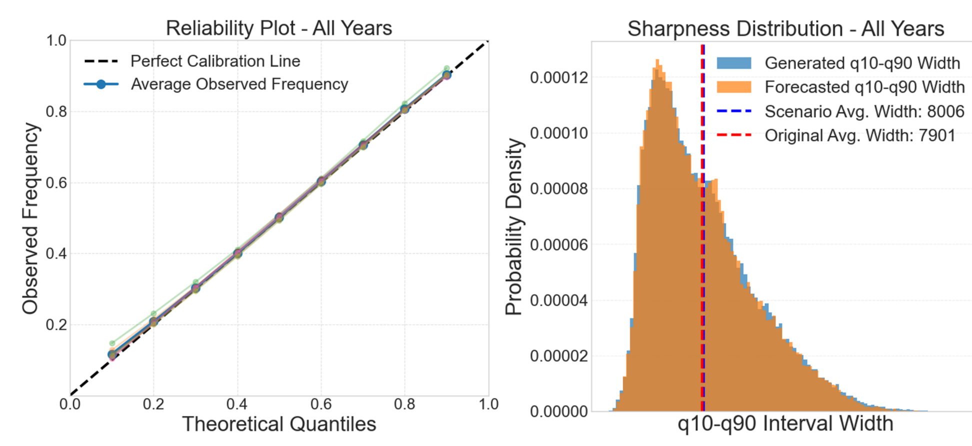

Fig.6. Reliability and sharpness diagram of the generated scenarios.

- ☐ Applied to electricity procurement, the generated scenarios enable better risk management. This strategy achieving annual savings of over **43 million CNY** compared to naive methods.