Panoramic Probabilistic Optimizer: Refined Annual 8760-hour Load Curve for Long-term Electricity Forecasting

***Abstract*—The annual 8760-hour load curve is vital for power system planning, operation and market transactions. This paper proposes a panoramic probabilistic optimizer, which can refine the long-term electricity forecasting. First, the characteristics of the refined annual 8760-hour load curve are analyzed across three time-scale: long-term trends, medium-term variations, and short-term variations. It points out the factors influence load behavior throughout the year, forming a basis for the panoramic probabilistic optimizer. Second, the panoramic probabilistic optimizer is introduced, employing a collaborative optimization approach across multiple time scales. It includes the short-term, medium-term, and long-term dimensions. By integrating insights from the characteristics, the optimizer synthesizes these dimensions to generate a complete and enhanced refined annual 8760-hour load curve for improved panoramic long-term electricity forecasting. Finally, it validates the approach by load data from Hubei and Guangxi, China. The results demonstrate the proposed method significantly improves both complete and robustness of annual electricity forecasting over the entire 8760-hour period.**

***Index Terms*—Long-term electricity forecasting, refined annual 8760-hour load curve, collaborative optimization, load characteristics, curve decomposition.**

I. Introduction

With the rising volatility and randomness of load patterns, it is crucial to assess operational performance over an extended timeframe, typically encompassing 8760 hours in annual power system operation. Therefore, the refined annual 8760-hour load curve serves several critical functions in electricity management and planning. Its primary applications includes the annual power system operation and as a valuable reference for long-term electricity market strategies in capacity planning. This necessitates a meticulous characterization of load dynamics to meet the power system operational demands, facilitating the exploration of a diverse array of scenarios with high temporal resolution [1-2].

At present, the electricity forecasting can be divided into two theories. The first is the feature-mapping theory, which calculates loads by finding strongly correlated influences and subsequently building mathematical models based on features. Linear Regression (LR) [3], Random Forest (RF) [4], Support Vector Regression (SVR) [5], and K Nearest Neighbors (KNN) [6], among others, fall into this category. The theory is based on the fact that loads are influenced by human activities, which are typically related to economic [7], meteorological [8], calendar [9], and seasonal-related factors. However, this method may not be directly applicable for annual 8760-hour load curve forecasting, as this curve is influenced by a wide range of factors spanning both short-term and long-term variations. Considering the volume of data in the annual 8760-hour load curve, it is likely that predicting a large amount of input data prior to estimating the curve will result in significant errors in the capacity planning.

The second is the auto-Machine Learning (auto-ML) theory. This approach primarily emphasizes the analysis of time series patterns, seeking to uncover the underlying structures that can be statistically examined or modeled. The representative models include such as Long Short-Term Memory (LSTM) [10], Gate Recurrent Unit (GRU) [11], Temporal Convolutional Network (TCN) [12], and Transformer [13]. Additionally, modal decomposition techniques, such as Variational Mode Decomposition [14], Complete Ensemble Empirical Mode Decomposition [15], and Discrete Wavelet Transform [16], can effectively extract load characteristics. Consequently, auto-ML models can leverage the inherent data properties of the sequence, achieving sufficient prediction accuracy in the short term [17]. However, the annual 8760-hour load curve requires an excessive amount of data for output, leading to significant inaccuracies in predictions when using auto-ML models. This suggests the used electricity forecasting theories may not provide reliable predictions for the refined annual 8760-hour load curve to plan annual power system operation.

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Since the traditional annual load forecast is difficult to meet the power system operational demands, some scholars have proposed the 8760-hour load curve. The annual 8760-hour load curve represents the hourly loads throughout the year, capturing load characteristics across short-term, medium-term, and long-term dimensions. The maximum value as a reference for extreme load predictions, while the hour-by-hour load superposition aids in forecasting electricity consumption [18]. At present, the annual 8760-hour load curve is usually obtained by typical curves[19]. For instance, one typical curve may be selected for each month, or two representative days can be chosen to illustrate seasonal variations, corresponding to summer and winter [20]. This approach is usually feasible because, while the accuracy of the load curve is essential for long-term production simulation and annual power system operation analysis, the shape of the curve deserves even greater attention as it directly influences planning outcomes. Therefore, the use of a typical curve or scenario is justified by the significant computational savings [21]. [22] conducts power balance simulations employing typical daily load curves for short-term analysis at an hourly resolution, while incorporating daily peak loads for long-term assessment. This temporal decomposition of the load curve significantly mitigates simulation complexity. [23] utilize random sampling of historical data and generated scenarios. The analysis continues until a duration of 8760-hour is reached, which serves as a basis for proposing joint planning methods. Nevertheless, this approach gets worse as the load becomes more complex. Analyses based on a limited number of typical curves may be insufficient because they ignore the uncertainty generated by the source load and other factors. This oversight can lead to discrepancies between simulation outcomes and actual operational conditions, resulting in jeopardizing the economy and security of power system operations. Consequently, it motivates the in-depth study of electricity forecasting for the refined annual 8760-hour load curve. It is necessary and challenging to decompose it into three time-scale of load characteristics for planning annual power system operation and the production simulation. To the best of the author’s knowledge, there has been limited research on predicting the refined annual 8760-hour load curve utilizing probability distributions and time dimension decomposition.

The refined annual 8760-hour load curve forecast presents a complex nonlinear modeling challenge. The primary objective of forecasting is to ensure that the outputs closely align with actual values while minimizing error [24]. The aforementioned models capture essential statistical properties and probability distributions to achieve this aim, particularly when working with intervals or probabilities derived from these distributions [25-27]. Consequently, these models are commonly employed in both short-term and long-term with coarse resolution [28]. However, the task becomes increasingly intricate when addressing the annual 8760-hour load curve. Loads across different temporal dimensions exhibit distinct statistical patterns and probability distributions, and the inherent complexity and interdependence within load curves impede direct simulation modeling. Furthermore, given that load curves encompass multidimensional information, the decomposition methods outlined are inadequate for analyzing the 8760-hour load curve, as they are difficult to effectively capture the various temporal dimensions. Therefore, it is crucial to accurately estimate dimensional characteristics through robust decomposition techniques and precise probability distributions.

To fill the aforementioned research gaps, the contributions of this paper are detailed as follows.

1) A refined annual 8760-hour load curve is proposed, which provides a panoramic perspective on load variations.

2) The three time-scale load characteristics is proposed by decomposing the refined annual 8760-hour load curve to extract multidimensional temporal information.

3) A panoramic probabilistic optimizer is proposed to collaboratively optimize the prediction of three-time-scale load characteristics, which is based on probability distributions and decomposition.

The rest of this article is organized as follows. In Section II, the structure of the refined annual 8760-hour load curve forecasting based on a panoramic probabilistic optimizer is introduced. In Section III, the refined annual 8760-hour load curve is described in detail. In Section IV, the panoramic probabilistic optimization method is proposed. In Section V, the analysis of a case study is discussed. The conclusion is made in Section VI.

II. Structure of Refined Annual 8760-hour Load Curve Forecasting

The structure of the refined annual 8760-hour load curve forecasting based on the panoramic probabilistic optimizer is shown in Fig.1. It consists of two parts: the refined annual 8760-hour load curve and the panoramic probabilistic optimizer.

In the first part, we analyze the refined annual 8760-hour load curve, highlighting its multidimensional temporal information. The refined annual 8760-hour load curve encompasses various time dimensions, which is decomposed and normalized accordingly. Consequently, the curve is represented by various load indicators categorized into three time-scale: long-term trends, medium-term variations, and short-term variations.

In the second part, we establish the panoramic probabilistic optimizer, which predicts load characteristics from the three time-scale and optimizes the solutions. For the unique characteristics of each dimension, differentiated models are developed for optimization. We construct the optimization model based on the Law of Large Numbers (LLN) and Bayes' theorem, ultimately resulting in the predicted outcomes for a panoramic refined annual 8760-hour load curve.

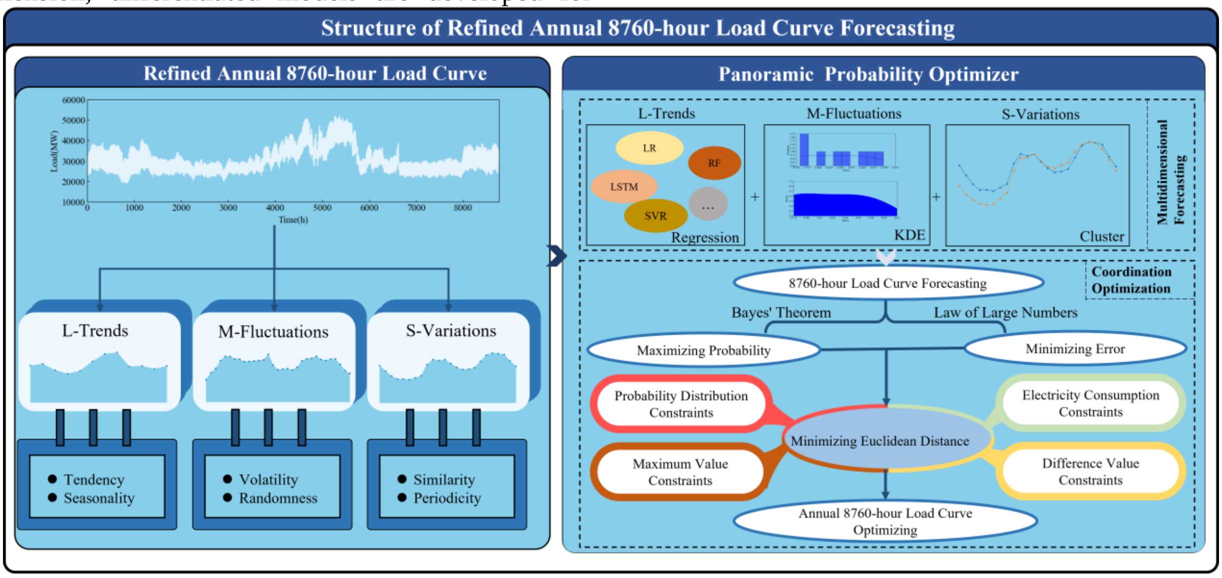


Fig. 1. The Structure of annual 8760-hour load curve forecasting.

III. Refined Annual 8760-hour Load Curve

To gain a deeper understanding of the complex characteristics of the refined annual 8760-hour load curve, it is essential to decompose and analyze it from multiple dimensions. By examining aspects such as seasonality, time of day, and load types, we can more clearly identify the various factors influencing electricity demand. This decomposition reveals potential patterns and trends within the load curve and provides more granular data support for forecasting. In the following sections, we will explore the multidimensional temporal load characteristics.

Based on the time dimension, the refined annual 8760-hour load curve($p_t^{8760}, 1 \le t \le 8760$) can be represented by components such as the annual peak load ($p_y^{\max}$, y represents the year of the curve), annual load curve ($\{p_{y,m}^{\text{annual}}\}, 1 \le m \le 12$), monthly load curve ($\{p_{y,m,d}^{\text{monthly}}\}, 1 \le d \le 31$), and daily load curve ($\{p_{y,m,d,h}^{\text{daily}}\}, 1 \le h \le 24$). This decomposition is expressed as

$$p_t^{8760} = p_y^{\max} \cdot p_{y,m}^{\text{annual}} \cdot p_{y,m,d}^{\text{monthly}} \cdot p_{y,m,d,h}^{\text{daily}} \tag{1}$$

The annual load curve, monthly load curve, and daily load curve are normalized as shown as

$$p^* = \frac{p}{p^{\max}} \tag{2}$$

where p^* is the result of normalizing, p is the original value, and $p^{\max}$ is the maximum load of the time scale.

After decomposition and normalization, multidimensional temporal information is obtained, with each curve exhibiting a maximum value of 1 and a minimum value that reflects the peak-to-valley difference.

To generate a refined annual 8760-hour load curve and establish the probabilistic optimization model, Table I outlines the load indicators which must be taken into account. As shown in Table I, the load characteristics indicators are divided into three parts according to different time-scale, the long-term trends, the medium-term variations, and the short-term variations.

Long-term trends encompass both tendency and seasonality, reflecting the overarching patterns in load characteristics over extended periods. This dimension helps identify consistent increases or decreases in demand, as well as seasonal variations that may influence energy consumption. Factors affecting long-term trends often include economic growth, demographic changes, technological advancements, and policy shifts aimed at energy efficiency. Understanding this dimension is crucial for long-term forecasting and strategic planning in energy management.

TABLE I
Load Characteristics Indicators

Indicator	Implication	Dimension
E_y^{year}	Electricity consumption of year y	Long-term trends
$p_y^{\max}$	Annual peak load of year y	Long-term trends
$e_{y,m}^{\text{annual}}$	Electricity consumption ratio of month m in year y	Long-term trends
$p_{y,m}^{\text{annual}}$	Monthly peak load of month m in year y	Long-term trends
$\gamma_{y,m}^{\text{annual}}$	Average daily load factor of month m in year y	Long-term trends
$\beta_{y,m}^{\text{annual}}$	Average daily minimum load factor of month m in year y	Long-term trends
$p_{y,m,d}^{\text{monthly}}$	Daily peak load of day d in month m, year y	Medium-term variations
$\mu_{m,d}$	Daily peak load mean of day d in month m	Medium-term variations
$\sigma_{m,d}$	Daily standard deviation of day d in month m	Medium-term variations
$[I_{m,d}^{\text{lower}}, I_{m,d}^{\text{upper}}]$	Daily confidence interval of day d in month m	Medium-term variations
$p_{y,m,d,h}^{\text{daily}}$	Hourly load of the daily load curve	Short-term variations

Medium-term variations capture the variability and randomness in load characteristics over intermediate timeframes. This dimension highlights how factors such as market conditions, weather patterns, and date types can lead to significant variations in energy demand. By analyzing these fluctuations, one can assess the impact of external influences, including calendar cycles and weather changes, on load patterns. Recognizing these variations is essential for effective resource allocation and optimizing energy distribution during transitional periods.

Short-term variations focus on the similarities and periodicity of load characteristics within brief intervals. This dimension is particularly sensitive to immediate factors such as daily weather changes, consumer behavior, and real-time events. Recognizing patterns in short-term variations allows for more responsive energy management strategies, ensuring that supply meets demand accurately. Key influencing factors might include peak usage times, special events, and sudden shifts in consumer habits. Analyzing these variations aids in fine-tuning operational practices and enhancing system reliability.

Based on the distinct characteristics of each time dimension, various models can be developed to enhance the accuracy. For the long-term trend, which encompasses both trend components and seasonality, linear regression and machine learning models are particularly suited. These models can effectively capture the underlying patterns and long-term relationships in the data, allowing for robust predictions over extended periods. In contrast, short-term variations, characterized by their similarities and periodicity, lend themselves well to clustering techniques. By grouping similar consumption patterns, these models can identify peak demand periods and respond dynamically to real-time changes in load. However, the medium-term variations present a more complex challenge due to their inherent variability and randomness. This dimension will be the primary focus of the study, as understanding the unpredictable nature is crucial for optimizing energy management strategies. Advanced statistical methods and hybrid modeling approaches may be employed to navigate these complexities, ensuring that the models remain adaptive and responsive to changing conditions.

Through this comprehensive approach, we can develop a robust framework known as the panoramic probabilistic optimizer, which addresses each dimension's specific characteristics. This optimizer will facilitate more precise and actionable load forecasting by integrating insights from long-term trends, medium-term fluctuations, and short-term variations. By leveraging diverse modeling techniques tailored to each time dimension, the panoramic probabilistic optimizer aims to fit the overall change trend and the fluctuation degree of load curve.

IV. Panoramic Probability Optimizer

A. Multidimensional Forecasting Constraints

Following the analysis of load characteristics across long-term trends, medium-term variations, and short-term variations, the next steps involve developing tailored models for each dimension.

Long-term trends typically exhibit features of both trending behaviors and seasonality, making them suitable for statistical analysis. Given the clear patterns observed in these trends, both feature-mapping and auto-ML models can fit the overall trend of the load curve. As a result, a diverse pool of models will be considered, including LR, RF, LSTM, SVR, and others.

The optimal model will be identified by comparing the predicted results of these various models on the test set.

For medium-term variations, which are more volatile due to the greater number of influencing factors, a more effective approach is required. As illustrated in Fig.2, time series are typically observed from a horizontal perspective. This method is usually feasible because load variations are generally regular. However, when examined over a time span of months or even years, daily peak load changes become volatility and challenging to control directly. This volatility arises because the daily peak load is influenced by factors such as temperature, type of date, and residential activity, making it highly unpredictable.

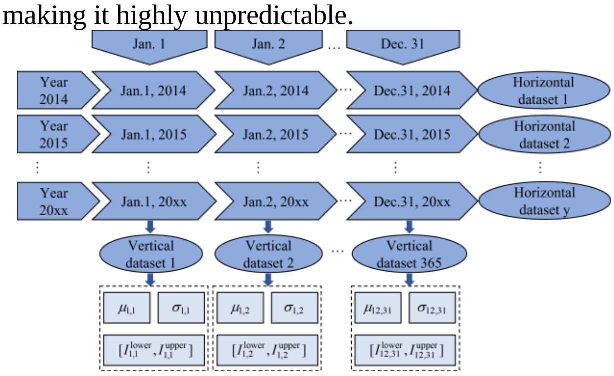


Fig. 2. Daily peak load dataset in different perspective.

Modeling a direct prediction of daily peak load for an entire year proves to be quite difficult. However, shifting the viewpoint to a vertical perspective allows for the identification of patterns in the changes of daily peak load [29]. Overall, these changes continue to correlate with seasonal and climatic variations. For instance, temperatures gradually increase from spring to summer, while load levels tend to be lower at the beginning of the month compared to the end. Conversely, the opposite trend is observed from summer to fall. Therefore, after disaggregation and normalization, the daily peak load should fluctuate within a more stable range throughout the month. The load probability distribution can be determined using Kernel Density Estimation (KDE) to obtain the mean, standard deviation, and confidence interval for each day of the year). In this study, the confidence level is set at 95%.

KDE enables precise estimation of PDF for random variables drawn from an unknown distribution [30]. For dataset $p^{\text{kde}} = \{p^{\text{daily}}_{1,m,d}, p^{\text{daily}}_{2,m,d}, \cdots p^{\text{daily}}_{n,m,d}\}$, the KDE of the overall density function at any sample is defined as

$$f(p) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{p - p^{\text{day}}_{n,m,d}}{h}\right) \tag{3}$$

where n is the dataset size, and in this paper, it is the number of history years, $K(p)$ is the kernel function, given by

$$K(p) = \frac{1}{\sqrt{2\pi}} e^{-\frac{p^2}{2}} \tag{4}$$

h is the bandwidth, given by

$$h = \left(\frac{4\hat{\sigma}_p^{5}}{3n}\right)^{\frac{1}{5}} \tag{5}$$

where $\hat{\sigma}$ is the sample standard deviation.

For short-term variations, a clustering approach effectively captures load shape patterns. To enhance the resilience and inclusiveness of the refined annual 8760-hour load curves, the following steps are taken to select typical daily load curves:

1) Separating Holiday Load Curves: Recognizing that residential and industrial activities on holidays differ significantly from those on weekdays, all holiday load curves are first differentiated.

2) Distinguishing between Different Week Types: Given that various week types exhibit different residential activity patterns, the daily load profiles are categorized based on calendar data.

3) Clustering by Date Types: Using k-means clustering, each broad category is clustered separately, with the number of clusters determined by profile coefficients [31].

4) Identifying Typical Load Profiles: The cluster center curves typically represent the average within their respective clusters. However, to capture the peak-to-valley variations more effectively, three curves corresponding to the 25th, 50th, and 75th percentiles of peak-to-valley differences are selected as typical load profiles. This approach ensures that the selected curves are both elastic and adaptable.

After obtaining the typical daily load profile, the daily load profile for the year is determined by the following steps:

1) Categorizing the Year: The year to be forecasted is categorized by holiday and week type.

2) Calculating Cluster Similarity: Cluster similarity is calculated on a day-by-day basis. The similarity metric is defined as in Eq. 6, indicating that the closer the dates of the two days, the more similar the shapes of their load curves are considered to be. The average similarity of all clusters relative to a specific category on a given day is calculated, and the cluster with the strongest similarity is selected as the load category for that day.

$$\eta(D_{y,m,d}) = \frac{1}{\sum_{l} \min\left(|D_{y,m,d} - D_l|\%365, 365 - |D_{y,m,d} - D_l|\%365\right)} \tag{6}$$

where η is the similarity coefficient, $D_{y,m,d}$ is the date to be forecasted D_l is the date of comparison.

3) Calculating Similarity of Typical Daily Load Profiles: In this classification, the similarity between the day to be forecasted and the three typical load curves is calculated, and the most similar curve is selected as the typical load curve for that day.

4) Obtaining Typical Load Profiles for the Year: Typical load profiles for the year are obtained by splicing the daily profiles together.

The daily load factor and daily minimum load factor of the spliced curves do not match those obtained from forecasting. Therefore, the typical load curves need to be corrected. Based on the forecasted results, the daily load factor and daily minimum load factor are adjusted, and the daily load curve is corrected according to the curve extension correction method described in [32]. The corrected daily load curve is obtained by sequentially reducing the adjusted loads. This process is repeated monthly to derive the corrected typical load curve for the entire year, consisting of 8760 hours.

B. Coordination Optimization

After determining the distribution of the three time-scale, further synergistic computation of the prediction results is necessary. At this stage, considering the curve decomposition process, the monthly load curve needs to be calculated.

The true value can be expressed as

$$p = \hat{p} + \varepsilon \tag{7}$$

where p and $\hat{p}$ are the truth values and the predicted values.

It can be seen from (7) that the data probability distribution should be fitted as much as possible in order to make the result more accurate. At the same time, the prediction error should be made as small as possible. That is $\max\{P(\hat{y}=y)\}$, which means $\min\{\varepsilon\} = \min\{p-\hat{p}\}$.

The LLN asserts that [33], under certain conditions, the sample mean of a sequence of random variables will converge to a specific real number as the sample size increases. This principle implies that, as we accumulate more observations, the sample mean stabilizes around the population average, reflecting the underlying distribution of the data. Consequently, we can interpret the load as oscillating around this established mean value.

In conjunction with this, Bayesian inference provides a framework for updating probabilities based on observed evidence [34]. Specifically, it posits that as more events supporting a particular attribute are recorded, the likelihood of that attribute occurring in the future increases. This perspective allows us to derive a probability density distribution from historical data, under the assumption that future loads will exhibit similar distributional characteristics to those observed in the past.

Building on these foundations, we propose a co-optimization model aimed at minimizing the distance between predicted values and the mean of the distribution. This optimization problem transforms the forecasting task into a systematic approach that seeks to align our predictions closely with the expected average load. By doing so, we leverage both the stability provided by the LLN and the adaptive nature of Bayesian inference, ensuring that our model is robust against fluctuations while remaining grounded in empirical evidence.

$$f = \min \sum_{m}^{12} \sum_{d}^{D_m} \left(\frac{\hat{p}_{Y,m,d}^{\text{monthly}} - \mu_{y,m,d}}{\sigma_{y,m,d}} \right)^2 \tag{8}$$

The constraints are as follows

1) Probability Distribution Constraints

$$I_{y,m,d}^{\text{down}} \le \hat{p}_{y,m,d}^{\text{monthly}} \le I_{y,m,d}^{\text{up}} \tag{9}$$

2) Electricity Consumption Constraints

$$\hat{P}_y^{\max} \cdot \hat{p}_{y,m}^{\text{annual}} \cdot \sum_{d}^{D_m} \hat{p}_{y,m,d}^{\text{monthly}} \cdot \sum_{h}^{24} p_{y,m,d,h}^{\text{daily}} = \hat{E}_y^{\max} \cdot \hat{e}_{y,m}^{\text{annual}} \tag{10}$$

3) Maximum Value Constraints

$$\max_{1 \le d \le D_m} \{\hat{p}_{y,m,d}^{\text{monthly}}\} = 1 \tag{11}$$

4) Difference Value Constraints

$$|\, \hat{p}_{y,m,d}^{\text{monthly}} \cdot p_{y,m,d,24}^{\text{daily}} - \hat{p}_{y,m,d+1}^{\text{monthly}} \cdot p_{y,m,d+1,1}^{\text{daily}} | \le \frac{1.5 \cdot \left| p^{\text{diff}} \right|}{\hat{P}_y^{\max} \cdot \hat{p}_{y,m}^{\text{annual}}} \tag{12}$$

$$|\, \hat{p}_{y,m}^{\text{annual}} \cdot \hat{p}_{y,m,D_m}^{\text{monthly}} \cdot p_{Y,m,D_m,24}^{\text{daily}} - \hat{p}_{y,m+1}^{\text{annual}} \cdot \hat{p}_{y,m+1,1}^{\text{monthly}} \cdot p_{y,m+1,1,1}^{\text{daily}} | \le \frac{1.5 \cdot \left| p^{\text{diff}} \right|}{\hat{P}_y^{\max}} \tag{13}$$

where p^{maxdiff} is the maximum load difference value.

C. Solution and Evaluation

To solve the optimization problem, we utilize the Gurobi commercial solver.

The standard performance metrics used to evaluate the prediction results include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2). MAE and RMSE reflect the accuracy of the predictions, with RMSE being more sensitive to larger errors. MAPE provides a percentage-based measure of prediction accuracy relative to actual values. R^2 indicates how well the model fits the data. For MAE, RMSE, and MAPE, smaller values signify lower prediction errors, whereas for R^2, a value closer to 1 indicates better model performance.

$$\varepsilon^{\text{MAE}} = \frac{1}{n} \sum_{i=1}^{n} \left| (p_i - \hat{p}_i) \right| \tag{14}$$

$$\varepsilon^{\text{RMSE}} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (p_i - \hat{p}_i)^2} \tag{15}$$

$$\varepsilon^{\text{MAPE}} = \frac{1}{n} \sum_{i=1}^{n} \frac{\left| (p_i - \hat{p}_i) \right|}{p_i} \tag{16}$$

$$\varepsilon^{\text{R}^2} = 1 - \frac{\sum_{i}^{n} (p_i - \hat{p}_i)^2}{\sum_{i}^{n} (p_i - \bar{p}_i)^2} \tag{17}$$

V. CASE STUDY

A. Dataset Setups

For this study, we selected two actual load datasets from Hubei and Guangxi, China. Hubei, located in central China, is characterized by a more temperate climate and a dense urban population, leading to varying electricity demand patterns throughout the year. In contrast, Guangxi, situated in southern China, is with higher humidity and temperature variations. These differences in climate and demographic factors provide a valuable foundation for analyzing the generalizability of findings across different regions. The key characteristics of these datasets are summarized in Table II. The proposed method was evaluated against several other models, as detailed in Table III. The comparison model also includes typical load curves, feature-mapping models, and auto-ML models.

TABLE II
EXPERIMENT SETUPS OF DATASET

	CASE 1	Case2
Province	Hubei	Guangxi
Geographic Location	Central China	South China
Time Period	2014.1.1-2022.12.31	2011.1.1-2022.12.31
Timespan	9 years	11 years
Data Sources	Government statistics, meteorological data, etc.	Government statistics, meteorological data, etc.
Economic Indicators	GDP, industrial structure, population growth rate, etc.	GDP, industrial structure, population growth rate
Climate Features	Average temperature, humidity, etc.	Average temperature, humidity, etc.
Training set	2014.1.1-2021.12.31	2011.1.1-2021.12.31
Testing set	2022 annual 8760-hour load curve	2022 annual 8760-hour load curve

The performance of the feature-mapping model is heavily influenced by the selection of input features. To enhance predictive outcomes, the model will utilize actual economic and meteorological data. However, it is important to note the predictive performance of such models may deteriorate over time in practical engineering applications. Additionally, when employing auto-regressive models, the implementation of a rolling forecasting approach can result in vanishing gradients beyond a certain time step, subsequently diminishing predictive accuracy. To address this issue, the model will incorporate data from the past year as input, thereby mitigating errors associated with excessive rolling prediction steps and ensuring the model's effectiveness and reliability.

These alternative models require careful parameter tuning based on prior expertise, given their complexity and sensitivity to adjustments. To optimize this process, we employed Particle Swarm Optimization (PSO) for model tuning [35].

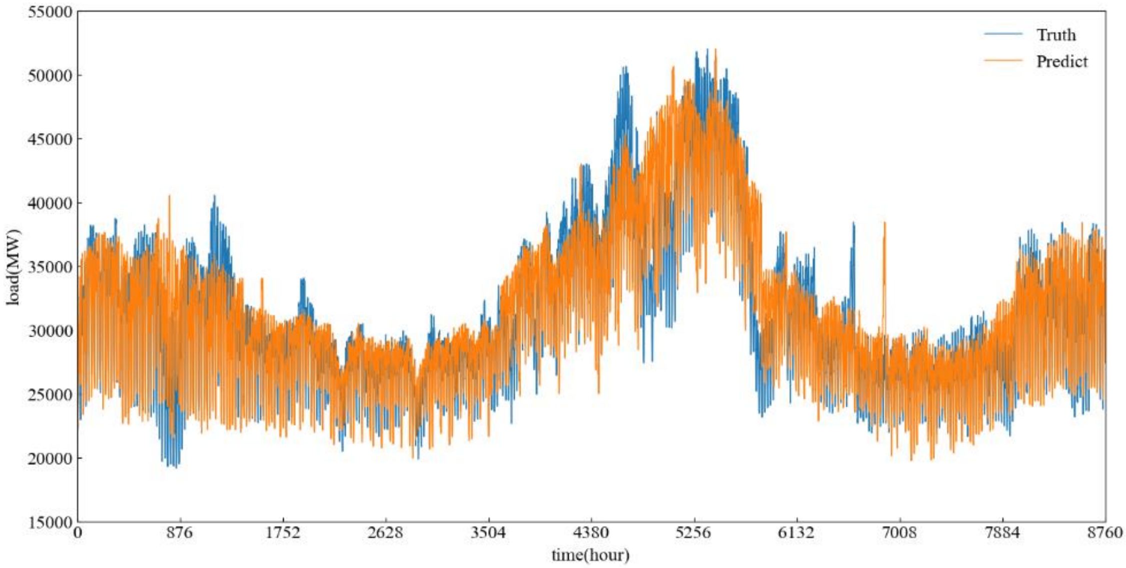
The whole process is implemented using Python 3.9 on a PC with 12th Gen 2.30 GHz Intel(R) Core(TM) i7(12700H) and 64 GB RAM.

TABLE III
EXPERIMENT SETUPS OF MODEL

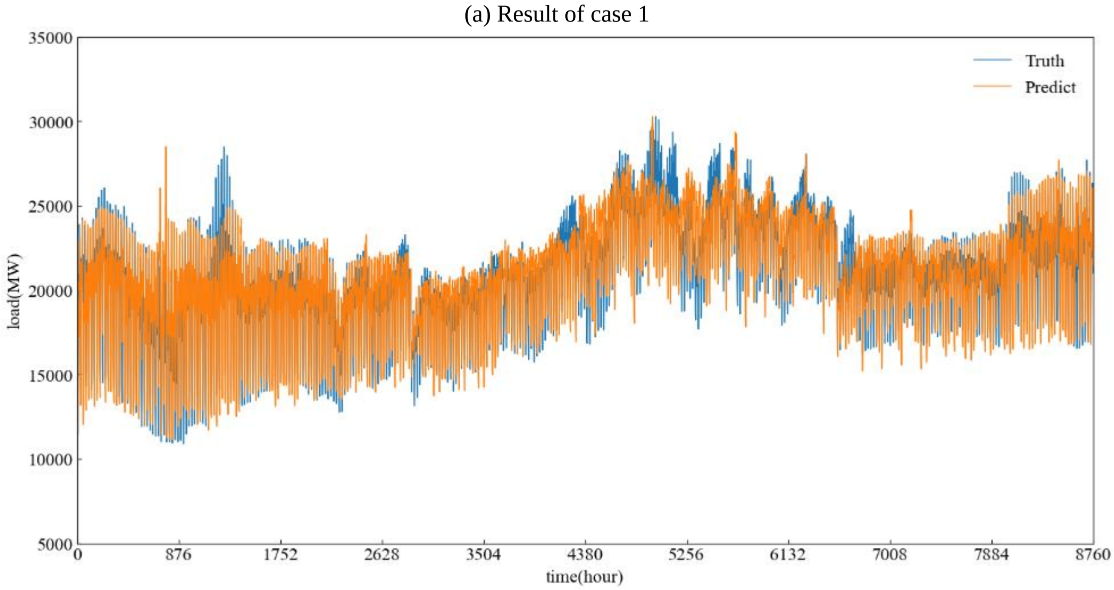
Alias	MODEL	Type
M1	2021 annual 8760-hour load curve	Typical curve
M2	LR	Feature-mapping
M3	RF	Feature-mapping
M4	SVR	Feature-mapping
M5	KNN	Feature-mapping
M6	LSTM	Auto-ML
M7	GRU	Auto-ML
M8	TCN	Auto-ML
M9	Transformer	Auto-ML
M10	Panoramic probabilistic optimizer	Proposed model

B. Comparison with Actual Load

Fig.3 illustrates the predicted results of the panoramic probabilistic optimizer compared to the true results. The results demonstrate a remarkable alignment with actual load data, highlighting the model's predictive accuracy. The predicted load curves closely mirror the actual load curves in overall shape and behavior. In the prediction results, long-term trends indicate a significant increase in load compared to the previous year, thereby reflecting real-world consumption patterns with greater fidelity. The optimizer exhibits consistency across various times of the year, effectively adapting to seasonal variations. For instance, during peak summer months, the model accurately forecasts spikes in demand associated with heightened air conditioning usage, while also capturing lower demand trends during cooler months. For the medium-term, the results reveal that the predicted monthly peak values align closely with observed maximum loads, exhibiting only minor discrepancies. Similarly, the predicted valley values correspond well to actual low-demand periods, ensuring that the model provides a realistic representation of energy consumption patterns throughout the year. For the short term, both datasets display similar daily patterns, characterized by distinct peaks during high-demand hours—typically in the late afternoon and early evening—and valleys during off-peak hours, such as late at night and early morning.



(a) Result of case 1



(b) Result of case 2

Fig. 3. Comparison with the Actual Load.

C. Comparison with Other Models

Table IV presents the results of the prediction error assessment for the different models. We computed the average MAPE for both the feature-mapping model and the auto-ML model, yielding results of 12.30% for the feature-mapping model and 11.77% for the auto-ML model. In contrast, the MAPE for the panoramic probabilistic optimizer is notably lower at 6.04%. These discrepancies highlight significant differences in predictive performance. The larger errors observed in the feature-mapping model can be attributed to its limited adaptability to varying load patterns, which hampers its ability to forecast accurately under fluctuating conditions. Similarly, the auto-ML model faces challenges in capturing the complexities of demand dynamics, resulting in less precise predictions.

In contrast, the panoramic probabilistic optimizer consistently outperformed these benchmarks. It demonstrated superior performance across all key metrics, including MAE, RMSE, MAPE, and R^2. This enhanced accuracy stems from its comprehensive analytical framework, which integrates multiple dimensions of load behavior, allowing for a more nuanced understanding of demand fluctuations. The method's capacity to make precise predictions from various dimensions enables it to synergistically combine insights for optimal forecasting results. Thus, this method not only surpasses traditional models but also establishes itself as a leading methodology in load forecasting.

Although the accuracy of the proposed model has decreased, when the real value of the long-term trends is replaced by the predicted value. However, considering the other model also involves predictive influences while considering the predictive inputs. So, the simulation is convincing.

TABLE IV
COMPARISON WITH OTHER MODELS

Alias	MAE(MW)	RMSE(MW)	MAPE(%)	R2
		Case 1		
M1	3156.41	4945.45	9.46	0.37
M2	4405.11	5558.64	13.89	0.2
M3	3480.52	4411.45	10.89	0.5
M4	5044.29	7042.42	14.48	-0.28
M5	2996.59	3838.09	9.88	0.62
M6	3673.28	5164.99	11.54	0.31
M7	3645.41	5209.17	11.29	0.3
M8	3329.63	4040.5	10.4	0.58
M9	3066.69	3774.2	9.57	0.63
M10	2044.82	2836.09	6.62	0.80
		Case 2		
M1	2138.61	2667.69	10.52	0.36
M2	2389.93	3005.9	11.83	0.18
M3	2376.51	2995.88	11.9	0.19
M4	2648.45	3240.9	12.91	0.05
M5	2526.71	3177.39	12.59	0.09
M6	2435.46	3057.37	12.19	0.15
M7	2609.09	3274.91	13.0	0.03
M8	2901.79	3269.92	13.83	0.03
M9	2593.89	2978.96	12.36	0.20
M10	1101.6	1441.69	5.45	0.81

D. Volatility Analysis

Table V presents the Arithmetic Mean (AM), Standard Deviation (SD), maximum values and minimum values of the results of the panoramic probabilistic optimizer. Compared with the auto-ML model in terms of AM and SD, the feature-mapping model shows great difference from the real value, because it cannot fully reflect different load types. In the representation of the maximum and minimum values, the auto-ML model is close to the real value, but there are still some differences. Moreover, the proposed model has the closely SD values to the truth values. Therefore, the data forecasted by the proposed model is the closest to the real data.

TABLE V
MODELS' VOLATILITY ANALYSIS

Alias	AM(MW)	SD(MW)	Max(MW)	Min(MW)
		Case 1		
M1	2665.38	452.56	4295.28	1327.12
M2	2140.46	188.62	2641.09	1708.46
M3	2181.73	377.20	3484.66	1744.41
M4	2047.20	112.28	2317.44	1799.03
M5	2165.18	357.11	3470.59	1519.47
M6	2747.38	466.67	4343.07	1377.19
M7	2677.22	446.77	4142.14	1344.70
M8	3090.87	573.36	4582.00	1936.58
M9	3087.71	579.20	4544.22	1958.37
M10	3074.71	600.53	5200.00	1994.23
		Case 2		
M1	2028.62	361.51	2893.04	988.60
M2	1330.24	148.72	1813.18	991.54
M3	1322.54	192.05	1875.03	872.44
M4	1211.63	98.56	1550.42	1039.66
M5	1307.78	191.441	1820.93	846.56
M6	2016.32	304.71	2484.09	1027.45
M7	2028.87	354.25	3022.89	1012.29
M8	2067.46	326.62	3015.17	1111.79
M9	2036.36	321.42	2921.27	1093.84
M10	2059.29	327.53	3027.23	1168.43

Considering the research on long-term trend prediction is relatively mature, the simulation mainly verifies the effectiveness of the panoramic probabilistic optimizer. So, the long-term input of the panoramic probabilistic optimizer is always the true value.

E. Generalizability Analysis

The generalizability of the panoramic probabilistic optimizer method is a critical factor in its effectiveness for load forecasting across diverse contexts. Our approach employs a differentiated analysis that considers multiple dimensions of load characteristics, allowing for tailored predictions and clustering based on the unique attributes of each dataset. As can be seen in Fig.3, by validating our methodology using data from both Hubei and Guangxi, we observe that it consistently achieves optimal refined annual 8760-hour load curve prediction accuracy, regardless of regional differences. This adaptability is rooted in the theoretical framework of the method, which integrates long-term, medium-term, and short-term load behaviors, ensuring that it captures the nuances inherent in various datasets. The ability to apply our model effectively across different provinces highlights its robustness against variations in geographic, climatic, and socio-economic factors. Each dataset's distinct features are accounted for, leading to reliable predictions that do not depend on a singular context. Furthermore, the probabilistic nature of the panoramic probabilistic optimizer allows it to incorporate uncertainty and variability, enhancing its predictive performance even in the face of fluctuating demand patterns. This versatility makes the method suitable not only for the regions studied but also for broader applications in energy management, where similar analytical techniques can be employed to optimize load forecasting in various environments.

In contrast, it can be seen from Table V, other models lack such generalizability, often struggling to maintain accuracy when applied to different datasets or varying regional contexts. For instance, traditional feature-mapping and auto-ML models typically rely on predefined patterns and assumptions that may not hold true across different environments. As a result, these models exhibit a significant drop in performance when confronted with the unique characteristics of new datasets, leading to less reliable forecasts.

By integrating these diverse characteristics—annual load trends, monthly fluctuations, daily peak and minimum loads, and their probability distributions—this method yields a comprehensive and interpretable model. It empowers stakeholders to make informed decisions regarding energy management, demand response initiatives, and the integration of renewable energy sources, ultimately leading to a more efficient and responsive energy system.

Moreover, the optimization framework enables stakeholders to identify key drivers of load variations, enhancing decision-making processes in energy management. This improved transparency allows for more informed strategies regarding resource allocation, demand response initiatives, and the integration of renewable energy sources. Consequently, the method not only produces accurate forecasts but also offers valuable insights into the underlying mechanisms of load behavior, making it a powerful tool for both researchers and practitioners in the field of energy planning

VI. Conclusion

This paper presents a significant advancement in the analysis of the refined annual 8760-hour load curve, providing essential support for achieving long-term power balance. Through a multi-dimensional analysis of load characteristics, we have explored the impacts of long-term trends, medium-term variations, and short-term variations on load behavior. This analytical framework not only reveals the complexity of load curves but also lays the groundwork for more accurate forecasting methodologies. Validation with load data from Hubei and Guangxi, China, demonstrates that our proposed method significantly has increased the annual load forecasting accuracy to 80% and 81%, which also improve the robustness, addressing the limitations of traditional approaches. Additionally, the propose model's generalizability is also guaranteed.

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