

Enhancing Direct Netload Forecasting through Functional Data Analysis: Evidence from Comparative Evaluation

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Abstract

This study aims to compare the performance of different time series and functional data analysis methods in forecasting Taiwan's electricity load and net load, and to examine the impact of hourly versus daily average meteorological variables on prediction accuracy. The models employed include SARIMA, NNARX, and their extensions incorporating Functional Principal Component Analysis (FPCA), using hourly load, renewable energy generation, and meteorological data from 2016 to 2023 for model development and validation. To address potential interference from unobserved common factors, the study adopts a design concept similar to the Common Correlated Effects (CCE) approach of Pesaran (2006), utilizing daily average meteorological variables as proxies for these latent common factors to mitigate endogeneity bias. Empirical results show that NNARX-based models consistently outperform SARIMA in overall prediction accuracy, with particularly high fidelity to the actual curves in net load forecasting. Moreover, incorporating daily average meteorological data improves model accuracy in most cases, offering greater practical value for medium- and long-term forecasting. In addition, FPCA demonstrates strong capability in capturing the patterns of net load curves, underscoring its advantage in controlling for common factors while preserving key modes of variation.

Keywords: Load forecasting, Net load, Time series analysis, Functional Principal Component Analysis (FPCA), Common factors, Common Correlated Effects (CCE)

1 Introduction

As the global power sector moves toward decarbonization and the integration of renewable energy, load forecasting and net load forecasting have become critical in power system dispatch and market operations. Accurate forecasting of future load variations not only improves grid stability and economic efficiency, but also serves as a core basis for power companies in generation scheduling, maintenance planning, energy storage deployment, and demand response strategies. With Taiwan’s “2050 Net Zero Emissions Roadmap” [1], it is expected that the share of renewable energy, particularly solar photovoltaics (PV) and wind power, will continue to increase, becoming one of the main sources of generation. However, the intermittent and uncertain nature of renewables complicates the overall balance of supply and demand, raising challenges for grid dispatch and reserve capacity management. In this context, precise load and net load forecasts play an essential role.

Traditionally, load forecasting relied on statistical time series models and machine learning methods, which build models from historical data to capture seasonality, trends, and the influence of weather variables[2]. In the field of net load forecasting, prediction strategies can generally be divided into two categories: the Indirect Method and the Direct Method. The Indirect Method, a conventional approach, constructs separate forecasting models for load and for renewable generation (e.g., PV and wind power), and then subtracts the latter from the former to estimate future net load [3, 4]. This approach reflects a structural assumption: load is primarily driven by demand-side factors such as temperature, holidays, and socioeconomic activity, whereas renewable generation is influenced by supply-side conditions such as solar irradiance and wind speed. As these drivers and explanatory variables differ significantly, it is considered appropriate to model them separately.

However, the accuracy of this approach is highly dependent on the precision of the two separate models, and the high volatility of wind power generation in particular can amplify the final net load forecasting errors [5]. Consequently, recent academic research has increasingly focused on the feasibility and performance of constructing net load forecasting models using the direct method [5–9]. This approach does not independently forecast renewable energy generation and load. Instead, it directly treats the raw net load data as the model-

ing target and establishes direct associations with external variables such as meteorological conditions and holidays, thereby potentially avoiding the accumulation of forecasting errors. For example, photovoltaic output is primarily driven by solar irradiance, but irradiance is typically highly correlated with temperature, while temperature is also a major determinant of load. In the indirect method, meteorological variables can be included as explanatory factors in both models, potentially introducing error interference and affecting the accuracy of the final net load forecasts. In contrast, the direct method is expected to capture the overall relationship between temperature and actual electricity demand more effectively, thereby improving the forecast performance.[10]

In addition, load and net load curves typically exhibit strong daily periodicity and structural patterns. This characteristic makes them highly suitable for functional data analysis (FDA). By treating each day's load or net load as a continuous function, FDA can more effectively extract information about the overall shape, peak timing, and smoothness properties of the curve, thereby enhancing the model's ability to capture peak periods, diurnal variations, and holiday effects. However, FDA has been applied only in a limited number of studies on load forecasting and has scarcely been explored for the direct prediction of net load. Moreover, comparative evaluations between FDA-based approaches and conventional forecasting methods remain rare in the existing literature. A key contribution of this paper is to address these gaps by applying FDA to net load forecasting and, in addition, providing a systematic comparison with traditional methods.

This study aims to compare the performance of functional data analysis methods and traditional approaches (time series and machine learning models) for load and net load forecasting using the direct method. The analysis uses hourly historical data on load, photovoltaic generation, and wind generation in Taiwan from 2016 to 2022 for model training, with data from 2023 serving as a test set for the evaluation of medium-term forecasts. By assessing the predictive accuracy of different models, this study aims to provide a more effective and interpretable modeling reference for forecasting in power systems with an increasing share of renewable energy.

2 Literature Review

Accurate forecasting of the load and net load plays a critical role in the operation and planning of power systems. As electricity consumption patterns become increasingly complex and the share of renewable energy continues to increase, both academia and industry have developed a variety of forecasting methods to enhance model accuracy and adaptability. In general, load and net load forecasting approaches can be categorized into three main groups: time series methods, machine learning methods, and functional data analysis methods.

2.1 Load Forecasting Methods

Traditional time series models, such as ARIMA [11–13], ARIMAX [14, 15], SARIMA [16–19], and Exponential Smoothing[20, 21]—are noted for their strong interpretability and clearly defined modeling structures and have been widely applied in the early literature for short-term and medium- to long-term load forecasting. Among these, the ARIMAX model incorporates exogenous variables (e.g., weather, holidays) to capture seasonal and trend variations. For example, [14] applied the ARIMAX model by including ‘time of day’ and ‘day of the week’ as exogenous variables, finding that the model produced more accurate forecasts compared to the AR, ARMA and artificial neural networks (ANN) approaches. [15] further refined the ARIMAX model to address structural breaks in the data.

The SARIMAX model, by incorporating seasonal components, is able to capture recurring and cyclical patterns in electrical load at longer time scales, such as monthly, quarterly and annual intervals. Unlike short-term forecasting methods that typically rely on intraday or intraweek patterns, the SARIMAX model can learn long-horizon fluctuation characteristics of load demand. Studies such as [18] and [16] applied SARIMAX to more than four years of hourly load data from Japan and Yunnan Province, China, respectively, to evaluate the performance of the 1-year load forecast.

However, when confronted with non-linear and highly volatile actual load variations, such models may suffer from insufficient accuracy. In recent years, machine learning approaches such as ANN, long- and short-term memory networks (LSTM) and support vector regression (SVR) have been increasingly applied to load forecasting, given their ability to handle

high-dimensional and nonlinear data features [22–24]. [23] employed LSTM and traditional models to perform load forecasts across various horizons, including 24-hour, 48-hour, 7-day, and 30-day intervals, with results indicating that LSTM outperformed traditional methods in short-term forecasting. [24] introduced feature selection algorithms for automated input variable selection and adopted Particle Swarm Optimization (PSO) to fine-tune SVR hyperparameters, thus enhancing prediction accuracy.

Hybrid forecasting frameworks, which integrate traditional time series methods with deep learning techniques, have been proposed in several studies to enhance both predictive accuracy and stability. For example, [25] first utilized LSTM to produce preliminary load forecasts, followed by ARIMA to model and correct the residuals, demonstrating that the hybrid model outperformed individual models. In contrast, [26] adopted the opposite sequence: first, applying SARIMAX for preliminary forecasting, then using LSTM to capture nonlinear structures within residuals for subsequent correction. Similar concepts are also reflected in ensemble learning techniques such as stacking [27, 28], whereby the strengths of multiple models are combined, and such hybrid architectures have been shown to significantly improve overall forecast performance.

In addition, existing research has examined the influence of different forecast horizons on model selection and performance, emphasizing the need to match model architectures to specific horizons [29]. Generally, short-term load forecasting (STLF) spans approximately one hour to one week and is primarily applied to operational decision making in power systems, such as real-time dispatching, load balancing, and reserve capacity allocation. Medium-term load forecasting (MTLF) covers periods from about a week to one year and often serves as a basis for unit commitment scheduling and fuel procurement strategies. Long-term load forecasting (LTLF) extends beyond one year, sometimes exceeding 20 years, and is primarily intended to support strategic decision making in grid infrastructure development, generation resource investment planning, and energy policy formulation. These studies highlight that as the forecast horizon extends, the nature of relevant predictive features becomes increasingly diverse, ranging from high-frequency weather and behavioral variables to structural economic, demographic, and policy factors. This diversity must be reflected in the choice and design of model architectures. The present study uses a one-year test set, and its findings

can serve as a reference for mid-term unit commitment scheduling and dispatch planning.

2.2 Net Load Forecasting Methods

Due to the high variability and limited controllability of renewable energy generation, forecasting net load, defined as total load minus renewable energy output, presents heightened challenges. Current approaches to net load forecasting can be broadly categorized into two types: the indirect method and the direct method.

The indirect method, a conventional mainstream approach, involves separately constructing forecasting models for load and renewable energy generation, then calculating the net load as the difference between the two. For example, [3] integrated an ANN model with an Enhanced Particle Swarm Optimization (EPSO) algorithm to forecast the aggregated load and renewable energy generation. [4] examined the effect of including or excluding behind-the-meter (BTM) photovoltaic generation data on net load forecasting errors. In the study, the penetration of low voltage PV exceeded 35%, and the results indicated that the highest prediction accuracy was achieved using the indirect forecasting strategy. However, compared to a single model direct forecast approach, the difference in forecast errors was minimal.

In contrast, the direct method treats net load as an integrated forecasting target, constructing a single predictive model directly. The primary advantage of this method lies in its ability to avoid the accumulation of errors between separate load and renewable energy models, and in capturing complex interaction effects, such as the simultaneous influence of temperature on both load and photovoltaic output. [6] employed historical net load data to develop a direct forecasting model using the Adaptive Neuro-Fuzzy Inference System (ANFIS). [5] used a wavelet neural network to build forecast models for load, wind power, and net load, finding that under low wind penetration, the predictive precision of both strategies was comparable; however, as wind penetration increased, the indirect strategy outperformed the direct strategy. [8] analyzed data from two different power systems, applying both direct and indirect strategies to forecast net load in varying renewable penetration scenarios. In general, as renewable penetration increased, the accuracy of the net load forecast declined, but the relative performance of the two strategies was context-dependent. Superior results in one power system or period did not guarantee similar results in others.

[9] compared three hierarchical net load forecasting strategies: directly forecast net load (aggregated strategy), separately forecast total demand and total supply before computing net load (partially aggregated strategy), and individually forecast each generation source and demand component before aggregation (disaggregated strategy). The study found that the partially aggregated strategy performed best. [7] combined a multi-input LSTM with wavelet transforms and fuzzy systems, achieving higher prediction accuracy than the direct or indirect method alone.

2.3 Functional Data Analysis

FDA is a statistical methodology specifically designed to handle data with inherent continuity. Its core concept is to treat each observation as a continuous function rather than as a single vector or a set of discrete points [30]. This approach is particularly suitable for situations where the data are naturally in the form of curves or can be represented as functions of time. FDA can address variability across curves by performing alignment, smoothing, clustering, and regression, while preserving the structural and smooth characteristics of the original data. In forecasting applications, FDA often employs Functional Principal Component Analysis (FPCA) to decompose functional data into a small number of statistically representative scores, which are then used as inputs to predictive models.

In recent years, FDA has been increasingly applied in the electricity sector [31]. [32] utilized functional clustering and ensemble learning to forecast daily load curves, demonstrating that the approach effectively enhances a model's ability to capture variations in load patterns. [33] applied a wavelet denoising algorithm to remove noise from load data prior to load forecasting with an Artificial Neural Network, improving prediction accuracy. [34] emphasized that peak shape forecasting is more critical than hourly load forecasting, as it directly influences dispatch and load management strategies. Using data from the U.S. Northeast power grid, the study found that incorporating FDA yields more robust peak shape forecasts. [35] decomposed load curves into deterministic and stochastic components, modeling the stochastic part using FARX, FAR, and AR, with FARX achieving the best performance.

Despite the growing body of research that applies FDA to load forecasting and leveraging

the continuity and structural features of daily curves to improve predictive performance, its use in net load forecasting remains limited. Most existing net load forecasting studies continue to rely on conventional time series and machine learning techniques, with a primary focus on comparing direct and indirect methods. Comparatively, little attention has been paid to examining the relative merits of different modeling approaches within the same method. In particular, for the direct forecasting strategy, which features a relatively simple architecture, reducing modeling cost and complexity, the development of robust models could significantly improve the practical efficiency of net load forecasting.

In power systems with high penetration of renewable energy, net load curves are shaped not only by demand-side behaviors of traditional loads but also by substantial supply-side variability from sources such as photovoltaic and wind power generation. The coupling of temporal structure and variability in such systems makes it difficult for conventional single-logic forecasting methods to fully capture the underlying patterns. By modeling the entire daily curve and retaining its shape characteristics, the FDA has the potential to address the limitations faced by existing forecasting methods in these contexts.

This study, using Taiwan’s hourly load and renewable energy data, adopts a direct forecasting framework to develop load and net load forecasting models based on traditional time series methods (SARIMAX), machine learning models (NNARX) and FDA-based approaches (FPCA-SARIMAX, FPCA-NNARX). By systematically comparing the accuracy and robustness of these models over a 1-year evaluation period, the study aims to clarify the suitability of different modeling strategies. In doing so, it aims to bridge the research gap in the application of FDA to net load forecasting and to provide practical guidance for selecting diverse modeling frameworks in operational forecasting.

3 Data

The load and renewable energy data used in this study were obtained from the publicly disclosed daily records provided on the official website of Taiwan Power Company. The dataset covers hourly load, photovoltaic (PV) and wind power generation, as well as installed capacity. With Taiwan’s ongoing energy transition, both installed capacity and renewable

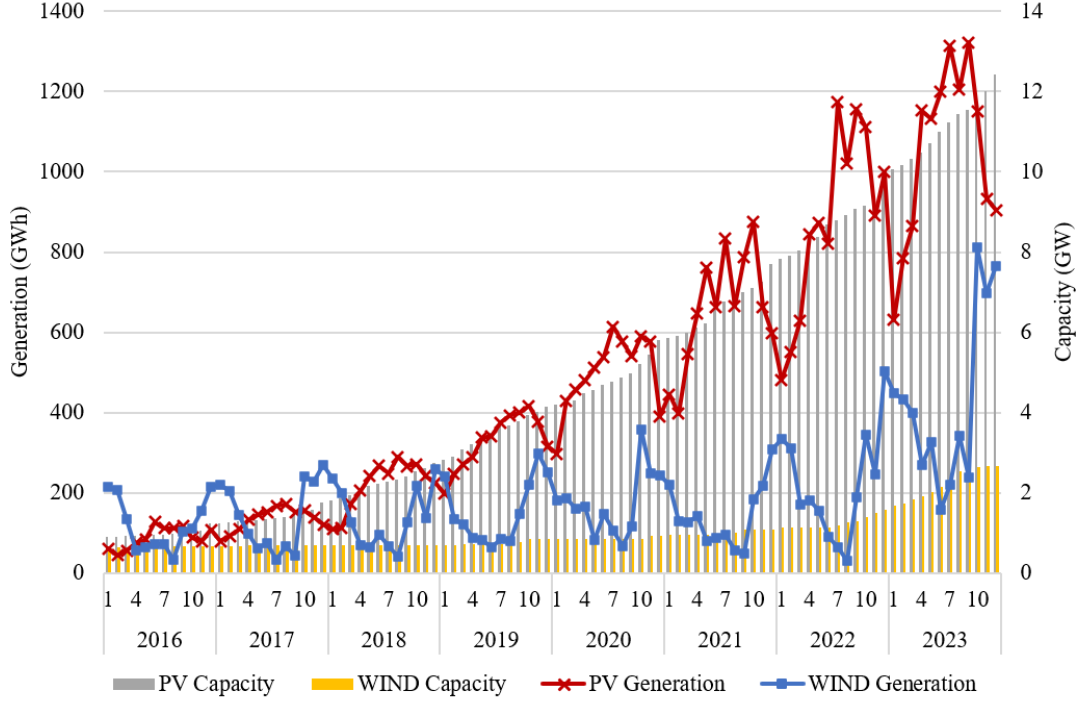


Figure 1: Growth trends in installed capacity (right axis, GW) and generation (left axis, GWh) from renewable energy in Taiwan during 2016–2023. Grey and yellow bars represent the installed capacities of PV and wind power, respectively, while red and blue lines denote monthly generation of PV and wind power. The figure illustrates the rapid expansion of PV capacity and its corresponding growth in generation, contrasted with the relatively stable development of wind power.

energy generation have shown a steady upward trend. By 2023, renewable energy accounted for 9.47% of total electricity generation, with PV contributing the largest share at 4.58%, followed by wind power at 2.20%.

As illustrated in Figure 1, the installed capacity of PV has increased rapidly since 2016, and its generation exhibits seasonal growth, peaking in the summer months (July to October). In contrast, wind power generation is largely influenced by monsoon conditions, occurring predominantly during the winter months (December to the following March), and its installed capacity also shows gradual growth over time.

Figure 2 illustrates the daily generation profiles of renewable energy sources, revealing that PV systems exhibit a stable generation pattern during the day (approximately 06:00–18:00). In summer, the prolonged duration of sunlight results in relatively longer generation periods. In contrast, wind power output shows greater variability, with peak generation

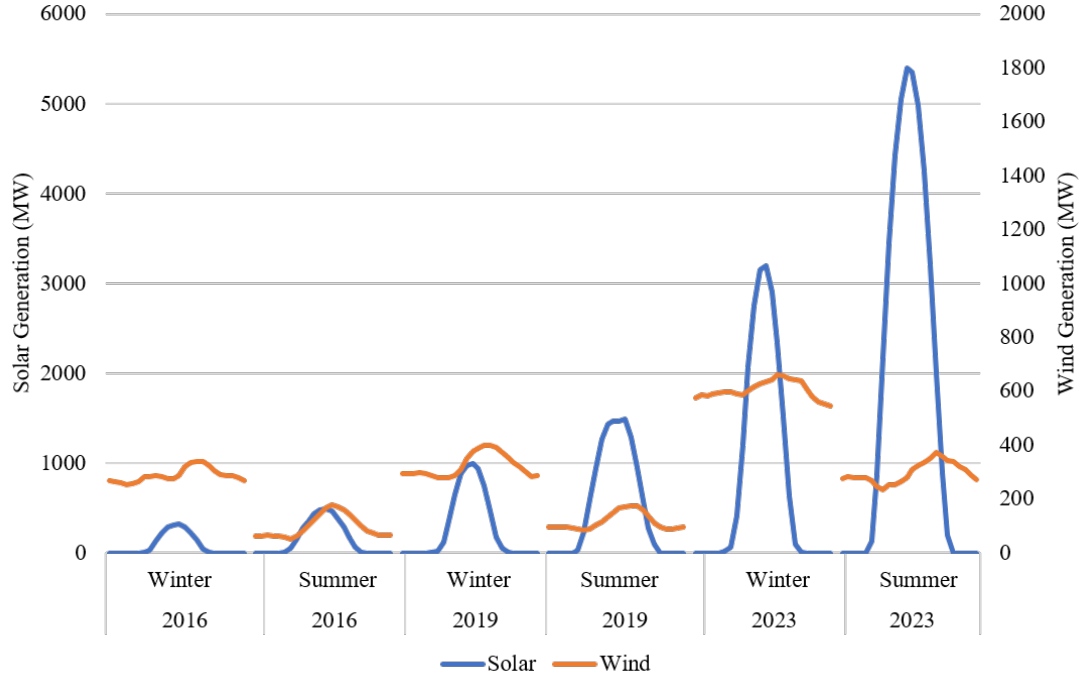


Figure 2: Renewable energy generation profiles during representative winter and summer seasons in 2016, 2019, and 2023. PV generation (left axis, MW) is shown in blue, while wind generation (right axis, MW) is shown in orange. The figure illustrates the pronounced diurnal variability of solar generation, with increasing peak magnitudes over time due to capacity expansion, contrasted with the relatively stable and less fluctuating wind generation profile.

often concentrated in the afternoon to early evening hours. These temporal characteristics have a direct impact on net load, particularly during periods of high PV generation, when the daytime net load tends to decrease sharply, producing the characteristic 'duck curve'.

As shown in Figure 3, Taiwan's load and net load profiles reflect the climatic characteristics of the country and seasonal demand patterns. Located on the boundary between the subtropical and tropical zones, Taiwan experiences a hot and humid climate that drives substantial cooling demand during the summer months. Consequently, load peaks typically occur during daytime hours, especially around noon, when rising temperatures intensify the use of air conditioning. In contrast, in winter, the absence of cooling demand shifts the load profile toward higher consumption in the evenings, driven largely by residential activities such as cooking, lighting, and use of appliances after work hours.

During summer, the load peak coincides with the period of maximum renewable gen-

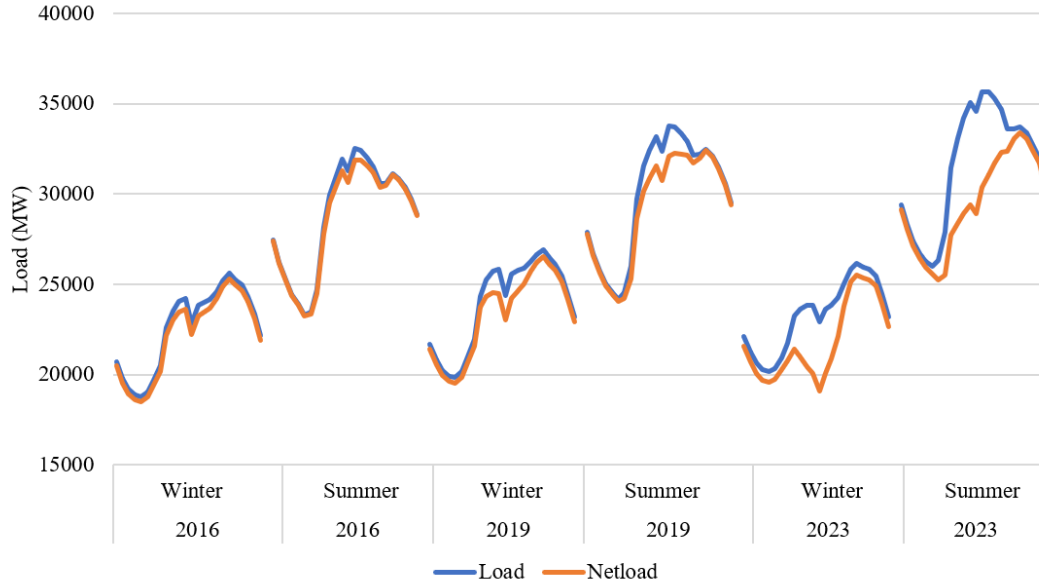


Figure 3: Load and net load curves during selected summer and winter seasons in 2016, 2019, and 2023. The vertical axis (MW) represents system demand, where the blue line denotes total load and the orange line represents net load after subtracting renewable generation. The figure highlights the increasing divergence between load and net load in recent years, particularly during daytime hours, reflecting the growing penetration of photovoltaic generation.

eration, particularly from solar photovoltaics. Although the net load peak emerges in the evening, the overall load begins to increase steadily in the early morning (around 7:00), thus diminishing the typical duck-curve phenomenon. In contrast, the peak of the winter load occurs already during the evening hours, while the daytime loads remain relatively low. Once renewable generation is subtracted, the net load exhibits a pronounced duck-curve pattern. This seasonal distinction differs from temperate regions such as California, where the duck-curve phenomenon is observed throughout the year. In general, Taiwan faces distinct operational challenges. In summer, the main concern is securing sufficient reserve margin during evening peaks, whereas in winter the challenge lies in managing steep ramping requirements at dusk that complicate system dispatch.

4 Models

This study adopts the Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) model and the Neural Network Autoregressive (NNAR) load forecasting model, the latter characterized by an autoregressive neural network structure, as representative approaches of traditional time series analysis and machine learning methods, respectively. These models are further compared with functional data analysis (FDA) techniques. The subsequent sections describe the theoretical foundations and implementation details of each forecasting method, providing the basis for the subsequent evaluation of model performance.

4.1 SARIMAX

The ARIMA model is commonly used for short-term load forecasting, as it effectively captures the trends and continuity in electricity consumption behavior. The ARIMA model consists of three components and can be expressed as $ARIMA(p, d, q)$, where the autoregressive component (p) represents the inclusion of p lagged values of the time series. The integrated component (d) ensures that the model operates on stationary time series data, with differencing performed to remove trends; for instance, $d=1$ means that the current value is subtracted from the previous value to eliminate any trend in the data. The Moving Average term (q) accounts for q lagged error terms, meaning that the model uses past forecast errors as explanatory variables to adjust the current forecast.

However, ARIMA models are limited in that they cannot account for the influence of exogenous variables, such as weather or holidays [36]. When additional exogenous variables are incorporated into the ARIMA model, it becomes the ARIMAX model, where "X" represents the time series data of external variables. SARIMAX is an extension of the ARIMAX model, and since load data often exhibits seasonal variation, and the dataset used in this study spans seven years, seasonal information is incorporated to enhance the accuracy of short-term load forecasting.

$$\begin{aligned}\Delta^d y_t = & c + \phi_1 \Delta^d y_{t-1} + \cdots + \phi_p \Delta^d y_{t-p} - \theta_1 \epsilon_{t-1} - \cdots - \theta_q \epsilon_{t-q} \\ & + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_k X_{kt} + s_t + \epsilon_t\end{aligned}\tag{1}$$

The general form of the ARIMAX model can be expressed as in Equation (1), with subsequent derivations and formulations following the standard approach presented in [37]. In this equation, y_t denotes the dependent variable at time t , Δ^d indicates the order of differencing applied to the data, and ϕ_p represents the autoregressive coefficients. ϵ_t stands for the error term at time t , while θ_q denotes the moving average coefficients. The terms $X_{1t} \dots X_{kt}$ represent exogenous variables, with $\beta_1 \dots \beta_k$ being the corresponding coefficients for the exogenous variables, and s_t represents the seasonal component.

Equation (2) is the result of rewriting Equation (1) using the autoregressive operator and the backshift operator.

$$\Phi_p(B) \nabla^d y_t = \Theta_q(B) \epsilon_t + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_k X_{kt} + s_t\tag{2}$$

Additionally, the seasonal component s_t represents the recurring cyclical patterns in the time series. The parameter s refers to the length of the seasonal cycle, which means that at every s time point, a seasonal effect occurs. The seasonal component can be expressed using seasonal autoregressive terms, seasonal differencing, and seasonal moving averages, as shown in Equation (3).

$$\Phi_P(B^s) \nabla_s^D y_t = \Theta_Q(B^s) \epsilon_t\tag{3}$$

Thus, the complete SARIMAX model is represented by Equation (4).

$$\Phi_P(B^s) \Phi_p(B) \nabla^d \nabla_s^D y_t = \Theta_Q(B^s) \Theta_q(B) \epsilon_t + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_k X_{kt}\tag{4}$$

4.2 NNARX

In this study, the machine learning approach employs the NNARX (Neural Network AutoRegressive with eXogenous inputs) model, implemented via the 'nnetar' package in R, to perform time series forecasting. NNARX extends the standard NNAR model by incorporating lagged values of the time series as input, in conjunction with exogenous variables, to establish a nonlinear mapping for prediction. The structural representation of the NNARX model can be formally expressed as shown in Equation (5) and illustrated in Figure 4, following the formulation in [38].

$$h(k) = g \left(b_{k0} + \sum_{i=1}^p w_{ki} y_{t-i} + \sum_{j=1}^p v_{kj} y_{t-jm} + \sum_{l=1}^L u_{kl} x_{l,t} \right) \quad (5)$$

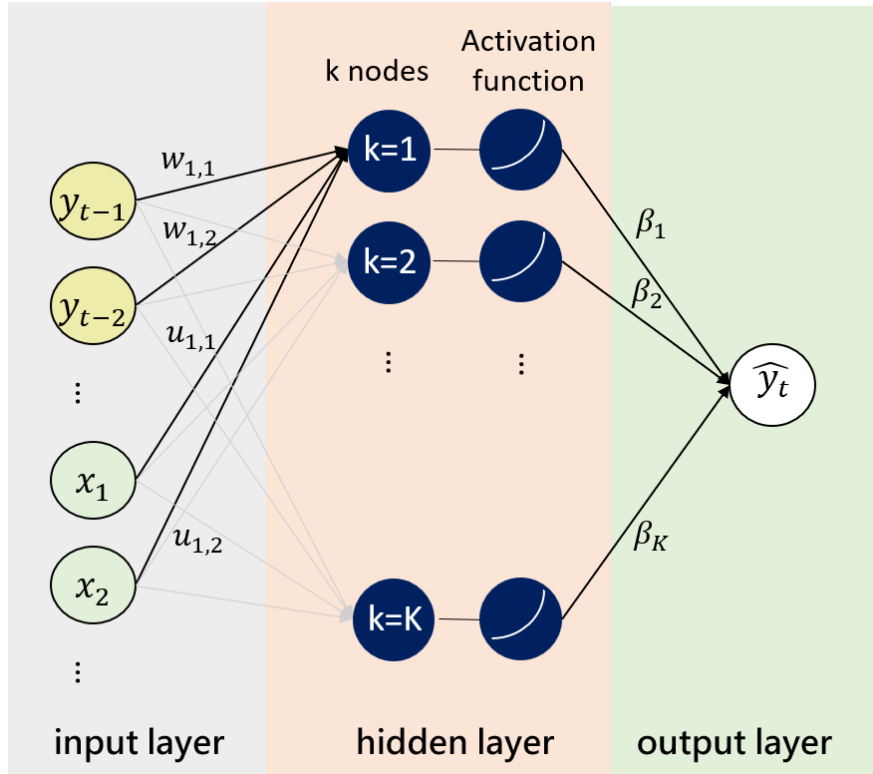


Figure 4: Structure of the NNARX Model.

In this context, $h(k)$ denotes the activation value of the k -th hidden layer neuron. The term y_{t-i} represents the lagged value of the primary variable (e.g., load or net load), with p

indicating the autoregressive order. The term y_{t-jm} corresponds to the seasonal lag of the primary variable, where P is the order of the seasonal autoregressive component and m is the duration of the seasonal period. The variable $x_{l,t}$ denotes the l -th exogenous variable (e.g., temperature, rainfall), with L specifying the total number of exogenous variables. The parameters b_{k0} , w_{ki} , v_{kj} , and u_{kl} are the model weight parameters.

The function $g(\cdot)$ denotes the nonlinear activation function, for which the logistic sigmoid function (Equation (6)) is used in this study. Mathematically, the logistic sigmoid function maps real-valued inputs to the interval $(0, 1)$, thus introducing nonlinearity to improve the model's fitting capacity, while also facilitating the capture of latent patterns and nonlinear dependencies within the input data.

$$g(z) = \frac{1}{1 + e^{-z}} \quad (6)$$

The final prediction result is obtained as a linear combination of the activation values of all neurons in the hidden layer, as expressed in Equation (7).

$$\hat{y}_t = \beta_0 + \sum_{k=1}^K \beta_k h(k) \quad (7)$$

4.3 FPCA

[39] were among the first and most influential researchers to apply FPCA to nonparametric forecasting of Functional Time Series (FTS). Their proposed approach can be divided into two main stages. First, FPCA is used to perform dimensionality reduction on daily curve data, projecting the original functional data onto a set of representative principal component bases and calculating the corresponding scores for each component. This step effectively preserves the primary structural variability present in the data. Second, these scores are treated as time series data and modeled using traditional time series methods to forecast the future evolution of the principal components. The predicted component scores are then used to reconstruct the overall future load or net-load curves. This methodology combines the structural advantages of functional data with the forecasting capability of time series models, and has since become a foundational framework for subsequent research in the FTS

field.

According to [31, 39], this study transforms the load data into functional form and performs forecasting through the following five steps:

1. Using spline basis functions to convert hourly load time series data into functional form (daily load curves).
2. Applying FPCA to decompose these functional data into:
 - The mean function $\mu(\tau)$,
 - Principal component functions $v_1(\tau), v_2(\tau), \dots, v_K(\tau)$,
 - Principal component scores $\beta_{t,1}, \beta_{t,2}, \dots, \beta_{t,K}$.

Each observed function can be expressed approximately as Equation (8).

$$Y_{tK}(\tau) = \mu(\tau) + \sum_{k=1}^K \beta_{t,k} v_k(\tau) + \varepsilon_t(\tau), \quad \tau \in [a, b], \quad t = 1, \dots, N \quad (8)$$

The number of principal components K is determined according to the Integrated Squared Forecast Error criterion proposed by [39].

3. The principal component scores $\beta_{t,K}$ vary over time and are modeled using approaches such as SARIMAX or NNARX.
4. The trained models are then used to forecast future values of $\hat{\beta}_{t,K}$.
5. The predicted principal component scores are subsequently combined with the principal component functions to reconstruct the functional values, as expressed in Equation (9).

$$\hat{Y}_{tK}(\tau) = \mu(\tau) + \sum_{k=1}^K \hat{\beta}_{t,K} v_k(\tau), \quad \tau \in [a, b], \quad t = N + 1, \dots, N + h \quad (9)$$

In summary, this study addresses the problems of load and net load forecasting by constructing, respectively, a traditional time series model (SARIMAX), a machine learning model (NNARX), and hybrid approaches integrating functional data analysis (FPCA-SARIMAX and FPCA-NNARX). The objective is to systematically evaluate the predictive

performance and robustness of these methods on both hourly and daily time scales. In terms of variable design, the formulation of the load forecasting model is presented in Equation (10).

$$Load_t = f (Load_{t,\text{lag}}, TEMP_t, PRE_t, H_t, EVENT_t), \quad t = 1, \dots, 24 \quad (10)$$

The net load forecasting model further incorporates renewable energy generation information, as shown in Equation (11).

$$\begin{aligned} \text{Netload}_t = f & \left(\text{Netload}_{t,\text{lag}}, TEMP_t, PRE_t, H_t, EVENT_t, \right. \\ & \left. (PV_c \times Radiation_t, WIND_c \times WindSpeed_t) \right), \quad t = 1, \dots, 24 \end{aligned} \quad (11)$$

In this study, $TEMP_t$ and PRE_t denote temperature and precipitation, respectively, H_t represents the holiday dummy variable, and $EVENT_t$ refers to short-term events. PV_c and $WIND_c$ denote installed PV and wind power capacities, respectively; $Radiation_t$ represents global solar radiation and $WindSpeed_t$ denotes wind speed.

Regarding the model architecture, both SARIMAX and NNARX adopt an hourly modeling framework, by which independent models are constructed for each of the 24 hourly intervals in a day to capture the varying sensitivity of different time periods to meteorological and periodic fluctuations. In contrast, FPCA-SARIMAX and FPCA-NNARX take the daily functional load curve as the modeling unit, using principal component scores as model inputs. The predicted scores are then combined with the functions of the principal components to reconstruct the forecast curve, providing an integrated load profile between periods.

5 Results

Table 1 presents a comparative summary of the forecasting models. Since SARIMAX and NNARX adopt an hourly modeling framework, this study considers two distinct temporal granularities for the exogenous variables: hourly data and daily average data. The former

Table 1: MAPE (%) of different forecasting models for load and net load on the test set

Model	Load	Net Load
SARIMA(hour)	4.19	5.40
SARIMA	3.83	5.52
FPCA-SARIMA	4.62	4.91
NNARX(hour)	2.83	3.75
NNARX	2.66	3.29
FPCA-NNARX	3.67	2.97

Note: Models labeled “(hour)” are trained using hourly meteorological data, while models without this label are trained using daily-averaged meteorological data.

corresponds to the SARIMA(hour) and NNARX(hour) models, while the latter corresponds to the SARIMA and NNARX models. The results indicate that models built with daily data generally outperform those constructed with hourly data, suggesting that coarsening the temporal scale of exogenous variables can, in certain contexts, enhance predictive accuracy.

This finding resonates with the central premise of the Common Correlated Effects (CCE) approach proposed by [40]. According to [41], when handling heterogeneous panel data with a sufficiently large time dimension (T), the mean effects of exogenous variables can be estimated using four approaches: the mean group estimator, pooled estimators, aggregate time-series estimator, and cross-section estimator. However, in the presence of dynamic models that include lagged dependent variables as regressors, only the mean group estimator yields consistent estimates; pooled and aggregate estimators produce inconsistent results, with potentially severe biases.

In this study, the SARIMA(hour) and NNARX(hour) designs resemble the mean group estimator in structure: here, N is defined as the 24 independent hourly segments within a day, T is the series of observations for that hour across different days, and separate estimations are made for the effects of exogenous variables (e.g., temperature) on load for each hour. This approach achieves superior forecast performance compared to the more common pooled estimators in the literature, where hours 1–24 are distinguished only through dummy variables while sharing the same slope parameter for temperature.

However, in panel data, exogenous variables are often simultaneously influenced by unobserved common shocks, such as macroeconomic fluctuations, changes in energy prices,

nationwide climatic conditions, and policy interventions. These common factors induce cross-sectional correlation in the individual error terms (region/industry/firm), which in turn leads to endogeneity bias. The Common Correlated Effects (CCE) method proposed by [42] suggests that, under such circumstances, the mean group estimator remains valid, provided that a sufficient number of time periods and an adequate number of cross-section averages are included to proxy for the unobserved common factors, thereby mitigating the endogeneity arising from these factors.

In this context, the present study further examines the approach of replacing hourly meteorological exogenous variables with daily average temperature and daily accumulated precipitation (corresponding to the SARIMA and NNARX models). Conceptually, this approach is analogous to the CCE framework, where cross-sectional average variables serve as proxies for common factors. Hourly temperatures within a single day often exhibit strong continuity and correlation, and electricity consumption behavior is driven not only by the temperature at a specific hour but also by the cumulative thermal effects of preceding hours. For example, prolonged high temperatures can cause air conditioning units to operate for extended periods, thus altering the electricity demand over subsequent hours. This intertemporal dependence is statistically analogous to common factors in that both reflect systematic sources of variation influencing multiple observational units (i.e., different hours).

When meteorological conditions within a day show a high degree of co-movement, replacing hourly weather data directly with daily averages can be regarded as incorporating a proxy variable for a “co-movement signal” into the model, helping to capture and control common shocks arising from large-scale weather patterns. Empirical results indicate that the incorporation of daily average meteorological variables generally leads to lower forecast errors compared to models using only hourly data. This finding carries practical significance, particularly for medium- to long-term load forecasting, where high-frequency weather data are often unavailable. If daily data-based models can outperform hourly data-based models in terms of forecast accuracy, they not only reduce data collection costs but also maintain or even improve predictive performance under conditions of limited information.

Moreover, NNARX-type models consistently outperform their corresponding SARIMAX counterparts in both load and net load forecasting tasks. This superior performance can be

attributed to the structural characteristics and advantages of the NNARX framework. First, NNARX is a feed-forward artificial neural network that incorporates both autoregressive inputs and exogenous variables, enabling it to capture complex nonlinear relationships in the data through nonlinear activation functions in the hidden layers. This allows NNARX to overcome the limitations of traditional linear time series models when modeling the highly nonlinear relationships between load and meteorological factors. Second, NNARX is capable of learning interaction features between load values and meteorological variables, which enhances the model’s adaptability and generalization capacity when confronted with highly volatile, non-stationary load curves subject to multiple interacting factors.

Finally, functional data analysis methods exhibit differentiated performance characteristics in forecasting tasks. In load forecasting, models incorporating FPCA (FPCA-SARIMA and FPCA-NNARX) generally underperform relative to pure time series and machine learning models. This suggests that when the data structure is relatively regular and the intraday variation patterns are stable, directly modeling hourly data is more effective for capturing temporal dynamics. In such cases, the dimensionality reduction and curve fitting inherent in FPCA can attenuate certain high-frequency information, thereby reducing forecast accuracy. In contrast, in net load forecasting scenarios, the advantages of FPCA become more pronounced. Because net load is influenced by the variability of renewable energy generation, its intraday curves tend to exhibit high nonlinearity and irregular fluctuations. FPCA can effectively extract the main modes of variation through principal components, filtering out high-frequency random noise, and thus improving the model’s ability to adapt to complex curve structures with improved robustness.

Given that net load curves are jointly shaped by load (demand side) and renewable generation output (supply side), both of which are highly dependent on meteorological conditions, where weather variations within a day show substantial continuity and correlation, the influence of common factors is particularly pronounced. By decomposing entire daily curves into principal components, FPCA effectively extracts the dominant modes of curve variation, which is conceptually equivalent to introducing low-dimensional factors that capture common variation into the modeling process. These low-dimensional factors serve a role analogous to the cross-section averages in the CCE method, acting as proxies for common

shocks arising from large-scale climatic conditions, systematic demand shifts, or changes in energy policy. Compared to hourly modeling approaches, FPCA can more effectively control the influence of common factors and allows an analytical perspective focused on 'how general daily weather conditions affect the overall daily net load curve', thus improving model robustness and predictive accuracy.

In contrast, in load forecasting contexts, where the intraday curve structure is more stable and the influence of common factors is relatively limited, direct hourly time series modeling is generally sufficient to capture the principal variation patterns. In such cases, the dimensionality reduction inherent in FPCA may instead cause the loss of certain detailed information, resulting in reduced accuracy. Therefore, the shared implication of FPCA and the CCE methodology is that when data contain significant and broadly influential sources of common variation, incorporating such information into the model via factor extraction or cross-section averages can improve the accuracy and robustness of dynamic forecasts.

Figures 5 show that the NNARX model consistently achieves lower MAPE values throughout all hours compared to SARIMAX, with the discrepancy particularly pronounced during daytime hours (approximately 08:00–18:00), when forecast errors are generally higher than those observed at night. For SARIMAX, the application of FPCA tends to increase load forecasting errors relative to the non-FPCA specification. However, in the case of net load forecasting, SARIMAX exhibits considerably larger errors in the early morning hours (00:00–07:00), leading to an overall MAPE that is greater without FPCA than with it. Although forecast errors are substantial during these early hours, their impact on system operations is limited because loads are relatively low and supply is comparatively abundant, implying that large errors during this period are less detrimental than those occurring during daytime peak demand periods.

In contrast, the NNARX model produces more stable load forecasts throughout the day and its errors remain consistently below those obtained with FPCA. The advantage of the non-FPCA specification is especially evident during daytime hours, when forecasting challenges are heightened by variability in demand. Nevertheless, when predicting net load, the incorporation of FPCA into NNARX improves accuracy, particularly during the day, when renewable energy generation amplifies fluctuations in the residual load. These findings

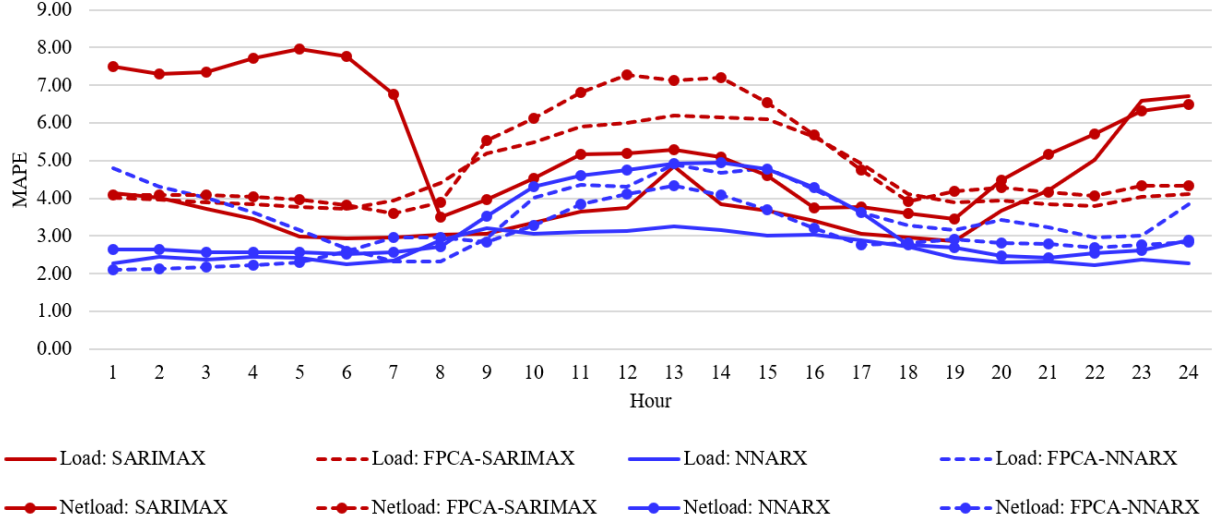


Figure 5: Hourly average MAPE for load and net load forecasting across different models. The horizontal axis denotes the hour of the day (1–24), and the vertical axis indicates MAPE values. Solid lines represent models without FPCA, while dashed lines denote FPCA-based models; lines with markers correspond to net load forecasts, whereas plain lines correspond to load forecasts; red lines represent SARIMAX-related models, while blue lines represent NNARX-related models. The figure shows that NNARX-related approaches generally outperform conventional SARIMAX models

indicate that FPCA, when combined with a nonlinear neural network framework, provides superior capability to capture the volatility of net load associated with renewable integration, whereas for load forecasting alone, NNARX without FPCA remains the more effective configuration.

Figure 6 shows that SARIMAX incurs substantially larger errors during the summer months (June–September) than in the rest of the year, whereas NNARX maintains a comparatively stable error profile across seasons, with only a slight elevation in winter–spring. This seasonal asymmetry suggests that the nonlinear structure of NNARX is more resilient to the high load volatility and renewable penetration characteristic of summer conditions. A pronounced January peak is also visible, plausibly reflecting the Lunar New Year holiday effects that distort otherwise regular demand patterns.

For SARIMAX, applying FPCA yields broadly similar month-to-month error shapes for both load and net-load forecasts, yet it delivers a clear improvement for net-load relative to the baseline SARIMAX specification, most notably outside the summer period. The

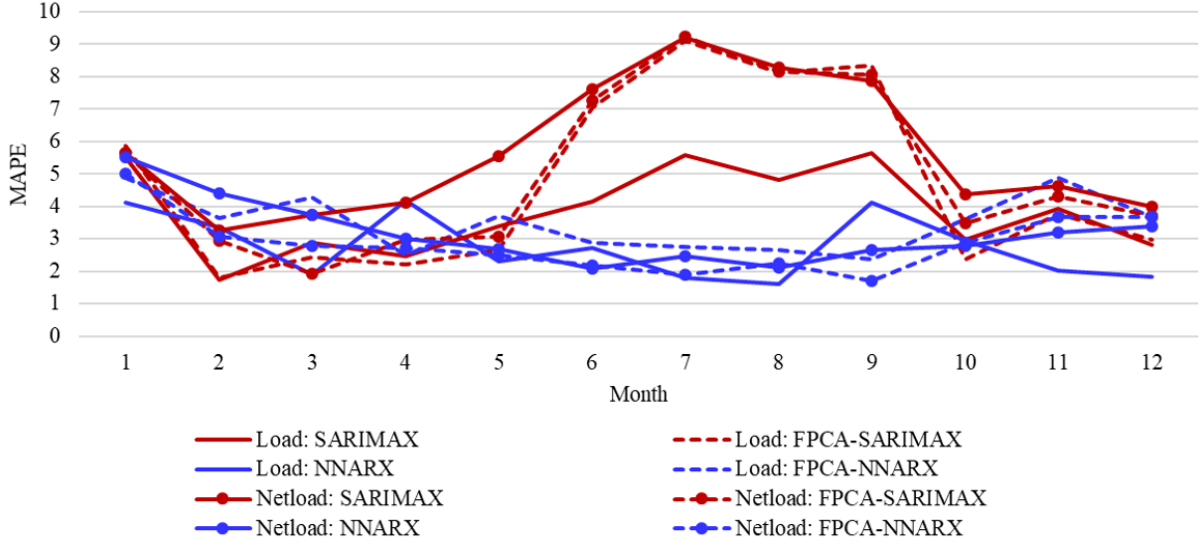


Figure 6: Monthly average MAPE for load and net load forecasting across different models. The horizontal axis denotes the month (1–12), and the vertical axis indicates MAPE values. The same line conventions as in Figure 5 are used.

substantial solar output during summer leads to significant daytime renewable injections, resulting in greater net-load variability compared with other seasons. This pattern highlights the limitations of SARIMAX in accurately capturing system dynamics under conditions of high renewable penetration.

By contrast, NNARX does not exhibit the same vulnerability. Differences between NNARX and FPCA-NNARX are minor for load forecasting across months, but for net load the FPCA-NNARX configuration attains lower errors in the winter–spring interval (January–May). Taken together with the seasonal asymmetry noted above, these results imply that NNARX provides a more robust baseline under high-variability, high-renewables conditions, while FPCA offers additional gains for characterizing net-load fluctuations.

Figures 7 and 8 illustrate the daily forecast results for load and net load, respectively. In addition to comparing the trends of model forecasts with the actual values, these figures also reveal the relative strengths and weaknesses of different models during specific periods. First, forecast errors are generally larger during the summer months (July to September), indicating that high temperatures, peak electricity demand, and fluctuations in renewable energy output during this period present greater challenges for model fitting.

Second, in terms of overall curve fitting, NNARX and FPCA-NNARX clearly outperform

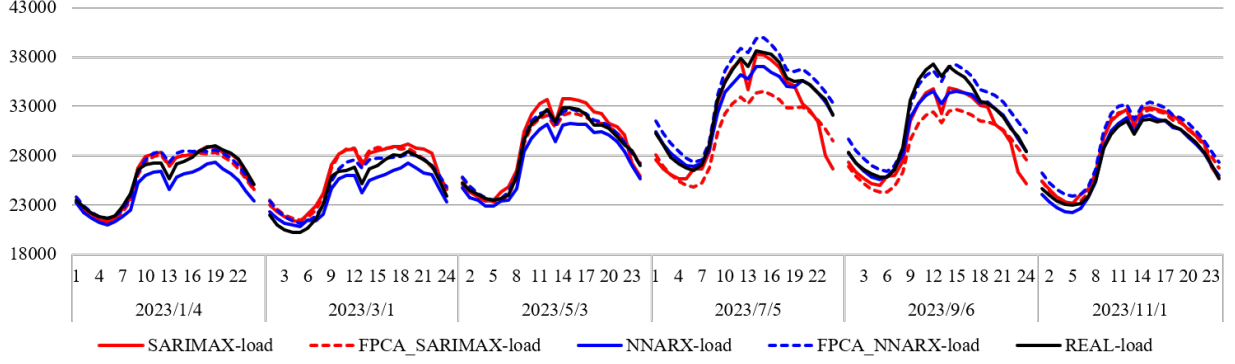


Figure 7: Forecasted load curves for selected days in 2023. The vertical axis represents system load (MW), and the horizontal axis denotes hourly intervals. Red and blue lines represent forecasts from SARIMAX-related and NNARX-related models, respectively, with dashed lines indicating FPCA-based variants. The black line shows the actual load.

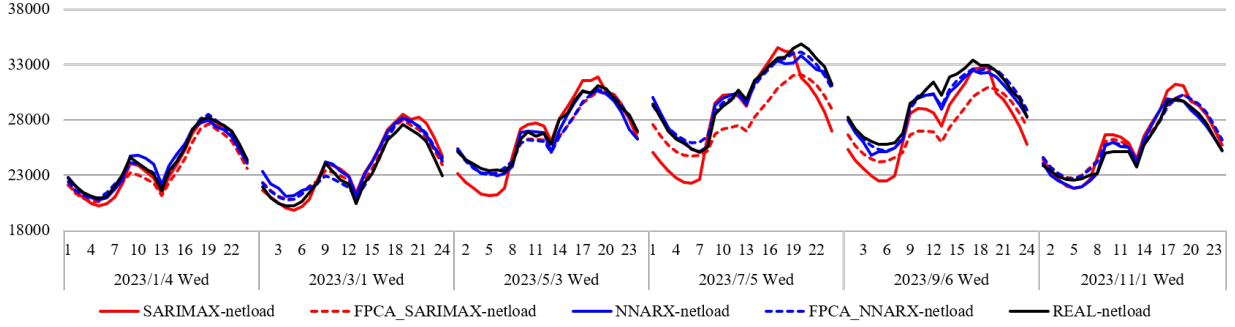


Figure 8: Forecasted netload curves for selected days in 2023. The vertical axis represents system load (MW), and the horizontal axis denotes hourly intervals. The same line conventions as in Figure 7 are used.

SARIMAX and FPCA-SARIMAX, particularly in net load forecasting, where the NNARX-based model curves almost coincide with the actual values, highlighting their superiority in capturing nonlinear and complex dynamic relationships. In contrast, while SARIMAX can achieve accurate forecasts in certain time periods, it exhibits relatively large errors in others, leading to deviations in the overall trend from actual observations. FPCA-SARIMAX, although prone to underestimation or temporal shifts (most apparent in July to September), still manages to capture the general shape and cyclical characteristics of the load curves, reflecting the stability of FPCA in preserving the principal modes of variation.

6 Conclusion

This study compares SARIMA, NNARX, and their extensions incorporating FPCA to examine the effectiveness of different data granularities and modeling approaches in load and net load forecasting. Empirical findings indicate that NNARX and its FPCA variants consistently outperform SARIMA in terms of predictive accuracy, particularly in capturing the dynamic features of net load curves, where forecasts align closely with actual observations. This result reflects the advantage of nonlinear neural networks in modeling complex nonlinear relationships between variables, and also underscores the contribution of FPCA’s dimensionality reduction in preserving the main modes of curve variation and controlling potential common factors.

With respect to data granularity, the results demonstrate that the incorporation of daily average meteorological variables can effectively serve as proxies for common factors such as global weather conditions, systematic demand fluctuations, or policy impacts, thus mitigating endogeneity bias. In most cases, using daily data not only maintains but even enhances forecast accuracy, while reducing the need for hourly meteorological data collection. This has substantial practical value for medium- and long-term forecasting, given that hourly data are often difficult to obtain in real-world applications, whereas daily data are more accessible.

Furthermore, FPCA preserves the principal variation structure of the entire curve during dimensionality reduction, enabling the model estimation process to capture and control potential common variation patterns, with its effect being particularly prominent in net load forecasting. As net load is influenced by both load and renewable generation, and both are highly dependent on meteorological conditions, the principal components extracted by FPCA share a similar nature with cross-sectional averages in the CCE method, acting as effective proxies for common factors.

Overall, this study confirms that the combination of NNARX with FPCA, while appropriately leveraging daily average meteorological variables, can deliver stable and accurate forecasts across different time scales and forecast requirements. This approach not only enhances the generalization capacity of the models, but also provides a practical and feasible

solution for medium- to long-term load and net load forecasting when data availability is constrained.

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