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Electricity Demand Forecasting Based on Flexibility Characterization

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Abstract

Electricity demand forecasting is essential for optimizing energy management and planning in microgrids and institutional contexts. The purpose of this article is to demonstrate how flexibility characterization can serve as a structural foundation for prediction, providing a contextualized framework that surpasses the limitations of traditional approaches. Representative trajectories (A–D), derived from entropy and variability metrics, were consolidated from historical user data and used as the basis for modeling. Two complementary approaches were implemented: ARIMA models, which capture endogenous dynamics, and ARX models, which extend this capacity by incorporating exogenous cyclical variables (hour, day of the week, month) and lagged predictors. A systematic grid search was conducted to identify optimal parameter configurations, followed by validation through rolling forecasts with a 24-h horizon, relevant for operators of microgrids, institutional managers, and energy planners. Performance was evaluated using MAE, RMSE, MAPE, and SMAPE, ensuring comparability across trajectories. Results show that ARIMA consistently achieved lower error rates in stable trajectories (A and C), with SMAPE values around 2.0%, while ARX provided substantial improvements in irregular ones (B and C), reducing SMAPE from 3.7–5.9% to approximately 2.2–2.6%. In highly irregular profiles (D), all models converged to similar accuracy (SMAPE ≈ 9.0%). When applied to individual users, predictive errors varied more widely depending on trajectory assignment: stable users showed SMAPE values around 3–4%, while irregular users exhibited much higher errors, exceeding 18–21%. Unlike conventional methods that treat characterization and prediction as separate processes, this study integrates both into a unified framework, enabling forecasts to capture stability, cyclicity, and adaptability. The methodology was further applied to individual users by assigning them to representative trajectories and adjusting predictions through baseline scaling. Overall, the findings demonstrate that embedding forecasts within characterized trajectories transforms prediction into a contextualized analysis of flexibility, enabling accurate short-term forecasts and supporting practical applications in energy planning, demand management, and economic dispatch. The framework has been designed to support electricity demand forecasting across multiple contexts, from microgrids and institutional systems to larger territorial and national scales. Through contextual calibration, the methodology ensures adaptability and broader relevance for energy forecasting and demand-side management.

Keywords: smartmetering; energy flexibility; electricity demand forecasting; autoregressive integrated moving average (ARIMA); autoregressive with exogenous variables (ARX); trajectory-based modeling; demand-side management

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1. Introduction

Electricity demand forecasting is a fundamental process for the efficient operation of smart grids and microgrids, enabling operators to anticipate consumption patterns, optimize resources, and ensure system stability. The purpose of this article is to demonstrate how flexibility characterization provides the structural foundation for electricity demand forecasting. In this study, flexibility is assessed through statistical metrics of variation and distribution, specifically the coefficient of variation and normalized entropy. These indicators quantify the mutability and dispersion of consumption profiles, and thereby provide a structural proxy for operational flexibility. Users with high variability and disorder in their profiles are more likely to redistribute or curtail demand in practice, whereas stable profiles correspond to limited shiftable load. In this way, statistical characterization enables forecasting models to anticipate not only numerical patterns but also the practical adaptability of end users.

The increasing penetration of renewable sources and the variability of user behavior have intensified the need for accurate short-term forecasting methods, particularly with a 24-h horizon that supports operational planning. Such forecasts are essential for operators of microgrids, institutional managers, and regulators, as they inform economic dispatch, demand-side management programs, and dynamic tariff design [1–3]. Advanced metering infrastructures (AMIs) provide high-resolution data that facilitate this task, yet the complexity of consumption profiles continues to pose significant challenges [4–7].

Traditional statistical approaches, such as ARIMA, have been widely adopted due to their interpretability, computational efficiency, and ability to capture endogenous dynamics of time series [8–10]. In contrast, ARX models extend this capacity by incorporating exogenous cyclical variables,such as hour of the day, day of the week, and month,as well as lagged predictors, aiming to improve predictive accuracy in irregular scenarios [11,12]. This methodological divergence has generated debate: some studies argue that ARIMA remains sufficient for stable trajectories [13,14], while others highlight the added value of ARX in capturing external influences and sudden peaks in consumption [10,15]. However, these approaches are not fully satisfactory: ARIMA relies solely on endogenous dynamics, while ARX incorporates exogenous variables without structural context. More importantly, both treat characterization and forecasting as separate processes, limiting their ability to capture user flexibility.

Previous studies on electricity demand forecasting have explored statistical approaches such as ARIMA, valued for their interpretability and efficiency [8,10]. Other works have incorporated exogenous variables through ARX models, aiming to capture cyclic patterns and irregularities [11,12]. More recent contributions emphasize clustering and trajectory-based approaches to account for heterogeneity in user behavior [7,16,17]. Metrics such as Shannon entropy and the coefficient of variation have been used to quantify variability and stability in consumption profiles [18–20], while clustering techniques like K-Means, SOM, and DBSCAN have proven effective for segmentation [12,16]. Deep learning methods, including LSTM and autoencoders, have also been applied to improve forecasting accuracy [13,15,21], although their scalability remains limited in contexts with restricted infrastructure [7,22].

Beyond single-task deep learning approaches, recent studies have explored multi-task learning frameworks to improve electricity demand analysis and non-intrusive load monitoring (NILM). For example, heterogeneous multiple-experts architectures have been proposed for low-frequency NILM, where specialized models collaborate to disaggregate appliance-level consumption from aggregated smart-meter data [23]. Other approaches combine signal decomposition techniques such as discrete wavelet transform with multi-task neural architectures to extract multi-scale features for appliance identification [24].

Additionally, multi-information fusion strategies have been proposed to jointly learn complementary representations across tasks, improving accuracy and generalization in NILM systems [25]. These contributions highlight the growing relevance of multi-task learning in smart grid applications, situating our trajectory-based framework as a complementary approach that emphasizes interpretability and computational efficiency. Despite these advances, most studies treat characterization and prediction separately, without a unified framework that links user segmentation with forecasting. This gap motivates the present work, which integrates flexibility characterization with predictive modeling to evaluate ARIMA and ARX across representative trajectories.

Building upon our previous work on flexibility characterization [26], where users were grouped into representative trajectories, this study focuses on trajectory-based forecasting of electricity demand. The central objective is to demonstrate how flexibility characterization provides the structural foundation for prediction, transforming forecasts into contextualized insights about stability, cyclicity, and adaptability. The novelty of this work lies in embedding forecasting within characterized trajectories, unifying segmentation and prediction in a single framework. ARIMA and ARX are used as reference models to test this framework, allowing us to evaluate the role of exogenous variables across different trajectories and extend the methodology to individual users through classification and scaling procedures. The framework is applicable to diverse levels of the power system, ranging from local and institutional environments to territorial and national contexts. Its scalability is achieved through contextual calibration, enabling forecasts to remain robust and relevant across different aggregation levels.

2. Characterization of Demand in Terms of Flexibility

The characterization of consumption profiles was based on the analysis of 48 months of hourly demand data provided by a distribution system operator. A preprocessing workflow was implemented to ensure data consistency, followed by the computation of normalized Shannon entropy and the coefficient of variation (CV) as indicators of variability and complexity.

For each user, hourly consumption distributions were aggregated by day type within each month (e.g., all Mondays of February). At each hour (0–23), the set of values across those days was used to compute variability through the coefficient of variation (CV) and disorder through normalized entropy. This procedure was repeated month by month, ensuring that the metrics captured consistent intra-day variability across comparable temporal segments. As a result, each user was represented by 336 variables (24 h × 7 day types × 2 metrics), forming the user–metric matrix that served as input for clustering.

The coefficient of variation (CV) was computed as the ratio between the standard deviation and the mean of hourly demand distributions:

$$CV = \frac{\sigma}{\mu} \tag{1}$$

Normalized Shannon entropy was calculated from bin-based histograms of hourly load using the Freedman–Diaconis rule:

$$H = -\sum_{j=1}^{k} p_j \log_2(p_j), \quad H_{norm} = \frac{H}{\log_2(k)} \tag{2}$$

This normalization ensures comparability across users and periods, with H_{norm} ranging from 0 (complete order) to 1 (maximum disorder).

These metrics revealed heterogeneous behaviors across users, highlighting the need to construct representative trajectories. For illustration purposes, Figures 1 and 2 present the distribution of entropy and CV for a single month, exemplifying the variability observed in the dataset.

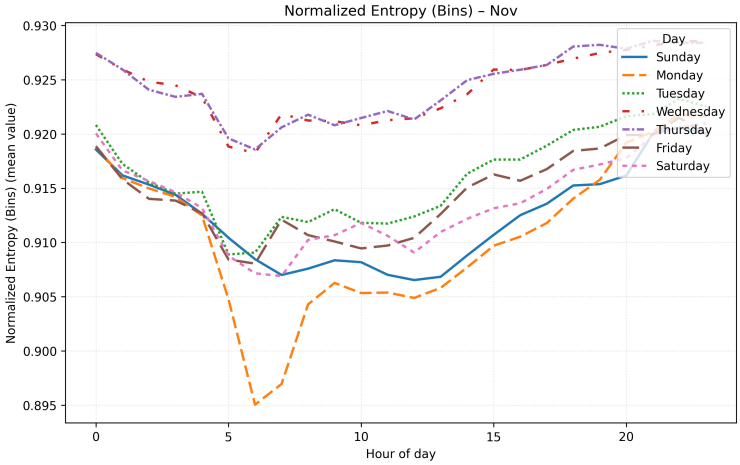

Figure 1. Example Month-Normalized Entropy Bins.

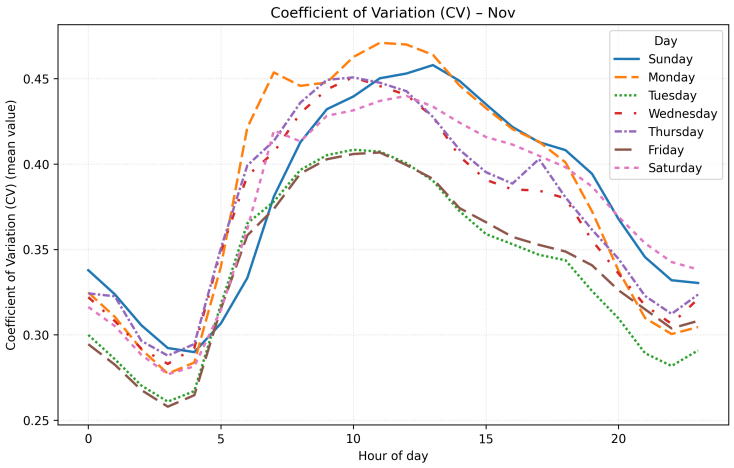

Figure 2. Example Month-Coefficient of Variation (CV).

High CV values reveal irregular and volatile demand, while high entropy values reflect dispersed and less structured load distributions. Together, these metrics serve as proxies for operational flexibility: profiles with greater variability and disorder are more likely to redistribute demand, whereas rigid profiles show limited adaptability.

To capture structural patterns, clustering techniques were applied to user–metric matrices constructed from hourly CV and entropy values. The combination of dimensionality reduction (NMF) and clustering (KMeans) enabled the identification of coherent and stable groups. Non-negative Matrix Factorization (NMF) was selected instead of more common dimensionality reduction techniques such as PCA or t-SNE because it preserves the non-negativity of electricity load curves. In PCA, negative coefficients may arise, which lack physical meaning in the context of consumption data [27], while t-SNE produces abstract embeddings that are difficult to interpret in terms of actual demand profiles. By contrast, NMF ensures that latent components are additive and non-negative, allowing centroid trajectories to retain the shape and magnitude of real load curves. This property provides direct physical interpretability, making the resulting clusters meaningful as representative consumption patterns rather than purely statistical abstractions [27,28].

This design was chosen because NMF preserves non-negativity, ensuring physical interpretability of load curves, while KMeans provides coherent segmentation of user profiles. This combination allows representative trajectories to retain the physical meaning of electricity demand patterns, unlike PCA or t-SNE which may produce negative or abstract embeddings.

User–metric matrices were constructed. Direct clustering with KMeans produced poor separation due to redundancy. To overcome this, Non-Negative Matrix Factorization (NMF) was applied to extract latent components dominated by CV or entropy. KMeans was then applied to the latent representation, yielding four coherent clusters (A–D) with improved quality indices and physical interpretability.

Clustering was applied independently to each monthly matrix, allowing the segmentation to reflect temporal stability and heterogeneity across the 48-month dataset. Cosine similarity analysis was then used to verify that the resulting clusters remained structurally stable across months, confirming the robustness of the representative trajectories (A–D).

As a result, four representative trajectories (A–D) were defined, each corresponding to a centroid profile that summarizes collective behaviors. Figure 3 presents one example month for each trajectory in a single visualization, illustrating their distinctive hourly structures.

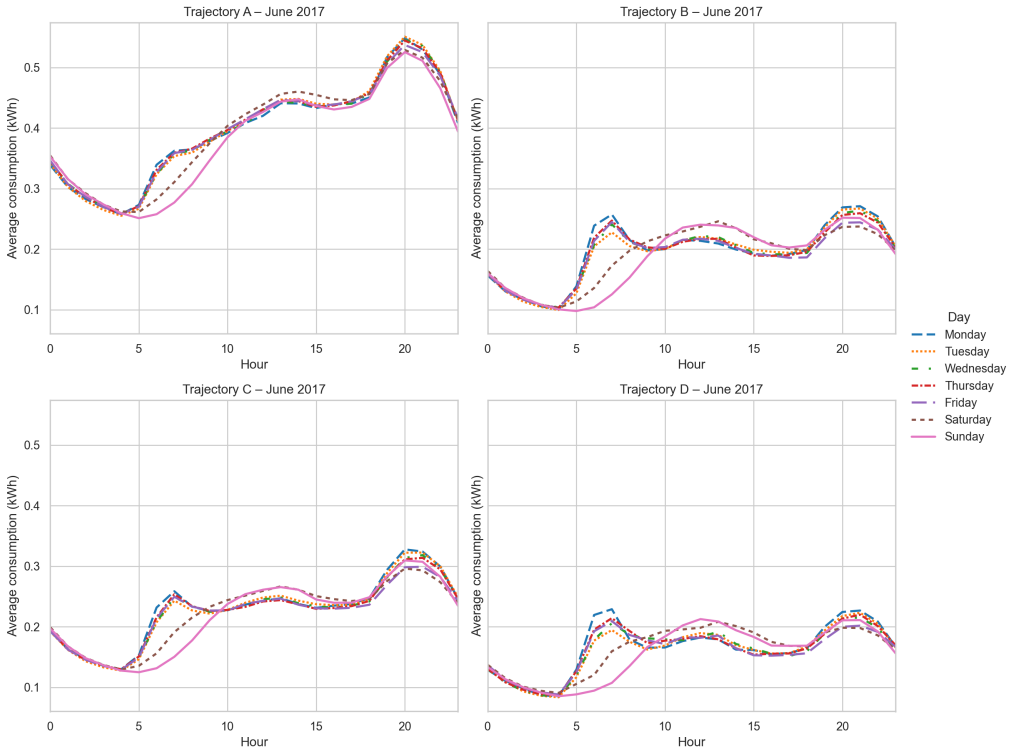

Figure 3. Representative Daily Load Curves by Trajectory.

Each trajectory corresponds to the centroid profile of its cluster, i.e., the average daily load curve that summarizes collective behavior. These centroids retain the physical shape of real demand curves, making them interpretable as representative routines rather than abstract embeddings.

Table 1 presents the structural characterization of latent functions for January 2017, reporting average values of CV and normalized entropy for each trajectory. These quantitative results reinforce the qualitative interpretation: Trajectories A and C exhibit lower variability (CV = 0.2396 and 0.3622, respectively) and higher entropy (0.9340 and 0.9299), consistent with rigid and structured routines. In contrast, Trajectories B and D show higher

variability (CV = 0.4819 and 0.6372) and lower entropy (0.9194 and 0.8931), reflecting heterogeneous behaviors and greater potential for demand-side flexibility.

Beyond their statistical form, these trajectories reflect real-world routines and the potential for flexibility. Trajectory A, with concentrated evening demand, corresponds to households with rigid schedules, where shifting consumption is more difficult. Trajectory B, with bimodal morning–evening peaks, represents users who can redistribute demand between periods, offering moderate adaptability. Trajectory C shows an intermediate pattern, with partial flexibility but still tied to evening routines. Trajectory D, with dispersed peaks across the day, reflects irregular schedules and diverse appliance usage, offering the highest potential for demand-side management.

Table 1. Structural characterization of latent functions (January 2017).

Function	Profile 0	Profile 1	CV	Entropy
A	0.0915	0.4329	0.2396	0.9340
B	0.2011	0.3344	0.4819	0.9194
C	0.1469	0.3849	0.3622	0.9299
D	0.2698	0.2635	0.6372	0.8931

This segmentation establishes the structural basis for the predictive stage: stable groups (A and C) are less adaptable, while variable groups (B and D) provide opportunities for load shifting, peak reduction, and improved forecasting. By grounding predictions in these representative trajectories, forecasting models capture not only statistical variability but also the operational flexibility of end users.

3. Materials and Methods

The materials used in this study include anonymized electricity consumption datasets collected through advanced metering infrastructures (AMI) between 2017 and 2020, consolidated into hourly time series. In our previous study on flexibility characterization (submitted manuscript), these datasets were grouped into representative trajectories (A, B, C, D). That characterization provides the structural foundation for the present work, where the trajectories serve as input for predictive modeling [16,29,30].

The methodological framework comprised normalization, parameter search, model training (ARIMA and ARX), and evaluation with standard error metrics (MAE, RMSE, MAPE, SMAPE). The following subsections describe each stage in detail.

3.1. Data Collection and Preprocessing

The dataset used in this study was obtained from advanced metering infrastructures (AMI) deployed in institutional and residential contexts between 2017 and 2020. Daily and monthly records were consolidated into continuous hourly time series for each user. We cleaned the data by removing duplicate entries, interpolating missing values, and excluding users with fewer than four complete days of valid records. This ensured robustness and comparability across samples [7,15].

Similar preprocessing strategies have been reported in AMI datasets, where anomaly detection and imputation are critical to ensure reliability [31,32].

The final dataset was organized into representative trajectories (A, B, C, D), previously defined through flexibility characterization and clustering in our earlier work (submitted manuscript). Each trajectory was stored in `.parquet` format, including temporal variables such as hour, day of the week, and month.

3.2. Normalization and Data Splitting

We normalized each trajectory by hour using the 95th percentile as reference. This approach reduces the influence of extreme values while preserving relative consumption structures [12,33].

Normalization and similarity measures have also been validated in time-series clustering studies [17,34]. The normalized series were divided into training (80%) and testing (20%) sets. A rolling forecast scheme with a 24-h horizon was applied to the test set, without reusing future information, simulating realistic short-term prediction scenarios [14,35].

The training set (80%) was used exclusively for parameter estimation and model fitting, while the testing set (20%) was reserved for out-of-sample evaluation. The best configurations reported in Section 4 were identified during this training/validation phase, whereas the subsequent forecast simulations and accuracy metrics were calculated on the testing set.

3.3. Model Implementation

Two complementary approaches were implemented:

- ARIMA models: capturing endogenous dynamics of the series through autoregressive, differencing, and moving average components [8,10].
- ARX models: extending ARIMA by incorporating exogenous cyclical variables (hour, day of week, month) encoded via sine and cosine functions, as well as lagged predictors (24 h and 48 h) to capture longer temporal dependencies [10–12].

ARIMA and ARX were selected as reference models due to their interpretability, scalability, and widespread adoption in electricity demand forecasting [8,10]. The central focus of this study is to leverage flexibility characterization as the structural foundation for prediction, and ARIMA/ARX serve as complementary statistical tools to test this framework. While more complex approaches such as LSTM or hybrid models have shown strong predictive performance, they typically involve higher computational cost and model complexity [13,15,21]. These approaches were not the primary objective here, since the aim was to evaluate the added value of exogenous variables within a computationally efficient and interpretable framework applicable in institutional contexts [7].

The exogenous variables included cyclical encodings of hour, day of the week, and month (via sine and cosine transformations), together with lagged predictors at 24 h and 48 h horizons. These variables were selected to capture daily and weekly seasonality as well as medium-term dependencies in consumption patterns [10–12]. Cyclical encodings allow periodic features to be represented without artificial discontinuities, while lagged predictors at daily horizons are commonly used in load forecasting models. Longer lag structures were not included because they increase model complexity without consistent performance gains, as reported in forecasting studies [10,13]. Comparative evaluation confirmed that exogenous variables improved accuracy only in specific trajectories, consistent with prior findings that additional regressors do not universally improve predictive performance [7,15].

Parameter selection was performed via exhaustive grid search over (p, d, q) orders, evaluating all combinations within bounded ranges ($p, d, q \leq 3$), a strategy commonly applied in ARIMA-based electricity demand forecasting and comparative time-series modeling studies [10,13]. Bounding the parameter ranges helps control model complexity and computational cost while preserving the ability to capture dominant temporal dependencies, as commonly recommended in practical ARIMA implementations [10]. Validation through rolling forecasts showed that higher-order configurations did not provide consistent performance gains, supporting the robustness of the selected ranges. For ARX,

additional configurations incorporated exogenous variables and lag structures following approaches reported in load forecasting studies [12].

The grid search for ARIMA was restricted to $(p, d, q) \leq 3$ to control complexity. Although electricity demand exhibits strong daily (24 h) and weekly (168 h) seasonality, Seasonal ARIMA (SARIMA) was not adopted. Our forecasting horizon was restricted to 24 h using three consecutive days as input, which makes weekly seasonality inconsistent with the rolling forecast scheme. Instead, exogenous cyclical variables (hour, day of week, month, weekend indicator, and lagged values at 24 h and 48 h) were incorporated into ARX models to capture daily and weekly periodicities in a computationally efficient way. This ensured methodological coherence between the training window and the prediction horizon, while the final model was trained on the entire dataset to exploit all available information.

While ARIMA and ARX provide valuable baselines, they are not fully satisfactory when applied in isolation. ARIMA captures endogenous dynamics but ignores external drivers, whereas ARX incorporates exogenous variables without structural context [10,13,15]. Both approaches treat characterization and forecasting as separate tasks, limiting their ability to reflect user flexibility [7,12]. The proposed trajectory-based framework surpasses these limitations by embedding prediction within characterized consumption trajectories, enabling contextualized forecasts that capture stability, cyclicity, and adaptability. This integration improves interpretability and scalability [7,10], ensuring that forecasts are not only numerical outputs but also structural descriptors of demand-side flexibility. The methodology is applicable to micro-grids and institutional systems, and since the dataset includes multiple cities across the country, the framework has already been validated at a territorial scale and can be extended to national contexts. The novelty of this work lies in unifying segmentation and prediction in a single framework, transforming electricity demand forecasting into a tool for both accuracy and flexibility analysis.

3.4. Evaluation Metrics

Performance was assessed using four widely adopted error metrics: Mean Absolute Error (MAE), Root Mean Square Error ($RMSE$), Mean Absolute Percentage Error ($MAPE$), and Symmetric Mean Absolute Percentage Error ($SMAPE$) [13,14]. These metrics capture both absolute and relative deviations, and their sensitivity to extreme values allows robust comparison across trajectories.

The following equations formally define the error metrics used in evaluation:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{4}$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t + 10^{-6}}\right| \tag{5}$$

$$SMAPE = \frac{100}{n}\sum_{t=1}^{n}\frac{2|y_t - \hat{y}_t|}{|y_t| + |\hat{y}_t| + 10^{-6}} \tag{6}$$

where (y_t) denotes the observed value and $(\hat{y}_t)$ the predicted value at time (t).

MAE and RMSE quantify absolute deviations, with RMSE penalizing larger errors more heavily. MAPE expresses relative deviations in percentage terms, facilitating comparison across trajectories, while SMAPE symmetrizes percentage errors to avoid bias when actual values are close to zero. All metrics were computed on the testing set to ensure that reported values reflect predictive accuracy rather than in-sample fitting.

3.5. Application to Individual Users

For individual-level prediction, we used three consecutive days of user consumption to construct a normalized profile. The forecast was then generated for the fourth day. Each user was assigned to the closest trajectory using cosine similarity and Pearson correlation, ensuring alignment with representative consumption patterns. The forecasts for the fourth day were then evaluated against the observed values using the same accuracy indicators applied to the trajectories.

The representative trajectories (A, B, C, D) were previously characterized through clustering techniques, where centroid profiles captured variability and entropy-based features of user demand [12,16,29,30]. This characterization provided the structural foundation for assigning individual users to trajectories.

The corresponding trajectory model (ARIMA or ARX) was then loaded, and predictions were dynamically rescaled using hourly normalization (95th percentile reference) and guardrail adjustments. Formally, the normalized forecast $\hat{y}_{\text{norm}}(t)$ was descaled by multiplying with the hourly percentile $P_{95}(h)$, capped by dynamic limits, and calibrated with coefficients α_h and β_h derived from recent mean and median values. The final prediction was blended with a baseline profile to ensure stability:

$$\hat{y}_{\text{final}}(t) = (1-\lambda)\left(\hat{y}_{\text{norm}}(t) \cdot P_{95}(h) \cdot \alpha_h + \beta_h\right) + \lambda \cdot \overline{y}_{\text{baseline}}(h) \tag{7}$$

Here,

$\hat{y}_{\text{norm}}(t)$ denotes the normalized forecast produced by the trajectory model.

$P_{95}(h)$ is the 95th percentile of consumption at hour h, used to recover the magnitude of the prediction. The coefficient α_h is a scaling factor obtained as the ratio between the recent mean consumption at hour h and the corresponding percentile:

$$\alpha_h = \frac{\overline{y}_{mean}(h)}{P_{95}(h)} \tag{8}$$

The coefficient β_h is a shift parameter calculated as the difference between the recent median and the scaled percentile:

$$\beta_h = \overline{y}_{med}(h) - P_{95}(h) \cdot \alpha_h \tag{9}$$

The term $\overline{y}_{\text{baseline}}(h)$ represents the average consumption profile of the last observed day, which provides a stable reference. Finally, λ is a blending parameter (between 0 and 1) that controls the trade-off between the dynamically adjusted forecast and the baseline, ensuring robustness against abrupt changes.

Forecasts were generated for the fourth day at hourly resolution, and evaluated against observed values using the same error metrics applied to the trajectories [13,14].

This approach is consistent with previous studies that emphasize the role of clustering and similarity measures in improving demand-side management [17,34]. Moreover, residential flexibility programs have highlighted the importance of tailoring predictions to individual profiles, enabling users to participate in demand response schemes [36,37]. By integrating trajectory assignment with predictive modeling, the methodology ensures scalability and adaptability across heterogeneous consumption behaviors [22,38].

4. Results

This section presents the outcomes of the predictive modeling framework applied to representative trajectories (A, B, C, D) and individual users. Results are organized into three parts: (i) performance evaluation on trajectories, (ii) application to individual

users, and (iii) comparative analysis between ARIMA and ARX models. Tables and figures summarize error metrics (MAE, RMSE, MAPE, SMAPE), highlighting differences across trajectories and users.

4.1. Performance on Trajectories

The predictive evaluation on trajectories A–D revealed heterogeneous behaviors depending on the internal dynamics of each group. Table 2 summarizes the best-performing configuration of ARIMA, ARX basic, and ARX with lags for each trajectory. ARIMA achieved lower errors in trajectories A and B (SMAPE ≈ 5–7%). ARX performed better in trajectory C (SMAPE ≈ 6–7%). In trajectory D, both models converged to similar accuracy (SMAPE ≈ 7–8%).

Table 2. Optimal ARIMA and ARX Configurations for Trajectories A–D.

Trajectory	Model Type	Order (p, d, q)	MAE	RMSE	MAPE	SMAPE
A	ARIMA pure	(1, 1, 3)	11.746	15.873	5.712	5.454
A	ARX basic	(0, 1, 0)	12.799	17.249	6.260	6.031
A	ARX lags	(3, 1, 1)	13.878	18.192	6.671	6.464
B	ARIMA pure	(1, 1, 3)	11.761	16.071	6.869	6.477
B	ARX basic	(0, 1, 0)	12.620	17.262	7.394	7.037
B	ARX lags	(2, 1, 0)	13.456	17.878	7.756	7.439
C	ARIMA pure	(1, 1, 3)	11.787	16.103	6.406	6.064
C	ARX basic	(0, 1, 0)	12.622	17.293	6.897	6.585
C	ARX lags	(2, 1, 0)	13.586	18.023	7.308	7.023
D	ARIMA pure	(3, 1, 2)	12.375	16.874	7.456	7.021
D	ARX basic	(0, 1, 0)	13.726	18.484	8.252	7.867
D	ARX lags	(2, 1, 0)	14.739	19.296	8.750	8.385

These results indicate that the effectiveness of exogenous variables depends on the temporal structure of each trajectory, with ARIMA being sufficient for stable patterns and ARX offering advantages in profiles with cyclic regularities. Final performance metrics after forecast simulations are reported separately in Table 3, where error values decrease substantially due to normalization and guardrail adjustments.

Table 3. Forecast Performance Metrics (*MAE*, *RMSE*, *MAPE*, *SMAPE*) for ARIMA and ARX across Trajectories A–D.

Trajectory	Model	MAE	RMSE	MAPE	SMAPE
A	ARIMA	4.63	6.04	2.04%	2.07%
A	ARX basic	4.52	5.93	1.96%	1.94%
A	ARX lags	4.40	5.61	1.92%	1.91%
B	ARIMA	7.03	7.97	3.63%	3.71%
B	ARX basic	3.95	5.08	2.21%	2.24%
B	ARX lags	3.93	5.08	2.20%	2.23%
C	ARIMA	12.99	16.72	5.74%	5.96%
C	ARX basic	4.86	5.79	2.66%	2.62%
C	ARX lags	4.90	5.74	2.67%	2.63%
D	ARIMA	15.49	20.07	9.83%	9.01%
D	ARX basic	15.49	20.07	9.83%	9.01%
D	ARX lags	15.49	20.07	9.83%	9.01%

Beyond SMAPE, Table 2 also highlights differences in MAE, RMSE, and MAPE across trajectories. In trajectories A and B, ARIMA achieved the lowest MAE (≈11.7) and RMSE (≈15.8), indicating smaller absolute deviations and reduced sensitivity to large errors compared to ARX variants. In trajectory C, ARIMA again minimized MAE and RMSE, while ARX models produced slightly higher values, confirming that exogenous variables did not provide additional gains in this case. In trajectory D, all models exhibited higher MAE and RMSE (≈12–19), reflecting the irregularity of this group. MAPE values followed similar trends, with ARIMA consistently outperforming ARX in trajectories A–C, while in trajectory D the differences were marginal. These complementary indicators confirm that the comparative advantage of ARIMA in stable trajectories is consistent across absolute and relative error measures, whereas ARX offers limited improvements in irregular profiles.

Table 2 presents the optimal configurations identified during the parameter search phase. These values reflect the grid search process, while the final performance metrics reported in Table 3 correspond to forecast simulations performed on random four-day blocks of each trajectory, where three consecutive days were used as input and the fourth day was predicted and compared against observed values, with normalization and guardrail adjustments.

Forecast Simulations and Prediction Metrics

To illustrate the practical application of the trained models, random blocks of four days (three for training and one for testing) were selected in each trajectory. Figures 4–7 show representative forecasts for the fourth day, comparing observed and predicted values. These simulations highlight the ability of ARIMA and ARX to reproduce hourly dynamics and anticipate consumption peaks. Complementing the graphical analysis, Table 3 reports the final error metrics (MAE, RMSE, MAPE, SMAPE) for ARIMA, ARX basic, and ARX with lags across trajectories A-D. In trajectory A, ARX with lags achieved the lowest errors (SMAPE ≈ 1.91%), closely followed by ARX basic (≈1.94%), while ARIMA performed slightly worse (≈2.07%). In trajectory B, ARX variants achieved SMAPE ≈ 2.23–2.24%, while ARIMA reached 3.71%. This confirms that exogenous variables improved accuracy in irregular profiles. In trajectory C, ARX models again surpassed ARIMA, reaching SMAPE ≈ 2.62–2.63%, whereas ARIMA showed substantially higher errors (≈5.96%). Finally, in trajectory D, all approaches converged to identical accuracy, with SMAPE ≈ 9.01%.

Beyond SMAPE, Table 3 also highlights consistent differences in MAE, RMSE, and MAPE across trajectories. In trajectory A, ARX with lags achieved the lowest MAE (4.40) and RMSE (5.61), confirming smaller absolute deviations compared to ARIMA (MAE 4.63, RMSE 6.04). In trajectory B, both ARX variants reduced MAE and RMSE by almost half relative to ARIMA, evidencing substantial gains in absolute accuracy. In trajectory C, ARX models again minimized MAE (≈4.9) and RMSE (≈ 5.7), while ARIMA produced much larger errors (MAE 12.99, RMSE 16.72). In trajectory D, all models converged to identical values (MAE 15.49, RMSE 20.07), reflecting the irregularity of this group. MAPE values followed the same trends, with ARX consistently outperforming ARIMA in trajectories B and C, while differences in A and D were marginal. These complementary indicators confirm that the improvements observed in SMAPE are consistent across absolute and relative error measures.

Overall, these findings demonstrate that the inclusion of exogenous variables can provide consistent improvements in certain trajectories (B and C), while in others (A and D) the differences are marginal or nonexistent. This confirms that the effectiveness of exogenous variables depends strongly on the temporal structure of each series. ARX offers advantages in trajectories with cyclic or irregular patterns, whereas ARIMA remains competitive in stable or convergent profiles. This comparative evidence reinforces the

importance of embedding predictive models within characterized trajectories, since the performance of each method is directly linked to the flexibility and variability of the underlying consumption group.

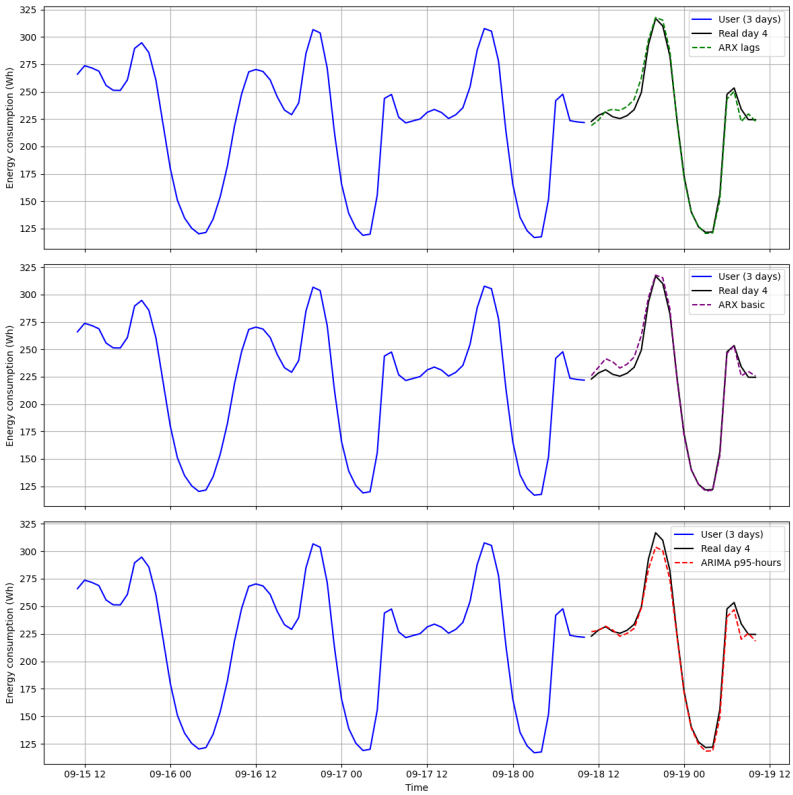

Figure 4. Trajectory A—Comparison of observed values and ARIMA/ARX predictions.

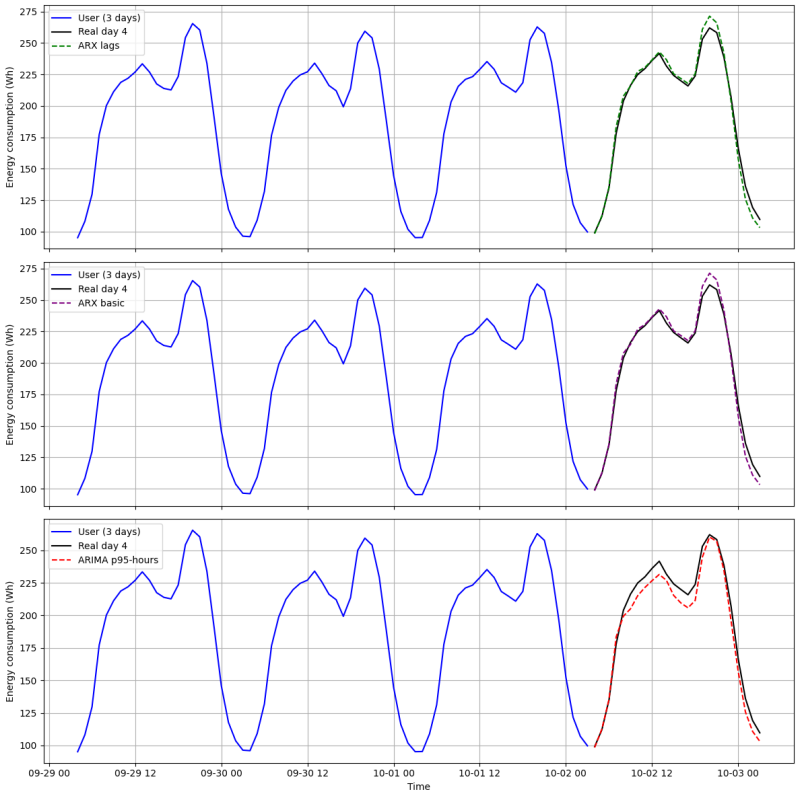

Figure 5. Trajectory B—Comparison of observed values and ARIMA/ARX predictions.

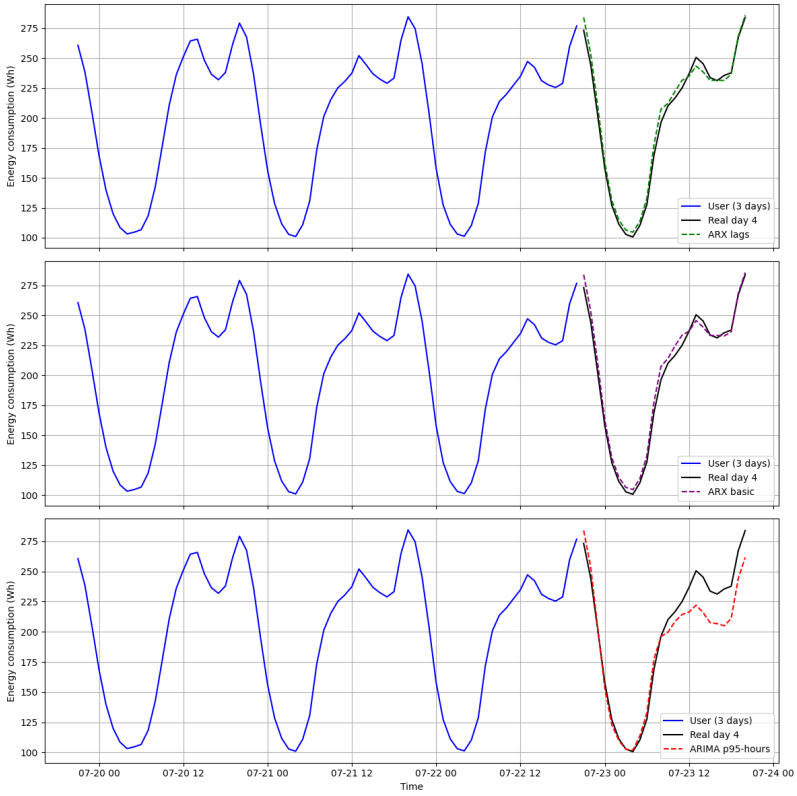

Figure 6. Trajectory C—Comparison of observed values and ARIMA/ARX predictions.

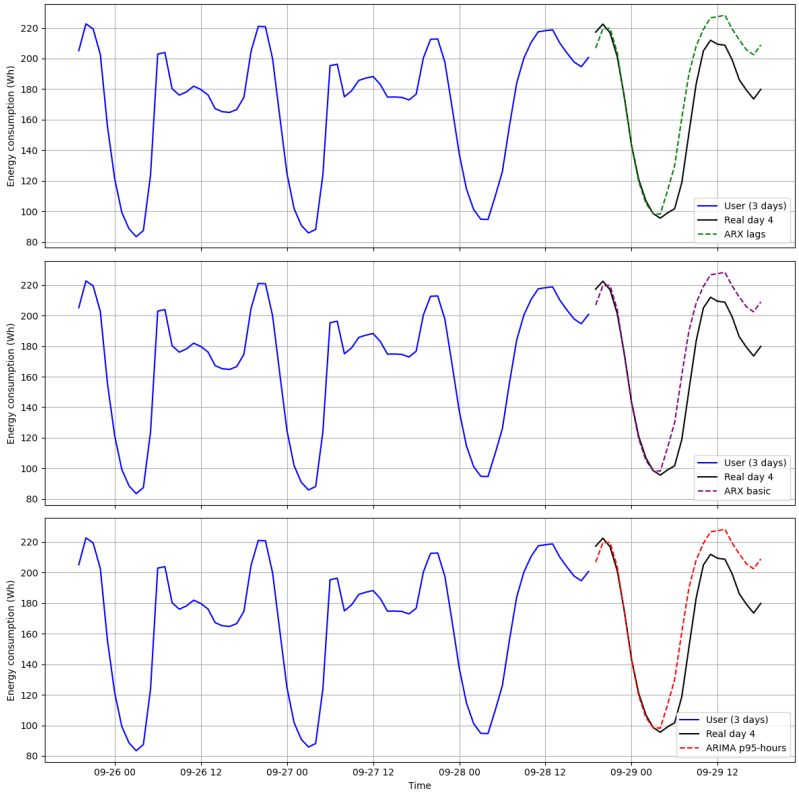

Figure 7. Trajectory D—Comparison of observed values and ARIMA/ARX predictions.

The identical error metrics observed for Trajectory D are not a reporting error. This group exhibits extreme irregularity, with dispersed peaks and limited cyclic structure. Under these conditions, exogenous variables and lagged predictors fail to provide addi-

tional gains, and all models converge to similar forecasts after normalization and guardrail adjustments. The convergence of MAE, RMSE, MAPE, and SMAPE values highlights that exogenous regressors improve accuracy only when the underlying trajectory exhibits regular cyclicity, whereas in highly irregular profiles their effect is negligible.

Beyond numerical accuracy, the results reveal concrete differences in responsiveness. Stable trajectories (A, C) showed limited adaptability, where ARIMA remained sufficient. In contrast, irregular or cyclic trajectories (B, D) exhibited greater responsiveness to external drivers, with ARX consistently outperforming ARIMA. This differentiation underscores the role of trajectory characterization in linking predictive performance with practical flexibility.

4.2. Application to Individual Users

Once the optimal configurations were identified for each trajectory, the models were applied to individual users in order to evaluate predictive performance at the disaggregated level. User profiles were constructed from three consecutive days of consumption and assigned to the closest trajectory using similarity measures (cosine distance and Pearson correlation). Forecasts for the fourth day were then generated and rescaled with user-specific adjustments to account for individual variability.

Representative cases for trajectories A-D are summarized in Table 4, which reports the error metrics (MAE, RMSE, MAPE, SMAPE) obtained for selected users. Figures 8–11 illustrate the comparison between observed and predicted values, together with residual plots that highlight the distribution of errors across the prediction horizon.

Table 4. Prediction Accuracy Metrics (MAE, RMSE, MAPE, SMAPE) for Representative Users in Trajectories A–D.

Trajectory	Model	MAE	RMSE	MAPE (%)	SMAPE (%)
A	ARIMA	2.91	4.44	3.83	3.74
A	ARX basic	2.99	4.51	3.89	3.80
A	ARX lags	2.99	4.51	3.89	3.80
B	ARIMA	49.71	72.10	18.78	21.75
B	ARX basic	41.88	61.88	16.33	18.20
B	ARX lags	43.03	64.40	16.76	18.83
C	ARIMA	3.99	4.68	5.85	5.79
C	ARX basic	3.99	4.68	5.85	5.79
C	ARX lags	3.99	4.68	5.85	5.79
D	ARIMA	10.83	13.00	9.59	9.35
D	ARX basic	10.69	12.78	9.43	8.99
D	ARX lags	10.80	12.77	9.49	9.12

Table 4 shows that predictive accuracy varies across user profiles. In trajectory A, all models achieved very low MAE (≈2.9) and RMSE (≈4.5), confirming that regular users can be forecasted with high precision. In trajectory B, errors were higher (MAE ≈ 40–50, RMSE ≈ 60–72), reflecting irregular demand. ARX variants reduced both metrics compared to ARIMA, showing the benefit of exogenous variables. In trajectory C, all models converged to identical metrics (MAE ≈ 4.0, RMSE ≈ 4.7, MAPE ≈ 5.8%), showing that exogenous regressors did not provide additional gains. In trajectory D, ARX models slightly improved MAE and SMAPE relative to ARIMA, but overall errors remained higher than in stable groups. These results confirm that while the framework is robust for regular users, irregular profiles require complementary mechanisms to handle abrupt peaks and variability.

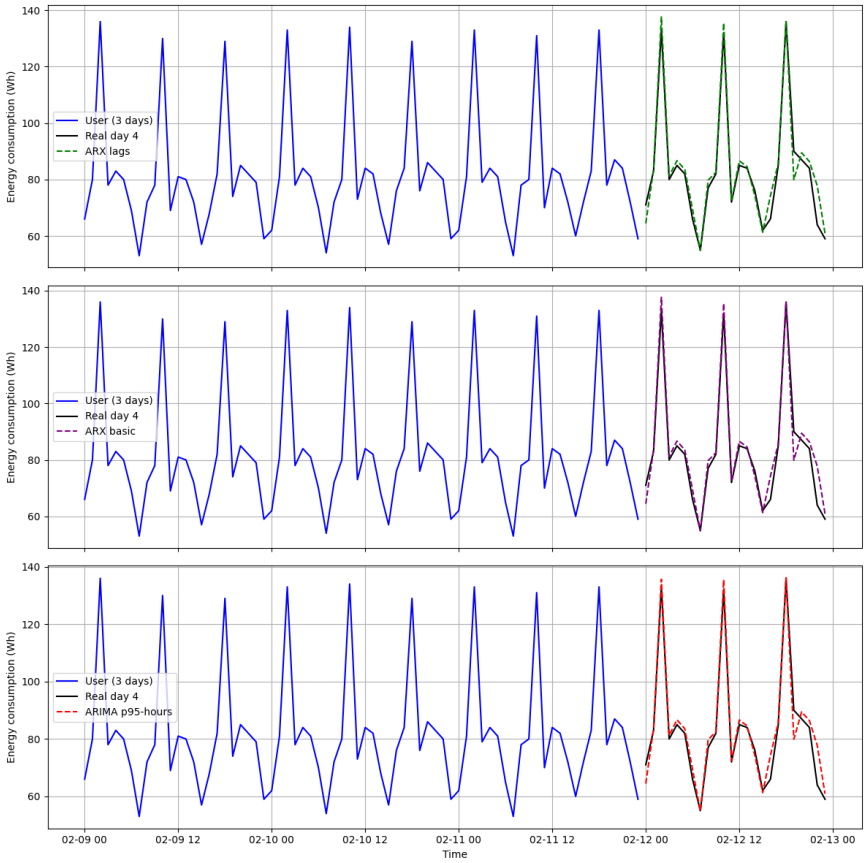

Figure 8. Trajectory A—Observed vs. Predicted Values (ARIMA and ARX).

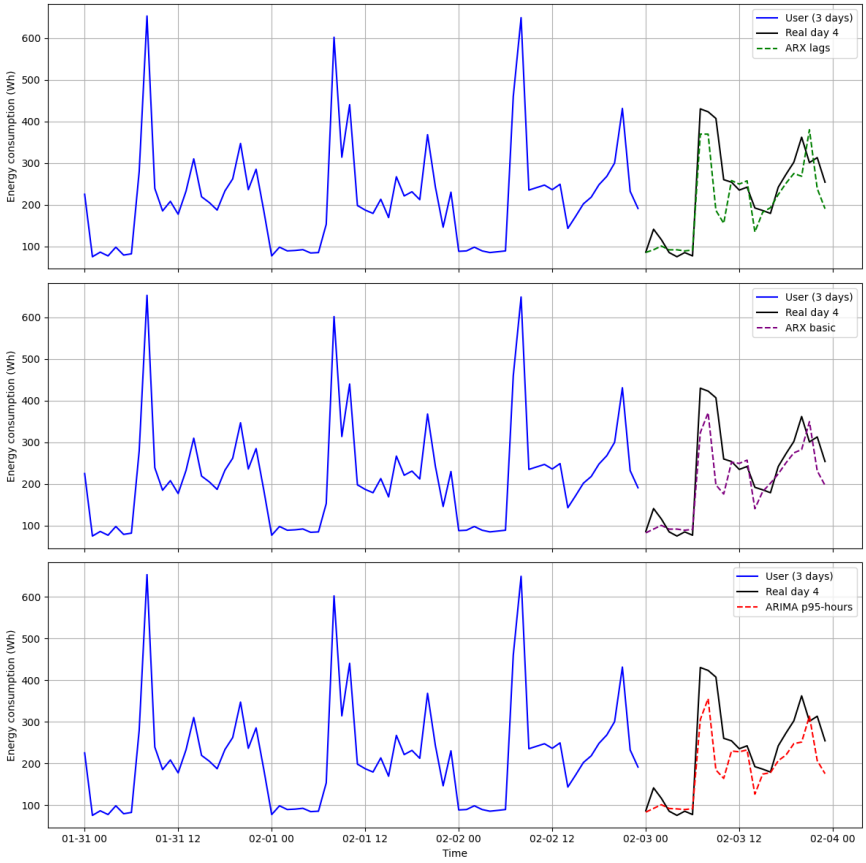

Figure 9. Trajectory B—Observed vs. Predicted Values (ARIMA and ARX).

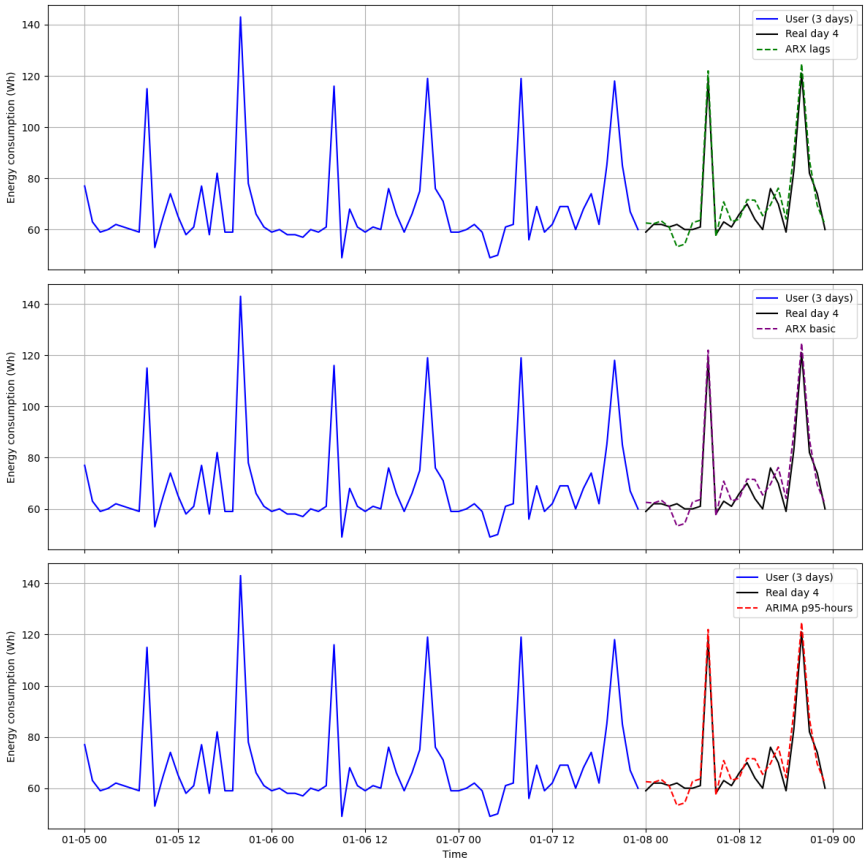

Figure 10. Trajectory C—Observed vs. Predicted Values (ARIMA and ARX).

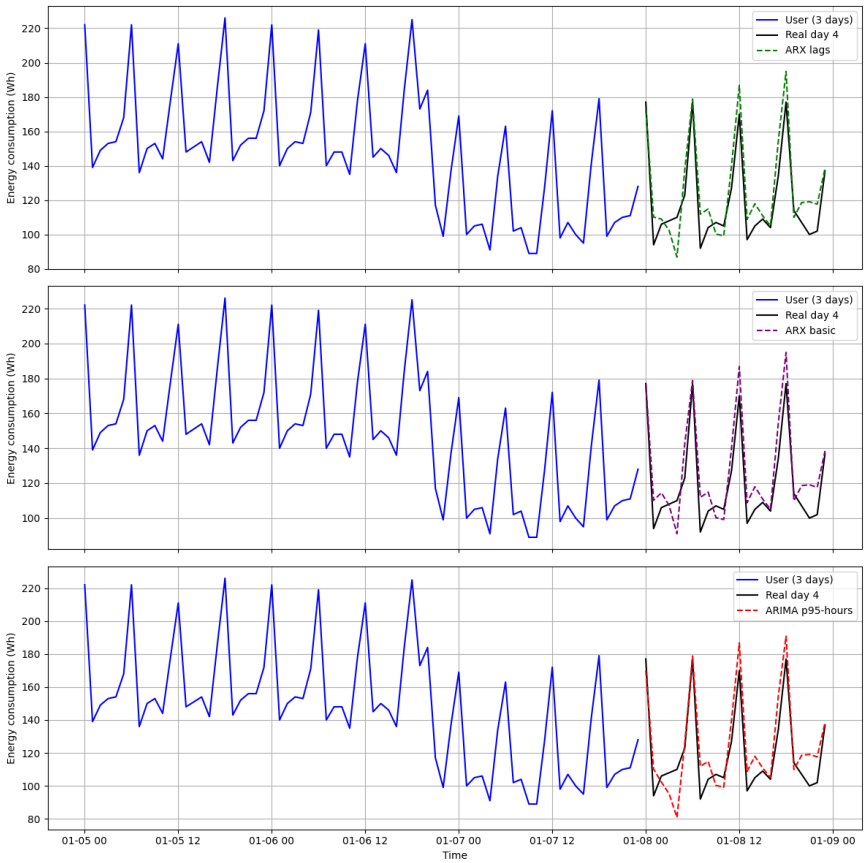

Figure 11. Trajectory D—Observed vs. Predicted Values (ARIMA and ARX).

Results confirm that the proposed approach is highly effective for users with regular consumption profiles, where ARIMA and ARX models achieve low error values and capture daily dynamics with precision. However, limitations appear in scenarios with abrupt peaks or irregular demand, where residuals increase and forecasts deviate from observed values. This evidences that while trajectory-based modeling provides a robust framework for generalization, additional mechanisms may be required to handle atypical consumption behaviors. In particular, anomaly detection or hybrid post-processing strategies could complement the current framework, ensuring adaptability in cases where sudden changes in demand compromise predictive accuracy.

4.3. Limitations in Irregular Profiles

To complement the favorable results, it is important to highlight scenarios where the models exhibited poor predictive performance. A representative case is shown for trajectory C (Table 5 and Figure 12), where abrupt peaks and irregular demand patterns produced large deviations between observed and predicted values. For instance, at hour 06 the real consumption reached 546 Wh, while ARIMA and ARX variants predicted values around 280–300 Wh, resulting in errors exceeding 250 Wh. This value corresponds to hourly energy consumption, consistent with the dataset structure where all records were consolidated into watt-hour measurements per hour. Similarly, at hour 10 the models generated fictitious peaks (240–266 Wh) against a real value of only 121 Wh. Global error metrics confirm this misalignment: ARX basic and ARX lags reached SMAPE values of 28–29%, while ARIMA performed even worse with SMAPE $\approx$ 33%. Residual plots further show that errors concentrate in specific hours, evidencing the inability of the models to adapt to sudden anomalies.

This example illustrates that while trajectory-based modeling is effective in regular profiles, its performance deteriorates in irregular scenarios with abrupt peaks or shifts in demand. Complementary mechanisms, such as anomaly detection, hybrid models, or post-processing adjustments, are therefore essential to enhance adaptability and ensure robustness in contexts where sudden demand changes compromise predictive accuracy. These tools would allow the framework to maintain reliability even under atypical demand conditions, bridging the gap between statistical forecasting and operational flexibility

Table 5. Prediction Accuracy Metrics for a Representative User in Trajectory C (Poor Performance Case).

Trajectory	Model	MAE	RMSE	MAPE (%)	SMAPE (%)
C	ARIMA	84.54	101.69	29.75	33.00
C	ARX basic	72.97	90.62	27.06	28.25
C	ARX lags	75.01	94.28	27.89	29.29

Table 5 confirms the deterioration in predictive accuracy under irregular conditions. MAE and RMSE values are substantially higher ($\approx$73–85 and $\approx$90–102, respectively), evidencing large absolute deviations. MAPE and SMAPE also increase to 27–33%, far above the thresholds typically considered acceptable (<10%), highlighting the inability of the models to adapt to abrupt peaks. ARX variants slightly reduced errors compared to ARIMA, but overall performance remained poor. Trajectory-based modeling is effective in regular profiles. However, irregular demand scenarios require complementary mechanisms such as anomaly detection or hybrid models to maintain predictive accuracy.

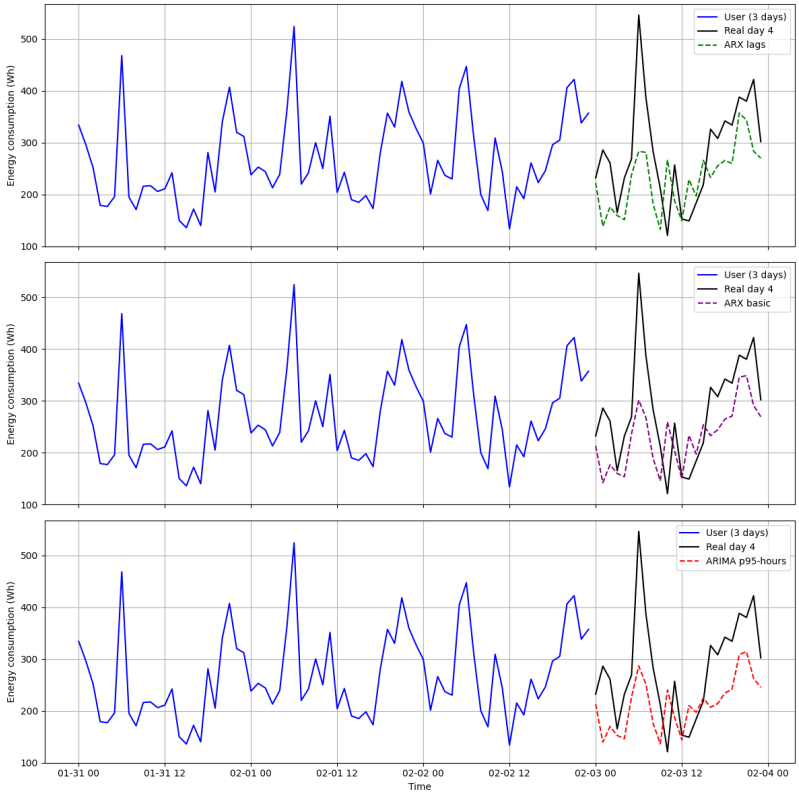

Figure 12. Trajectory C—Observed vs. Predicted Values (Poor Performance Case, ARIMA and ARX).

5. Discussion

The analysis of trajectories A–D confirms that predictive performance is strongly conditioned by the temporal structure of consumption profiles. In line with the working hypothesis, ARX achieved superior accuracy in trajectories with irregular or cyclic dynamics (B and D), while ARIMA remained competitive in stable or convergent profiles (A and C). This reinforces the idea that the contribution of exogenous variables is conditional rather than universal and highlights the importance of model selection tailored to the intrinsic characteristics of the series. Forecasts acquire meaning only once trajectories are characterized. Without the prior classification, predictions would remain isolated numerical outputs. With the characterization, however, forecasts become contextualized projections embedded within representative consumption patterns. This contextualization enables comparative analysis of flexibility. Trajectories with stable dynamics (A and C) exhibit limited adaptability, whereas those with cyclic or irregular structures (B and D) reveal greater responsiveness to external drivers. Such differentiation is crucial for demand-side management, as it allows strategies to be designed according to the flexibility potential of each group.

The cross-comparison between models and trajectories further clarifies their complementary roles. In stable trajectories (A and C), ARIMA proved sufficient, as the inclusion of exogenous variables did not significantly improve accuracy. Conversely, in variable or cyclic trajectories (B and D), ARX clearly outperformed ARIMA, demonstrating the value of external drivers in capturing complex dynamics. Predictive accuracy is therefore not determined solely by the modeling technique but by the compatibility between the model and the temporal structure of the trajectory. At the individual-user level, the trajectory assignment mechanism proved effective in generalizing predictive performance, bridging aggregate trajectory modeling with personalized forecasting. However, limitations appeared in cases with abrupt peaks or sudden shifts in demand, where residuals concentrated in specific hours and global errors increased. These results highlight a structural

challenge of time-series models when faced with anomalies, confirming that predictive accuracy is closely tied to the regularity of the underlying consumption pattern.

Beyond the numerical evaluation with MAE, RMSE, MAPE, and SMAPE, the results emphasize that electricity demand is inherently variable and never constant. Even within similar trajectories, users adjust their routines daily, responding to contextual factors such as schedules, weather, or institutional activities. This mutability underscores the importance of embedding forecasts within flexibility categories. By considering trajectories as structural descriptors, ARIMA and ARX models gain practical relevance, since they anticipate not only statistical patterns but also behavioral evolution. In this way, prediction is not limited to error minimization but becomes a tool to interpret and manage the dynamic nature of demand. The advantage of trajectory-based forecasting lies precisely in acknowledging that end-users can modify their demand in real time, and that prediction must adapt to the evolving nature of consumption. This perspective adds value to forecasting, as it transforms it into a decision-support instrument that integrates flexibility into operational planning.

From a methodological perspective, ARIMA and ARX should not be seen as competing paradigms but as complementary approaches. ARIMA efficiently captures stability, while ARX leverages exogenous information to anticipate cyclic behaviors. Together, they provide a dual perspective of stability and complexity that enriches the interpretation of consumption dynamics. The characterization of trajectories A–D enables this dual perspective, providing the structural foundation to decide when stability is sufficient and when complexity must be incorporated. Future research should therefore focus on hybrid or adaptive frameworks that integrate both perspectives, ensuring robustness across heterogeneous demand scenarios. Knowing how users behave from a flexibility perspective is crucial for control centers and demand management operators. Accurate forecasts embedded within characterized trajectories enable more efficient economic dispatches, as system operators can anticipate which groups of users are more responsive to external signals and which remain stable. This differentiation supports the design of targeted demand response programs, dynamic pricing schemes, and load-shifting strategies that optimize resource allocation. In practice, trajectory-based predictions allow utilities to integrate flexibility into operational planning, reducing costs, improving reliability, and enhancing sustainability.

Beyond predictive accuracy, ARIMA and ARX also differ in terms of computational cost and ease of implementation. ARIMA, with its limited parameterization (p, d, q), is lightweight and straightforward to deploy, making it suitable for institutional contexts with restricted infrastructure. In contrast, ARX requires additional preprocessing to encode cyclical variables and incorporate lagged predictors, which increases model complexity and computational demands. This added cost is justified only in trajectories with irregular or cyclic dynamics, where ARX consistently outperforms ARIMA. In stable or convergent profiles, however, ARIMA remains sufficient, as the inclusion of exogenous variables does not yield significant improvements. Thus, methodological selection must balance predictive gains against implementation effort, ensuring that forecasting frameworks remain both accurate and operationally viable.

Trajectory-based forecasting can therefore be directly applied to economic dispatch in microgrids and institutional systems, where differentiated responsiveness enables more efficient resource allocation. In demand-side management, this approach supports the design of dynamic tariffs and targeted demand response programs, aligning incentives with user flexibility potential. Beyond operational planning, the framework also provides valuable input for regulators and policymakers, offering a structured methodology to quantify flexibility and promote energy efficiency at the system level. In this way, forecasting ceases to be a purely technical exercise and becomes a strategic instrument for both operational and regulatory decision-making.

Beyond the specific limitations observed in irregular profiles, three broader challenges emerge regarding the generalization of the proposed methodology. First, the framework was tested with hourly data, but its behavior under different granularities (e.g., sub-hourly) remains an open question. Higher-resolution inputs could improve peak detection and enhance responsiveness analysis, yet they may also introduce noise and increase computational demands, requiring adaptive preprocessing strategies. Second, transferring the methodology to other countries poses additional challenges, as flexibility characterization is strongly influenced by tariff structures, regulatory frameworks, and the penetration of renewable sources. Contextual calibration would therefore be necessary to ensure predictive validity across heterogeneous energy systems. Finally, in scenarios with abrupt peaks or sudden anomalies, complementary mechanisms such as anomaly detection, hybrid models, or post-processing adjustments are essential to enhance adaptability. These tools would allow the framework to maintain robustness even under atypical demand conditions, ensuring that trajectory-based forecasting remains effective across diverse contexts and data environments.

Although deep learning architectures (e.g., LSTM, GRU, and time-series transformers) were excluded from this study due to computational cost and scalability concerns, the trajectory-based approach proposed here can serve as a pre-processing stage for such models. By clustering users into representative trajectories and applying dynamic rescaling with guardrails, the method reduces heterogeneity and stabilizes input sequences. This structured representation could be directly integrated into lightweight generative models or specialized time-series transformers, thereby enhancing their efficiency and interpretability. In this sense, the methodology is not only an alternative to deep learning but also a complementary step that facilitates its application in large-scale demand-side management contexts.

Overall, the discussion underscores that predictive performance is not determined solely by the modeling technique but by the compatibility between the consumption profile and the temporal dependencies captured by the model. By embedding forecasts within characterized trajectories, prediction becomes a comparative analytical exercise that reveals differences in flexibility potential across user groups. This insight contributes to the broader literature on energy forecasting and emphasizes the importance of flexible methodologies that adapt to the variability and heterogeneity inherent in real-world demand.

6. Conclusions

This work evaluated the predictive capacity of ARIMA and ARX models across representative consumption trajectories and individual users. The results show that ARX models achieve superior accuracy in trajectories with irregular or cyclic dynamics, while ARIMA remains competitive in stable or convergent profiles. Thus, the contribution of exogenous variables is conditional and depends on the temporal structure of the series.

At the user level, the trajectory assignment mechanism proved effective for generalizing forecasts, enabling consistent performance in regular profiles. However, in cases with abrupt peaks or sudden shifts in demand, both ARIMA and ARX exhibited limitations, confirming that predictive accuracy is closely tied to the regularity of consumption patterns.

In practical terms, the methodology offers scalability and interpretability, providing reliable forecasts in stable scenarios and supporting institutional applications. Its limitations in irregular profiles highlight the need for complementary strategies to improve adaptability. Beyond these findings, the conclusions emphasize that the comparison between ARIMA and ARX is meaningful only when trajectories are characterized. Forecasts acquire interpretability once they are embedded within representative profiles, allowing consumption dynamics to be understood in terms of stability, cyclicity, and flexibility. ARIMA emerges as a reliable tool for convergent and stable trajectories, while ARX proves

advantageous in capturing irregularities and cyclic behaviors. The characterization of trajectories A–D thus provides the foundation for contextualized predictions, transforming forecasting into a comparative analytical exercise rather than a purely technical one.

This comparative perspective also reveals broader implications for demand-side management. Stable trajectories highlight limited adaptability, whereas cyclic or irregular ones expose greater responsiveness to external drivers. Such differentiation facilitates targeted strategies and supports institutional applications where resource allocation must be tailored to heterogeneous user groups. Overall, trajectory-based modeling enriches predictive analysis by enabling structured model selection, comparative evaluation of flexibility, and broader conclusions about the heterogeneity of real-world demand.

Ultimately, trajectory-based forecasting not only improves predictive accuracy but also provides actionable insights for demand-side management. By linking prediction with flexibility characterization, utilities and control centers can design differentiated strategies that align with the responsiveness potential of each user group. This enables more efficient economic dispatches, supports dynamic pricing and demand response programs, and strengthens operational planning. Knowing how users behave from the perspective of flexibility is therefore invaluable for control centers, as it transforms forecasting into a strategic tool for optimizing resources, reducing costs, and enhancing the sustainability of energy systems. This dual contribution, greater predictive accuracy and practical guidance for demand-side management, underscores the relevance of trajectory-based forecasting for both academic research and operational practice.

Looking ahead, future work should explore the behavior of the methodology under different data granularities, particularly sub-hourly inputs, to assess its adaptability to high-resolution scenarios. Extending the framework to diverse regulatory contexts and tariff structures will also be essential to validate its generalization potential across heterogeneous energy systems. Finally, integrating anomaly detection, hybrid models, or post-processing adjustments could enhance robustness under atypical demand conditions. These directions will ensure that trajectory-based forecasting continues to evolve as both a methodological contribution to energy forecasting and a practical instrument for demand-side management in increasingly complex and flexible power systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AMI	Advanced Metering Infrastructure
ARIMA	Autoregressive Integrated Moving Average

ARX	Autoregressive model with Exogenous variables
LSTM	Long Short-Term Memory
SOM	Self-Organizing Map
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
NMF	Non-Negative Matrix Factorization
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
SMAPE	Symmetric Mean Absolute Percentage Error
CV	Coefficient of Variation
p_i/p_j	Probability of event i or j
H	Shannon entropy
H_{norm}	Normalized entropy
σ	Standard deviation
μ	Mean (average)

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