ORIGINAL PAPER

COMPARATIVE ANALYSIS ON THE PREDICTION PERFORMANCE OF STATISTICAL MODELS AND NEURAL NETWORKS. A CASE STUDY BASED ON ENERGY CONSUMPTION FROM RENEWABLE SOURCES

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Abstract. *This article aims to forecast energy consumption from photovoltaic (PV) sources by implementing and comparing three different predictive models to improve interpretability, accuracy, and computational efficiency. The models selected in this approach are: ARIMA (Auto Regressive Integrated Moving Average), a statistical model for linear dependencies and trends, SARIMA (Seasonal ARIMA), an extension of ARIMA for seasonal fluctuations; and NAR (Nonlinear Auto Regressive Neural Network), a machine learning model for nonlinear relationships. The performance of these techniques is tested and confirmed using a dataset of real measurements related to the energy from photovoltaic sources consumption, monitored at 15-minute intervals in 2024. The results of the predictive performance of the three models are analysed for day-ahead and week-ahead forecasting horizon. The added value of the proposed approach consists in proving how improved forecasting directly contributes to energy efficiency and loss reduction in PV systems, by enabling better energy management and demand-response strategies.*

Keywords: *energy; consumption; photovoltaic panels; forecasting; neural network; regression.*

1. INTRODUCTION

Prosumers have become new actors in the energy market of tomorrow, where energy is considered a key topic for the growth of any economy and an essential factor in evaluating the progress of any country [1]. Tools that implement efficient energy-saving models are essential in reducing energy costs.

The main technologies used for residential purposes are (i) power generation systems (solar panels or wind turbines at smart grid) and (ii) solutions to reduce consumption (energy consumption optimization), respectively, the implementation of smart management systems that could schedule the operation of the smart grid appliances by switching off the appliance for an energy saving condition when not in use [2]. Smart systems are used in many fields [3]. The adoption of new approaches, for example, the installation of photovoltaic panel systems

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for energy production, is supported through programs such as the "Photovoltaic Green House" that provides funding only for photovoltaic systems of at least three kWp [4]. For small prosumers who have installed photovoltaic systems with a low capacity of 3-200 kW to cover mainly the consumption needs in their smart grids, supplying energy to the national grid is mostly a disadvantageous approach and economically inefficient. They rather prefer to: (i) store the produced energy in their rechargeable batteries; (ii) install an intelligent system to manage efficiently the energy consumed. According to the European Union (EU), “smart grid automation system” is a word that refers to devices that connect to the Internet or provide better services to people who live in the smart grid. One of the ten action areas of interest in Europe's energy investment strategy is “smart dwellings” [5]. The smart grid technology business will grow quickly in the future and will likely play a key part in future energy transitions [6]. Smart grid technologies have already expanded to 7.5% of global houses [7]. A 30% annual growth rate is estimated [8].

The challenge that power providers face at peak times, is optimizing power consumption from smart grids. These considerations have a considerable impact on the power system's reliability [9]. As a result, power companies have implemented dynamic pricing systems that offer different prices depending on the time of day, with energy costs being higher during peak times due to higher demand and lower during off-peak times. The smart grid's power management problem [10] is when you manage smart grids operating according to a dynamic pricing scheme at appropriate times.

Energy Management Systems controlling distributed power with risk costs and index limits [11] and use multi-objective optimization to minimize energy costs and improve prosumers' satisfaction [12] by proposing a pricing-based demand response system for grids considering prosumers' behaviors. A multipurpose smart Demand-Side Management with Energy Storage System was proposed to cut energy costs and peak load demand. The Mixed-Integer Linear Programming technique was utilized to implement the grids. [13].

“A smart energy management system is a technology platform comprised of both hardware and software that allows the user to monitor energy usage and production and to manually control and/or automate the use of energy within a household” [14].

Innovative smart grid technologies are gradually integrated into our daily activities and our physical and emotional relationships with our communities [15, 16]. The idea of smart grid automation is designed to interfere with specific and many consumer activities [17]. This trend could be primarily justified by the lower cost and financial advantages of industrial manufacturing and technologies in academic research [18]. In the past, smart grid management was limited to strategic sectors, but it is now actively interested in domestic activities, for example, network control systems [19].

Smart grid energy management (SEM) was seen as a potential solution due to its ability to manage energy demand in a smart grid and to monitor and collect data that includes the generation, distribution, and transmission of energy [20, 21]. Nowadays, intelligent grid management on the demand side for smart grid system users is the key to success [22]. Due to growing concerns about the sustainability of renewable energies and environmental emissions, SEM was created to manage renewable energies locally [23]. According to the rapid developments in the field of advanced innovations in energy and sustainable energy, these intelligent systems could be scaled to home energy management systems, for example [24].

Key challenges for an SEM are the decentralized generation, demand reduction, and peak periods to provide consumers or service providers with adequate solutions [25]. Lately technologies have been deployed like advanced metering infrastructure [26], smart sensor technologies [27], smart grid appliances [28], smart grid area networks [29], and smart grid energy storage systems [30].

In this context, our proposal will likely become essential for residential customers for the successful demand-side management of smart grids [31]. These systems have to deal with real-time monitoring, with the aim of energy cost reduction and energy utilization efficiency improvements. To overcome these challenges, this paper aims to forecast energy consumption from photovoltaic (PV) sources by implementing and comparing three different models, in order to improve interpretability, accuracy, and computational efficiency.

In this framework, this paper is structured into five sections, each addressing a specific aspect of the area of research addressed. The introduction section provides the context and emphasizes the necessity of the approach proposed in this paper. Secondly, the modelling section introduces and explains the three chosen models: ARIMA (Auto Regressive Integrated Moving Average), a statistical model for linear dependencies and trends; SARIMA (Seasonal ARIMA), an extension of ARIMA for seasonal fluctuations; and NAR (Nonlinear Autoregressive Neural Network), a machine learning model for nonlinear relationships. A real energy consumption dataset, monitored at 15-minute intervals throughout 2024, highlighting its key characteristics and the pre-processing steps undertaken. The simulation section outlines the 24-hour and a week-ahead forecasting simulation conducted to evaluate the predictive performance of the three models. The tests and results section presents the performance metrics used for assessment and the conclusion sections discuss the key findings for each model and the work in progress.

2. MODELLING

2.1. AUTO REGRESSIVE INTEGRATED MOVING AVERAGE

To forecast energy consumption from photovoltaic (PV) sources, we implemented and compared three predictive models: ARIMA (Auto Regressive Integrated Moving Average) a statistical model designed for time series forecasting, primarily handling linear dependencies and trends; SARIMA (Seasonal ARIMA) is an extension of ARIMA that incorporates seasonal components to better capture periodic fluctuations in energy consumption and NAR (Nonlinear Autoregressive Neural Network) a machine learning-based model capable of learning nonlinear relationships within time series data. The choice of forecasting models was driven by the need to balance interpretability, accuracy, and computational efficiency.

ARIMA is a popular time series forecasting model that predicts future values based on past observations. In general, this model combines three main parameters. The first one is the AR (Autoregressive) part which uses past values of the series to predict future values. This shows how past values affect the current value and how the past values influence future values. The second parameter of the ARIMA model is the MA (Moving Average). It uses past forecast errors to improve predictions. In case of negative values of MA, the past forecast errors negatively affect future forecasts. The last parameter of ARIMA is the variance of innovations (σ^2) which is the variance of the white noise level.

In our studies, ARIMA was parametrized as a model with seasonal differencing approach. This configuration implied: no autoregressive (AR) terms, a first-order differencing term (d = 1) to remove trends, no moving average (MA) terms and seasonal differencing (Ds = 1) with a seasonal period of S = 96 (see eq. 1).

$$Y_t - Y_{t-1} = \varepsilon_t \tag{1}$$

where:

- $Y_t$is the time series at time t
- $Y_{t-1}$is the previous value.
- $\varepsilon_t \sim N\ (\sigma^2)$ is a white noise error term.
- The differencing term ($D_s = 1$) removes trends in the data.

If seasonal differencing ($D_s = 1$) is applied with seasonality S = 96 (e.g., for 15-minute data with a daily cycle), the equation becomes:

$$(Y_t - Y_{t-1}) - (Y_{96} - Y_{97}) = \varepsilon_t$$

The choice of S=96 corresponds to the dataset's 15-minute interval sampling frequency, meaning that each daily cycle consists of 96-time steps (24 hours × 4 data points per hour). By applying seasonal differencing, the model removes daily fluctuations in energy consumption, making the time series stationary and improving its predictive performance for short-term forecasting.

Since ARIMA relies solely on differencing, the model does not use past values (AR) or past forecast errors (MA) for prediction. In consequence, the model assumes that the best forecast for the next time step is simply the previous observed value adjusted for seasonal trends. It does not explicitly capture short-term dependencies beyond the differencing operation. Furthermore, we proved trough the simulation tests that the model lacks complexity in handling energy consumption variations. While ARIMA approach is computationally efficient and works well for simple stationary time series, it was necessary to explore more complex models like SARIMA to capture more complex patterns.

2.2. SEASONAL AUTO REGRESSIVE INTEGRATED MOVING AVERAGE

SARIMA model is an extension of the ARIMA that manages seasonal time series data by incorporating seasonal autoregressive (SAR), seasonal moving average (SMA), and seasonal differencing terms (see eq. 2).

$$(1 - \phi_1 B - \phi_2 B^2)(1 - B)(1 - B^S)Y_t = (1 + \theta_1 B + \theta_2 B^2)(1 - \Phi_1 B^S)\varepsilon_t \quad (2)$$

where:

- B is the backshift operator: $BY_t = Y_{t-1}$
- ϕ_1 and $\phi_2$are non-seasonal AR terms.
- θ_1 and θ_2 are non-seasonal MA terms.
- Φ_1 is the seasonal AR term.
- S seasonal period (e.g., 96 for 15-minute data in a daily cycle).
- $\varepsilon_t \sim N\ (\sigma^2)$Gaussian white noise error term.

To address ARIMA's limitations, a SARIMA (2,1,2) model was chosen. The parameter selection was based on: (p = 2): two autoregressive (AR) terms to model short-term dependencies in energy consumptions; (d = 1): first-order differencing to remove trends and achieve stationarity; (q = 2): two moving average (MA) terms to correct for past forecast errors; a single seasonal autoregressive term (SAR = 1) to account for long-term periodicity; a seasonal differencing (D = 1) to eliminate daily trends, and no seasonal moving average (SMA = 0), as exploratory analysis showed that including it did not significantly improve model performance while increasing complexity.

The exclusion of SMA (Q = 0) was based on residual diagnostics. Since the residual autocorrelation structure did not show strong seasonal lag correlations, adding a seasonal moving average term would not provide additional explanatory power. Instead, the SARIMA (2,1,2) structure sufficiently captured both short-term fluctuations and daily energy consumption cycles without unnecessary complexity.

The backshift operator B is used in SARIMA models to represent lagged values in the time series. This one allows the model to express dependencies over multiple time lags compactly, making it easier to analyse and interpret.

While SARIMA efficiently captured linear and seasonal trends, a forecasting model was needed to provide adaptability for nonlinear dependencies. Consequently, we select Nonlinear Autoregressive (NAR) Neural Network.

2.3. NONLINEAR AUTOREGRESSIVE NEURAL NETWORK

NAR is a recurrent neural network used for time series prediction, where the future value is predicted based on past values of the same time series. Precisely, it uses past energy consumption values to predict future demand of energy. The number of input delays (d = 10) was chosen evaluating different lag values. The analysis showed that a window of 10 previous values provided the best balance between model complexity and prediction accuracy. Moreover, given the dataset's 15-minute intervals, a delay of 10 corresponds to a 2.5-hour lookback window, which was optimal for capturing immediate consumption trends. Last, using too many delays could introduce noise, while too few would fail to capture necessary dependencies.

The NAR model follows the equation 3:

$$Y_t = f(Y_{t-1}, Y_{t-2}, Y_{t-3}, \dots, Y_{t-d}) + \varepsilon_t \tag{3}$$

where:

- Y_t is the predicted value at time t.
- d is the number of input delays (in our case studies, 10).
- f(·) is the nonlinear function learned by the neural network.
- ε_t is the error term (noise).

The function *f*(·) represents the nonlinear relationship between past and future energy consumption values. Unlike SARIMA, which assumes linear relationships, the NAR model learns complex, data-driven dependencies. The function is approximated using activation functions such as sigmoid or ReLU, allowing the network to model: sudden changes in energy consumption, non-additive seasonal effects, and irregular fluctuations influenced by external factors.

The NAR model rely on a feedforward recurrent neural network (RNN) architecture with (Fig. 1): 1 input node (energy consumption at past time steps), 2 hidden layers with nonlinear activation functions; 10 past values used as input delays; 1 output node (predicted energy consumption) and bias terms in both hidden and output layers for improved learning stability.

Bias terms are additional parameters that help the network learn complex patterns by shifting activation functions. Their role in the NAR model is crucial because they allow neurons to activate at different thresholds, improving flexibility in modelling energy consumption patterns and help capture systematic variations in the data that pure weight-based transformations might miss.

The number of input delays (d = 10) was chosen based on a 2.5-hour lookback window (10 × 15-minute intervals) to capture recent consumption trends. These values allowed us to avoid excessive memory use while retaining key short-term dependencies and proved to have, in simulation tests, the best performance without overfitting.

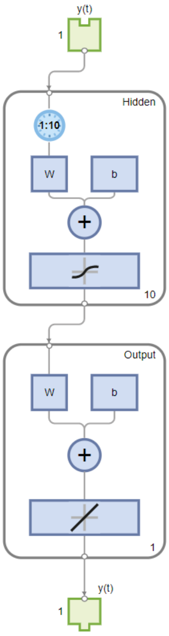


Figure 1. NAR architecture.

The Levenberg-Marquardt (LM) algorithm is used to train NAR due to its efficiency. It updates weights using a combination of Gauss-Newton and gradient descent, making it a powerful optimization method for training neural networks.

Given a neural network with parameters w (weights and biases), it aims to minimize the error function, as shown in eq. 4:

$$E(w) = \frac{1}{2}\sum_{i=1}^{N} e_i^2 \tag{4}$$

where:

- $E(w)$ Total error function (sum of squared errors).
- $e_i = y_i - y_i^{pred}$ difference between target (y_i) and predicted output (y_i^{pred}).
- N = Number of training samples.

LM algorithm proved to have fast convergence speed, making it well-suited for time series forecasting, being robust to small datasets, meaning that it does not require extensive training samples compared to other deep learning techniques.

All three models were selected based on the available data characteristics and on the forecasting needs. The energy consumption patterns in the dataset are influenced by the institute's working hours. Peak energy usage aligns with operational hours (8:00 AM -5:00 PM), while significant drops are observed during non-working periods. This periodicity introduces challenges for forecasting models that assume stationary time series. As a result, models capable of handling seasonality and temporal dependencies, such as SARIMA, were prioritized to account for these fluctuations.

Moreover, given the nature of the dataset and its periodic variations, the selected forecasting models: ARIMA, SARIMA, NAR, were chosen based on their ability to handle different aspects of the data: ARIMA was considered for its effectiveness in modelling linear dependencies and trend-based forecasting, SARIMA extended ARIMA by capturing seasonal fluctuations inherent in the dataset, and NAR was employed due to its ability to model nonlinear dependencies and learn from complex data structures.

In the simulation section, these models were implemented in MATLAB, which provides robust functions for both statistical and neural network-based time series forecasting, while the Deep Learning Toolbox was used to train and optimize the NAR model. The goal was to ensure a comprehensive and systematic approach to energy consumption prediction in PV systems.

3. SIMULATION

3.1. DATA PREPROCESSING

The dataset used for training, testing, and validating the three forecasting models represents real data monitored from a research institute with an installed capacity for photovoltaic (PV) energy production. The dataset, monitored at 15-minute intervals throughout 2024, includes real energy consumption data.

However, the dataset contains missing values, noise, and inconsistencies due to external factors such as system errors and operational irregularities. These data quality issues have influenced both model selection and prediction accuracy. To mitigate the impact, preprocessing techniques such as noise filtering were applied before model training.

The dataset comprises paired values of time (input variable, $x(i)$) and energy consumption (target output, $y(i)$). The variable $y(i)$ represents the measured energy consumption (kWh) from PV sources, while $x(i)$ corresponds to the timestamp of each recorded measurement. The models utilize past energy consumption values to predict future demand, adjusting for seasonal trends and external influences.

This data set serves (Fig. 2) as a benchmark for evaluating the performance of statistical and machine learning models in energy forecasting.

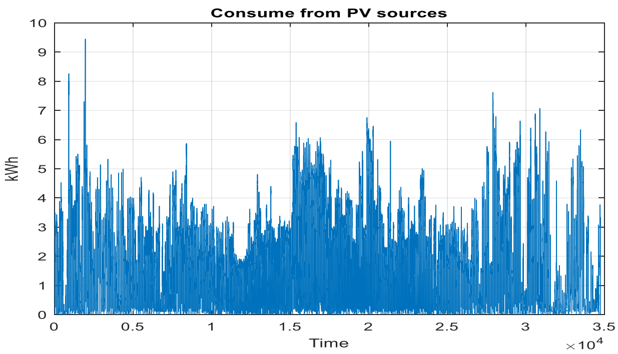
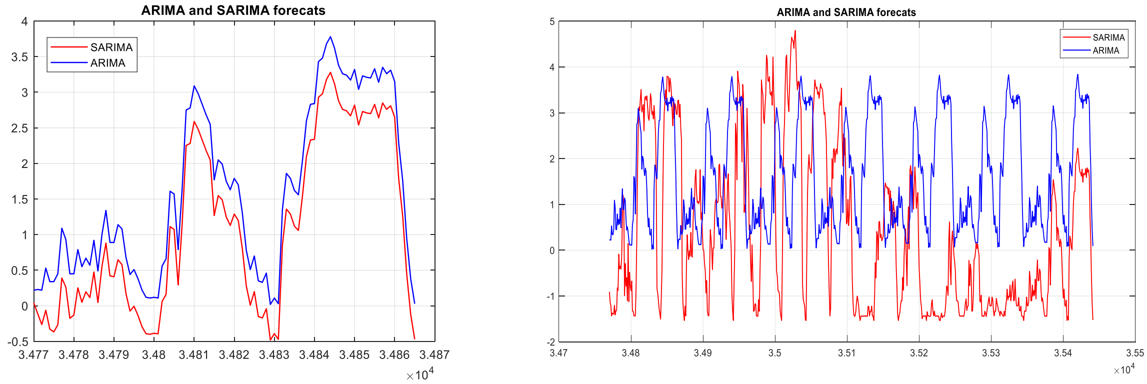


Figure 2. Benchmark of energy consumption from PV.

It enables a comparative analysis of model accuracy, residual error characteristics, and computational efficiency. The benchmark data also highlights the strengths and limitations of different modelling approaches in handling short-term versus long-term energy consumption predictions.

The characteristics of the available data, such as the 15-minute interval and the presence of periodic variations due to working hours, lead to the selection of ARIMA, SARIMA, and NAR models for forecasting. The simulations were conducted, in MATLAB [32], to evaluate the predictive performance of the three forecasting models: ARIMA, SARIMA, and NAR using real energy consumption data monitored at 15-minute intervals over the year 2024.

First, the models were simulated 24 hours ahead (see Fig. 3a) and one week ahead of forecasting horizons (see Fig. 3b) to assess their suitability for different planning scenarios.

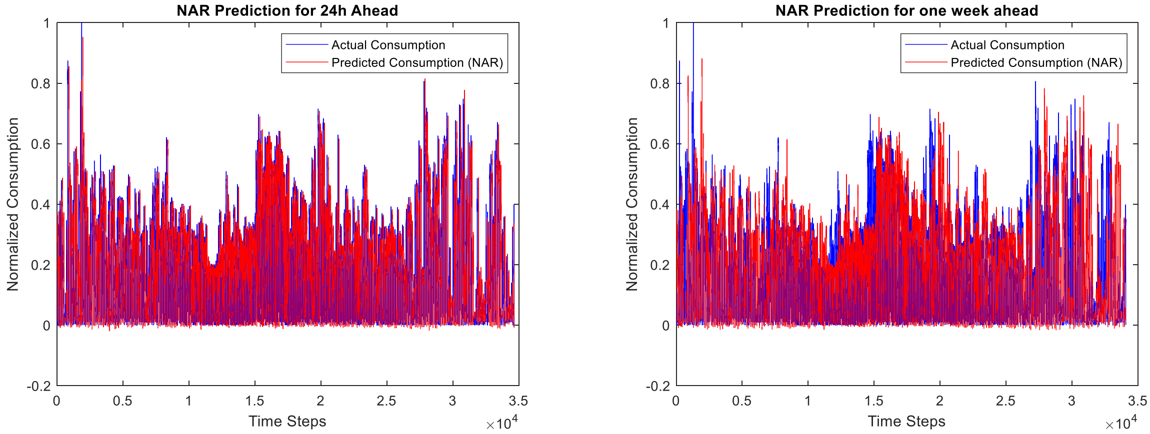


a) **b)**

Figure 3. a) 24 hours ahead; b) One week ahead forecasting of ARIMA and SARIMA

As Fig. 3a) presents, the predictions of autoregressive integrated moving average and seasonal ARIMA models, for short-term horizon of energy consumption from PV. The ARIMA is not predicting based on past values or past errors. This model just uses the difference from the earlier value and the seasonal pattern. The lack of AR and MA terms means the model assumes the best prediction for the next value is just the last observed value adjusted for seasonality. Being a statistical-based model, ARIMA proved to be good for stationary, linear time series, easier to interpret and implement. On the other hand, SARIMA model proved to be well-suited for a daily seasonal pattern with daily because of the first-order differencing which removes trends, making the series stationary. For short time forecasting SARIMA model proved to have smaller forecasting errors. The explainability of the predictions made weighted in our model selection. However, for long-term forecasting (Fig. 3b), both models struggled with long-term dependencies. The benchmark used had some missing data and/or noise affected ones. Due to these ones, the prediction errors increased significantly, in both cases of the models used. This cause was significant especially in case of SARIMA model.

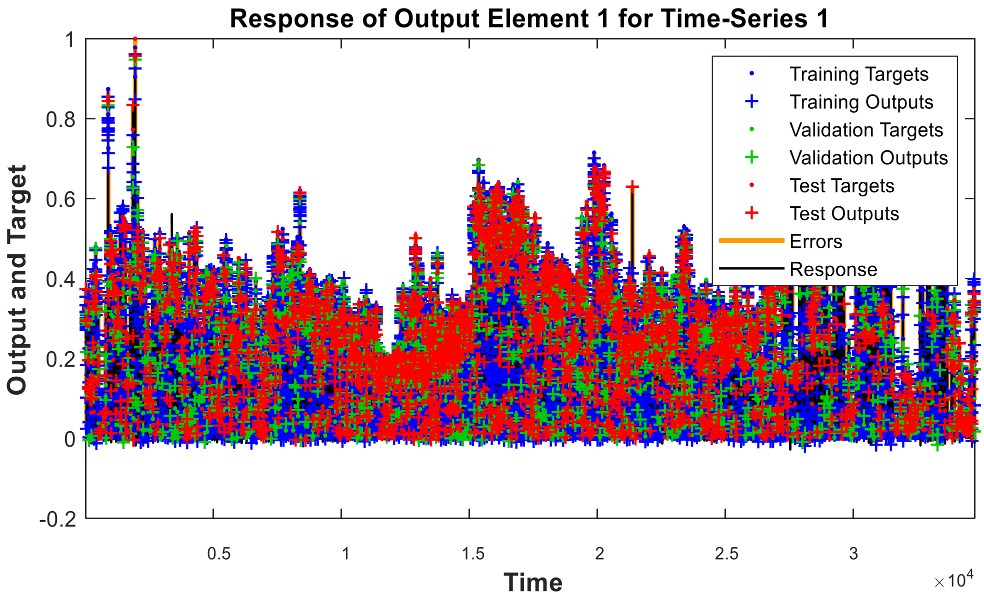
Fig. 4a) indicates the application of NAR model for 24-hour prediction horizon of energy consumption and one week ahead (Fig. 4b). NAR captures well nonlinear relationships in data on short term forecasting horizon (Fig. 4a) because can learn seasonal patterns automatically, with enough data available for training, and are fit for modelling complex seasonal effects without manual tuning. Moreover, for long term forecasting (Fig. 4b) these proved to be robust to moderate noise.



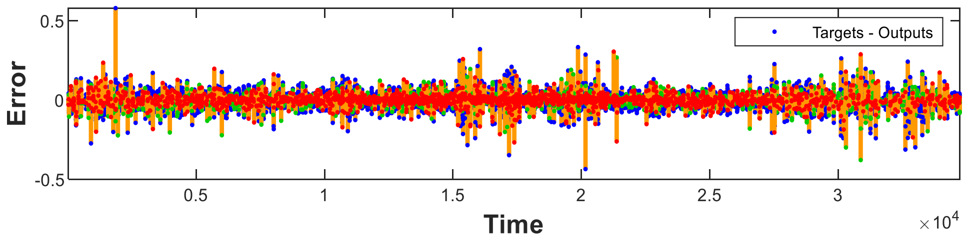
a) b)

Figure 4. a) 24 hours ahead forecasting; b) One week ahead forecasting of NAR.

However, NAR requires significant tuning hyper-parameters and training (Fig. 5a) to be suitable for long-term adaptive learning.



a)



b)

Figure 5. a) NAR tuning parameters; b) NAR error.

In addition, the forecasting for long-term trends (weeks/months) is better only if it is trained correctly. Even though this aspect, NAX learned from noisy data but is proved to be sensitive to missing values. Their background as “black box” neural network models makes the predictions difficult to interpret.

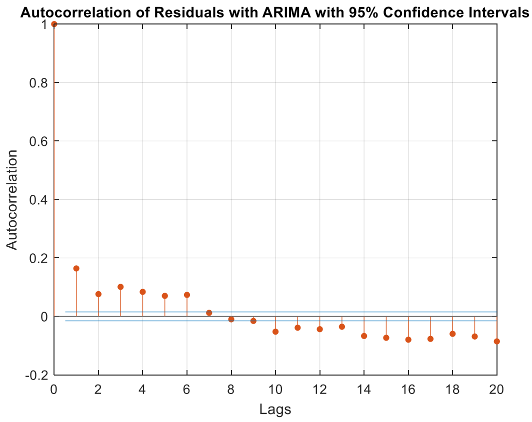
The simulation for one week forecasting horizon was useful to understand the models' capabilities for short-term operational planning and longer-term strategic decision-making.

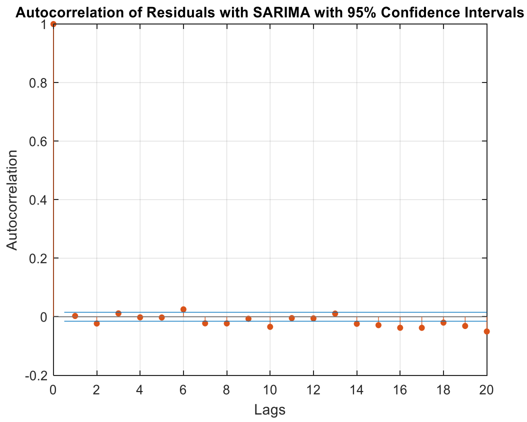
4. FORECASTING PERFORMANCE ASSESMENT

Performance metrics such as autocorrelation of residuals, prediction accuracy and mean squared error (MSE), were used for assessment of the forecasting performances. Figs. 6 a-b focus on ARIMA and SARIMA residuals, as well as the differences between predicted and actual values) autocorrelation.

Firstly, the visual check of the residual’s randomness, at different time lags, allowed us to see if they behave like white noise. Random and uncorrelated residuals with a mean of zero are desirable characteristics, assessing that the models adequately capture the underlying data patterns.

The presence of autocorrelation in the residuals of ARIMA models shows that the model has not fully captured the underlying patterns in the data. Thus, has been chosen another linear time series forecasting model, the SARIMA which can consider the seasonal patterns from the benchmark in the forecasting process. Ranging in the confidence interval, the residuals in case of SARIMA prove improved randomness, confirming the inclusion of seasonal components.

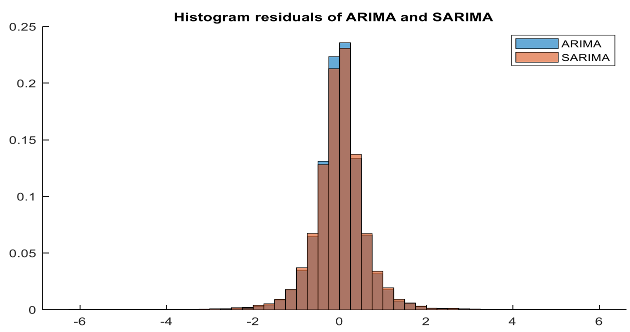


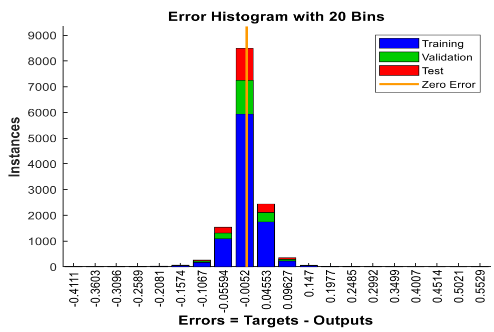


a) b)

Figure 6. a). ARIMA b). SARIMA autocorrelation of residuals

The histograms of errors for ARIMA, SARIMA and NAR models (Figs. 7 a-b) allow a visual comparison of the accuracy and potential biases of the different approaches.





a) b)

Figure 8. Histogram of errors for: a) ARIMA and SARIMA; b) NAR.

NAR's error distribution highlights its adaptability but also its sensitivity to missing data. As a result, the short-term prediction performance improved, as can be seen from the Table 1. Such a model could be successfully used to make short-term precision predictions.

Table 1. Performance indicators for a day-ahead forecasting.

Models	MSE	Variance of errors	Standard error
ARIMA	0.028581	0.014776	0.020547
SARIMA	0.044221	0.014771	0.020544
NAR	0.036320	0.036120	0.001644

The table summarizing the performances of the proposed modes highlights that while SARIMA offer better short-term accuracy, NAR proves potential for long-term forecasting with sufficient training data.

5. CONCLUSIONS AND PERSPECTIVES

The structured approach of this paper, which included a review of existing work, model selection, data analysis, and performance evaluation, provided a comprehensive assessment of forecasting strategies. The results highlighted the strengths and limitations of different models, contributing to the broader understanding of predictive analytics in energy management.

This comparative analysis set up a solid foundation for the continued development of advanced forecasting models in energy systems. The findings emphasize the necessity of ongoing innovation in predictive analytics to support sustainable energy management and smart grid optimization.

Future research should focus on refining hybrid forecasting models to enhance their adaptability to varying energy consumption patterns. Exploring deep learning-based approaches and integrating real-time adaptive mechanisms could further improve forecasting accuracy and efficiency. Additionally, expanding the dataset beyond a single monitoring period and incorporating external factors such as weather conditions and market dynamics could provide a more robust and scalable predictive framework.

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