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Adaptive Set Membership Photovoltaic Energy Generation Forecasting

Andres Cordoba-Pacheco * **Eduard Godayol** * **Fredy Ruiz** *

* *Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, Milan, Italy ({andresfelipe.cordoba, fredy.ruiz}@polimi.it, eduard.godayol@mail.polimi.it)*

Abstract: Integrating Distributed Energy Resources, such as solar photovoltaic systems, is increasingly critical for modern power grids. However, their inherent variability presents significant challenges for accurate prediction and uncertainty handling, making real-time forecasting essential for efficient energy management. This paper presents the development of an adaptive forecasting model for solar energy generation using a Set Membership approach, focusing on generating multiple forecast scenarios to address uncertainty in stochastic Model Predictive Control frameworks. The method leverages a two-year dataset of photovoltaic generation in southeastern Finland sampled at a 15-minute rate. The proposed solution dynamically updates the set of feasible model parameters to capture the inherent variability of solar generation. Results demonstrate the model's ability to adapt to dynamic changes. The Adaptive Set Membership approach outperforms classic auto-regressive models, improving forecasting accuracy up to 4.3% across various prediction horizons. Furthermore, based on the uncertainty bounds on model parameters, the methodology provides effective tools to generate scenarios that properly represent the variability of future generation profiles.

Keywords: Set Membership estimation, photovoltaic generation, generation Forecasting, Adaptive Models, Solar Energy.

1. INTRODUCTION

The integration of Distributed Energy Resources (DERs) is fundamental to the evolution of modern energy grids. These systems reduce reliance on non-renewable energy sources while enabling sustainable energy management Rout et al. (2022). However, the inherent variability of DERs makes accurate forecasting of energy generation essential for effective decision-making Del Duca et al. (2024). Reliable forecasts not only support optimal energy management but also facilitate the integration of renewable energy sources, strengthening grid stability and advancing sustainability goals Ismail et al. (2023).

Photovoltaic (PV) generation depends on several dynamic factors such as weather conditions, time of day, and seasonal changes, which complicates maintaining consistent energy output levels Razmi et al. (2022). Therefore, accurate predictions of solar generation are crucial for maintaining grid stability, ensuring efficient energy management, and determining the power required from or available to the grid. These predictions contribute to ensuring optimal energy flows and improving economic efficiency Diaz et al. (2019); Iqbal et al. (2020).

Although different forecasting techniques have been explored, ranging from physics-based models that rely on weather data to Autoregressive (AR) models, the fast fluctuations in solar output often challenge these conventional methods, Das et al. (2018). To overcome these challenges, diverse forecasting techniques have been explored and implemented, each with different strengths and limitations Pardeep et al. (2022). Physical models require frequent recalibration to adjust for changing conditions and depend on weather forecasts, which introduces additional uncertainty El-Basit et al. (2013). Similarly, while AR models can capture seasonal variations and nonlinearities to some extent, they also demand periodic recalibration to remain accurate under dynamic conditions Ding et al. (2021); Phinikarides et al. (2013).

Machine learning and deep learning models have emerged as attractive alternatives by leveraging historical data to learn complex, nonlinear patterns without explicit physical modeling, Iqbal et al. (2020); Aslam et al. (2021). For example, deep learning models exploit neural networks. By enabling advanced feature extraction and sequence modeling, these models are well-suited for time series forecasting in DERs. They excel at capturing temporal dependencies, effectively handling both short-term fluctuations and long-term trends, and adapting to seasonal and daily variations in solar energy generation Mukherjee et al. (2023); Ismail et al. (2023). Despite their potential, these approaches often require large datasets and significant computational resources, and their complex architectures can limit their interpretability and analysis, which is a critical factor for energy management.

In contrast, the Set Membership (SM) approach combines accuracy, adaptability, and computational efficiency, as

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described in Milanese and Novara (2011). It can provide an efficient method for system identification and prediction by adapting the set of model parameters compatible with the available information in real-time, based on the observed data and predefined error bounds. Unlike traditional forecasting techniques that rely on probabilistic models or pointwise coefficients, this method exploits the concept of feasible sets of parameters consistent with the data, offering enhanced interpretability, crucial for energy management systems. Moreover, it operates without requiring extensive historical data, resulting in lower computational requirements Diaz et al. (2019), making it particularly well-suited for PV systems with significant data variability and resource constraints.

An important requirement in forecasting DERs production or consumption is the possibility of incorporating uncertainty in the predictions. In energy management systems it is important to minimize the cost of the energy between the scheduled plan and real-time operation taking into account the uncertainties in the system Cordoba-Pacheco and Ruiz (2024). Uncertainty information becomes crucial in stochastic approaches to energy management, such as those based on the scenario approach, see e.g.,Del Duca et al. (2024). In this sense, the intrinsic parameter sets provided by SM estimation algorithms can be easily integrated into stochastic day-ahead dispatches and Model Predictive Control (MPC) frameworks.Different MPC strategies have been proposed to deal with these challenges, for instance, the Scenario MPC (SC-MPC optimizes control inputs over a finite horizon and guarantees robust constraint satisfaction under a set of random uncertainty scenarios, see Schildbach et al. (2014). A connection between SC-MPC and SM forecasting can be established, by enabling the generation of multiple forecast scenarios from uncertain parameter sets, that accurately capture the variability of the system. These scenarios can then be used in the scenario optimization to test and optimize the energy management system costs, ensuring robust operation even under uncertain conditions.

This paper aims to develop and evaluate an adaptive prediction model for solar energy generation using the Set Membership approach. The proposed method not only provides punctual generation forecasts over a 6-hour horizon, based on real data from a plant in Lappeenranta, Finland, but also generates multiple forecast scenarios to address uncertainties in stochastic MPC frameworks. This research demonstrates the potential of the adaptive SM methodology to capture the dynamic variability of PV generation, offering a scalable and generalizable model that could transform forecasting and other model applications.

The paper is organized as follows. In Section 2, the photovoltaic forecasting is presented. The adaptative SM approach and the scenario generation are described in Section 3. Section 4 presents the analysis of results, followed by the conclusions in section 5.

2. PHOTOVOLTAIC FORECASTING

Accurate PV forecasting is essential in energy management, grid stability, and electricity markets. While high-resolution data improve predictions, they also increase computational costs, for that reason, optimizing the data usage is crucial for balancing accuracy and efficiency.

In this study, the dataset used was collected from solar installations in Lappeenranta, Finland, leveraging real-world data, including its inherent variability and seasonality, to evaluate the accuracy of the proposed power generation modeling. The system has a maximum capacity of $65kW$, with an average generation of $5.7kW$. The dataset $\mathcal{D}$ provides a reliable representation of the power generation patterns, it covers the period from October 2021 to October 2023, with data recorded at 15-minute intervals, resulting in a total of 70,080 data points, which provides the foundation for analyzing PV generation in the region.

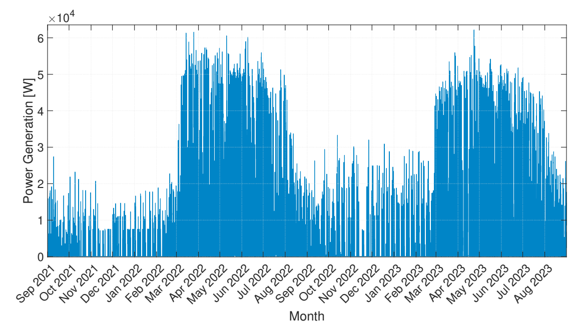

Fig. 1. Overview of photovoltaic generation dataset

The dataset is illustrated in Figure 1 showing clear seasonal trends throughout the observed period. Instead of different transitions among the four seasons, it demonstrates two levels of PV generation, one with higher output during the warmer months and lower production during the colder months. Both years exhibit similar patterns, highlighting the consistency of solar generation trends between hot and cold seasons in Lappeenranta.

3. ADAPTIVE SET MEMBERSHIP APPROACH FOR SCENARIO GENERATION

This work aims to represent PV production as a linear time series, adaptively updating the coefficients of the time series model, and estimating the uncertainty associated with the models.

3.1 Set Membership linear models

Consider an AR signal model described as

$$y_{\tau+1} = \sum_{i=0}^{n_a} \theta_i * y_{\tau-i} + \varepsilon_\tau \tag{1}$$

where y_τ is the signal to be predicted and modeled as the output of a linear system, and τ is the time index. It is described as a linear combination of current and past values of the signal, $y_{\tau-i}$), θ_i are the model parameters, n_a is the order of the system and ε_τ is an Unknown But Bounded (UBB) signal driving the system dynamics.

In the Set Membership framework, it is assumed that the UBB signal is bounded as

$$||\varepsilon_\tau||_p \leq \epsilon \tag{2}$$

being ϵ the bound on the maximum energy of the noise.

The model in Eq. (1) is linear and time invariant. However, as stated in the problem formulation, the characteristics of the PV energy signal vary during the year. We propose to adapt the model parameters based on the evolution of the uncertainty of the forecast.

Let the information matrix F be,

$$F = \begin{bmatrix} y_{n_a} & y_{n_a-1} & \cdots & y_0 \\ y_{n_a+1} & y_{n_a} & \cdots & y_1 \\ \vdots & \vdots & & \vdots \\ y_{N-1} & y_{N-2} & \cdots & y_{N-n_a-1} \end{bmatrix},$$

and the target output vector Y

$$Y = \begin{bmatrix} y_{n_a+1} \\ y_{n_a+2} \\ \vdots \\ y_N \end{bmatrix},$$

where n_a represent the maximum order of model and N is the total number of samples in $\mathcal{D}$.

From the previous assumptions, the Feasible Parameter Set (FPS) is defined as the set of coefficients

$$\theta = [\theta_0, \theta_1, \ldots, \theta_{n_a}]^T$$

that are consistent with the data $\mathcal{D}$ and the noise bounds, that is,

$$FPS = \left\{\theta \in R^{n_a+1} : ||Y - F\theta|| \leq \epsilon\right\} \tag{3}$$

If hypotheses are true, the parameters of the true system generating the data, θ^o, belong to the FPS, and for any new regressor,

$$f_\tau = [y_\tau,\ y_{\tau-1},\ \ldots,\ y_{\tau-n_a}],\quad \tau > N$$

the estimate $\hat{y}_{\tau+1} = f_\tau^T\theta$ does not deviate from the true system output by more than ϵ, for any time τ,

$$||y - \hat{y}|| \leq \epsilon.$$

Following the SM theory, the noise bound ϵ and the set of central coefficient θ are determined, this process also guarantees a non-empty FPS composed of all the parameters not falsified by the available data,

$$\begin{aligned} \epsilon = \arg\min_{\epsilon_a, \theta\in\Theta} \quad & \epsilon_a \\ \text{subject to} \quad & \|Y - \theta * F\|_p \leq \epsilon_a, \\ & \epsilon_a \geq 0 \end{aligned} \tag{4}$$

Once ϵ is determined, the uncertainty in the coefficients is quantified by identifying the upper and lower bounds of each coefficient as,

$$\begin{aligned} \overline{\theta_i} = \arg\max_{\theta\in FPS} \quad & \theta_i \\ \text{subject to} \quad & \|Y - \theta * F\|_p \leq \epsilon\alpha, \end{aligned} \tag{5}$$

$$\begin{aligned} \underline{\theta_i} = \arg\min_{\theta\in FPS} \quad & \theta_i \\ \text{subject to} \quad & \|Y - \theta * F\|_p \leq \epsilon\alpha, \end{aligned} \tag{6}$$

where α is a tolerance gap, typically around 10% Lauricella and Fagiano (2020).

Finally, the optimal model parameters vector, $\hat{\theta}$, is computed as the Chebyshev center of the FPS,

$$\hat{\theta} = \frac{\overline{\theta} + \underline{\theta}}{2} \tag{7}$$

3.2 Adaptive AR signal models

To develop an Adaptive SM (A-SM) approach, an iterative update mechanism is designed to adjust the model over time, based on new available data. The principle of the adaptive approach is to iteratively recalculate the FPS, continuously updating the parameters according to the observed prediction error.

The adaptive forecasting procedure starts by predicting the next signal value using the current $\hat{\theta}$ coefficients. If the predicted output leads to a prediction error that exceeds the predefined bound $||y-\hat{y}|| \geq \epsilon$, a new dataset is built by selecting a subset of the recently measured samples, along with past observations from the training dataset.

Let's define the new information matrix for retraining the model as

$$F_{new} = \begin{bmatrix} y_{k_1+n_a} & y_{k_1+n_a-1} & \cdots & y_{k_1} \\ y_{k_1+n_a+1} & y_{k_1+n_a} & \cdots & y_{k_1+1} \\ \vdots & \vdots & & \vdots \\ y_{k_2-1} & y_{k_2-2} & \cdots & y_{k_2-n_a-1} \end{bmatrix},$$

where k_1 denotes the starting index of the retained historical data, and k_2 is the index of the most recent sample in the online dataset. Correspondingly, the new target output vector is

$$Y_{new} = \begin{bmatrix} y_{k_1+n_a+1} \\ y_{k_1+n_a+2} \\ \vdots \\ y_{k_2} \end{bmatrix},$$

Using this updated dataset, the FPS is updated following the same procedure in Eq. (3). In the same way, the parameter bounds are recomputed following the optimization process described in Equations (4) to (7). The forecasting then continues with the updated parameters $\hat{\theta}_{new}$, until the error bound is exceeded again, triggering another model update. The proposed adaptive forecasting strategy is outlined in Algorithm 1.

Algorithm 1 Adaptive Set Membership Forecasting

Input: Dataset $\mathcal{D}$.
Initialize: Obtain Initial Model Parameters ϵ, $\hat{\theta}$ from $\mathcal{D}$, using SM approach (Eq. 3 to Eq. 7).
for each forecasting time step t **do**
  Predict: next values using the current $\hat{\theta}$.
  Compute prediction error:
  if $||y - \hat{y}|| \geq \epsilon$ **then**
    1.Build a new dataset F_{new}, Y_{new}.
    2.Update ϵ, (Eq. 3 to Eq. 4).
    3.Estimate new parameters $\hat{\theta}_{new}$, (Eq. 5 to Eq. 7).
  end if
end for
Output: Forecasting Process $\hat{Y}_\tau$

3.3 Forecasting and Scenario Generation

Once the A-SM model set has been derived given the most recent data points, the next step is to exploit the model set to predict the evolution of the PV time series as,

$$\hat{y}_{t+1} = \sum_{i=1}^{n_a} \hat{\theta}_i y_{t-i+1}. \quad (8)$$

However, taking into account the requirement to forecast not only the output at the next time step but several steps ahead, an iterative procedure is applied where the predicted values from previous steps are used as inputs for the subsequent steps, that is,

$$\hat{y}_{t+k} = \sum_{i=1}^{n_a} \hat{\theta}_i \tilde{y}_{t+k-i}, \quad k = 1, 2, \ldots, h \quad (9)$$

where h is the maximum prediction horizon, and $\tilde{y}_{t+k-i}$ represents either observed values (if available) or previously predicted values. This recursive update mechanism enables the model to generate multi-step forecasts while progressively incorporating prior predictions into subsequent computations.

Referring to the Scenario MPC framework employed in Cordoba-Pacheco and Ruiz (2024) for the energy management of microgrids, a finite number of scenarios must be generated to represent possible generation profiles over the prediction horizon. Based on the upper and lower bounds of each model parameter in (5), (6), a set of possible parameters θ_q is randomly generated from the box outer approximation of the FPS as,

$$\left\{\theta_q \in R^{n_a+1} : \left|\, \underline{\theta} \le \theta_q \le \overline{\theta} \quad q = 1, 2, \ldots, N_s \right.\right\}, \quad (10)$$

where N_s is the required number of scenarios. This formulation simplifies the generation of scenarios with respect to the direct usage of the FPS, and leads to generating scenarios that remain within the uncertainty bounds provided by the approximated set, while accounting for possible variations in the system. Therefore, the recursive forecasting is extended to the scenario-based generation, where each model θ_q generates a corresponding forecast trajectory.

On the other hand, the UBB signal ε driving the system is assumed to be uniformly distributed and bounded by ϵ,

$$\varepsilon_\tau \sim \mathcal{U}(-\epsilon, \epsilon). \quad (11)$$

This ensures that the noise remains within the predefined uncertainty bounds and is valid for the generation of scenarios.

4. ANALYSIS AND RESULTS

This section presents the results of applying the A-SM to PV forecasting, focusing on the performance of the adaptative method and its capacity to generate bounds and different forecasts.

To establish a baseline estimation model for PV energy generation, a time-invariant AR model from Eq. 1 is employed to predict the future energy output. To determine the most relevant time lags for the AR model, a Partial Autocorrelation Function (PACF) analysis is performed, evaluating the direct relationship between past observations and future values. This selection process is crucial not only for reducing computational complexity but also for balancing accuracy and efficiency by identifying the optimal number of coefficients.

Figure 2 presents the PACF results analyzing up to 96 lags (24 hours) to assess the influence of each parameter over time. This ensures that only the most relevant lags are incorporated into the forecasting model, optimizing performance while maintaining computational feasibility. To improve computational efficiency while maintaining accuracy, only six coefficients are selected for the AR model, which means that some of the θ_i parameters are constrained to assume a zero value. As observed in Figure 2, the most significant lags appear both at the beginning and toward the end of the analyzed range (1 to 100 lags). To assess the impact of lag selection, two sets are compared: $[1, 2, 3, 4, 5, 6]$ and the PACF-suggested $[1, 2, 3, 78, 82, 85]$. The AR models are trained using the first year of $\mathcal{D}$ and tested on the second year for different prediction horizons. Table 1 summarizes the Root Mean Square Error (RMSE) and Percentage RMSE (PRMSE) results, comparing forecasts with actual values.

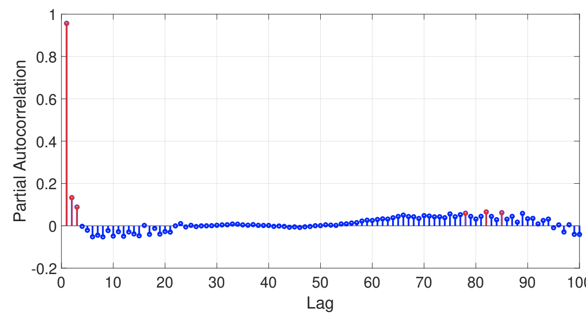

Fig. 2. PACF analysis of PV generation data. The six most relevant lags are highlighted in red, while the overall behavior is shown in blue.

Table 1. RMSE and PRMSE values - lag selections and prediction horizons

Lags	Error	15 min	30 min	1 hour
[1,2,3,4,5,6]	RMSE [W]	3364.4	4473.5	5897.7
	PRMSE [%]	27.81%	36.97%	48.74%
[1,2,3,78,82,85]	RMSE [W]	3283.9	4224.8	5151.3
	PRMSE [%]	27.11%	34.88%	42.53%

As expected, using the lags suggested by the PACF results in lower error metrics. Figure 3 illustrates the performance of the AR model with these selected lags that support the information presented in the table. Once the lags are determined, the Algorithm 1 is executed. However, before doing so, it is crucial to define key parameters for running the algorithm:

- A single month of 2021 is selected to train the initial model for the A-SM, which means N=2880 samples.
- The maximum model order is set to $n_a = 85$.
- The model is updated every 15 days, provided that $||y - \hat{y}|| \ge \epsilon$. If this condition is met, F_{new} and Y_{new} are updated by erasing half of the data for the oldest days and appending the information of the 15 newest days (1440 samples). This process leads to:

$$k_1 = \tau - 1 - 2880, \quad k_2 = \tau \tag{12}$$

- The prediction horizons are [15-min,30-min,1-hour, 2-hours, 3-hours, 6-hours].
- The SM problems are analyzed using the 2-norm with $\alpha = 1.1$ which means 10% of tolerance gap.
- To generate the scenarios, it is assumed that the UBB ε is zero.

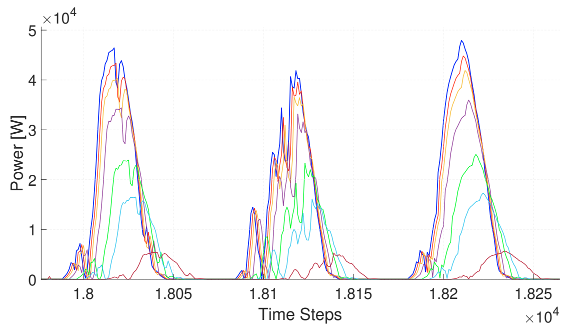

Fig. 3. Actual vs. Predicted PV Production using the AR model with lags [1, 2, 3, 78, 82, 85]: Actual data (blue), 15-min ahead prediction (red), 30-min ahead prediction (yellow), 1-hour ahead prediction (purple), 2-hours ahead prediction (green), 3-hours ahead prediction (cyan), 6-hours ahead prediction (brown).

The A-SM was evaluated using an entire year of data, and its performance was compared with the time-invariant AR model across the mentioned forecasting horizons. First, the θ parameters are analyzed to observe their evolution over time. Figure 4 illustrates their behaviour, reflecting the model's adaptation to varying solar generation patterns throughout the year. Additionally, Figure 5 presents the estimated θ_2 along with its lower and upper bounds, which play a crucial role in the subsequent scenario generation process.

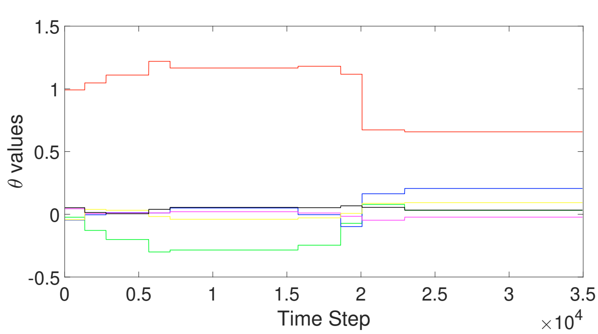

Fig. 4. Evolution of θ parameters over the year: θ_1 (red), θ_2 (green), θ_3 (blue), θ_4 (purple), θ_5 (yellow), θ_6 (black)

After analyzing the evolution of θ, the next step is to evaluate its impact on predictions. Additionally, the performance of the A-SM should be compared with the baseline AR model. Both models were evaluated by comparing their forecasts with actual values, calculating RMSE and PRMSE for each through the prediction horizons. Figure 6 shows the performance of the A-SM method. From a visual perspective, some improvements in prediction accuracy can be seen, particularly in the 6-hour horizon that compared with the AR model in Figure 3 the A-SM

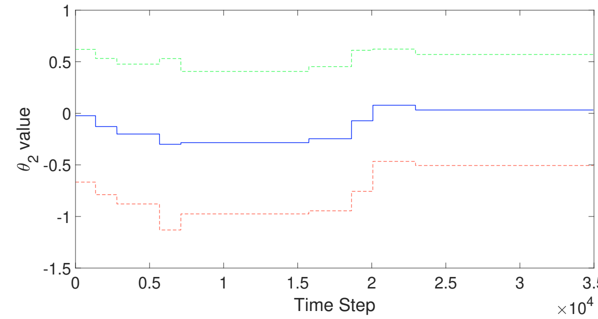

Fig. 5. Evolution of θ_2 parameter over the year with upper lower bounds: θ_2 (blue), Upper bound(green), Lower bound (red)

presents a better forecast reducing discrepancies in long-term predictions.

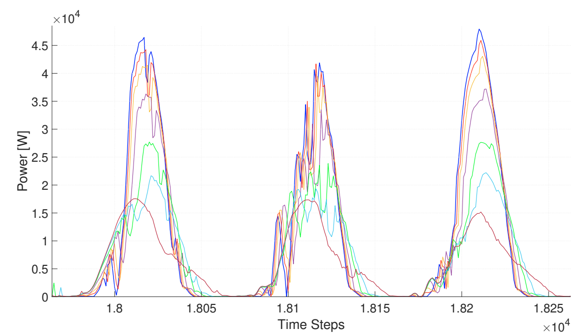

Fig. 6. Actual vs. Predicted PV Production using the A-SM model with lags [1, 2, 3, 78, 82, 85]: Actual data (blue), 15-min ahead prediction (red), 30-min ahead prediction (yellow), 1-hour ahead prediction (purple), 2-hours ahead prediction (green), 3-hours ahead prediction (cyan), 6-hours ahead prediction (brown).

With the aim of supporting the observation made from the figures, Table 2 presents the forecasting RMSE and the PRMSE values for both A-SM and AR models. The results demonstrate that the A-SM method improves prediction accuracy across all forecasting horizons, with enhancements of up to 4.3% from short- to long-term predictions.

Table 2. Forecastin RMSE and PRMSE A-SM and AR models

Prediction Horizon	A-SM		AR	
	RMSE [W]	PRMSE [%]	RMSE [W]	PRMSE [%]
15-min	3223.4	26.62%	3283.9	27.11%
30-min	4116.3	33.99%	4224.8	34.88%
1-hour	4973.8	41.07%	5151.3	42.53%
2-hours	5960.2	49.21%	6244.6	51.56%
3-hours	6452.4	53.27%	6869.3	56.71%
6-hours	6968.6	57.52%	7493.2	61.85%

With the improved forecasting accuracy achieved through the A-SM model, even if the improvement is marginal, the next step is to leverage these predictions for generating the scenarios that can dynamically adapt as new data is available. This process plays a crucial role for posterior uncertainty handling, so by using the estimated

θ parameters and their corresponding bounds obtained with the A-SM, different possible forecast trajectories of PV generation are built. After generating the scenarios

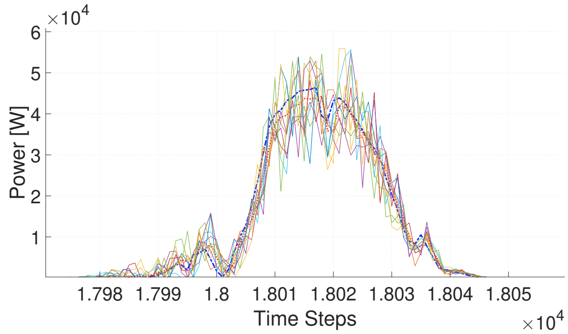

Fig. 7. Scenario Generation - PV Forecasting: Actual data(blue), θ Central (Red), Scenarios (Random colors)

by selecting random values between the θ bounds, as described in Eq. 10, the spread of the scenarios over time can be analyzed to visually assess the model's uncertainty representation. This analysis also helps to evaluate if the scenario generation process captures realistic variations in PV production, as shown in Figure 7. Moreover, since the scenarios are constructed based on the θ bounds, they inherently remain within these limits, ensuring that the generated predictions satisfy the error bound $||y - \hat{y}|| \leq \epsilon$.

5. CONCLUSION

This work has presented an adaptive forecasting model for solar energy generation based on the Set Membership approach. The Adaptive Set Membership approach demonstrated significant adaptability, effectively adjusting to real-time conditions and continuously refining predictions in response to changing conditions. A key achievement of this study is the model's ability to dynamically update parameter bounds, capturing the dynamic variability of PV generation for generating different scenarios to address forecasting uncertainties. The A-SM method consistently outperformed a time-invariant auto-regressive model across all forecasting horizons, achieving accuracy improvements of up to 4.3% . Additionally, the integration of scenario generation allowed for capturing the uncertainty in PV forecasts based on the bounds of model parameter coefficients. This approach has a significant value for energy management decisions due to its capability to capture the variability of distributed energy resources subject to seasonality changes and time-variant effects.

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