Impact of Forecast Time-Step on PV Production Accuracy Using Machine Learning for Micro-Grid Efficiency

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Abstract: Efficient energy management solutions are becoming more important with emergence of micro-grids that include photovoltaic generation & storage. Their prediction of energy output over the near to long term is an important part of their work. An essential parameter influencing the forecast's accuracy, optimum control time discretisation, efficiency, and computing load is the forecast time-step. This trade-off is measured by putting four machine learning (ML) forecast methods through their paces on two different sites, with time-steps ranging from 2 to 60 minutes as well as horizons from 10 minutes to 6 hours. The methods are evaluated on both horizontal and tilted global irradiance charts, depending on the availability of data. All of the methods show comparable findings, which show that for predictions less than an hour and between one and six hours, the error measure may be decreased by up to 1.9% every minute on the time-step, and by up to 2.8% every ten minutes. Additionally, it is demonstrated that for short-term horizons, it could be beneficial towards make high-resolution forecasts & then average results at time-step required by energy control scheme.

Keywords: Micro-Grid, PV Generation, Accuracy Forecasting, Machine Learning, Energy Control System.

1. Introduction

Rapid expansion has led to a photovoltaic (PV) industry that will top 627 GWp by 2020, with a further 115 GWp added the following year. Globally, PV accounts for 2.7% to 3.2% of the energy output; however, this varies greatly from country to country, with Honduras accounting for 14.9% and Norway for 0.2%. The grid operators have issues due to the intermittent nature of PV as its contribution grows [1]. This calls for complicated operations to balance production and demand. Particularly in nations where PV adoption is strong, this unpredictability makes energy management more difficult [2-5].

Costs associated with solar energy grid integration are higher for smaller, non-interconnected networks, such as those found on islands. These expenses vary between 6.16 and 10 €/MWh as a result of solar intermittency. Smart grids, improved energy storage, and more accurate prediction tools are needed to meet this problem. Estimating reserves, planning power systems, managing storage, and optimising market trading are all aided by accurate forecasts [6-8]. As the grid's integration of PV grows, the need of an accurate forecasting tool grows; it lowers integration costs, operational expenditures, reserve shortages, and curtailments.

The associated prediction models are necessary for the energy provider to manage his system across time horizons ranging from one second to one year. A group of algorithms, often housed in an EMS, use an optimisation solver to map out the power transfers across the various grid components, with the goal of obtaining the optimal dispatch schedule. The Method Predictive Control process often makes use of evolutionary algorithms, dynamic programming, or mixed-integer linear programming [9-12]. They rely heavily on the accuracy and resolution of the predictions as they plan for future consumption and output; low resolution forecasts, which average out the data, are less inaccurate but take longer to get to their ideal points. Contrarily, higher resolution predictions allow for more frequent optimisation, but at the cost of a larger inaccuracy at each stage. Adding to that, the optimizer's computing cost grows exponentially with the number of points.

In an energy-management System, the Tilos project effectively proved the need for efficient predictive algorithms with different time spans and resolutions [13-15]. A little Greek island was to be become electrically self-sufficient via the usage of renewable energy to the fullest extent possible as part of the H2020 Tilos campaign. A 160 kWp Photovoltaic plant paired with an 800-kW turbine for wind power truly produces the power of the island, and the project has successfully concluded. A saltwater battery bank and a diesel backup generator round out the system. The grid EMS keeps an eye on everything running well and adjusts the energy storage and production methods based on the predictions made by the platform for weather forecasts.

The created models can accurately predict future load demand, as well as solar and wind power output. Particularly, this paper's machine learning techniques are used by a few of the PV models for forecasting. All the way throughout the dispatch scheduling spectrum, with varying temporal resolutions, every variable is estimated at a separate horizon. In order to generate day-ahead, intra-day & short-term dispatch schedules, the EMS receives the results. In particular, this technology allowed Tilos Island to meet as much as 90% of its electrical demand with renewable energy, with the goal of increasing that percentage to between 70% and 75% each year. Different methods for forecasting use distinct time-steps, scopes, and algorithms. As an example, a Neural Network method is suggested for hourly consumption predicting one day in advance, which may be used to energy trading in both intra-day and one day ahead markets [16-18]. Nevertheless, it lacks the precision needed for optimum micro-grid storage management. Quicker adaption to weather shifts might be possible with finer, infra-hour predictions.

The paper's research is centred on ML algorithms that can be utilised to estimate worldwide horizontal and slanted irradiance in the future. Its goal is to put a number on the cost-benefit analysis of various time horizons' prediction resolution and inaccuracy. Assisting the EMS designer in selecting optimal time-steps for the many required forecast methods is the primary goal. The need of solar output prediction and the current status of short-term forecasting models using machine learning were introduced in the first part. In the second part of the research, the data that went into training the forecast methods, getting a prediction, and calculating the error metrics are detailed. In the third part, the outcomes of the five procedures are shown. It all starts with comparing the models and test sites [19, 20]. The method's results are then shown using error vs timing-step graphs for time parameters that were evaluated, and they are fitted using a first-order polynomial. Additionally, benefits of averaging the predicted principles are covered.

Last but not least, the approach is evaluated on slanted irradiance with an eye towards incorporating those findings into a micro-grid EMS.

2. Methods and Materials

The study's overarching concepts are laid forth in this section. Section one specifies where the tests were conducted and which time series were used. The clear sky method required to get stationary data is presented in the second subsection. In the third part, not only are the reference models explained, but also the forecast models that were employed. Following this, the fourth part details the procedures for training and using models & 5th section defines fault measure and how it is calculated. The procedure for calculating trade-off is then suggested.

2.1 Weather Information Input

This research makes use of information collected from two locations, each with its own unique combination of meteorological circumstances and pyranometric sensors. At a one-minute time-step, the numbers recorded represent the global irradiance over a three-year period. Training and validation took place over the course of a year in each instance, with testing taking place over the course of two years. Located close to town of Ajaccio, George Peri Research Centre is first location on the hilly Mediterranean island of Corsica. This coastal station has a sunny, warm summer and a moderate, rainy winter, making it an perfect location for solar power. The second site is Odeillo's massive solar furnace, which is situated in the highlands some 100 kilometres inland from the coast. The weather is often unpredictable at this meteorological station because of its high elevation. Even in the driest months, it may still provide heavy rainfall and has considerable nebulosity.

2.2 Index and Clear Sky Modeling

Most machine learning-based forecasting techniques need stationary inputs. During data preprocessing, the radiation time series is rendered stationary to meet this criterion. A simple way to achieve this is to divide the observed irradiance by the projected irradiance under perfect cloud cover. The literature has several clear sky methods. Because of its outstanding performance in the places under consideration, the SOLIS method is selected for this work. Radiative transmission models, Beer Lambert purpose applied to the entire solar spectrum, & information from satellites were used to construct it. To get the Global Horizontal Irradiance (GH Ics(t)) below Clear Sky circumstances, researcher use Equation (1).

$$\mathrm{GHI^{cs}(t)} = \mathrm{H_0}.\, \mathrm{e}^{\frac{-\tau}{\sin^b}}.\, \mathrm{h_s(t)}\sin\big(\mathrm{h_s(t)}\big) \quad (1)$$

using the solar elevation hs(t), the top atmospheric irradiance H0, atmospheric depth τ, & fitting parameter b. Locations determine the values for the remaining two parameters.

The forecast methods relie on the clear sky index Kt(t), which is defined as ratio of observed Global Horizontal Irradiance GH I to GH Ics, and is presumed to be steady enough.

$$\mathrm{K_t(t)} = \frac{\mathrm{GHI(t)}}{\mathrm{GHI^{cs}(t)}} \quad (2)$$

2.3 Reference and Forecast Methods

The research took into account four of the most popular machine learning prediction methods found in published works. The forecasting methods output will be denoted with â throughout this publication.

An easy-to-understand model for weather forecasting is the persistence of current circumstances. The clear sky approach allows it to be expressed as:

$$\widehat{\mathrm{GHI}}(\mathrm{t}+\mathrm{l}) = \mathrm{GHI(t)} \times \frac{\mathrm{GHI^{cs}(t+l)}}{\mathrm{GHI^{cs}(t)}} = \mathrm{k_t(t)} \times \mathrm{GHI^{cs}(t+l)} \quad (3)$$

Where $\widehat{\mathrm{GHI}}(\mathrm{t}+\mathrm{l})$ represents the horizon l forecast, GHI(t) represents the current data, and $\mathrm{GHI^{cs}(t+l)}$ and $\mathrm{GHI^{cs}(t)}$ represent clear sky values at the horizon l & instant “t”, correspondingly. Although this concept is known as Scaled Persistence in this study, it goes by other names in literature, such as Persistence and Smart Persistence. The accuracy of this technique rapidly declines with increasing horizon length, yet it performs well with extremely small horizons. The method's simplicity, however, makes it a common naïve baseline for comparing the efficacy of more complicated methods.

$$\widehat{GHI}(t+l) = \overline{K}_t \times GHI^{cs}(t+l) \qquad (4)$$

2.4 Data Processing

The raw measurements need to go through a number of processes to guarantee the models work well before they can be used for training or forecasting. Here are the steps involved in the preprocessing:

1) Inspection for quality: the usefulness of the observed data is confirmed. When problems arise in the acquisition chain, it is possible for the time series to include mistakes. Among the things that the GEOSS-based quality control method verifies is whether or not the measured values fall within the range of zero to extraterrestrial irradiance.

2) Information filtering: separates out relevant information from dataset. At this stage, the sun angle h_s is used to remove the night hours. Nearby objects may obscure the pyranometers at sunrise and sunset, interfering with the training process. In addition, pyranometers usually have larger uncertainty at low sun angles. Researcher eliminate from the result set all measurements where ($h_s < 8^\theta$) for the reasons stated above and in accordance with the solar masks of both locations.

3) Stationarization: irradiance time series are seasonal and periodic. Time series forecasting algorithms often demand stationary data. A framework that calculates solar irradiance under clear sky circumstances & clear sky indices for every data point is a good way.

4) Averaging: Information is averaged according to predetermined model time-step (Δt). Global horizontal irradiance GHI_i is average of observed values in [ti, ti + Δt]. This study focusses on this stage. The prediction resolution affects the forecast error, as will be shown.

The data may be utilised for training the model for subsequent irradiance estimate after cleaning and averaging. The Time Series Forecasting method's total number of data points (p) is calculated by taking the Partial Auto Correlation Factor (PACF). The first time the PACF crosses the range of confidence interval is at this p-value lag. Although PACF isn't the best choice for ML models, it's employed here since it's simple. Train the framework using 80% training data and 20% validation data; an optimisation technique minimises prediction errors. Initial evaluations demonstrate that training using data from a single year is enough to capture weather seasonality.

2.5 Method Error Evaluation

The method is evaluated using data from two years after training is finished. In order to prepare the measurements for use in the model, they must first undergo stages 1–4. The output is a matrix containing q predictions of the Clear Sky Indicator $\widehat{K}_t$ performed at Δt intervals during the assessment period. In Figure1, the "post-processing" step, the predicted irradiance $\widehat{GHI}$ is obtained by multiplying those $\widehat{K}_t$ with the relevant Clear Sky values.

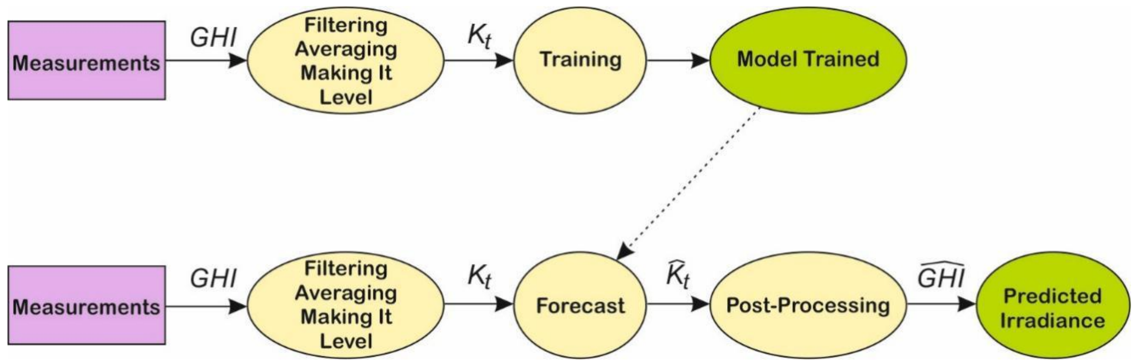

Figure 1. Block designs for training and forecasting

Therefore, at a certain time ti, the models take into consideration the p previous measurements $[\mathrm{GHI}_{i-p+1}, \ldots \mathrm{GHI}_i]$and provide q predictions for $[\widehat{\mathrm{GHI}}_{i+1}, \ldots \widehat{\mathrm{GHI}}_{i+q}]$. In order to assess the methods efficacy, they compare the predicted $\widehat{\mathrm{GHI}_k}$ value to the actual GHI_k value and calculate the Normalised Root Mean Squared errors using Equation 7, where [] is mean purpose.

$$\mathrm{nRMSE} = \sqrt{\frac{[(\mathrm{GHI} - \widehat{\mathrm{GHI}})^2]}{(\mathrm{GHI})}} \qquad (7)$$

2.6 Investigational Method

Chosen replicas are all set up with time-steps of 10, 15... 60 minutes and a maximum view of 6 hours. A year is spent training the models, and then another two years are used for testing. Each time-step length contains error for every horizon, and thus produces eleven sets of nRMSE values. The two series differ in the number of points they include; the 10-minute time-step series contains 36 values, while the 60-minute time-step series has only 6. Each value is extrapolated to coincide with the 10-minute time-step sequence in order to simplify the visual depiction. Using infra-hour predictions to get more accurate system set-points may enhance the optimum regulation of a certain micro-grid. So, for the really near term, currently have trained and tested an additional set of algorithms. This scenario has a time-step ranging from two minutes to 10 minutes & horizon ranging from 10 minutes to an hour.

3. Results

Five parts comprise presentation of the outcome. In first, we compare all 4 prediction models & choose best one to go into depth in the second part of the article. The second part of the section compares the outcomes for a single setup at both sites. Metrics for the worldwide horizontal irradiance are calculated for various time-steps and horizons, and the key findings are reported in the third part. The benefits of performing many predictions with a modest time-step instead of one unique forecast are briefly discussed in the fourth paragraph. At last, slanted irradiance in Ajaccio is subjected to the approach.

3.1 Comparing Forecast Methods

A unified technique has been used to test all the models stated in Section 2.3. Some of the outcomes at Odeillo are shown in Figure 2. To retain the article manageable and not overwhelm the readers with too many examples, they simply plot the data for 20-to-60-minute time-steps for 1 site.

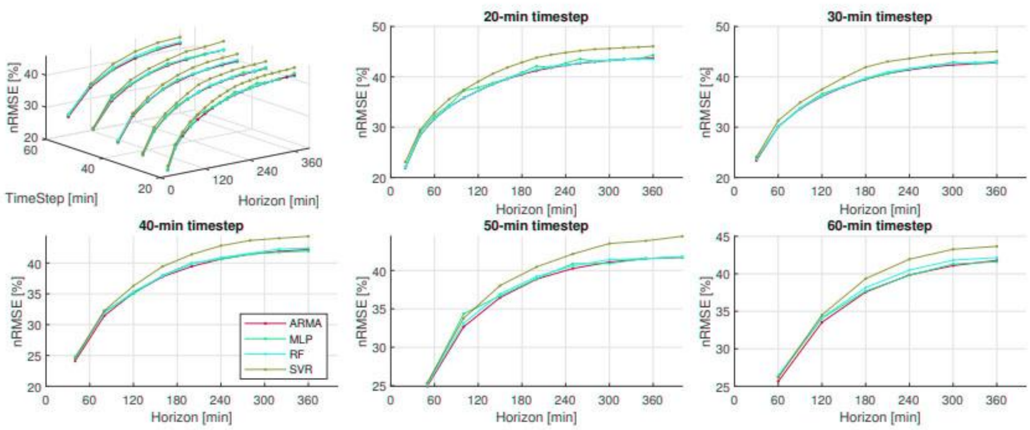

Figure 2. Comparison of Odeillo Forecasting Technology for Various Timesteps and Views

The tested range is equally covered by Random Forest, Auto Regressive Mobile Average, and Multi-Layer Perceptron. On the other hand, SVR methods fare somewhat worse. Optimisation of the methods meta-parameters could lead to better results, but that's beyond the focus of this work. Although the models exhibit identical behaviour, ARMA often provides superior results. This approach is also the fastest and simplest to implement. The irradiance's short-term development is definitely quasi-linear, and using more sophisticated approaches has little effect on performance improvements. Nonlinear models may outperform ARMA with more data for training, however this quantity of data is seldom accessible. Therefore, in order to keep things concise and adhere to the remainder of the research, they will only provide results that were obtained using ARMA methods.

3.2 Compare Test Locations

The research has been conducted in two locations to ensure its reliability. It boosts trust in the results, but it's not enough to draw any broad conclusions. The findings for a 30-minute time-step in both sites are compared in Figure 3. The prediction error for ARMA as well as Scaled Persistent methods grows with the horizon, as predicted. The irradiance in mountainous areas is quite variable, therefore it is less in Ajaccio than in Odeillo. The findings corroborate this, since they compare the simulation's performance on four datasets that exhibit varying degrees of weather unpredictability.

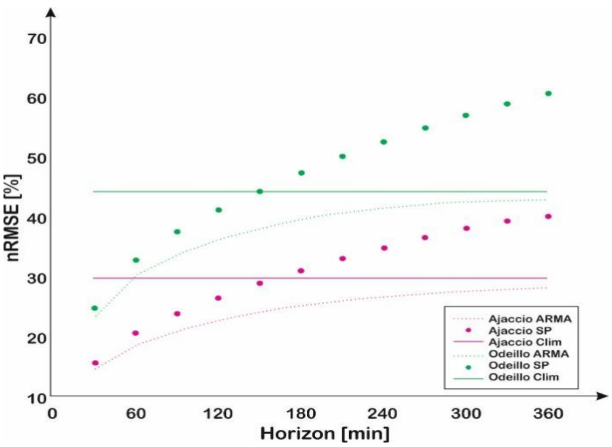

Figure 3. nRMSE for ARMA, Scaled Persistence, and Climatology Models (30-min Time Step)

In near term, the Scaled Persistence prediction performs better than the Climatology approach, but after three hours or less, it starts to perform worse. Even as the 6-hour horizon approaches, ARMA remains the optimal strategy due to its tendency for error to approach a horizontal asymptote. Error measurements are calculated over a two-year period, as specified in Section 2.6. Figure 4 shows nRMSE development for the ARMA approach with a 30-minute time-step & an hour-long horizon; this time-span is sufficient to achieve convergence.

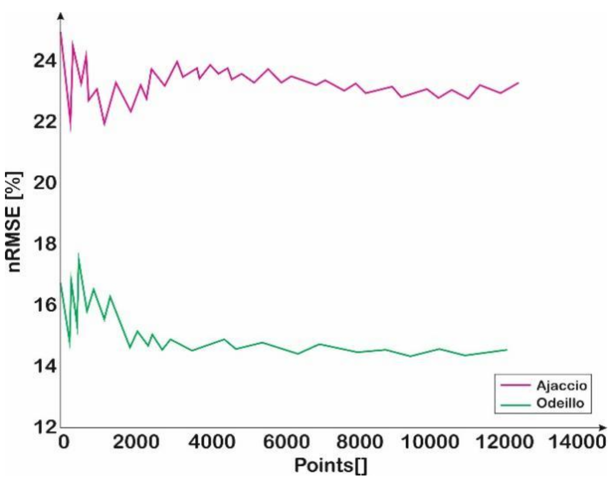

Figure 4. nRMSE Convergence for ARMA Model vs. Random Points Selection

This figure is generated by taking the mistakes in a random order and then computing the cumulative nRMSE. In other words, 2000 points on the axis that is horizontal represent 2000 points randomly selected over the two-year testing program. The first two thousand points would have marked the beginning of the testing session and thereafter been subject to seasonal change since they hadn't been randomly assigned. Due to the complexity of the metrics convergence issue, it will be addressed in future publications and will not be addressed in this study.

3.3 Horizontal Irradiance Errors

Figure 5 displays the ARMA findings for Ajaccio as well as Odeillo as a function of time-step, which ranges from 10 minutes to an hour, and a maximum view of 6 hours or approximately longer. The first step is reached after 6 hours; hence the maximum value horizon is supplied by that. It is not feasible to achieve precisely 360 minutes with certain time-steps. The findings are adjusted to align with the 10-minute time-step in order to facilitate surface plotting and better comparison.

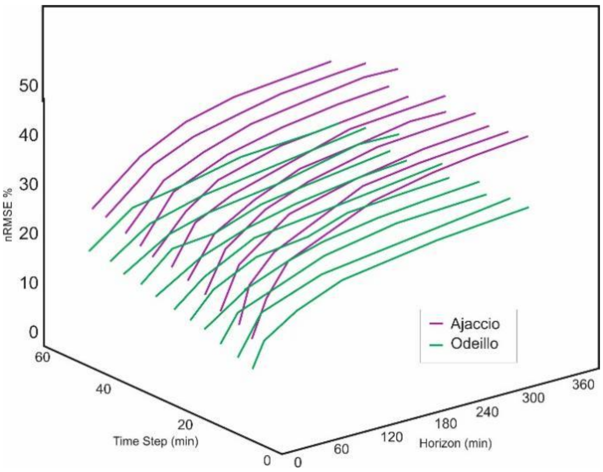

Figure 5. ARMA findings for Ajaccio as well as Odeillo

An "easier" prediction is produced by averaging out the short-term unexpected fluctuations in irradiance, which in turn reduces variability. Figure 6 shows the result of an irradiance measurements with 10-, 30-, and 60-minute average window lengths, illustrating this point. An improvement over the algorithm's predictions, the 60-minute window graphic follows the data trend more closely.

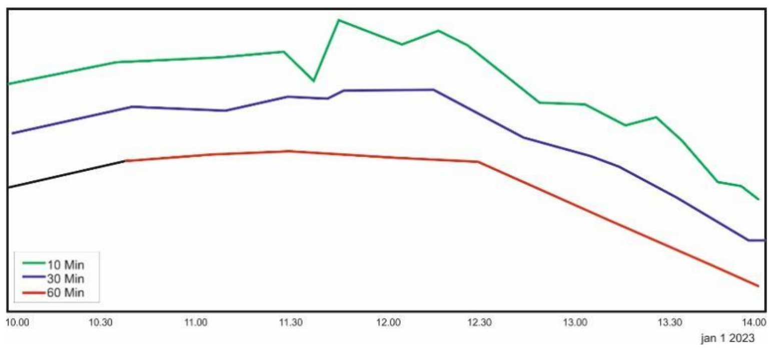

Figure 6. Result of an Irradiance Measurements

The 3D methods are just included for visual purposes since they are not easy to work with. The surface is divided into 6 horizons, ranging from an hour to 6 hours, in order to measure the nRMSE reduction with resolution. The nRMSE decrease across a broad range is seen in Figure 7, which displays the combined findings. It demonstrates the consistency of the findings by displaying a steeper slope for the shorter time-step predictions.

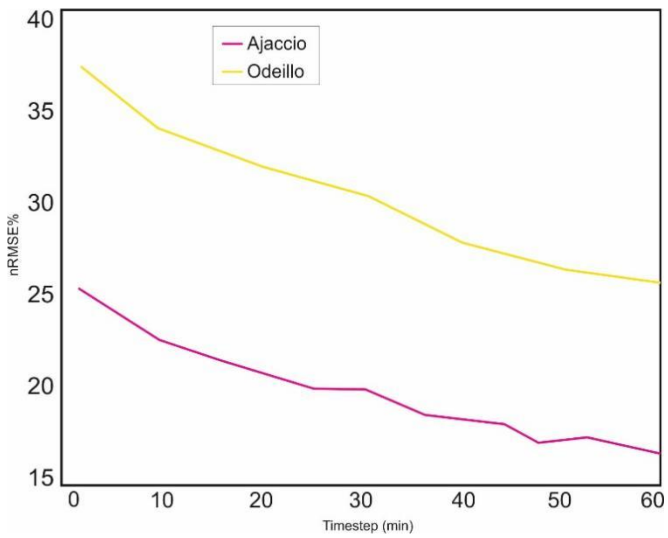

Figure 7. nRMSE Decrease Across a Broad Range

3.4 Average Forecast

The inaccuracy is smaller on average for large time-steps, but it's still larger for little ones. In other words, instead of doing a single prediction with a 60-minute time-step, it is more accurate to conduct many smaller forecasts covering the period between t as well as t + 60 minutes in terms of average irradiance. As an example, the hourly value may be obtained by averaging six predictions with a 10-minute time-step. As an example of this claim, in Ajaccio, ARMA model is used to evaluate 60-minute forecasts of many models with time-steps ranging from 2 to 60 minutes. The average of 30 predictions is used for the 2-minute time-step, 20 for the 3-minute model, and so on. Figure 8 displays their nRMSE. For Ajaccio, the nRMSE may be reduced by 1.7% by switching from a 60-minute time-step to a 5-minute one. Going below 5 minutes, however, has little effect on the precision of the prediction. However, this enhancement is not as noticeable over longer time frames.

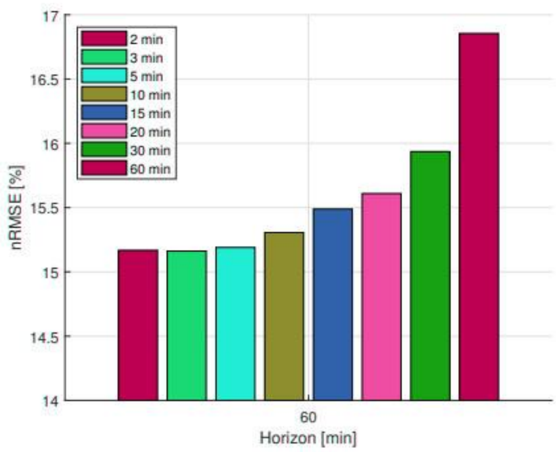

Figure 8. nRMSE Results

The upgrade is most helpful in the morning, when there is no data accessible throughout the night. Because they are dependent on irradiance data from the prior day, univariate models are vulnerable to inaccuracies caused by weather changes that occur throughout the night. There is a 60-minute delay after dawn for new data in a 10-minute time-step method, whereas there is only a 10-minute wait in a 60-minute time-step method. More precise predictions are the result of this quicker update. Unfortunately, for efficient micro-grid management, the minimal prediction time-step is inadequate due to measurement interval of available information, that is often hourly, especially from older weather stations.

3.5 Tilted Irradiance Errors

The research focused on worldwide horizontal irradiance to align with existing literature and readily accessible data. In most circumstances, PV panels want to produce more. The PV panels' global irradiance incident is the most important measurement for microgrid functioning. The study's validity on slanted data is tested by using the same approach to global irradiance data on a 45◦ plane facing south at Ajaccio. The ARMA method now uses GTI instead of GHI.

4. Conclusion

In this study, researchers showed how the prediction error changed as a function of the forecast time-step. There have been two years of testing on two French locations, Ajaccio and Odeillo, of four methods: ARMA, MLP, RF, and SVR. They exhibit identical behaviour, and the research proceeds to demonstrate ARMA, the model that provided the greatest results. For time-steps ranging from just over 2 minutes to an hour and horizons spanning from 10 minutes to six hours, the error measures are calculated. The findings demonstrate that, in the case of the Global Horizontal Irradiance, a decrease in the nRMSE of up to 1.9% every minute at short term in Odeillo may be achieved by increasing the time-step. While the accuracy of the Global Tilted Irradiance projections decreases with each 10-minute time-step increment for the one-hour horizon, the inaccuracy may be decreased by 2.8% overall. In order to choose the optimal time-steps for their algorithms, future designers of EMS for integrated micro-grids may find this paper's technique useful. The computational expense of optimising at high resolution and the prediction inaccuracies at tiny time-steps must be balanced. Future research will evaluate convergence of error measures and provide a system for comparing errors over time-steps. Tilted irradiance and sunrise performance will be enhanced in the models. Testing adaptive time-steps to meet EMS resolution needs all day is the idea.

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