

Power Generation Forecasting From Solar Plants Based on Weather Conditions for Kazakhstani Region

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Abstract—This paper presents a comprehensive approach to forecast solar power generation in the Kazakhstani region, leveraging historical and weather data. The main challenge with solar power lies in its dependency on weather conditions, which significantly impacts day-ahead output planning and grid operations. To address this, we have employed advanced time-series forecasting models like ARIMA, Facebook Prophet, and XGBoost to predict the power output for the next day. By utilizing the real data from two solar plants located in Kazakhstan and analyzing region's historical weather patterns, our proposed model were carefully validated with walk-forward model validation approach. Obtained results highlight superior performance of XGBoost model, outperforming plant dispatcher's predictions and demonstrate the potential of utilizing machine learning in enhancing the reliability of solar power forecasts. This research provides practical insights for both academics and practitioners, including grid managers and plant dispatchers, aiming to optimize solar power integration and reliable operation of the power grid.

Keywords—Solar Power Generation, Time Series Forecasting, SARIMAX, Facebook Prophet, XG Boost.

I. INTRODUCTION

As the global community accelerates its transition towards renewable energy sources, solar power plants has emerged as a cornerstone in the quest for sustainable energy. The widespread adoption of solar photovoltaic (PV) systems around the world underscores the critical role these systems play in mitigating climate change, reducing carbon emissions, and fostering energy independence. However, the intermittent nature of solar energy, primarily due to its dependency on weather conditions, presents unique challenges for energy forecasting, grid integration, and management.

The highest solar potential is estimated in Kazakhstan (compared to other Central Asian countries) - at 3.760.000 MW of solar photovoltaic energy [1]. CADGAT (Central Asia Data Collection and Analysis Group) estimates the potential to be 6.684 TWh/year [2]. With 2200–3000 hours of sunlight per year, solar radiation is $1200\text{--}1700\text{ kW/m}^2$ [3] or, according to another source, $1300\text{--}1800\text{ kW/m}^2$ [4]. The gross, technical and economic potential of solar energy in Kazakhstan is estimated at 1 billion GWh, 1 million GWh, and 10 GWh, respectively [5]. Another source estimates the total

annual solar energy generation potential in Kazakhstan at 3.9–5.4 billion kWh [4].

The efficiency of solar panels is significantly influenced by a range of meteorological factors, including but not limited to solar irradiance, temperature, cloud cover, and humidity [6]. These elements not only affect the instantaneous power output of solar PV systems but also introduce variability and uncertainty into power generation forecasting. Accurate forecasting models are therefore essential to optimize the operation of solar power plants, enhance grid stability, and facilitate the effective integration of solar energy into the power mix.

Despite the advancements in solar technology and forecasting methodologies, there remains a considerable gap in accurately predicting solar power output in the face of dynamic and often unpredictable weather conditions. Traditional forecasting models frequently fall short in capturing the complex interrelations between various weather parameters and their impact on solar power generation. This limitation underscores the need for innovative approaches that leverage advanced data analytics, machine learning algorithms, and comprehensive weather data to improve the precision and reliability of solar power plant forecasts.

In light of these challenges, our research is dedicated to advancing the field of power generation forecasting from solar plants by integrating detailed weather condition analysis. By harnessing cutting-edge statistical methods and machine learning techniques, we aim to develop a robust forecasting framework that offers more accurate predictions of solar power generation. This paper delves into the intricacies of modeling the relationship between weather conditions and solar power output, presenting a novel forecasting model that has been meticulously validated using real industrial data.

The innovation and contribution of this study involves the following aspects: (i) Introducing comprehensive forecasting framework by utilizing ARIMA, Facebook Prophet and XGBoost models. (ii) While other papers explore solar power forecasting in general, our research is specifically tailored to the Kazakhstani region, which has been less covered in the literature. (iii) Utilizing a walk-forward validation, our methodology reflects a real-world operational settings, thus improving the applicability and accuracy of our forecasts.

The implications of this research extend beyond academic interest, offering practical insights for solar plant operators, grid managers, and policymakers. Improved forecasting capabilities can lead to more efficient solar plant operation, better grid management strategies, and ultimately, a more resilient and sustainable energy system. Through this contribution, we endeavor to support the ongoing efforts to optimize renewable energy resources and realize their full potential in the Kazakstani energy landscape.

The remainder of the paper is organized as follows. The review of recent advancements in solar forecasting are discussed in Section II. The methodology and algorithms, presenting the data processing, model development and validation steps are detailed in Section III and IV. Sequentially, the results of the solar power generation forecasting are shown and discussed in Section V. Finally, the Section VI summarizes the implications of our findings and outlines directions for future research.

II. LITERATURE REVIEW

A. Technical Setup

“Plant-1” was created in 2014 with a capacity of 50 MW. Specialists from Europe were involved in the work; all equipments, including 192192 solar panels, was produced in Europe. The solar power “Plant-2” was installed later in 2018, with the same capacity. The work process is fully automated and is under constant supervision of specialists. Their main task is to prevent system failure. Note that on sunny days one power plant produces up to 330 thousand kilowatt hours per day. Both plants Plant 1 and Plant 2 are in the south of Kazakhstan. Kazakhstan’s unique weather conditions greatly influence solar power generation. The region is characterized by extreme temperature fluctuations and high levels of solar irradiance in southern parts.

Table 1 contains technical characteristics of installed solar panels on both plants [7].

TABLE I. TECHNICAL CHARACTERISTICS OF SW260 MONO BLACK

Parameter	Value	Units
Maximum Power, P_{max}	260 Wt	Watt
Open circuit voltage, V_{oc}	38.9 V	Volt
Maximum power point voltage, V_{mpp}	30.7 V	Volt
Short circuit current, I_{sc}	9.18 A	Amper
Maximum power point current, I_{mpp}	8.56 A	Amper
Operating Temperature	-40 °C to +85 °C	Celcius
Length	1675 mm	millimeters
Width	1001 mm	millimeters
Height	31 mm	millimeters
Cell type	Mono crystalline	-

Geographically, the distance between two plants is approximately 200 km. Moreover, the number of solar panels in “Plant-2” is 185000.

B. Related Works

Forecasting of solar power plants for day-ahead plays an important role [8]. Authors of [8] used 5-minute resolution data and KNN methods to predict 3 different scenarios of generation profile: sunny day, partially cloudy day and cloudy day. Systematic review of implemented 128 algorithms with different input parameters was described in [9]. They showed

in detail how searching process were made, what type of scientific databases they used, classification of different methods, filtering by performance metrics and etc.

The results of LSTM, SVM, BP neural network and ELM algorithms for predicting solar and wind generation defined by authors of [10]. Then by using different performance metrics for a comparative analysis with other existing algorithms, researchers described their own ENN model, and proved that their model works better in terms of accuracy and efficiency.

A case study of 100kW roof-top Grid Connected PV plant power output forecasting is discussed in [11]. The authors have employed the Deep Neural Network technique using LSTM networks for predicting the PV Power generation.

In simulation methodology of [12] paper used 5-min resolution data. Total 15 scenarios of solar capacities were tested and their results discusses about operational challenges for balancing load. In general combination of flexible solar resources and energy stores can increase the productivity of the whole system.

III. INPUTS AND METHODS

This research outlines a standard methodology for forecasting solar power production. Figure 1 illustrates the workflow for the generation prediction module. Initially, the dataset is divided into train and test subsets: where 70 % of original data was assigned for training and remaining 30 % of data was used for testing. Subsequently, the data undergoes preprocessing prior to the training phase, after which time series methodologies like ARIMA, FB Prophet and XGBoost are employed to forecast future solar power generation.

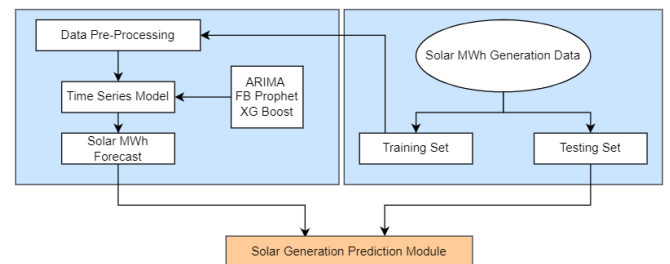


Figure 1 - Solar Generation Forecasting Flowchart

A. Dataset Information

Industrial data contains the information about power generation (actual values) of solar panels with 1-hour resolution from 2017 to 2021, irradiation in W/m^2 , weather temperature of that period. Moreover, dataset contains one column called as “plan” which means that expert’s forecast for 1 day in advance. His decision mainly depends on the time of day, the weather forecast for the next day, and of course is based on historical data.

The Figures 2 and 3 shows the 3d plot of PV power output generation and weather temperature for the whole year of 2019. From the solar generation profile, we can observe usual daily generation pattern of solar panels, that rises to peak between 10:00 and 15:00 hours, and also in terms of monthly patters we see high generation during the summer season days. Similarly, the temperature profile in Fig. 3 follows an expected curve, where temperature values change with respect to seasonal patterns.

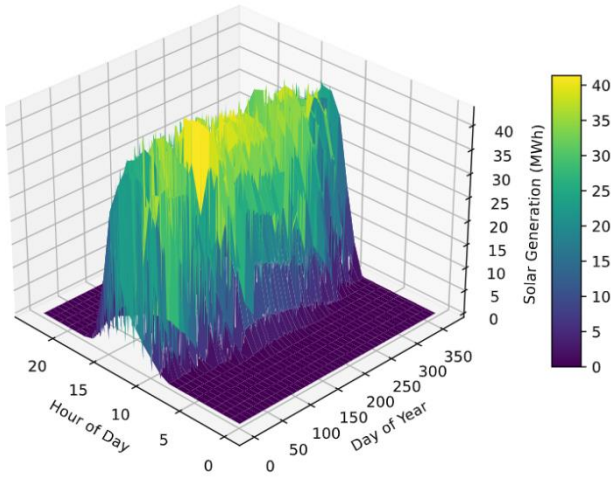


Figure 2 - 3D Surface Plot of Solar Generation (MWh) in 2019

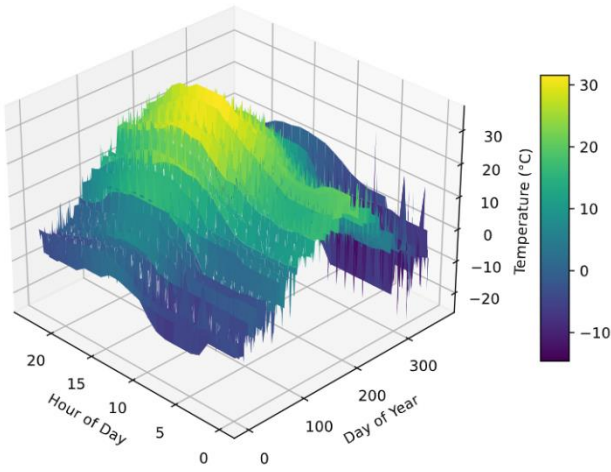


Figure 3 - 3D Surface Plot of Temperature (°C) in 2019

B. Model Selection

a) ARIMA is a time series forecasting model that combines autoregression (AR), differencing (I), and moving average (MA) components. It's effective for analyzing and forecasting time series data with trends and/or seasonality.

Components:

- Autoregression (AR): Previous values in the time series are used to predict future values.
- Differencing (I): The differencing step removes trends from the time series data.
- Moving Average (MA): Past forecast errors are used to predict future values.

The ARIMA (p, d, q) model is represented by the equation:

$$Y_t = c + \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (1)$$

where:

- Y_t is the value of the time series at time t ,
- c is a constant,
- $\phi_1, \dots, \phi_p$ are the autoregressive parameters,
- ε_t is white noise,

- $\theta_1, \dots, \theta_q$ are the moving average parameters,
- d is the degree of differencing, and
- q is the number of moving average terms.

When dealing with seasonal time series, it is common to utilize the seasonal ARIMA that integrates both seasonal and non-seasonal components into the model framework. The general form of a model is represented as $ARIMA(p, d, q) * (P, D, Q)_S$. Here, additionally, we have the order of seasonal autoregressive component (P), degree of seasonal differencing (D), order of seasonal moving average (S), and period of seasonal cycle (S).

b) Facebook Prophet Model

Prophet is a forecasting model developed by Facebook, designed to handle time series data with strong seasonal patterns and multiple seasonality components.

Components:

- Trend: A piecewise linear or logistic growth curve modeling the non-periodic changes.
- Seasonality: Weekly and yearly seasonal components.
- Holiday Effects: Incorporation of holiday effects if provided.
- Uncertainty Intervals: Provides uncertainty intervals for the forecast.

Prophet model does not have a specific equation but utilizes a generalized additive model (GAM) framework to model the time series components mentioned above.

c) Extreme Gradient Boosting

XGBoost is a powerful machine learning algorithm based on gradient boosting, widely used for regression and classification tasks. It builds a series of decision trees sequentially, where each new tree corrects the errors made by the previous ones.

Components:

- Decision Trees: Weak learners used as base estimators.
- Gradient Boosting: Learning is based on minimizing a loss function.
- Regularization: Controls overfitting using regularization parameters.
- Gradient Descent Optimization: Used to minimize the loss function.

XGBoost minimizes the following objective function:

$$Obj(\theta) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (2)$$

where:

- l is the loss function,
- $\hat{y}_i$ is the predicted value,
- y_i is the true value,
- Ω is the regularization term,
- f_k is the k -th tree in the ensemble, and
- K is the total number of trees.

C. Performance Metrics

To assess the performance of proposed models, the Root-Mean-Square Error (RMSE) metric is used. It estimates the

residuals between the actual and predicted values. The RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value and n is the total number of observations. The main advantages of using RMSE is that it penalizes large residuals and scales the values to the same units of forecasted values (i.e., solar generation in MWh).

IV. THE ALGORITHMS

In this research, the ARIMA, FB Prophet and XG Boost algorithms were developed for forecasting time series based on multi-step forecast with re-estimation approach. In this approach, before making a forecast, the model is re-trained at each iteration with the newly observed data [13]. This technique is also called "walk-forward model validation".

A. ARIMA Algorithm

ARIMA is a type of time series models that capture the temporal patterns in time series data. It is based on linear regression, and it describes time series data by using linear dependency on past values and the past forecast errors.

The power output of solar power plant highly depends on weather conditions, which in turn depends on a season of the year as we see in Figures 2 and 3. To adequately capture these dynamics, we employed a seasonal ARIMA model that combines both non-seasonal and seasonal factors. Additionally, we have added the weather information (temperature and cloudiness) as an external predictor, also called 'exogenous variables' into the model. The considered model is called the SARIMAX model.

In order to describe the algorithm without delving into the details, we present the logic in the form of pseudo-code, as shown in Algorithm 1. The algorithm firstly takes input time series data, weather information and splits the data into train and test set (Lines 1-5). It then builds a forecasting model, that gets updated every 24 hours (Lines 9-22) and finally, reports RMSE value of the predictions (Lines 23-24).

In this study, we used a SARIMAX(1, 1, 0)x(1, 1, 1, 24) model as the foundational framework for forecasting. The parameters were decided by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. It is a robust baseline model given the size of the data and computational resources available at our disposal.

B. FB Prophet Algorithm

In the context of solar power generation prediction, which is influenced by several factors including weather and seasonal changes, the FB Prophets capability to capture non-linear relationships with daily, weekly, and yearly patterns makes it an excellent fit. Moreover, the possibility of inclusion of additional regressors allows us to consider the effect of weather variables like cloudiness and temperature.

Algorithm 1 Rolling SARIMAX with Exogenous Variables

```

1:  $total\_size \leftarrow \text{length}(\text{series})$ 
2:  $test\_size \leftarrow \text{int}(total\_size \times 0.30)$ 
3:  $train \leftarrow \text{series}[0 : -test\_size]$ 
4:  $test \leftarrow \text{series}[-test\_size : \text{end}]$ 
5:  $exog\_train \leftarrow$  exogenous variables from  $train$ 
6:  $exog\_test \leftarrow$  exogenous variables from  $test$ 
7:  $predictions \leftarrow$  list to store forecast results
8:  $observed \leftarrow$  list to store actual values
9: for  $day = 0$  to  $\text{len}(test)/24$  do
10:    $start\_idx \leftarrow day \times 24$ 
11:    $end\_idx \leftarrow start\_idx + 24$ 
12:   if  $day > 0$  then
13:      $new\_observation \leftarrow test[start\_idx : end\_idx]$ 
14:      $new\_exog \leftarrow exog\_test[start\_idx : end\_idx]$ 
15:     Update model by appending observed values
16:   end if
17:    $steps \leftarrow 24$  or remaining steps if less than 24
18:    $forecast \leftarrow$  model forecast for  $steps$  ahead
19:    $yhat \leftarrow$  predicted values from forecast
20:   Extend  $predictions$  list with  $yhat$ 
21:   Extend  $observed$  list with actual values from  $test$ 
22: end for
23:  $RMSE \leftarrow \text{sqrt}(\text{MSE}(\text{observed}, \text{predictions}))$ 
24: return  $RMSE$ 

```

Similar to our SARIMA model discussed earlier, the Prophet model is implemented in a walk-forward validation manner to predict the future time series data. With this approach, the model is re-trained with the recent observed data to generate the forecast for the next 23-hour period. The step-by-step process with FB Prophet model is described in Algorithm 2.

Algorithm 2 Rolling Forecasting with FB Prophet

```

1:  $total\_size \leftarrow \text{length}(\text{df\_prophet})$ 
2:  $train\_size \leftarrow \text{int}(total\_size \times 0.70)$ 
3:  $train\_df \leftarrow \text{df\_prophet}[0 : train\_size]$ 
4:  $predictions \leftarrow$  empty list
5:  $observed \leftarrow$  empty list
6: for  $start\_idx = train\_size$  to  $total\_size$  by 24 do
7:    $end\_idx \leftarrow \min(start\_idx + 24, total\_size)$ 
8:    $current\_train\_df \leftarrow \text{df\_prophet}[0 : start\_idx]$ 
9:    $model \leftarrow \text{PROPHET}$ 
10:   $model.\text{ADD\_REGRESSOR}(\text{Cloudiness})$ 
11:   $model.\text{ADD\_REGRESSOR}(\text{Temperature})$ 
12:   $model.\text{FIT}(current\_train\_df)$ 
13:   $future \leftarrow \text{df\_prophet}[start\_idx : end\_idx][['ds', 'Cloudiness', 'Temperature']]$ 
14:   $forecast \leftarrow model.\text{PREDICT}(future)$ 
15:  Append  $forecast['yhat']$  to  $predictions$ 
16:  Append  $\text{df\_prophet}[start\_idx : end\_idx]['y']$  to  $observed$ 
17: end for
18:  $RMSE \leftarrow \text{sqrt}(\text{MSE}(\text{observed}, \text{predictions}))$ 
19: return  $RMSE$ 

```

This process leverages Prophet's non-linear modelling abilities for predicting solar power generation, by capturing seasonal variations, weather changes and re-training with available data as in a real-world scenario.

C. Gradient Boosting Algorithm

XGBoost is a powerful machine learning algorithm that is widely known for its performance and speed in regression, classification and ranking problems. Its predictive strengths is achieved through an ensemble of decision trees, implemented in a sequential manner, with each subsequent tree attempting to correct the prediction errors of the prior.

For the solar power generation prediction, we have adjusted the time series data into supervised learning framework, by deriving the lagged generation values for previous 24-hour period and weather conditions as features for our machine learning model. Thus, the day-ahead solar generation profile is generated by using previous lagged values that capture the temporal structure and meteorological data like cloudiness and temperature. XGBoost algorithm is also implemented with walk-forward validation approach, updating our model at each prediction step as described in Algorithm 3.

Algorithm 3 Rolling Forecasting with XGBoost

- 1: Prepare the dataset with lagged features for temporal dependencies
- 2: Define the test dataset size to be 30
- 3: Initialize an empty list for predictions
- 4: Create a new XGBRegressor model
- 5: **for** each 24-hour block in the test data **do**
- 6: Split the current data into features and the target
- 7: Fit the model on the training data
- 8: Predict the power generation for the next 24 hours
- 9: Append the predictions to the list
- 10: Update the training dataset with the actual values
- 11: **end for**
- 12: Compute the RMSE using the predictions and the actual observed values
- 13: **return** the RMSE value

V. RESULTS AND DISCUSSION

The time series dataset is processed by the proposed algorithms for solar power generation forecasting. The dataset spans the period from 1 June 2018 to 26 March 2021, which is taken from the real historic operation of solar plant in one of the Kazakhstan regions. This dataset also contains the planned generation values decided by solar plant dispatcher that were submitted to the day-ahead market. The dataset was divided into 70% and 30% proportions, for training and testing purposes respectively as depicted in Figure 4. Thus, the records from 1 June 2018 to 21 May 2020 is used for training, and from 21 May 2020 to 26 March 2021 is used for testing. Then, the models were trained, and the performance was checked by the RMSE parameter in a walk-forward validation manner.

The Table II provides the performance results for the proposed models. It also includes the computed RMSE metric for the forecast values predicted by the solar plant operator, which equals to 5.561. It indicates that for the test period in total, the operator was wrong for an about 5 MWh in solar output generation. As we can see from the table, the seasonal ARIMA models performs the worsts with RMSE value of 10.649, as it only able to capture linear relationships, which may not consider the complex temporal non-linear characteristics between predictor variables and the target.

Nevertheless, we see that the proposed XG Boost algorithm gives the lowest RMSE value of 2.642, by outperforming other methods, especially, the solar plant operators predictions more than by two times for the test period.

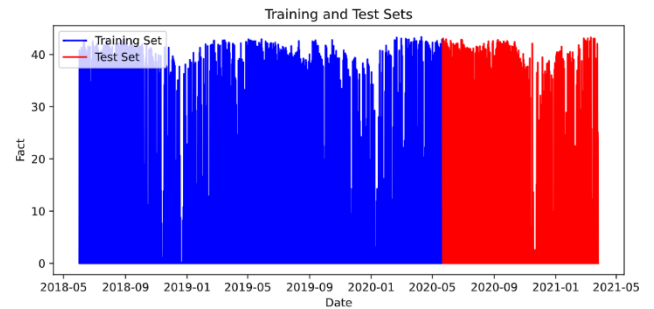


Figure 4 - Train and Test sets

TABLE II. EVALUATION RESULTS OF PROPOSED ALGORITHMS

Model	Performance metric
	RMSE
Human expert's forecast	5.561
SARIMAX	10.649
FB Prophet	6.076
XGBoost	2.642

The Figure 5 compares the actual values and the XGBoost forecasted values of the solar power generation prediction for the test period.

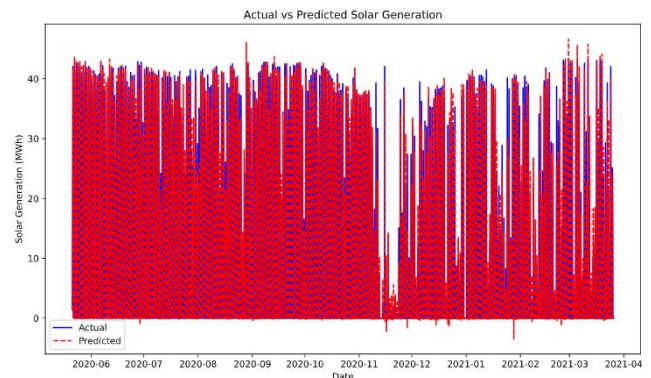


Figure 5 - XGBoost Solar Generation Forecast vs Actual for the Test Set.

Likewise, the Figure 6 presents and compares the actual, planned (predicted by solar plant operator), and forecast values (via XG Boost) of solar power generation for a specific day from the test set, 11 November 2020. With XGBoost ability to handle nonlinear relationships, we can see from the plots that the model's predictions closely follow the actual generation values.

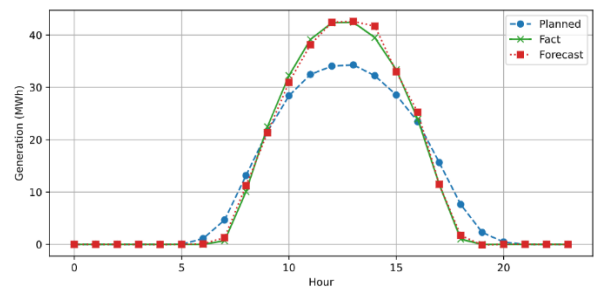


Figure 6 - Planned vs Actual vs Forecasted Solar Generation on 2020-10-11

VI. CONCLUSION

In conclusion, to enhance the grid stability and reliable power delivery, the precise forecasting of variable renewable sources like PV power plant is crucial for power system operation. This research proposes several learning models, seasonal ARIMA, FB Prophet and XG Boost for solar energy production forecasting based on walk-forward validation manner. The XGB model demonstrated superior performance when applied to our historical industrial dataset. This research significantly fills a gap in the literature by providing localized insights into solar power forecasting for Kazakhstan. The obtained results are valuable for utilization and forecasting of solar power in regions with similar variability in weather conditions. The effectiveness of the proposed models has been verified with real operational data. The methods discussed might be beneficial for utility companies in forecasting PV power output, which, in turn, aids utilities performances in day-ahead market and improves the reliability of its operations.

In future work, the authors plan to investigate additionally deep learning methods in forecasting PV power generation, and also apply methods to predict the energy balance. This applications will further improve the reliability and efficiency of variable intermittent energy sources in power system operation.

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