Project Pitch 3
Solar Power Generation in India

Team 6 – Section A1

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1. Business case and use cases

Business Case

Defining the Business Case

Description of Opportunity

Understand and predict relationship between weather and power generation in the plants in order to:

i. Identify faulty equipment in real time in order to improve reaction time when reparations are needed.
ii. Predict generation for the near future and plan power production and supply accordingly (grid management).
iii. Analyze the possibility of expanding into new cities.

And as a result, increase the company’s revenues.

Industry

Energy production in India

Use Case 1: Identifying faulty equipment

Description of Opportunity

Compare levels of generated power with levels expected under full functionality to identify power inverters that require maintenance. Subsequent actions prevent significant losses in revenue due to reduced power generation over prolonged periods.

Context

Functionality of solar power inverters can be impaired to different reasons. The connected panels generate less energy when they are covered in dirt. Further, they may overheat or suffer from other minor technical difficulties.

Use Case 1: Identifying faulty equipment

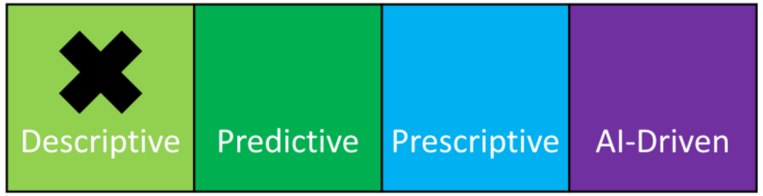
Model

Performance measure as difference between predicted and actual level of power generation per inverter.

Implementation

Mapping the difference between generated AC power per inverter per hour, that is expected with fully functioning equipment, and the actual rate of each inverter. The development of the rates is displayed on a one-day time frame to detect any previous drops on a given day. Creating dashboard on monthly Over-/Underperformance on plant- and inverter-level for long term overview.

Maturity Level:



Over-/Underperformance measure only describes/indicates functionality. Reaching a high-level conclusion about the cause of the problem and prescribing a solution is beyond the scope of this model.

Use Case 1: Identifying faulty equipment

Value / ROI Calculation

Timely intervention in case of faulty equipment prevent loss in revenue:

- Loss of revenue to due faulty equipment: The drop in power generation due to underperforming equipment in case of no intervention can be up 5 M kWh per month. This would translate to a loss in revenue of 345,000 Euro per month (0.069 Euro/kWh) (GlobalPetrolPrices, 2020).

Opportunity size

Under the assumptions derived from the given data, up to 345,000 Euro could be saved per month. The yearly value would indicate an opportunity size of 4,140,000 Euro.

Use Case 2: Short-term generation predictions

Description of Opportunity

Predict solar power generation accurately for the near future in order to keep solar power supplies balanced with demand and to keep power systems operating within tightly constrained limits. There is a big improvement opportunity for better management of electricity grid and solar energy trading.

Additionally, the company could use these short-term predictions to improve the planning of inverter's periodical maintenance (i.e. it is better to perform maintenance on a day where expected generation is low).

Context

Energy should be produced on demand: Energy is usually difficult to store in large amounts. Several techniques such as Grid Management often find ways to match power generation and consumption in order to avoid incurring into additional costs. (Penn State University, n.d.)

Variability and uncertainty of solar energy production: "Conventional energy systems gave the luxury of a fully controllable and deterministically manageable energy production. Renewable energies are uncertain and often unavailable at the time of demand […] Wind and solar energies are highly variable, dependent on atmospheric and climatic conditions and unpredictable." (Demetris, 2016)

Use Case 2: Short-term generation predictions

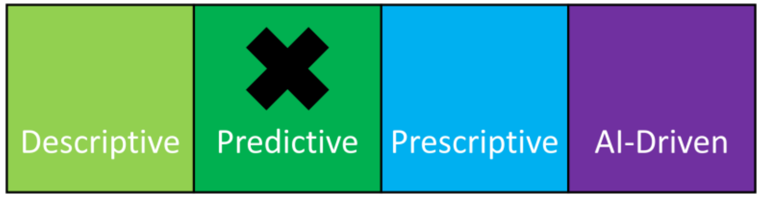
Model

Power generation prediction based on projected ambient temperature and irradiation.

Implementation

Short-term forecasts about these weather indicators can be found in several online sources. Using this near future projections, the model can be used to predict the amount of powered that will be produced by the plants. Further steps with this information will be comparing this generation forecasts with demand forecasts and thus, improve the quality of operational planning in terms of power storage and distribution.

Maturity Level:



Predictions about the near future will be made which will allow the company to make better decisions but do not give specific recommendations to it.

Use Case 2: Short-term generation predictions

Value / ROI Calculation

Better generation predictions will result in matching better the demand, which translates in:

- Storage costs savings (better planning translates into less excess power, which equals less storage costs): The estimated price of storing energy today is around 130 Euro/kWh for a renewables storage system (Roberts, 2019) (Shruti, 2020) (IRENA, 2017).
- Reduction in supply shortages (and related costs): Energy price in India is 0.069 Euro/kWh (GlobalPetrolPrices, 2020). Having supply shortages will represent lost sales for the company.
- Decrease in supply costs thanks to matching supply and demand: Every dollar spent on efficient grid management and demand matching production with demand can yield up to 4 dollars. (Penn State University, n.d.)

Opportunity size

For the company: multiplying the cost of shortages and extra supply costs, by the yearly standard deviation of daily power production by inverter: 1.2 M EUR per year.

Use Case 3: New plant location evaluation

Description of Opportunity

Based on two main parameters, sun irradiation and ambient temperature, we can predict the potential level of solar energy generation for given locations, and thus make important decision for further business development.

Context

The determination of where to build solar power plants is highly related to weather conditions of the prospective locations. Using our prediction model, we can compare locations based on the resulting discrepancy in power generation and consequently revenue, assuming the operational functionality of our existing plants.

Use Case 3: New plant location evaluation

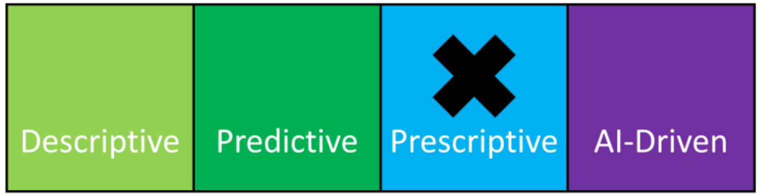
Model

The model uses weather conditions of different locations to analyzes them with respect to potential kWh generation on monthly and yearly basis.

Implementation

The models simply needs to be feed with the data on sun irradiation and ambient temperature. It analyzes the data and shows the differences with respect to potential power generation as well as the provided weather data itself.

Maturity Level:



The model clearly indicates the most profitable one out of considered locations and thus which initiative to pursue.

Use Case 3: New plant location evaluation

Value / ROI Calculation

- Differentiating between prospective locations for solar power plants is useful information for business development. In our example the location of Sriperumbudur would generate 206M/ kWh in 2018 more than Gandhinagar whose generation would be 176M/ kWh, leading to a difference in revenue of 1.72M Euro, Yet the mere identification of differences in weather conditions allows to pick one location over another. Therefore, it is difficult to estimate the monetary opportunity size in this particular use case.

Opportunity size

2. Model creation and main results

Model Training

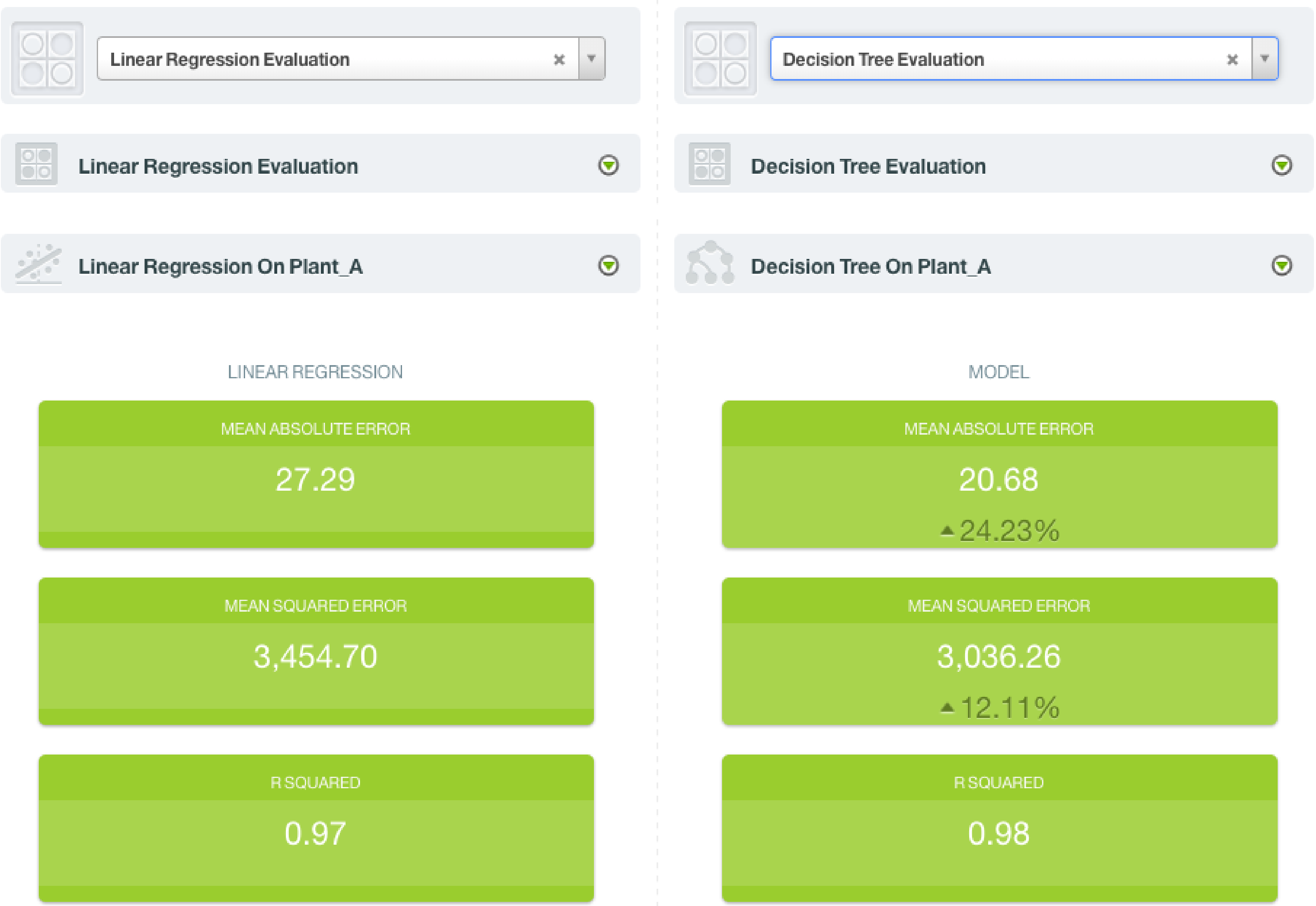
- For training the model, we only used data of Plant A since this data better represents the relationship between the weather and the AC power that an inverter **<u>should</u>** generate. The many problems with the inverters of plant B would introduce an unwanted bias into the model.
- Furthermore, we used time-based sampling (training: May 15th – June 11th (80%); test: June 11th – June 17th (20%)). Since our aim is to predict future values, our validation strategy should also consist of future values in order to better simulate the context in which our model will be used. In this way, our test set (and therefore also our evaluation metrics) give a more accurate view of what the model performance will be like.

Model Selection

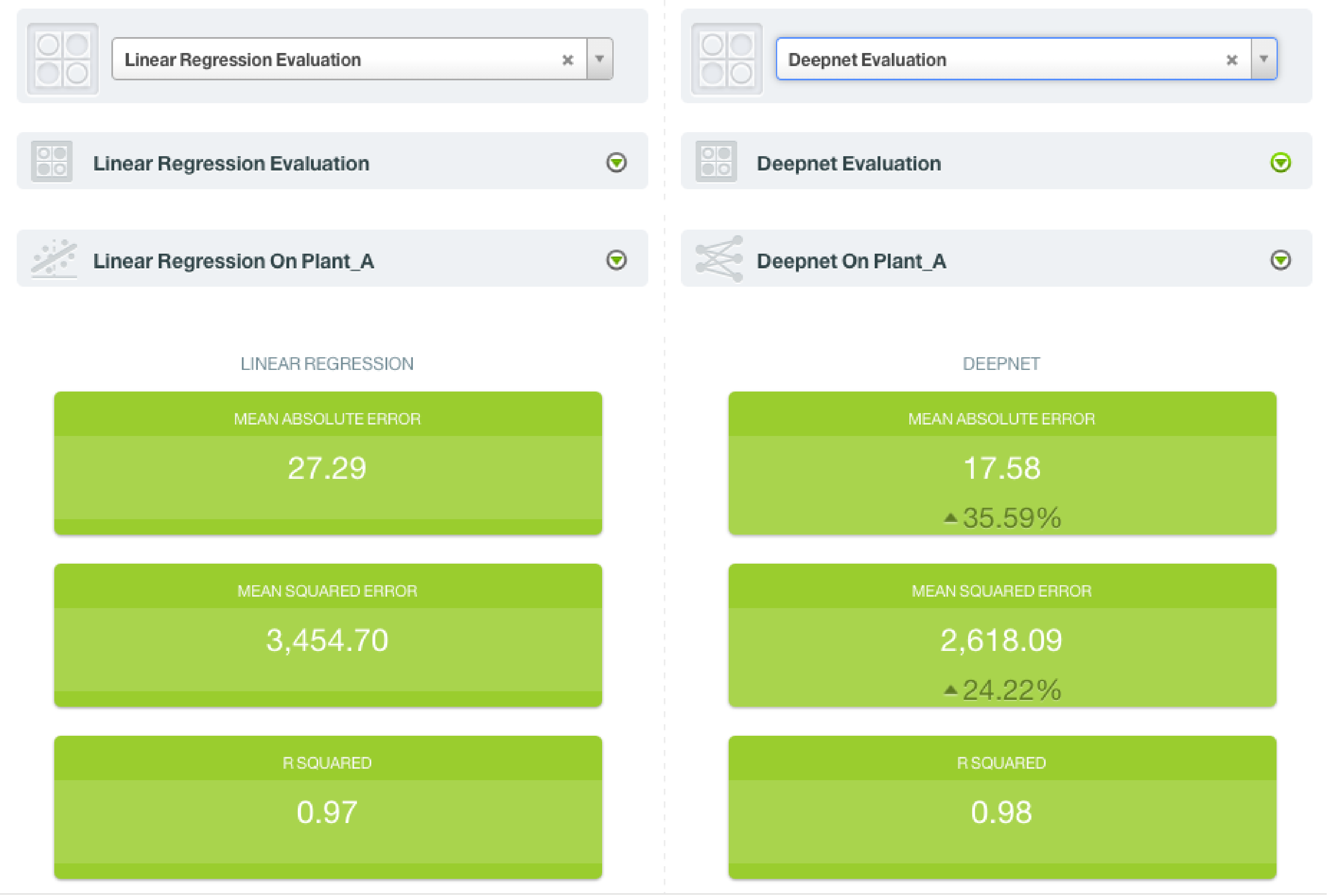
- We tried the following models: Deepnet, Linear Regression, Boosted Tree, Random Forest and Decision Tree.
- The best performing model was the Deepnet, followed by respectively Random Forest, Decision Tree, Boosted Tree and finally Linear Regression.
- The results were the following:

	LINEAR REGRESSION	MEAN	RANDOM
MEAN ABSOLUTE ERROR	27.29	328.28 ▼1000%+	565.32 ▼1000%+
MEAN SQUARED ERROR	3,454.70	135,460.89 ▼1000%+	467,298.48 ▼1000%+
R SQUARED	0.97	0.00	-2.45

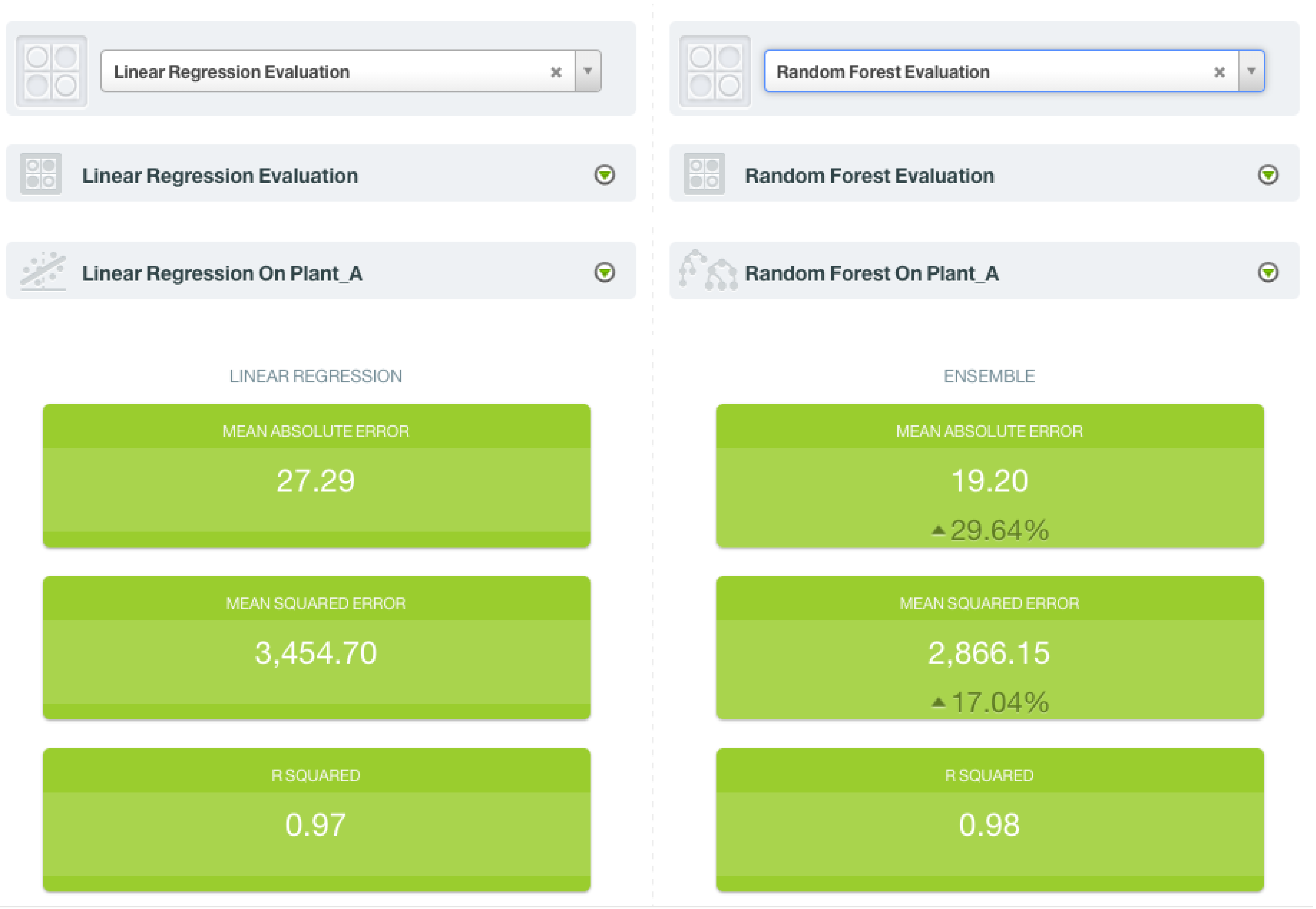
Model Selection



Model Selection



Model Selection



Model Selection

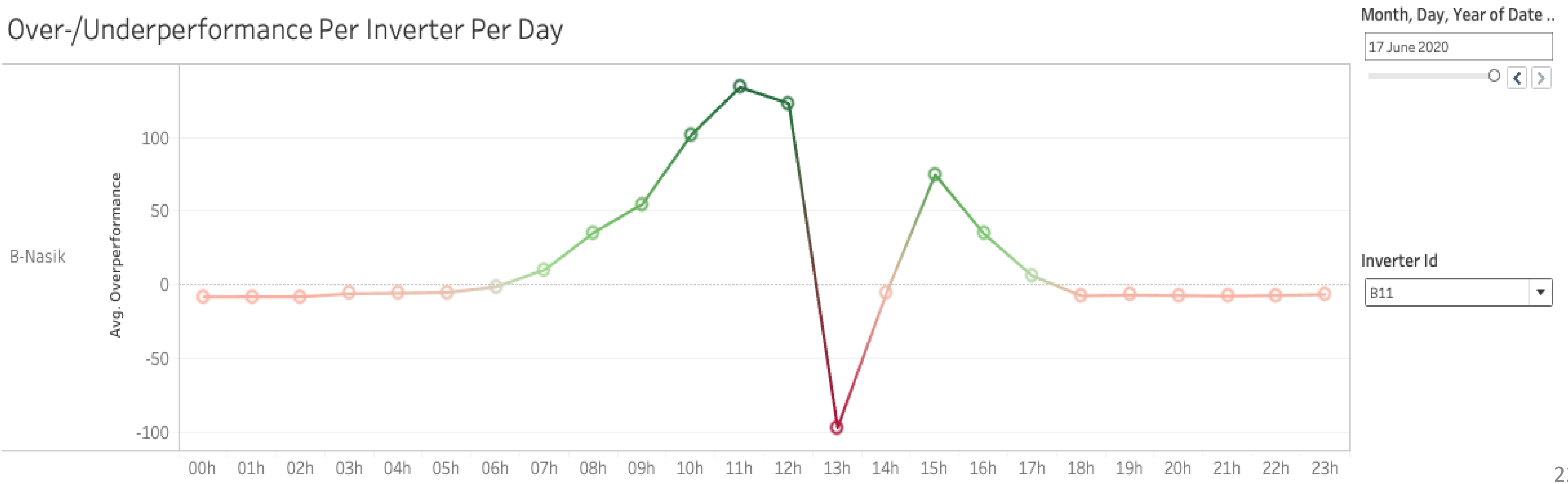
- As our final model we have opted for the linear regression model despite it being the model with the worst performance. The reasoning behind this is that it is the most interpretable model, and that the performance is not significantly worse when compared to the other models. Moreover, we deem that a Mean Absolute Error (MAE) of 27.29 and an R-squared of 97% are more than sufficient for our intended use. For example, the deepnet's better MAE of 17.58 and R-squared of 98% do not outweigh the lack of interpretability at least in this case.
- Furthermore, it should be noted that the linear regression (our 'worst performer') still outperforms the mean model and random model by over 1000%.

Demo Use Cases – Case 1: Identifying faulty equipment

Practically, the faulty inverter detection would work as follows. The company has real-time weather data for each inverter from its own weather sensors. It can use this data to compute the expected amount of power generation for each inverter via our model. Since our model is a linear regression, this computation can be performed rapidly which is ideal for real-time dashboarding purposes. Furthermore, the company also has real-time data for the actual power production for each inverter. Therefore, it can compare the actual power produced by each inverter to what is expected by the model to get the ‘over-/underperformance’. Since both the expected power generation and the actual generation are provided to the company in real-time, the faulty inverter detection can also happen on a real-time basis.

Demo Use Cases – Case 1: Identifying faulty equipment

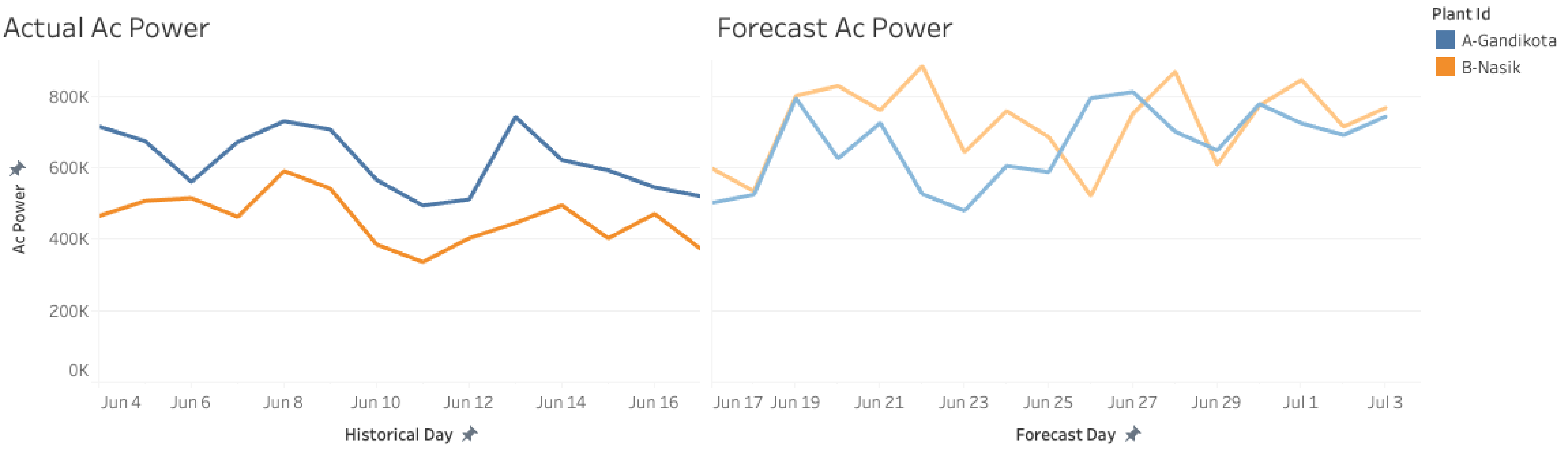
As a demonstration, consider that we are currently 17 June 2020. The shown graph will be constructed on a real-time basis. So for instance if it's 9am, we would see exactly this graph but obviously only from 00:00 until 09:00. On June 17th, everything seemed to go fine for inverter B11 until 13:00. Then it seems that some sort of problem occurred since there is a sudden rapid decrease in performance with no clear explanation. Since this graph will be constructed on a real-time basis, the plant manager would notice this performance drop at 13:00. Therefore, he can send a stand-by maintenance worker to inspect inverter B11 immediately. The problem is likely dust on the panels, a loose cable, etc. In this way, the problem can be identified and resolved immediately.



Demo Use Cases – Case 2: Short-term predictions

For the purpose of demonstrating, we gathered real-life weather (i.e. ambient temperature and solar irradiation) data for Gandikota and Nasik respectively from Solcast, a company that sells high-quality (forecasted) weather data for different cities to companies.

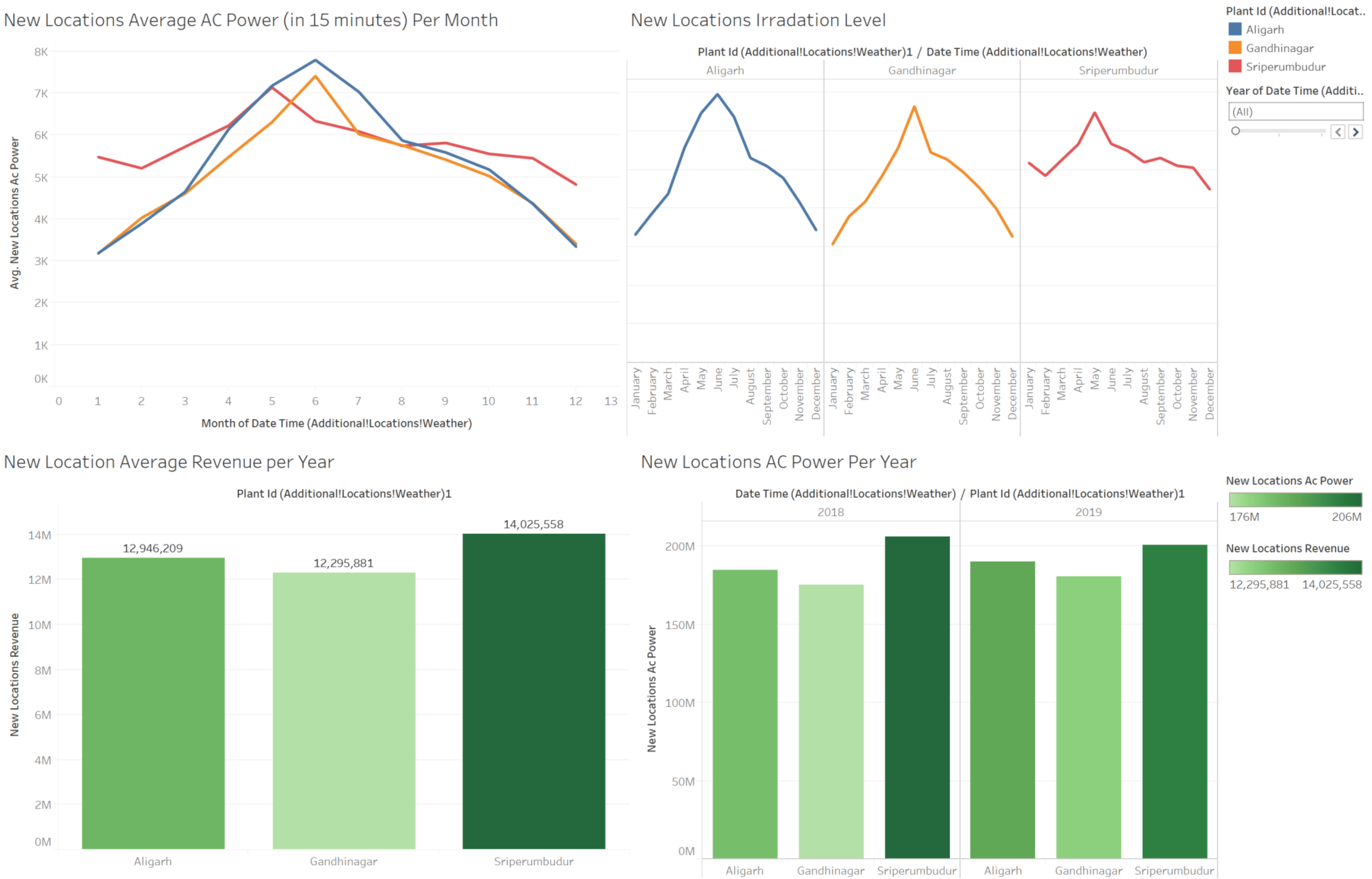
Based on this data, we could run our linear regression model to predict the AC Power generation in the near future. In the graph, you can find the forecasted values per day.



Demo Use Cases – Case 2: Short-term predictions

The practical implementation would -similarly to our demo- be as follows. The solar power company can get an agreement with Solcast to connect to their weather forecast API. This is a real service that Solcast provides to businesses for a monthly fee of $20 per location (Solcast, n.d.). In this way, the company is provided with high-quality weather forecast information which it can use to make short-term power forecast predictions via our model. It can then use these short-term forecasts to improve its power grid management. Concretely, its clients can get a better view of how much power each plant will be able to provide in upcoming periods, the company can adjust its operations to these forecasts (for example if there needs to be any maintenance that requires an inverter to go offline for 10 hours, it’s best to perform this maintenance on a day where it is expected to not generate much power), etc.

Demo Use Cases – Case 3: New plant location evaluation



Demo Use Cases – Case 3: New plant location evaluation

In the dashboard, we first see the average AC power that each plant would generate per month giving us an overview of the power generation during the year. Interesting to see that Sriperumbudur has a stable production through the whole year. The graph on right top corner indicates us the level of irradiation through the year per location, it is highly relevant as it is the main factor influencing the AC power generation. The left graph below indicates the average revenue per year and location while the second one shows the yearly estimated production for each plant for the last two years.

To implement this analysis, we downloaded the necessary weather data on each city thanks to our Solcast API. Then, based on the model created on the data from plant A, we created the power generation estimations based on the local weather data for the last two years and based on a same capacity (number of panels) as in the other plants. Those estimations gives a good understanding of the best location which is Sriperumbudur, a location close to Chennai (7 million inhabitants).

In a real scenario, we would gather data on longer time period like 5 years to gain for higher confidence. However, the student access does not enable such long time period (credit limits).

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