A NOVEL APPROACH TO DEVELOP ENERGY PREDICTION MODEL FOR LARGE INDUSTRIES USING ARTIFICIAL INTELLIGENCE

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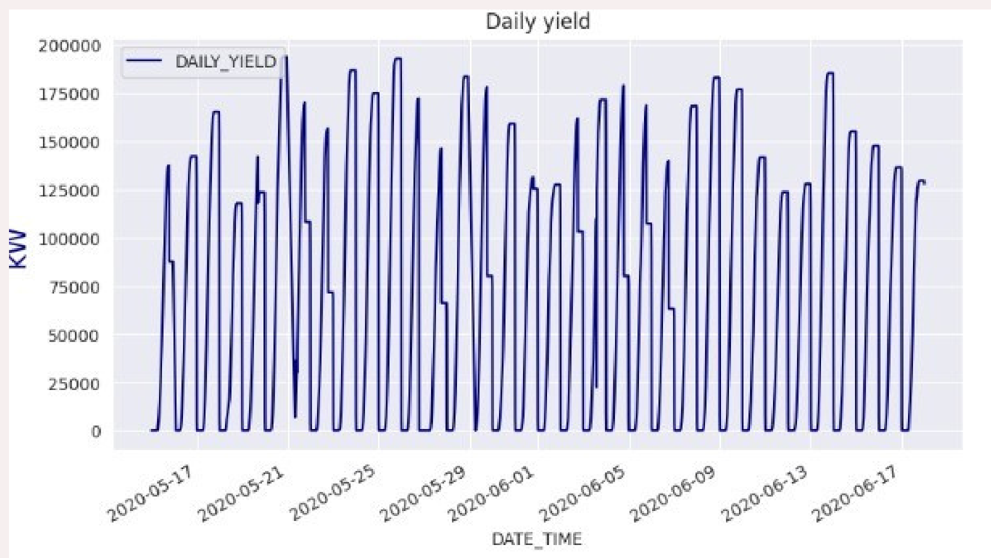
INTRODUCTION

Energy Is The Major Concern Of The Development Of Any Nation. Accurate Estimation Of Solar Energy Is Necessary As Demand And Dependency Of Solar Energy In Total Power Is Increasing Worldwide. Moreover, Accurate Estimation Is Required By Energy Planners And Electric Utilities.

ABOUT THE PROJECT

As The Need To Predict Solar Energy Output Is Essensial For The Industry, Machine Learning Models Can Be Deployed To Create More Accurate Predictions.

Our Project does that exactly, along with the added benefits of being able to identify the sub-optimally performing Solar Panels.



THE PROPHET MODEL

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.The procedure makes use of a decomposable time series model with three main model components: trend, seasonality, and holidays.

Prophet fits several linear and non-linear functions of time as components. In its simplest form;

$y(t) = g(t) + s(t) + h(t) + e(t)$, where:

$g(t)$ - trend models non-periodic changes (i.e. growth over time)

$s(t)$ - seasonality presents periodic changes (i.e. weekly, monthly, yearly)

$h(t)$ - ties in effects of holidays (on potentially irregular schedules ≥ 1 day(s))

$e(t)$ - covers idiosyncratic changes not accommodated by the model

Rate of Change -

The market does not allow for stagnant technology. Advances like those seen over the past decade in handheld devices, app development, and global connectivity, virtually ensure that growth rate is not constant. Because this rate can quickly compound due to new products, the model must be able to incorporate a varying rate in order to fit historical data.

We incorporate trend changes in the growth model by explicitly defining changepoints where the growth rate is allowed to change.

The rate at time t is then $k+a(t)^T\delta$. When the rate k is adjusted, the offset parameter m must also be adjusted to connect the endpoints of the segments. The correct adjustment at changepoint j is easily computed as;

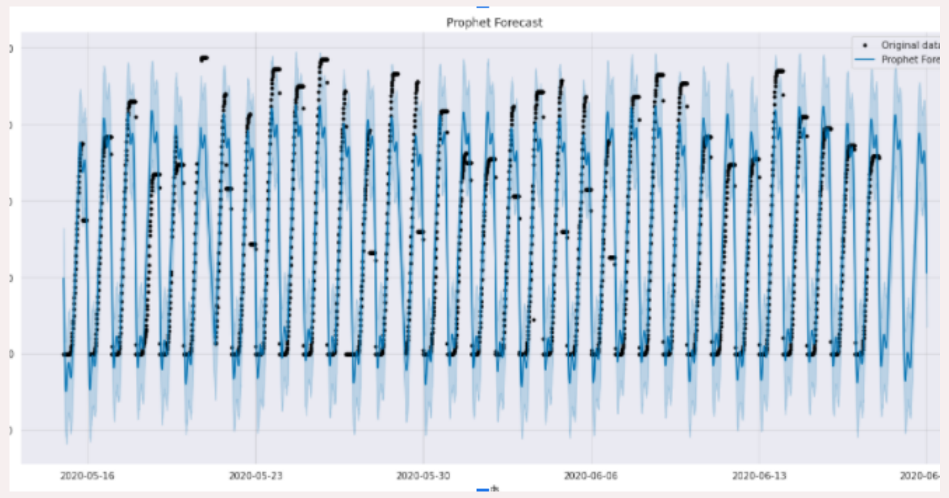
$$\gamma_j = \left(s_j - m - \sum_{l<j} \gamma_l\right)\left(1 - \frac{k + \sum_{l<j} \delta_l}{k + \sum_{l \le j} \delta_l}\right)$$

At last, the piecewise growth='logistic' model is reached -

$$g(t) = \frac{C(t)}{1 + \exp(-(k + \mathbf{a}(t)^\intercal \boldsymbol{\delta})(t - (m + \mathbf{a}(t)^\intercal \boldsymbol{\gamma})))}$$

PREDICTIONS

The prediction on the input data by **Prophet** (shown by the continuous curve in blue) and the original data.



CONCLUSION

In this work, we have created an application which takes the solar weather data and uses it to forecast solar energy for days in the future. Also it was able to identify sub-optimally performing solar panels which needed cleaning or maintenance.

We find that employing time series models is a complex procedure due to the non-stationary energy time series. In contrast, machine learning techniques were more straightforward to implement. In particular, we find that the Prophet performs best on average across all the data.