## **Literature Survey:**

## **Existing Problem:**

Wind energy plays increasing role in the supply of energy world-wide. The energy-output of a wind farm is highly dependent on the weather conditions present at its site. If the output is predicted more accurately, the energy suppliers can coordinate the collaborative production of different energy sources more efficiently to avoid costly overproduction. In this paper, we do energy prediction based on weather data and analyse the important parameters as well as their correlation on the energy output.

## **Proposed Solution:**

Our aim is to map weather data to energy production. We wish to show that even data that is publicly available for weather stations close to wind farms can be used to give a good prediction of the energy output. Furthermore, we examine the impact of different weather conditions on the energy output of the wind farms. We are building an IBM Watson Auto AI Machine Learning technique to predict the energy output of wind turbine. We deploy the model on IBM cloud to get scoring end point. It can be used as API in mobile app or web app building. We are developing a web application which is built using node red service. We use the scoring end point to give user input values to the deployed model. The model prediction is then showcased on User Interface to predict the energy output of wind turbine.

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