

Analysis of Regression Models for estimating the main bearing loads of wind turbines

Master Thesis Mithun Nagesh Shet Aachen, 12.08.2022





Structure







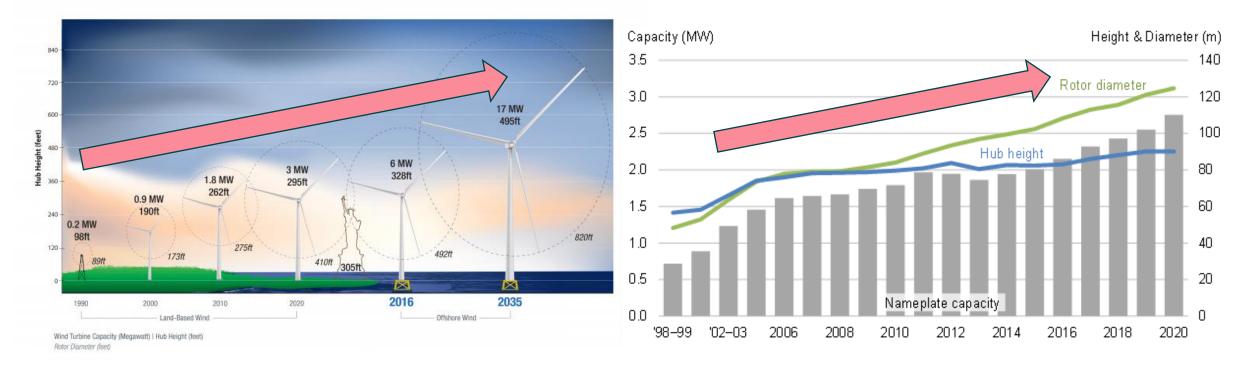
MOTIVATION







Motivation



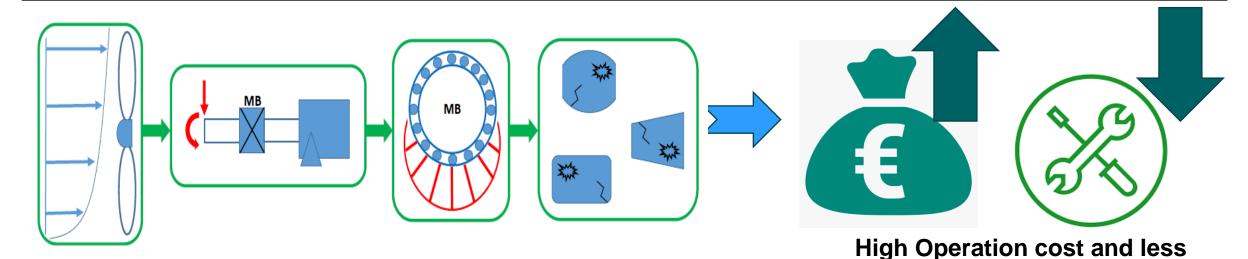
- Wind is set for largest increase in renewable energy generation growing by 275TW by 2021.
- The trend shows that there is substantial increase in diameter of turbine blades and size of hub every decade by an amount of 40 percent every decade.
- This increased size has significantly increased the torque and non torque loads.

Source: Office of energy efficiency and renewable energy





Motivation



- Under ideal conditions, lifespan of wind tubine is around 20 years.
- In actual, the wind turbine lasts for about 6 years.

Reason:

- Fatigue mechanism
- Wear and tear due to bearing misalignment
- Bearing unseating, skewing and sliding due to high axial to radial loads.

Solution:

Load monitoring system to monitor loads and send signals prior to observed failures.





service life



BACKGROUND

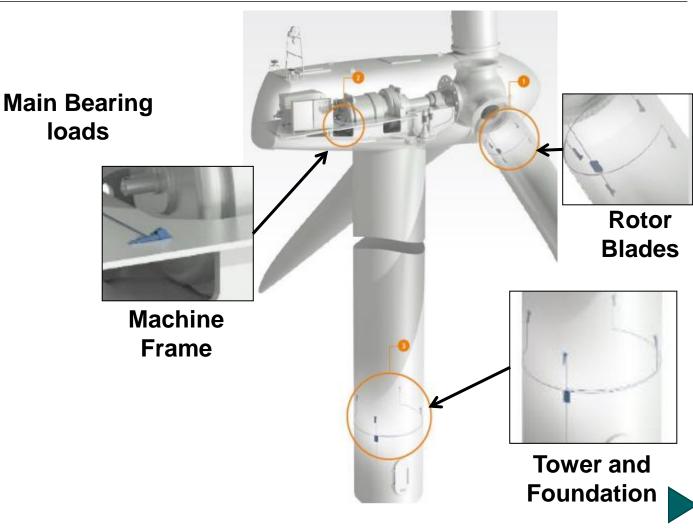




Background



- Currently strain based load estimation is used.
- Measurement based on linear relationship between strains and loads.
- Vulnerable to calibration error and signal drift.
- Limited lifetime.
- A better technology is necessary which is long-lasting and robust.



Source: Leine Linde Systems



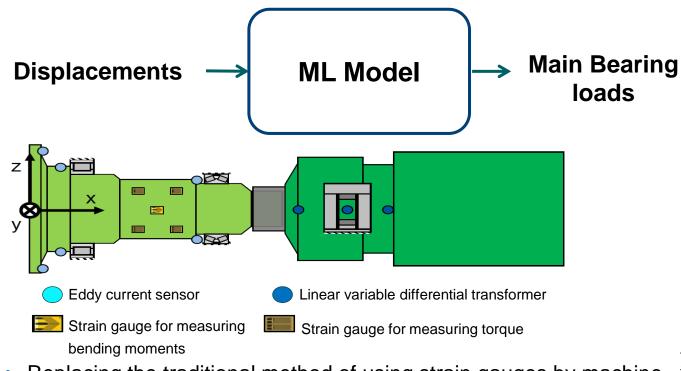


OBJECTIVE



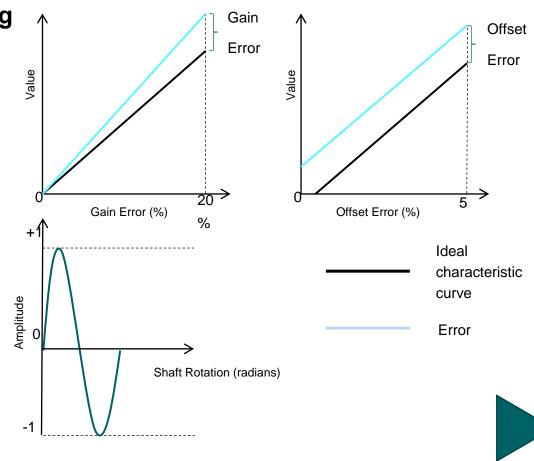


Objective



- Replacing the traditional method of using strain gauges by machine learning models.
- Training, building and testing the models from displacement signals recorded by Eddy current sensors to predict loads.
- Checking robustness of models to errors like Gain error, Offset error and sinewave error.

Model Robustness





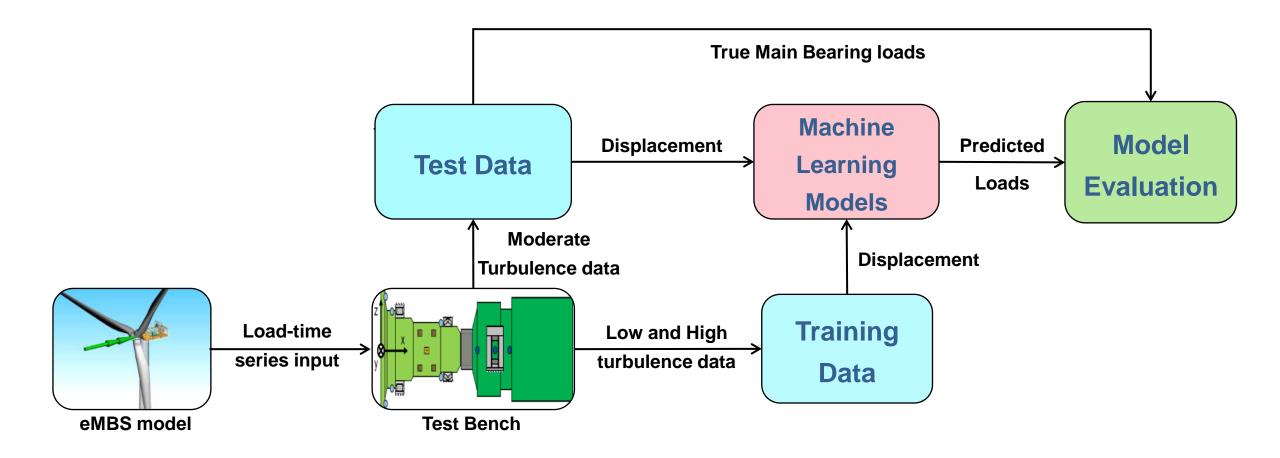


METHODOLOGY





Methodology









EDA and Feature Engineering

EDA

LPR

TM

SVR

GPR

EBT

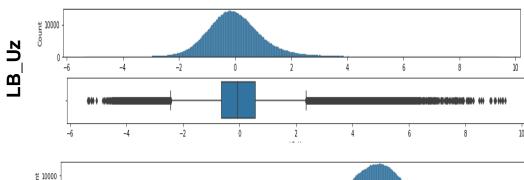
ANN

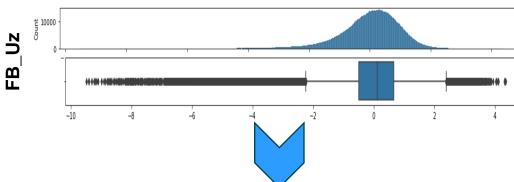
Variables study

| Independent Variables | | Response Variable |
|-------------------------------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|
| Fixed Bearing (FB) | Loose Bearing (LB) | Main Bearing Loads |
| Linear Displacements | Linear Displacements | Fixed Bearing Loads |
| x direction - FB_Ux y direction - FB_Uy z direction - FB_Uz | x direction - LB_Ux y direction - LB_Uy z direction - LB_Uz | x direction - FB_Fx y direction - FB_Fy z direction - FB_Fz |
| Angular Displacements | Angular Displacements | Loose Bearing Loads |
| y axis - FB_PHIy z axis - FB_PHIz | y axis - LB_PHIy z axis - LB_PHIz | y direction - FB_Fy z direction - FB_Fz |

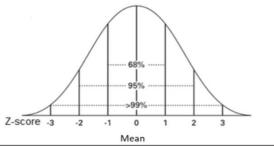
- Performance of regression models depend on quality of data and outliers can lead to high variance.
- The training data was split in 80% for training and 20 % for validation.
- The data was normalized using **Z-score** method.

Outlier Detection









$$z = \frac{x - \mu}{\sigma}$$

$$\mu=$$
 Mean

$$\sigma=$$
 Standard Deviation







Linear and Polynomial Regression

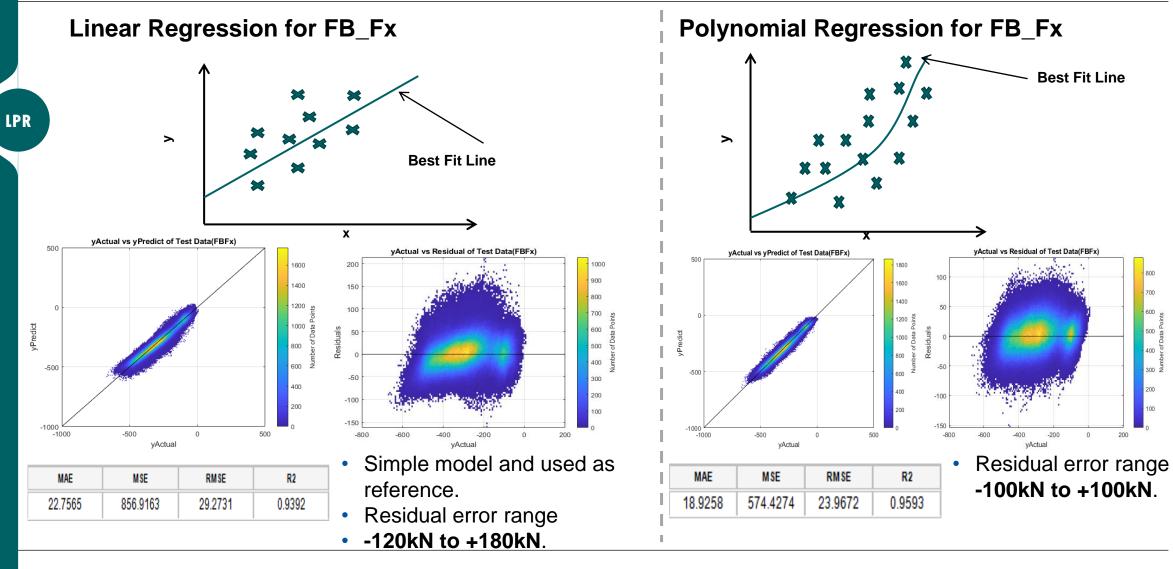
EDA

TM

SVR

GPR

EBT







Regression Tree Model

EDA

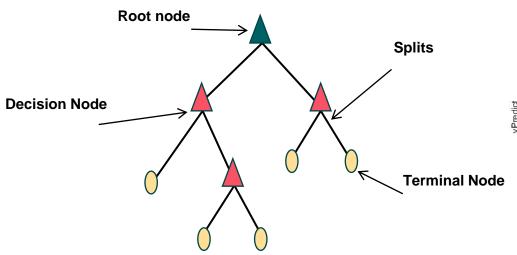
LPR

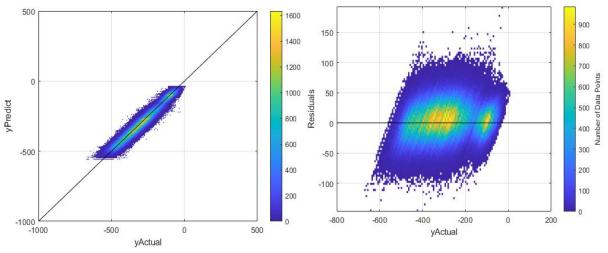
TM

SVR

GPR

EBT





- Flexibility to capture nonlinear predictorresponse relationship.
- Minimum leaf size set at 35 to 40 for balanced fit.
- Residual error varying between ±110kN with high density points found at around ±25kN

| MAE | MSE | RMSE | R2 |
|---------|----------|---------|--------|
| 20.6247 | 681.8551 | 26.1124 | 0.9516 |





Support Vector Regressor

EDA

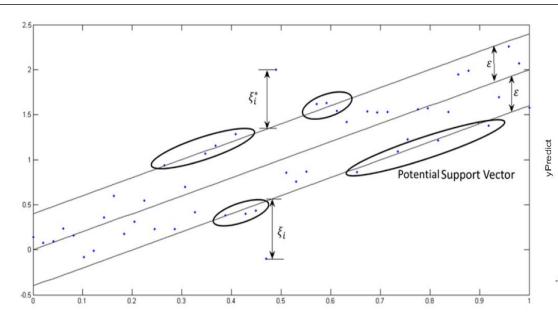
LPR

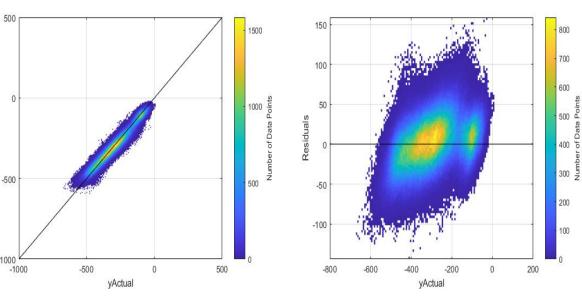
TM

SVR

GPR

EBT





- Consists of E tube which reformulates the optimization problem to find best tube that approximates continuous valued function.
- The kernel was set as polynomial of order 2.
- The residual error varied between ±120kN with high density of points seen around ±35kN.

| MAE | MSE | RMSE | R2 |
|---------|----------|---------|--------|
| 22.3663 | 796.6266 | 28.2246 | 0.9435 |





Gaussian Process Regressor

EDA

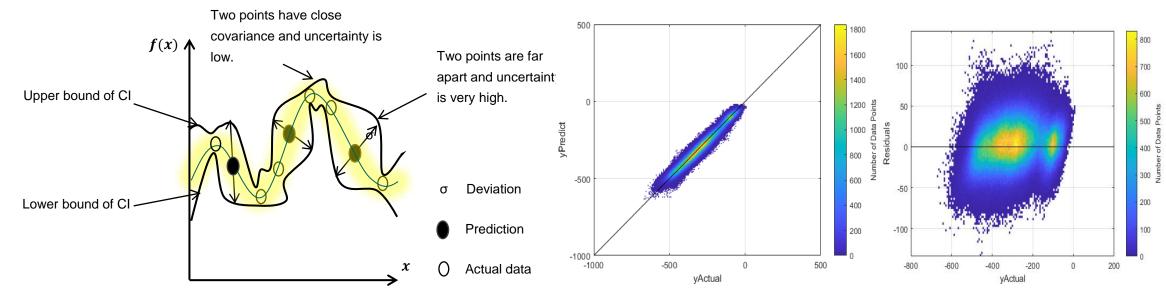
LPR

TM

SVR

GPR

EBT



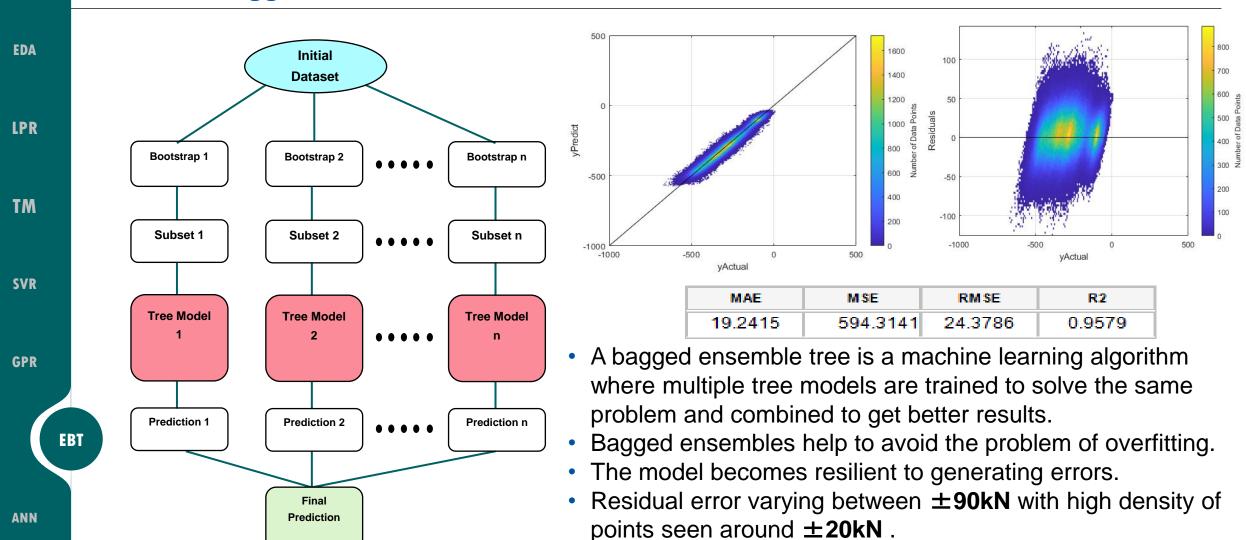
- Gaussian process regression (GPR) models are nonparametric kernel based probabilistic models.
- Kernel function used is squared exponential based on the data distribution.
- The residual error varies between ±95kN with high density of points seen around ±25kN.

| MAE | MSE | RMSE | Rsq |
|---------|----------|---------|--------|
| 18.5603 | 553.0644 | 23.5173 | 0.9608 |





Ensemble Bagged Tree







Artificial Neural Network

EDA

LPR

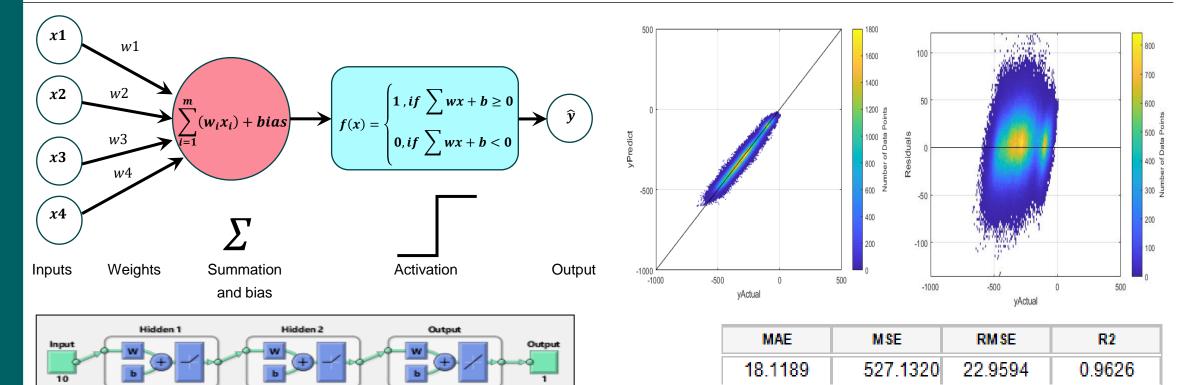
TM

SVR

GPR

EBT

ANN



- To model a better nonlinear correlation between the displacements and the loads.
- The model was built with 2 hidden layers with RELU as activation function.

Residual error varying between
 ±80kN with high density of points seen around ±20kN.





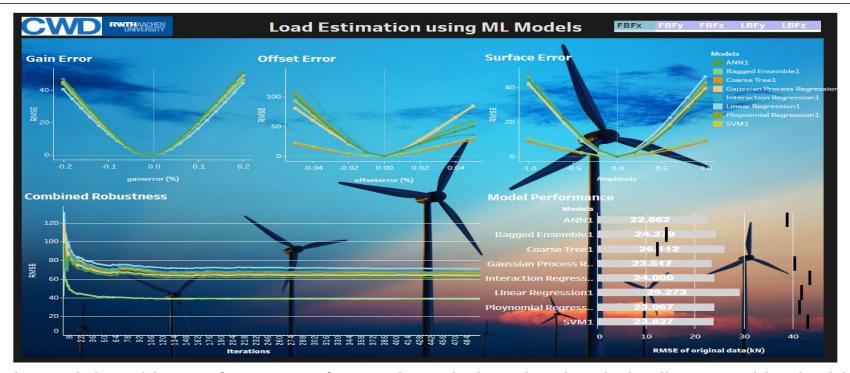


RESULT STUDY





Result Study



The results of each model and its performance for each main bearing loads is discussed in dashboard which can be accessed using below link.

https://public.tableau.com/views/Thesisresults_dashboard_v3/Dashboard1?:language=en-US&publish=yes&:display_count=n&:origin=viz_share_link







Summary and Outlook





Summary and Outlook

Summary:

- With approach presented in thesis, Regression models can estimate main bearing loads from displacement values with certain degree of error.
- Apart from linear model, all models could capture nonlinearity due to bearing surface and clearance with Bagged ensemble showing highest robustness.
- Bagged Tree ensemble model consistently showed strong robustness for all main bearing loads.
- ANN model showed good performance with original dataset and captured nonlinearity but was inconsistent in robustness test.
- Compromise made between the accuracy and robustness.

Outlook:

- Models can be further trained with dataset consisting all kinds of error for better performance to capture nonlinearities.
- Further study is needed on the minimum threshold for accuracy and robustness required to be implemented in real world.







Thank you for your attention.

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