

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

Master Thesis Mithun Nagesh Shet Aachen, 12.08.2022





### **Structure**







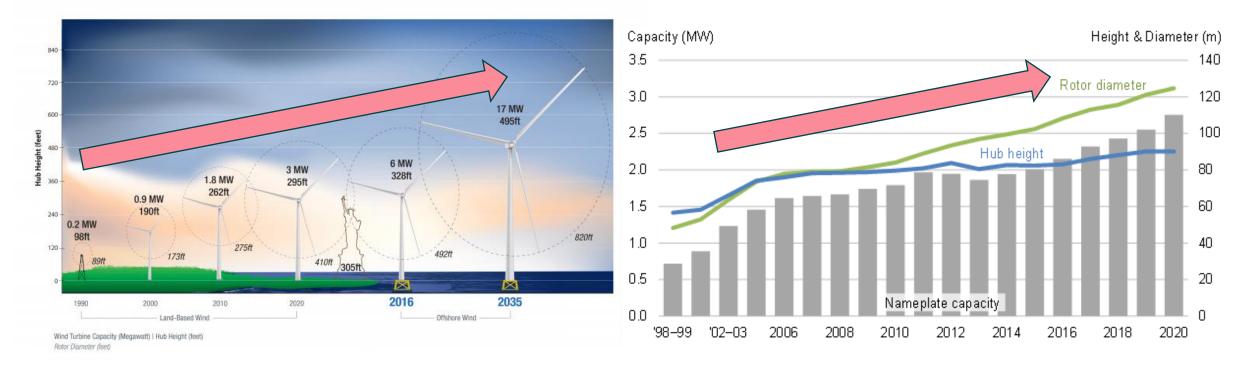
## **MOTIVATION**







#### **Motivation**



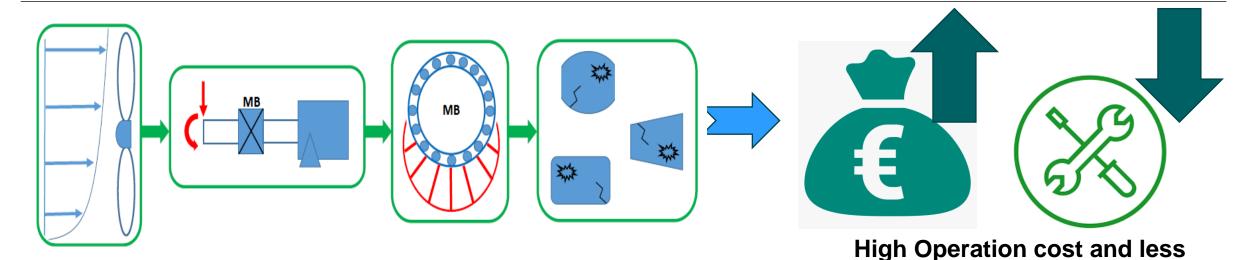
- Wind is set for largest increase in renewable energy generation growing by 275TW by 2021.
- The trend shows that there is substantial increase in diameter of turbine blades and size of hub every decade by an amount of 40 percent every decade.
- This increased size has significantly increased the torque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

Source: Office of energy efficiency and renewable energy





#### **Motivation**



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

#### Reason#:

- 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.

# Source: Wind turbine main-bearing loading and wind field characteristics, Edward Hart





reliability



## **BACKGROUND**

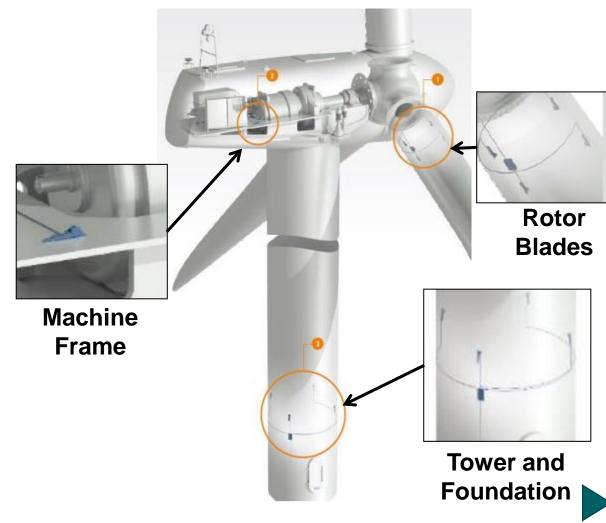




## **Background**



- 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 typically 1 to 3 years\*.
- A better technology is necessary which is long-lasting and robust.



# Source: Fibre Optic Blade Monitoring for optimisation of offshore wind farm O&M, TW Verbruggen





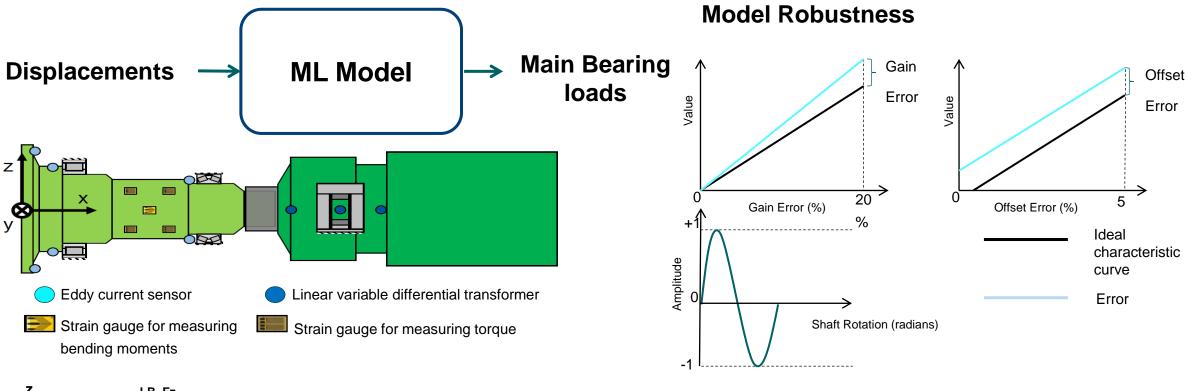
Source: Leine Linde Systems

## **OBJECTIVE**





## **Objective**





- 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.



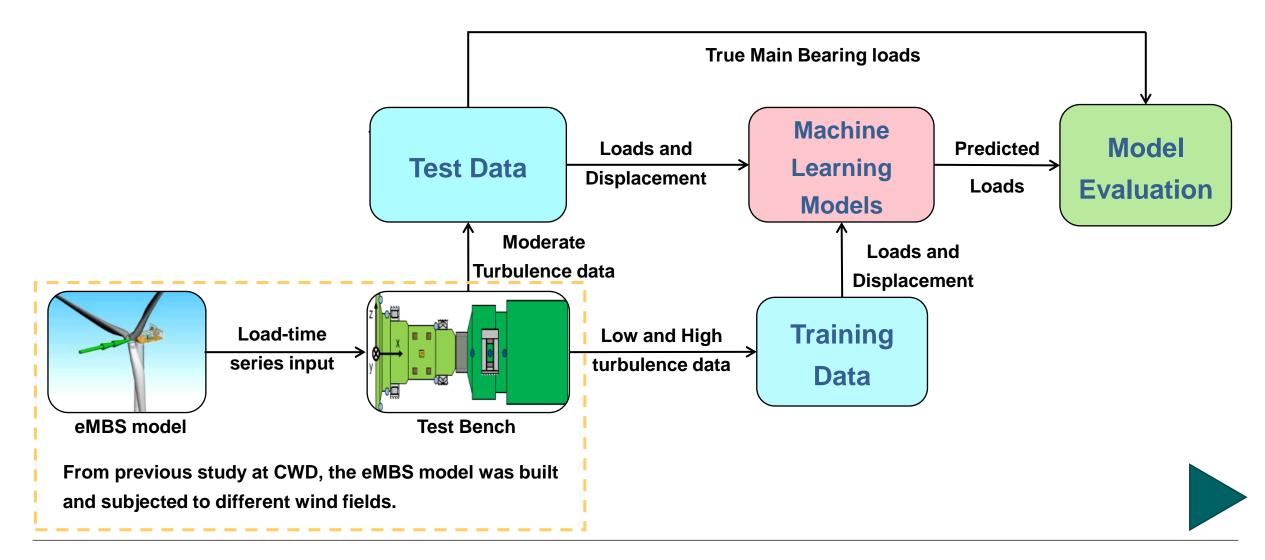


## **METHODOLOGY**





## **Methodology**







## **EDA** and Feature Engineering

EDA

LPR

**TM** 

**SVR** 

**GPR** 

**EBT** 

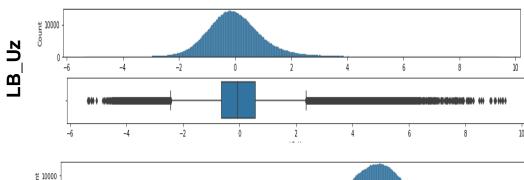
ANN

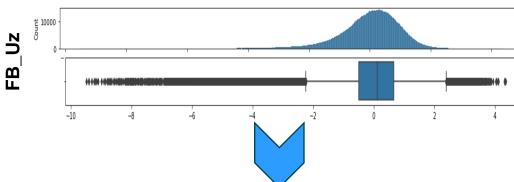
## Variables study

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	

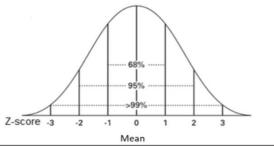
- Performance of regression models depend on quality of data and outliers can lead to high variance.
- The training data was split in 80% for training and 20 % for validation.
- The data was normalized using **Z-score** method.

#### **Outlier Detection**









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

$$\mu=$$
 Mean

$$\sigma=$$
 Standard Deviation







## **Linear and Polynomial Regression**

**EDA** 

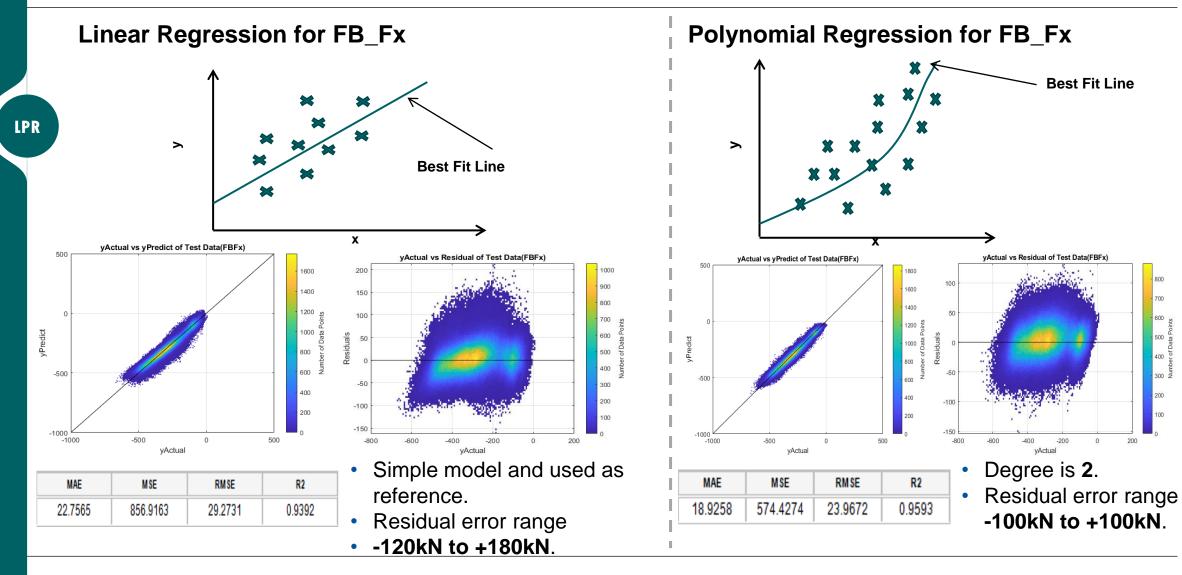
TM

SVR

**GPR** 

**EBT** 

ANN







## **Regression Tree Model**

**EDA** 

LPR

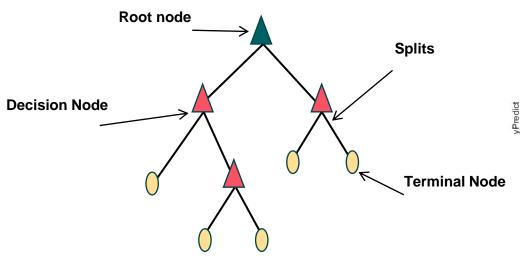
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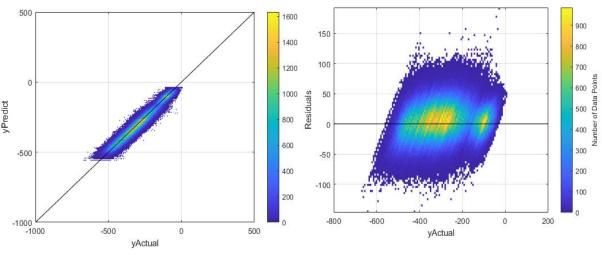
**SVR** 

**GPR** 

**EBT** 

ANN





- 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** 

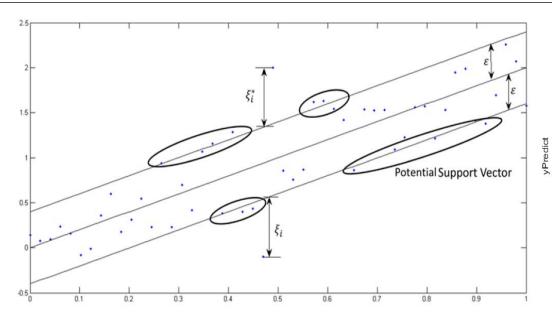
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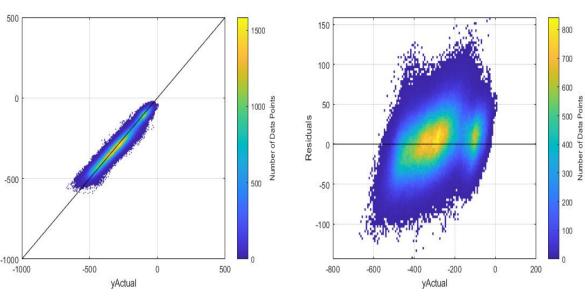
SVR

**GPR** 

**EBT** 

ANN





- 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





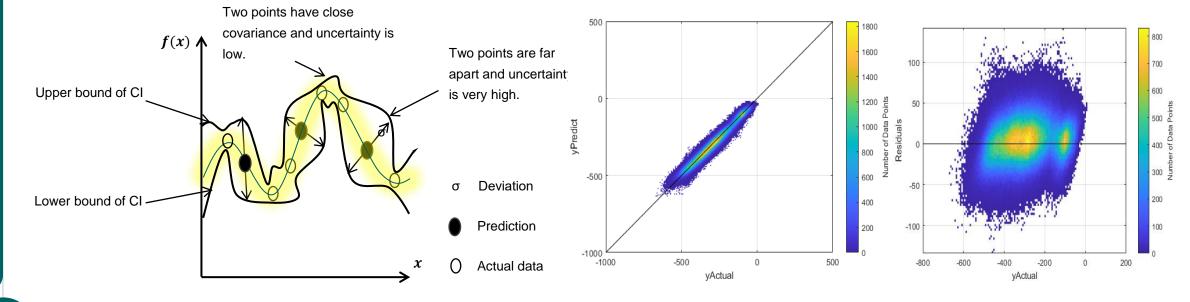
## **Gaussian Process Regressor**

EDA

LPR

TM

**SVR** 



GPR

 Gaussian process regression (GPR) models are nonparametric kernel based probabilistic models.

MAE	MSE	RMSE	Rsq
18.5603	553.0644	23.5173	0.9608

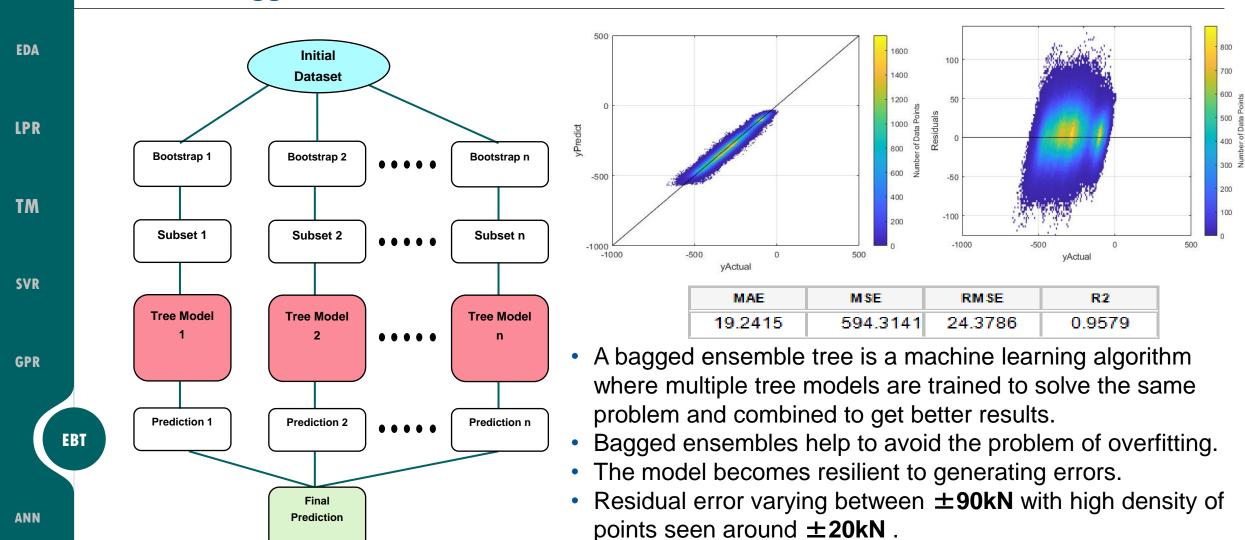
- Kernel function used is squared exponential based on the data distribution.
- The residual error varies between ±95kN with high density of points seen around ±25kN.





**EBT** 

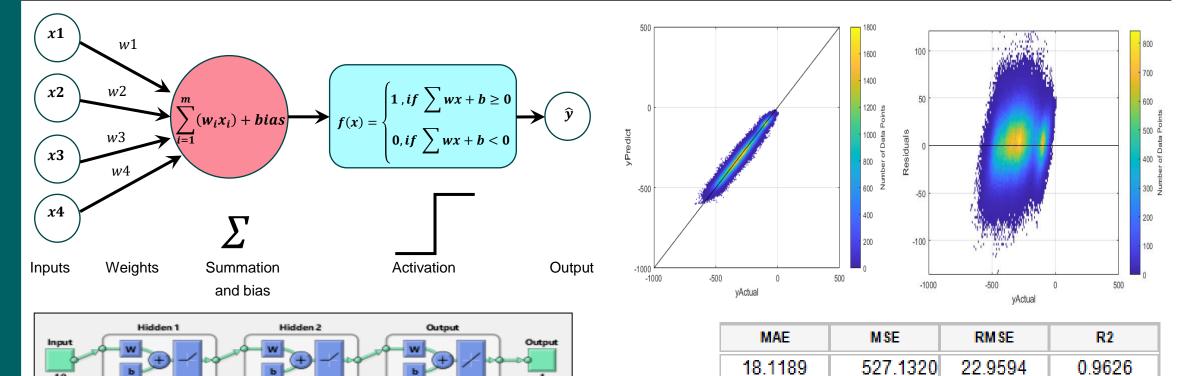
### **Ensemble Bagged Tree**





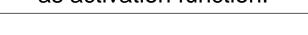


#### **Artificial Neural Network**



 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.







ANN

EDA

**LPR** 

TM

**SVR** 

**GPR** 

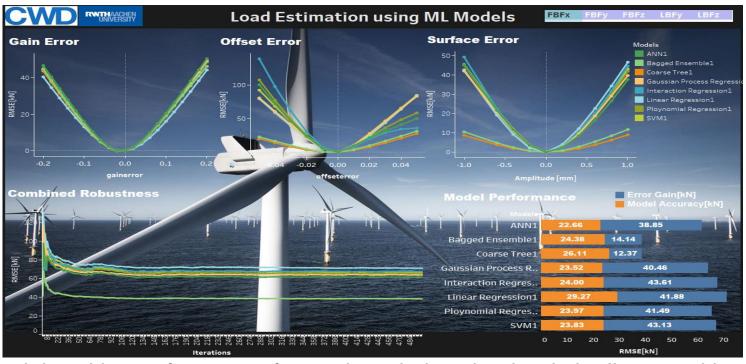
**EBT** 

## **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\_v4/Dashboard12?: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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