Expected wind turbine load estimation based on the wind field joint pdf constructed using the mixture Gaussian-EM algorithm.

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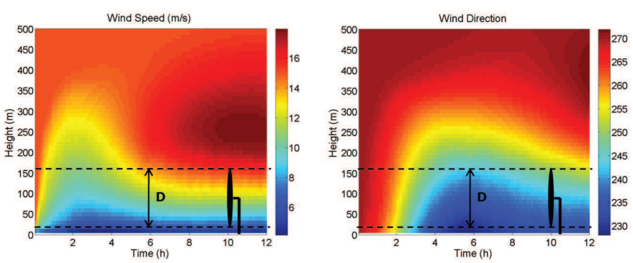
1 Introduction

1.1 Motivation

The stable boundary layer (SBL) is a stably stratified atmospheric layer that usually forms in the night over land when the earth cools as a result of a net loss of radiation[7]. The wind field characteristics in SBL distinctly differ from those in unstable boundary layer that forms in the daytime. Figures 1(a) and 1(b) show how the longitudinal wind speed and the wind direction change with the time. The variations in wind field characteristics accordingly affect the wind turbine responses such as extreme load, power output, and fatigue damage. Understandings in the wind field characteristics variation and the corresponding impacts on a wind turbine, therefore, very important not only for designing but also for managing a wind turbine effectively.



(a) Longitudinal wind speed (b) Wind direction

Figure 1: Evolution of the wind field with time. The 3D wind field is simulated by large-eddy simulation by Prof Basu from NCSU

1.2 Objective

The machine learning algorithms are applied, in this paper, to understand i) how the wind field characteristics change depending on atmospheric conditions and ii) how wind turbine loads are affected by different wind field characteristics. The variations in wind field characteristics are investigated by comparing the joint probability distribution function (PDF) for wind field input features. Gaussian Mixture Model (GMM) is implemented to construct the PDFs conditional on the time, day and night times. The influence of wind field on wind turbine loads are studied by constructing the wind turbine load classification model mapping wind field input features to wind turbine load statistics. To this end, multi-class classification algorithm based on Gaussian Discriminative Analysis (GDA) is implemented.

On the basis of the two separately constructed statistical models, the joint pdf for wind field features and the wind turbine load classification function, the expected wind turbine class can be calculated in a probability framework. From a lifetime health monitoring perspective, it is important to tack the expected wind turbine load given a certain atmospheric condition rather than simply identifying abnormal loads. The instantaneously monitored abnormal loads do not necessarily indicate the deterioration in a wind turbine system since these loads can be caused by strong wind in a short duration. In contrast, if the expected load changes over a time, it can possibly indicate that the system is under abnormal conditions. The expected wind turbine load classes are compared between the day and night time conditions as an example. The overall framework and objectives are summarized in Figure 2.

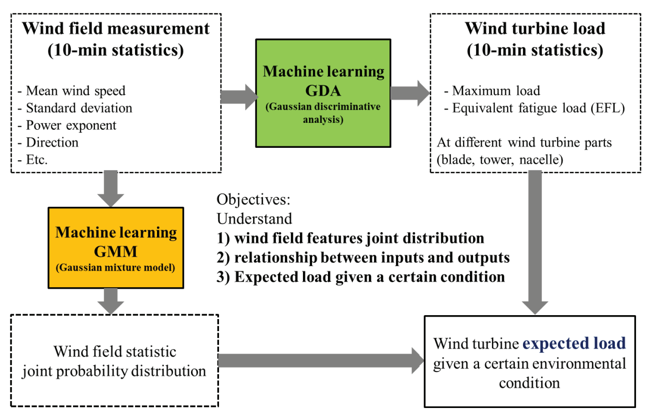


Figure 2: Machine learning approaches and the objectives

2 Methodology

2.1 Input and output data

We use wind fields simulated by the computational fluid dynamic code (large eddy simulation) and the corresponding wind turbine load responses simulated by the aerodynamic wind turbine load analysis code (FAST[3]). The characteristics of a 10-min long wind field are described by time-averaged statistics. The mean wind speed at a wind turbine hub height μ_U, the power exponent α describing the steepness of the vertical wind profile, and the standard deviation of wind speed σ_U measuring the level of turbulence. Wind turbine blade bending moment statistics, the 10-min maximum load and the equivalent fatigue damage, are used as outputs. The input and output statistics are depicted in Figure 3

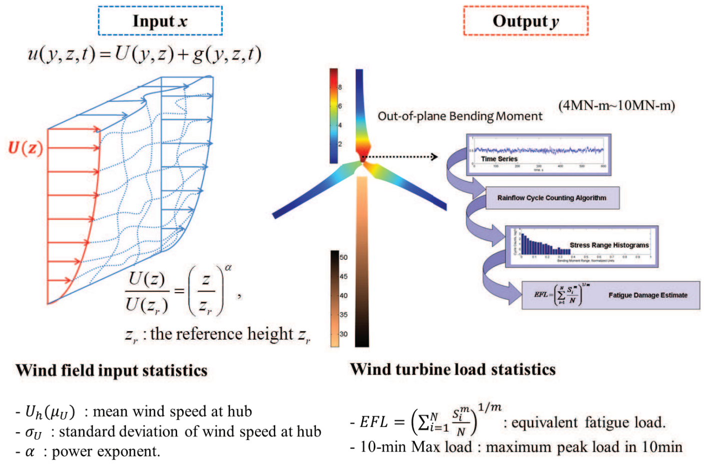


Figure 3: Wind field input features and the output load statistics

2.2 Procedures

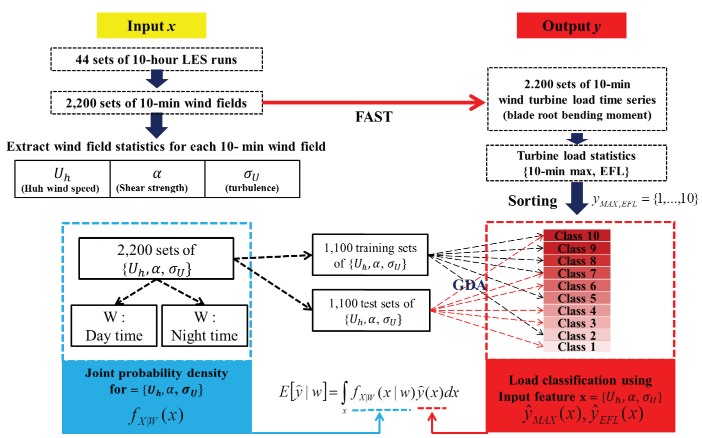


Figure 4: Implementation of machine learning algorithms on the extracted data set

To validate the proposed framework, we compare the expected wind turbine loads between the two operating times, day (unstable atmosphere) and night (stable atmosphere). Given 2,200 10-min wind field time series and the corresponding 2,200 wind turbine load times series, we extract the 2200 sets of input wind feature vectors, $x = (\mu_U, \alpha, \sigma_U)$, and the corresponding 2200 load statistics $y = (y_{Max}, y_{EFL})$. Figure 4 shows how the sets of wind field input feature vectors and the wind turbine load statistics are used for modeling the statistical model via the GMM and the GDA. For the GMM, we first classify wind field input data into two groups, day time and night time data on the basis of the time. Then, the conditional PDFs are modeled for the day time $f_{X|W}(x^{(i)}|w = day)$ and for the night time $f_{X|W}(x^{(i)}|w = night)$ using GMM and EM algorithm. The two PDFs can be updated during the daytime and the night time, respectively. With respect to GDA, the wind field input data are divided into training and testing data sets, both of which consists of 1100 sets of input output pairs $(x^{(i)}, y^{(i)})$. The wind input features from both daytime and the night time are included to the training data to exposure the the leaning algorithm to wide range of input feature space. Note that the GDA algorithm can be continuously updated regardlessly of the time since the output are assumed to depend only on the input feature vector x

3 Background

3.1 Gaussian discriminative analysis

There are two types of classification methods in machine learning. One is discriminativeäpproach that directly map input x to output y using parametric fitting. The other approach is ëgenerativeälgorithm differentiating data on the basis of input features' distributional information learned from data. For both classification methods, two-class, binary classification algorithm have been matured, while multi-class classification has not yet extensively studied. [1] surveyed different type of supervised multi-class classification methods, most of which are based on binary classifications. [4] has proposed Linear Discriminative in classifying multi labeling problem. In this study, Gaussian Discriminative Analysis (GDA) will be implemented in classifying the wind turbine load statistics.

The wind turbine load function $l(x)$ is constructed using the Gaussian Discriminative Analysis (GDA). The GDA is a generative learning algorithm that classify the input feature's label using the learned input feature distribution. Given the training data set, the posterior distribution on y given x is modeled according to Bayes rule as follows:

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} = \frac{p(x|y)p(y)}{\Sigma_y p(x|y)p(y)} \tag{1}$$

where $p(x|y)$ is the input feature distribution given the output label y, and $p(y)$ is the class priori. Then, to classify the label for the new input feature x_{new}, the label can be selected according to the maximum a posteriori detection (MAP) principle as follows:

$$\begin{aligned} y = \arg\max_y P(y|x_{new}) &= \arg\max_y \frac{p(x_{new}|y)p(y)}{P(x_{new})} \\ &= \arg\max_y p(x_{new}|y)p(y) \end{aligned} \tag{2}$$

In particular, GDA models $p(x|y = j)$ using the multivariate normal distribution as follows:

$$p(x|y = j) = \frac{1}{\sqrt{(2\pi)^n|\Sigma|}} exp\left(-\frac{(x-\mu_j)^T\Sigma^{-1}(x-\mu_j)}{2}\right) \tag{3}$$

and the class prior is modeled as:

$$p(y = j) = \phi_j \sim \text{Multinormial}(\phi) \tag{4}$$

The parameters ϕ, Σ, and μ can be found based on the maximum likelihood (ML) estimation. The log-likelihood of the data is given by

$$\begin{aligned} l(\phi, \mu, \Sigma) &= log \prod_{i=1}^{m} p(x^{(i)}, y^{(i)}; \phi, \mu, \Sigma) \\ &= log \prod_{i=1}^{m} p(x^{(i)}|y^{(i)}; \mu, \Sigma) p(y^{(i)}; \phi) \end{aligned} \tag{5}$$

and the parameters can be found By maximizing Eqn 5 with respect, respectively, to μ, Σ, and ϕ, the parameters can be obtained.

3.2 Mixtures of Gaussian Model Density Estimation Using EM

Finite mixture models are effective way for statistical modeling of data, which has been widely used for unsupervised clustering and density estimation[2]. In structural health monitoring community, Gaussian mixture model has been used for identifying damages in a structure on the basis of estimated output feature distribution[5]. In this paper, the wind field features characterizing the wind field are depicted by the their joint probabiilty density function constructed by Gaussian mixture model. The centers, shapes, and dispersion of PDFs depending on different atmospheric condition can give us insight into how the wind field evolves.

The join PDF $f_{X|W}(x|w)$ conditional on an atmospheric condition w is constructed on the basis of the Mixtures of Gaussian model whose parameters are derived by the Expectation Maximization (EM) algorithm. The mixture density is given as

$$f(x) = \sum_{j=1}^{k} \phi_j f_j(x) = \sum_{j=1}^{k} \phi_j p(x|\mu_j, \sigma_j) \tag{6}$$

where $p(x|\mu_k, \sigma_k)$ is the density of kth component, and it is expressed, in Gaussian Mixture Model (GMM), as a joint PDF for x as

$$p(x|\mu_j, \sigma_j) = \frac{1}{\sqrt{(2\pi)^n |\Sigma_j|}} exp \left(- \frac{(x-\mu_j)^T \Sigma_j^{-1} (x-\mu_j)}{2} \right) \tag{7}$$

In addition, ϕ_k is the weight (probability) of the jth Gaussian component.

To construct the mixture density we need to estimate the parameters μ_k, σ_k, and ϕ_k for each kth component. Given the independent data sets $\{x^{(1)}, ..., x^{(m)}\}$, the log-likelihood of the data is represented as

$$\begin{aligned} l(\theta) &= \sum_{i=1}^{m} \log \quad p(x^{(i)}; \phi, \mu, \Sigma) \\ &= \sum_{i=1}^{m} \log \sum_{z^{(i)}=1}^{k} p(x^{(i)}|z^{(i)}; \mu, \Sigma) p(z^{(i)}; \phi) \end{aligned} \tag{8}$$

where $z^{(i)}$ is the random variable drawn from the kth possible values ($z^{(i)} \sim$ Multinomial(ϕ)), and it specifies one of the k possible Gaussian components from which $x^{(i)}$ is drawn. When $z^{(i)} = j$, $p(x^{(i)}, z^{(i)}; \mu, \mathbf{\Sigma}) \sim N(\mu_j, \sigma_j)$ and $p(z^{(i)} = j|\phi) = \phi_j$. The fact that $z^{(i)}$ is not known makes the estimation of parameters based on the maximum likelihood principle difficult.

The expectation-maximization (EM) algorithm gives an efficient method for estimating parameters given the hidden (latent) random variables. The EM algorithm is composed of the two iterative steps: i) E-steps - evaluate the probability of $z^{(i)}$ given the current data and the previously estimated parameters as follows:

$$Q_i(z^{(i)} = p(z^{(i)}|x^{(i)}; \mu, \mathbf{\Sigma}, \phi) \tag{9}$$

and ii) E-step - choose the parameters that maximize the likelihood function

$$\begin{aligned} &\sum_{i=1}^{m} \sum_{z^{(i)}=1}^{k} Q_i(z^{(i)}) \log \frac{p(x^{(i)}, z^{(i)}; \mu, \mathbf{\Sigma}) p(z^{(i)}; \phi)}{Q_i(z^{(i)})} \\ &= \sum_{i=1}^{m} \sum_{j=1}^{k} Q_i(z^{(i)} = j) \log \frac{p(x^{(i)}|z^{(i)} = j; \mu, \mathbf{\Sigma}) p(z^{(i)} = j; \phi)}{Q_i(z^{(i)} = j)} \\ &= \sum_{i=1}^{m} \sum_{j=1}^{k} w_j^i \log \frac{\frac{1}{\sqrt{(2\pi)^n |\Sigma_k|}} exp \left(- \frac{(x-\mu_j)^T \Sigma_j^{-1} (x-\mu_j)}{2} \right) \phi_j}{w_j^i} \end{aligned} \tag{10}$$

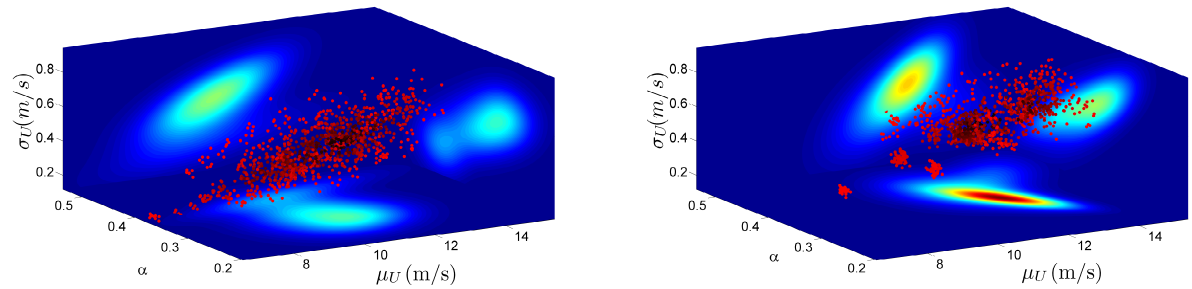
where $w_j^i = Q_i(z^{(i)} = j)$ is the soft classifier representing the probability that $x^{(i)}$ is drawn from the jth Gaussian component. In general EM framework, E-step is equivalent to constructing the lower bound on the likelihood function, and M-step is equivalent to maximizing the lower bounded maximum likelihood function. These two steps continue until the parameters converge. The formulas are from [6]

3.3 Expected Wind Turbine Load Class

The expected wind turbine load can be described as

$$E[y|w] = \int_x y(x) f_{X|W}(x|w) dx \tag{11}$$

where y is the wind turbine load, x is the wind field characteristic feature vector, and w represents the external atmospheric condition (e.g., location, time). To evaluate the expected load, the two functions are need to be defined: $y(x)$ mapping the input wind field features to the corresponding wind turbine load and $f_{X|W}(x|w)$ describing the joint PDF for wind field input features given a certain atmospheric condition. Note that the wind turbine loads only depend on the wind field input features x, and the PDF for x is subject to change according to different atmospheric conditions. In this sense, $E[y|w]$ can give us deep insights into how a wind turbine experiences different levels of a load given a easily observable atmospheric condition. In addition, the variation of $E[y|w]$ can possibly indicate the deterioration in a structure.



(a) Joint PDF (Undatble)

(b) Joint PDF (Stable)

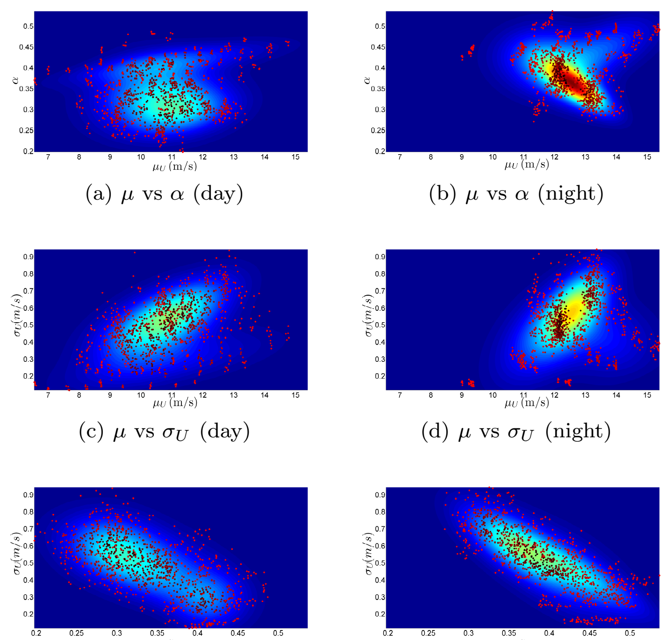
Figure 5: Comparison of joint PDF for wind field characteristics between the day and night times

4 Results

4.1 Construct Joint PDF for Wind Flow Characteristics

Figure 5 compares the 3D joint PDFs of wind field input features for the day and night time. The x, y, and z axes represent, respectively, the mean wind speed at the hub height μ_U, power exponent α, and standard deviation of wind speed σ_U. Therefore, the location of each dot specifies a 10-min wind field characteristic, and the color of the dot shows the relative probability calculated by the joint PDFs constructed by GMM. For the construction of PDFs, four Gaussian mixtures are used and EM algorithm is applied. Due to the modeled PDFs, the probability of any combination of wind field input features $x = \{\mu_U, \alpha, \sigma_U\}$ can be calculated. The calculated probability of wind input features are shown in three marginal PDFs, which are the projections of the 3D PDFs on the subspace spanned by the three combination of input features, (μ_U, α), $(\mu_U, \sigma_U$, and $(\alpha, \sigma_U)\}$. The marginal PDFs are shown in Figure 7 for the day and night times.

The two 3D PDFs clearly show the variation in the characteristics of wind field between the day and night time. Wind fields in the daytime has more large dispersion in each input feature than the night time wind field. This is because unstable boundary layer (daytime) has more active air flow mixing due to the convection.



(a) μ vs α (day)

(b) μ vs α (night)

(c) μ vs σ_U (day)

(d) μ vs σ_U (night)

(e) α vs σ_U (day)

(f) α vs σ_U (night)

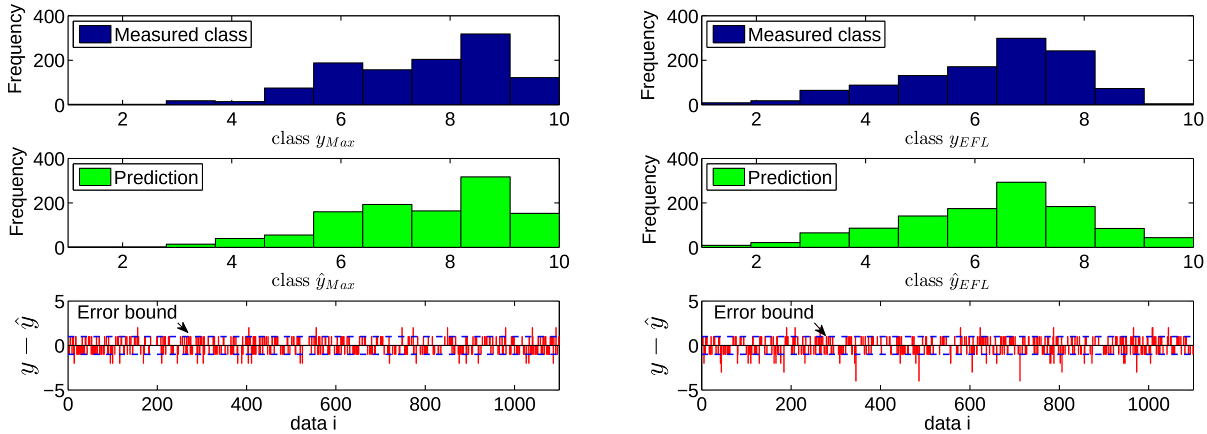
Figure 7: Marginal joint distribution

4.2 Classification of Load using GDA

Wind turbine load classification results are summarized in Figure 6. The two blade load statistics 10-min maximum and equivalent fatigue load corresponding to 1100 set of input features vectors are classified into 10 levels. The histogram for the measured and predicted classes are compared in each figure (Figure 6a for the 10-min maximum load and Figure 6b for the equivalent fatigue load). The distribution of classes (histogram) for the measured and predicted cases are compared and are shown to be comparable. In addition, the classification errors, defined as $y - \hat{y}$, are plotted for each input-output pair. The percentage of the exact classification ($y - \hat{y} = 0$) is about 50% due to the small input feature dimension (3) and large number of classes (10). However, if the error criterion is relaxed ($|y - \hat{y}| \leq 1$), the error percentages reduce to 3.55% and 2.91% for 10-min maximum load and equivalent fatigue damage. To increase performance, the second order polynomial kernel technic is used. It is worth noting that the exact load classification is not necessary for the wind turbine life cycle management perspective, but is is important how the distribution of the classes vary depending on the atmospheric and wind turbine operational conditions.

4.3 Comparison of Expected load

The expected class depending on atmospheric condition can be calculated on the basis of the input feature joint PDF and the class mapping function. The expected classes conditional on the day and night times are compared in Table1. For the estimation, 1100 sets of input feature vectors (550 from day time and 550 form night time) are used, and the predictions are made for the each of 550 sets of input feature vectors of day and night time that are not included into



(a) Maximum load

(b) EFL

Figure 6: Multi labels Gaussian discriminative analysis: comparison between measured and predicted classes. $|\hat{y} - y| \geq 1$ is considered as error. The error rate for y_{Max} is 3.55 % and the error rate for y_{EFL} is 2.91 %

Table 1: Comparison of the expected classes conditional on the wind turbine operational time

	Measured classes		Predicted classes	
	$\sum_{i=1}^{N_w} y^{(i)} f_{X\|W}(x^{(i)}\|w)$		$\sum_{i=1}^{N_w} \hat{y}(x^{(i)}) f_{X\|W}(x^{(i)}\|w)$	
	w=day	w=night	w=day	w=night
$E(y_{max}$ (MN-m)	7.9379	8.3024	7.9320	8.4337
$E(y_{EFL}$ (MN-m)	5.4452	7.4850	5.3040	7.5471

the training data. The effectiveness of statistical model can be evaluated by comparing the expected class based on the measured class and the predicted class, which show a great agreements. The trend of load statistic variations can be studied by comparing the day and night time expected values. Both of the expected load classes, especially EFL, are higher in the night time, whose trends are well captured by the statistical model used in this research.

5 Conclusion

In terms of the Statistical models,

- Gaussian Mixture model can be used for constructing a joint PDF for wind field input characteristics
- Gaussian Discriminative analysis can effectively predict the wind turbine blade load classes, even for multiple classes.
- GDA and GMM model can be integrated to estimate the expected wind turbine load in a certain condition.

For the understanding of wind field and wind turbine load output characteristics,

- In the night, wind speed is faster, less turbulent, and increase sharply with height. In addition, turbulence and the shear profile is negatively correlated.
- Maximum wind turbine blade load is higher in the day time, but the fatigue load higher in the night time.

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