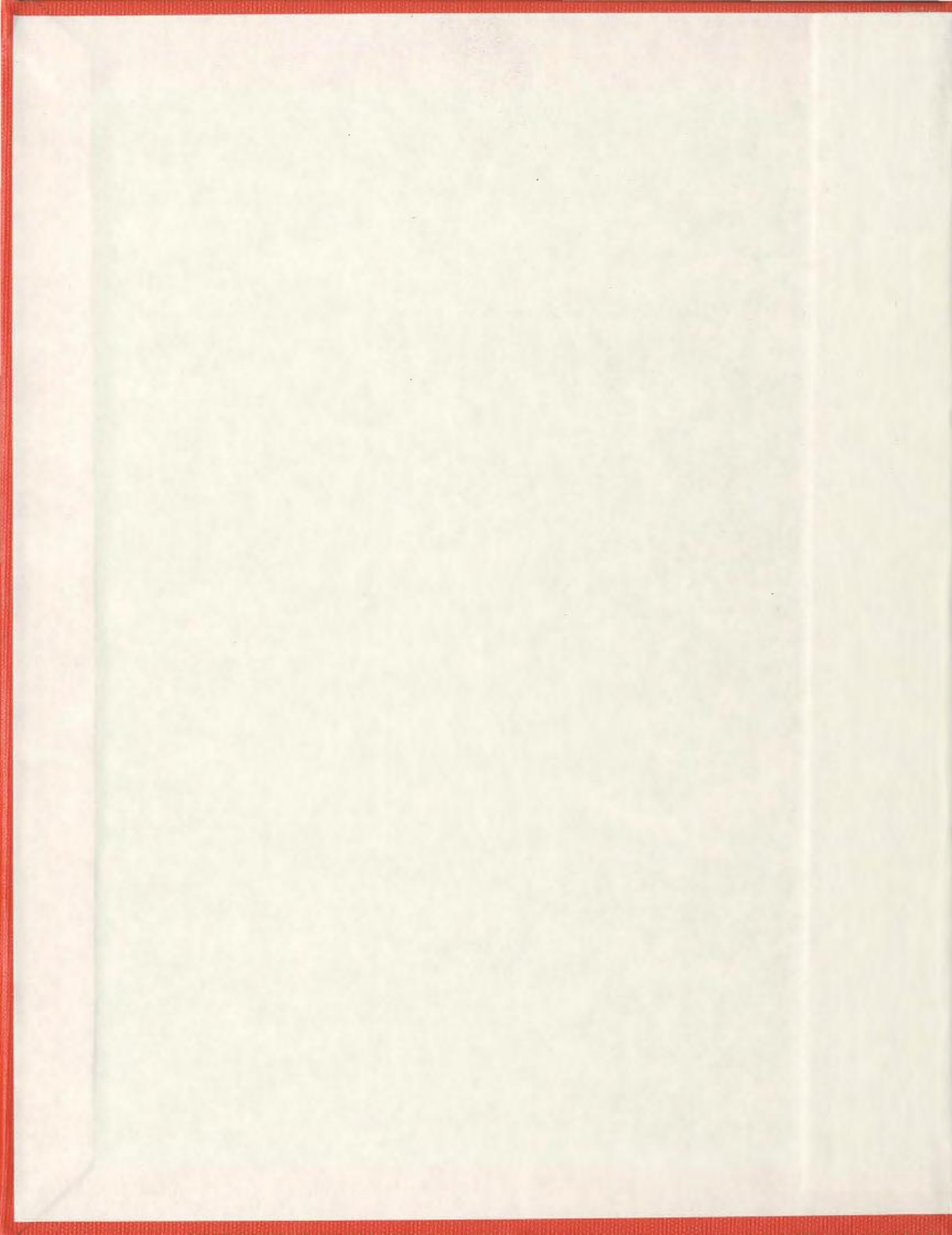


MODELLING AND SIMULATION OF WIND SPEED  
AND WIND FARM POWER PREDICTION

DEEPA PAGA



**MODELLING AND SIMULATION OF WIND SPEED AND  
WIND FARM POWER PREDICTION**

**by**

**© DEEPA PAGA**

**A Thesis submitted to the  
School of Graduate Studies  
in partial fulfillment of the requirements for the degree of**

**MASTER OF ENGINEERING  
Faculty of Engineering and Applied Science  
Memorial University of Newfoundland  
St. John's, Newfoundland**

**October, 2013**

## **ABSTRACT**

In this research, the wind speed model and the wind farm power model is developed and the results are estimated and simulated in the MATLAB from the designed algorithm using the historic input wind data. For the wind speed forecasting, the historic input wind speed data is used to estimate and forecast the wind speed in advance from the wind speed models. For the wind farm power model the input to the power model is the historic wind speed, pressure, temperature, wind direction, and air density. The wind farm power is determined from the designed algorithm simulated in the MATLAB.

The wake effect is considered in the wind farm power model and it depends on the wind direction and the wind farm layout. Transmission loss due to the power transmission in the cables is determined for the wind farm. Using this approach the wind farm power of the Fermeuse wind farm and the Cedar Creek Colorado wind farm is determined. This thesis presents the details and results of research.



## **ACKNOWLEDGEMENTS**

During the completion of this research work, I have worked with several personnel whose contributions to this work deserve special mention. It is a great pleasure for me to convey my deepest gratitude to them.

First of all I would like to place my special gratitude to my supervisor Dr. Tariq Iqbal for his valuable advice, guidance, and constant support from the very beginning of the research work, to its final stage. His experience in the field of Wind Energy was invaluable, as he provided me with steadfast encouragement through valuable ideas that helped me to grow as a research student. It is an honor for me to be a student under his supervision.

I would like to record my sincere gratitude to my co supervisor Prof. Andy Fisher for his guidance, advice and supervision. He always guided me on the right track in pursuing this degree. It was a pleasure to have him as my co supervisor.

This research work has been supported by the AMEC Earth and Environment. I would like to acknowledge them and thank all the members of the group.

I would like to thank Michael Abbott for his guidance in the very beginning of the project. I would like to thank him for providing the resources that helped me in the completion of the project.

I would like to thank David Bryan for his guidance and advice in the completion of the project. His experience in the field of Wind Energy is invaluable. He was very kind to assist me in this project.

I would like to thank Queen Elizabeth II library for assisting me with the map of the Cedar Creek Colorado wind farm through ARC GIS software that helped me in finding the distance between the nearest wind turbines.

I would like to thank Qiu Hongyuan for his help in the project.

During my research work, I always had support from my family members. It is a great pleasure for me that I can acknowledge them. My special thanks to my husband Pavan Kumar Purohit for his constant support, encouragement, and understanding from the very beginning of the research work. I would like to thank my daughter Priyamvada Purohit for being a lovely child and her understanding and cooperation throughout the completion of my research work. I would also like to thank my mother Arundhati Paga, my father Gururaj Paga, my sister Dr. Vani Kulkarni, my parents inlaws Dr. Muralidhar Purohit and Laxmi Purohit for their endless support and encouragement.

## Table of Contents

ABSTRACT .....	ii
ACKNOWLEDGEMENTS .....	iii
Table of Contents .....	v
List of Tables.....	x
List of Figures .....	xiii
List of Appendices .....	xxv
Chapter 1 .....	1
Literature Review of the Wind Speed Model and the Wind Power Model .....	1
1.1 Introduction .....	1
1.2 Summary of the Research Papers.....	2
1.3 The Wind Speed Forecasting Models .....	6
1.4 Design Overview of the Wind Power Physical Model .....	8
1.5 Research Goals.....	9
1.6 Typical Method or Technique Applied in Predicting the Wind Power of a Wind Turbine .....	10
1.7 Thesis Outline .....	11
Chapter 2 .....	12
Short Term Wind Speed Prediction .....	12
2.1 Background Information on the Wind Speed Prediction .....	12
2.2 Design of Five Hours In-advance the Wind Speed Predictor .....	13
2.2.1 Introduction.....	13
2.3 Detail Overview of the Wind Speed Prediction Models.....	13

2.3.1 Detailed Overview of the ARMA Model.....	17
2.4 The Mathematical Model of the ARMA Model .....	17
2.5 The Wind Speed Modeling Using ARMA Model .....	19
2.6 MATLAB Implementation of the ARMA Model.....	20
2.7 The MATLAB Simulation Results .....	21
2.8 An Hour Ahead Wind Speed Prediction Using the Kalman Filter and the Unscented Kalman Filter.....	24
2.8.1 Introduction .....	24
2.9 Part I: System Identification Toolbox GUI.....	26
2.9.1 Best fit estimation for the Auto Regressive Model.....	26
2.10 The Kalman Filter Wind Speed Estimation Using Auto Regressive Model	29
2.10.1 Detail Overview of the Kalman Filter.....	29
2.10.2 The Kalman Filter State Estimation .....	30
2.10.3 Filter Parameters and Tuning .....	32
2.10.4 MATLAB Implementation of the Designed Algorithm of the Kalman Filter.....	33
2.10.5 Observability and Controllability Test.....	33
2.11 MATLAB Simulated and Corrected Wind Speed Estimation Using Kalman Filter .....	35
2.12 Wind Speed Estimation Using Unscented Kalman Filter: .....	38

2.12.1	Algorithm of the Unscented Kalman Filter.....	38
2.13	MATLAB Results of the Unscented Kalman Filter Using Autoregressive Model .....	40
2.14	PART II: System Identification Toolbox GUI.....	42
2.14.1	Best fit estimation for the non linear Auto Regressive Exogenous Model .....	42
2.15	MATLAB Code analysis of the 2nd order non linear ARX Model .....	45
2.16	MATLAB simulated results of the Unscented Kalman filter using Non Linear Autoregressive Exogenous model .....	47
2.17	Conclusion .....	49
Chapter 3	.....	52
	Power Prediction of the Fermeuse, Newfoundland Wind Farm .....	52
3.1	Introduction .....	52
3.2	Wind Turbine Power Estimation.....	53
3.3	The Fermeuse Wind Farm Power Estimation .....	56
3.3.1	Layout of the Fermeuse Wind Farm .....	58
3.4	Methods/ Techniques Applied in Estimating Wind Turbine Power .....	62
3.5	Designed Algorithm of the Wind Power Model .....	63
3.5.1	Wind power of a wind turbine with no-wake effect .....	63
3.5.2	Wind power of a wind farm with no-wake effect .....	65



3.5.3	Wind power of a wind turbine with the wake effect .....	66
3.5.4	Wind power of a wind farm with the wake effect.....	68
3.5.5	Wake coefficient of the wind turbines in the wind farm.....	68
3.6	Detail Overview of the Fermeuse Wind farm .....	69
3.7	Transmission Loss in the Wind Farm .....	80
3.8	Wind Farm Power Calculation Results .....	82
3.8.1	Simulated MATLAB results using the designed algorithm to estimate the wind farm power .....	82
3.9	Conclusion .....	93
Chapter 4	.....	95
	Power Prediction of the Cedar Creek, Colorado Wind farm .....	95
4.1	Introduction .....	95
4.2	Wind Turbine Power Estimation.....	96
4.3	The Cedar Creek Wind Farm Power Estimation.....	99
4.3.1	Layout of the Cedar Creek Colorado Wind farm .....	99
4.4	Wind power of a wind turbine with no-wake effect .....	104
4.5	Wind power of a wind farm with no-wake effect .....	107
4.6.1	Wind power of a wind turbine with the wake effect .....	107
4.6.2	Wind power of a wind farm with the wake effect.....	111
4.6.3	Wake coefficient of a wind turbines in the wind farm .....	111

4.7 The Cedar Creek Wind Farm Data.....	111
4.8 Transmission Loss in the Wind farm .....	133
4.9 Wind Farm Power Calculation Results .....	136
4.9.1 Simulated MATLAB Results using the designed algorithm to estimate wind farm power .....	136
4.10 Conclusion .....	151
Chapter 5 .....	153
Conclusion and Future Work .....	153
5.1 Research Overview .....	153
5.2 Research Contribution.....	154
5.3 Future Work on the Wind Speed and the Wind Power Forecasting .....	156
Bibliography.....	158
Appendices.....	164

## **List of Tables**

Table 2.1 : Data Analysis of the Actual and the Predicted Wind Speed.....	23
Table 3.1: Specification of the Vestas V90 3 MW Wind Turbine.....	69
Table 3.2: Wind Turbines Details in the Fermeuse Wind farm .....	70
Table 3.3: Nearest Distance between the Neighboring Wind Turbines.....	70
Table 3.4: Wind direction and shadow region of the wind turbines (WT_Ash) in the Fermeuse wind farm.....	71
Table 3.5: Wind speed estimation of the physical factors effecting wind turbine-2 in the Fermeuse wind farm determined from the input wind speed data file1 .....	72
Table 3.6: Wind speed estimation of the physical factors effecting wind turbine-2 in the Fermeuse wind farm from the input wind speed data file2.....	72
Table 3.7: Wind speed estimation of the physical factors effecting wind turbine 2 in the Fermeuse wind farm from the input wind speed data file3.....	73
Table 3.8: Wind speed estimation of the physical factors effecting wind turbine-2 in the Fermeuse wind farm from the input wind speed data file4.....	73
Table 3.9: The wind power of the wind turbine -2 showing the effect of the individual physical factors considered from the input wind speed data file1 .....	75
Table 3.10: The wind power of the wind turbine -2 showing the effect of the individual physical factors considered from the input wind speed data file2. ....	75
Table 3.11: The wind power of the wind turbine -2 showing the effect of the individual physical factors considered from the input wind speed data file3. ....	76

Table 3.12: The wind power of the wind turbine -2 showing the effect of the individual physical factors considered from the input wind speed data file4. ....	76
Table 3.13: The Wake coefficient data determined from the wind direction and the shadow effect of the wind turbines in the wind farm.....	77
Table 3.14 Estimated average value of the wind power of the wind turbine-2 operating at the discspeed in the Fermeuse wind farm. ....	78
Table. 3.15 Estimated average value of the wind power of the wind turbine-2 operating at the wake speed in the Fermeuse wind farm. ....	78
Table 3.16: Estimated average value of the wind farm power of the Fermeuse.....	79
Table 3.17: The Fermeuse wind farm power estimated before and after aconstant transmission loss (TL) of 1% in the wind farm with and without wake effect....	81
Table 3.18: The estimated average value of the loss in power, given a constant transmission loss of 1%, with the wake effect and without wake effect.....	82
Table 4.1: Specifications of the Wind Turbines.....	112
Table 4.2: Layout data of wind turbines of Colorado wind farm [9]. Here FID is nearest feature identity. ....	112
Table 4.3: Wind Direction and Area of Shadow of the Wind Turbines in the Wind farm .....	119
Table 4.4: MATLAB estimated results of the wind turbine-2 from the input wind data file4. ....	126
Table 4.5: MATLAB estimated results of wind turbine-2 using the input wind data file #3. ....	126

Table 4.6: MATLAB estimated results of wind turbine-2 for an input wind data file 2.	
.....	127
Table 4.7: MATLAB estimated results of wind turbine-2 using the input wind data	
file 1. ....	127
Table 4.8: The wind power of a wind turbine -2 in the windfarm with the input time	
series data file 1.....	128
Table 4.9: Wind power of wind turbine -2 in the Colorado windfarm with the input	
wind data file 2.....	129
Table 4.10: Wind power of a wind turbine -2 in the windfarm using the input wind	
data file 3.....	130
Table 4.11: Wind power of a wind turbine -2 in the Colorado windfarm with the input	
wind data file 4.....	131
Table 4.12: Wake coefficient data determined from the wind direction and shadow	
effect of the wind turbines in the wind farm. ....	132
Table 4.13: Estimated power output of the Colorado wind farm.....	132
Table 4.14: Estimated Colorado wind farm power before and after transmission loss	
(TL) in wind farm.....	134
Table 4.15: Estimated Loss in the power of the Colorado wind farm due to power	
transmission. ....	135



## List of Figures

Figure 1.1: Average power curves for various turbulence intensities (5% (red), 10%(blue), 15%(green), 20%(yellow)) [4] .....	3
Figure 1.2: Wind turbine power curve with different air density [3] .....	5
Figure 2.1: Autocorrelation of the input wind speed data.....	21
Figure 2.2: Partial autocorrelation of the input wind speed data .....	22
Figure 2.3: Input hourly wind speed data.....	22
Figure 2.4: Predicted hourly five hours in advance wind speed data .....	22
Figure 2.5: Predicted wind speed using armax (1, 1) for a time span of 500 hours .....	23
Figure 2.6: Comparison of the actual and the predicted wind speed data in km/hr and time in hours.....	23
Figure 2.7: Input wind speed is plotted with respect to time .....	26
Figure 2.8 : Input wind speed has 2/3rd data as training data (green) and 1/3rd data as validation data (red) .....	26
Figure 2.9: Wind speed data processing in the system identification .....	27
Figure 2.10: Best fitted one step ahead wind speed data tested with AR model and the ARMA model of different model order in the system identification toolbox.....	28
Figure 2.11: One step ahead estimated AR 2nd order model and percentage of the best fit estimate. ....	29
Figure 2.12: Autocorrelation of the residual estimated using AR, 2nd order model ....	29
Figure 2.13: Properly tuned Kalman filter wind speed estimation .....	36
Figure 2.14: Kalman filter estimation with increase in measurement noise .....	36

Figure 2.15: Kalman Filter estimation with increase in process noise ( $Q_f$ ) and the measurement noise ( $R_f$ ) is remaining constant .....	37
Figure 2.16: Section of Kalman filter with increase in process noise ( $Q_f$ ).....	37
Figure 2.17: Principle of Unscented Transform [28] .....	38
Figure 2.18: Unscented Kalman Filter response at properly tuned.....	40
Figure 2.19: Unscented Kalman Filter response with the introduction of .....	41
Figure 2.20: Unscented Kalman Filter response with the introduction of process noise .....	41
Figure 2.21: Non linear ARX model compared with various model order.....	43
Figure 2.22: Training and Validation data for the wind speed in System Identification toolbox .....	43
Figure 2.23: Comparison of the best fit nlarx model of various order .....	44
Figure 2.24: The nonlinear ARX best fitted 1st and 2nd order model.....	44
Figure 2.25: Autocorrelation of residuals for the nlarx model.....	45
Figure 2.26: Nonlinear best fit estimation of the non linear arx 2nd order model.....	45
Figure 2.27: Process noise and measurement noise is reduced with UKF properly tuned.....	48
Figure 2.28: UKF performane with increase in process noise .....	48
Figure 2.29: UKF performane with increase in measurement .....	49
Figure 3.1: Vestas V90 3MW wind turbine [46] .....	54
Figure 3.2: Fermeuse wind farm layout [36] .....	58
Figure 3.3: Flowchart of the wind power model.....	60
Figure 3.4: Flow chart of the wind farm wake model.....	61

Figure 3.5: Wake effect in a wind farm [44].....	66
Figure 3.6: Power vs. Wind Speed characteristics of the Vestas V90 3 MW wind turbine (supplied power curve) .....	83
Figure 3.7: Power vs. Wind Speed characteristics of the Vestas V90 3 MW wind turbine (digitized and curve fitted).....	83
Figure 3.8: Recorded sensor height wind speed data for the Vestas V90 3MW wind turbine-2. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	84
Figure 3.9: Hub height wind speed is estimated for the Vestas V90 3MW wind turbine-2 at the hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	85
Figure. 3.10: Turbulence adjusted wind speed estimated for the Vestas V90 3MW wind turbine-2 at the hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	85
Figure 3.11: Estimated disc speed adjusted for turbulence and shear for the Vestas V90 3 MW wind turbine-2 at the hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	86
Figure 3.12: Wake speed estimated for Vestas 3 MW wind turbine-2 at hub height (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	87
Figure 3.13: Estimated power curve of the Vestas 3MW wind turbine adjusted with air density .....	87
Figure 3.14: Comparison of the wind power of the wind turbine -2 operating at the wake effect (black) and no wake effect (red) .....	88

Figure 3.15: Estimated wind farm no-wake power with respect to time (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	89
Figure 3.16: Estimated wind farm wake power with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	89
Figure 3.17: Comparison of estimated wind farm power with the wake effect (red) and without wake effect (black) is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	90
Figure 3.18: Wind direction (degrees) at the wind farm site for a time span of 10,000 minutes. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	91
Figure 3.19: Wake coefficient determined from the wind direction is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	91
Figure 3.20: Wind direction (degrees) at the wind farm site for a time span of 5000 minutes. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	91
Figure 3.21: Wake coefficient determined from the wind direction is plotted with respect to time (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	92
Figure 3.22: Wind farm output power with power loss (1%) in transmission with no wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	92

Figure 3.23: Wind farm output power with power loss in transmission (1%) and the wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	93
Figure 4.1: Mitsubishi Wind Turbine [48].....	97
Figure 4.2: Cedar Creek- I Wind farm Layout [47] .....	100
Figure 4.3: A section of the Cedar Creek Wind farm Layout [47] .....	100
Figure 4.4: Flowchart of the wind power model.....	102
Figure 4.5: Flow chart of the wind farm wake model.....	103
Figure 4.6: Wake Effect in a Wind farm [51] .....	108
Figure 4.7: Power vs. Wind Speed characteristics of Mitsubishi 1 MW wind turbine (supplied power curve).....	136
Figure 4.8: Power vs. Wind Speed characteristics of GE 1.5 MW wind turbine (supplied power curve).....	137
Figure 4.9: Power vs. Wind Speed characteristics of Mitsubishi 1 MW wind turbine (curve fitted).....	137
Figure 4.10: Power vs. Wind Speed characteristics of GE 1.5 MW wind turbine (curve fitted).....	137
Figure 4.11: Sensor height wind speed data for the GE 1.5 MW wind turbine-2 recorded from MET tower1. (Note: Time Scale: X axis:1 unit =10 minute; 1000 unit = 10000 minutes) .....	138
Figure 4.12: Sensor height wind speed data for the Mitsubishi 1.0 MW wind turbine-2 recorded from MET tower2. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	139



Figure 4.13: Hub height wind speed estimated for the GE 1.5 MW wind turbine-2. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	140
Figure 4.14: Hub height wind speed estimated for the Mitsubishi 1MW wind turbine-2. (Note: Time Scale: X axis: 1 unit =10 minute;1000 unit = 1000 minutes).....	140
Figure 4.15: Turbulence adjusted wind speed estimated for GE 1.5 MW windturbine-2 at hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	141
Figure 4.16: Turbulence adjusted wind speed estimated for Mitsubishi 1.0 MW wind turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	141
Figure 4.17: Estimated disc Speed (adjusted for turbulence and shear) for GE 1.5 MW wind turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	142
Figure 4.18: Estimated disc speed (adjusted for turbulence and shear) for Mitsubishi 1.0 MW wind turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	142
Figure 4.19: Wake speed estimated for GE 1.5 MW wind turbine-2 at hub height (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	143
Figure 4.20: Wake speed estimated for Mitsubishi 1.0 MW wind turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	143
Figure 4.21: Estimated power curve of GE 1.5 MW wind turbine-1 adjusted with air density. ....	144

Figure 4.22: Estimated power curve of the GE 1.5MW wind turbine-2 adjusted with air density .....	144
Figure 4.23: Estimated power curve of the Mitsubishi 1MW wind turbine-1 adjusted with air density .....	144
Figure 4.24: Estimated power curve of the Mitsubishi 1.0 MW wind turbine-2 adjusted with air density .....	145
Figure 4.25: Comparison of power estimated with wake (black) and without wake (red) effect for GE 1.5 MW wind turbine-2. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	145
Figure 4.26: Comparison of power estimated with wake (black) and without wake (red) effect for Mitsubishi 1.0 MW wind turbine-2. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	146
Figure 4.27: Estimated wind farm no-wake power with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	146
Figure 4.28: Comparison of estimated wind farm power with wake effect (red) and no-wake effect (black) with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes) .....	147
Figure 4.29: Wind direction (degrees) at the wind farm site for a time span of 10000 minutes. (Note: Time Scale: X axis: 1 unit =10 minute;1000 unit = 10000 minutes).....	148
Figure 4.30: Wake coefficient determined from wind direction is plotted with respect to time. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).....	148

Figure 4.31: Wind direction (degrees) at the wind farm site for a time span of 5000 minutes. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	148
Figure 4.32: Wake coefficient determined from wind direction is plotted with respect to time (Note: Time Scale: X axis: 1 unit =10 minute;1000 unit = 10000 minutes) .....	149
Figure 4.33: Wind farm output power with power loss (1%) in transmission with no wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	149
Figure 4.34: Wind farm output power with power loss (1%) in transmission and wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	150
Figure 4.35: Actual estimated wind farm power with transmission loss of 1% due to wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	150
Figure 4.36: Actual estimated wind farm power with transmission loss of 1% with no wake effect is plotted with respect to time (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).....	151

## List of Symbols

GPuncor = Uncorrected GE wind turbine power

MPuncor = Uncorrected Mitsubishi wind turbine power

U1 = Sensor height wind speed

H = Hhub = Hub height of wind speed

H1 = Sensor height of MET tower

0.143 = Shear exponent

Iu = Turbulence intensity

$\sigma$  = Standard deviation of wind speed

U = Mean or average wind speed

U' (TI) = Turbulence adjusted speed

$\alpha$  = Shear exponent determined from turbulence adjusted speed

U'2(TI) = Turbulence adjusted speed at unknown height

U'1(TI) = Turbulence adjusted speed at sensor height

H2 = Unknown height

$\bar{U}_{Disk}$  = Disc speed of wind turbine

A = Area of wind turbine

H-R = Hub Height – Radius of Rotor Disc

H+R = Hub Height + Radius of Rotor Disc

Uz = Power law equation of shear or Unknown speed estimated using numeric

integration from lower rotor tip to upper rotor tip of the wind turbine to find equivalent disc speed and this value is assumed at hub height

$R$  = Radius of rotor disc

$Z$  = Height range to find disc speed using numeric integration from lower rotor tip to upper rotor tip of wind turbine

$dz$  = Step size to specify height range

$\rho$  = Air density or actual density

$P$  = Pressure

$T$  = Temperature

$P1(\text{corr})$  = Corrected Power

$P1(\text{uncorr})$  = Uncorrected Power

$R_x$  = Radius of the shadow cone

$R$  = Radius of the rotor disc

$X$  = Distance between neighboring wind turbine

$\tan\alpha = 0.04$  (no-wake) or  $0.08$  (wake)

$C_t$  = Thrust coefficient of wind turbine

$U_{\text{wake}}$  = Wake speed of the wind turbine

$A_S$  = Area of shadow region

$A$  = Area of wind turbine rotor disc

$GP(\text{wake-uncorr})$  = Uncorrected wake power of GE 1.5 MW wind turbine

$MP(\text{wake-uncorr})$  = Uncorrected wake power of Mitsubishi 1 MW wind turbine

$P2(\text{corr\_wake})$  = Corrected wake power

$\sum_{n=1}^n P1(\text{corr}) = \Sigma P(\text{nowake})$  = Total wind farm no wake power

$P2(\text{uncorr\_wake})$  = Uncorrected wake power



$$\text{Actual density} = 3.4837 \cdot P/T$$

$$\text{Density at STP} = \text{Density at STP is } 1.225 \text{ kg/m}^3$$

$$\sum_{n=1}^n P_2(\text{corr\_wake}) = \sum_{n=1}^n P_1(\text{corr\_wake}) = \text{Total wind farm wake power}$$

## **Abbreviations**

MET tower = Metrological tower

WC = Wake Coefficient

Near FID = Near Feature Identity or nearest wind turbine

ARMA = Auto Regressive and Moving Average

ARIMA = Autoregressive Integral and Moving Average

ANN = Artificial Neural Network

NWP = Numeric Weather Prediction

AR = Auto Regressive

ARX = Auto Regressive Exogenous

CFD = Computational Fluid Dynamics

MATLAB = Matrix Laboratory Software

WRF = Weather Research and Forecasting

UKF = Unscented Kalman Filter

UT = Unscented Transform

MA = Moving Average

TL = Transmission Loss

Arc GIS = Arc Geographic Information System

## List of Appendices

### Contents

Appendices .....	164
Appendix A .....	164
Appendix B .....	164
Appendix C .....	164
Appendix D .....	165
Appendix E .....	166
Appendix F .....	167
Appendix G .....	168
Appendix H .....	169
Appendix I .....	171
Appendix J .....	183
Appendix K .....	184
Appendix L .....	209
Appendix M .....	210
Appendix N .....	211

## **Chapter 1**

### **Literature Review of the Wind Speed Model and the Wind Power Model**

#### **1.1 Introduction**

In this research, the wind speed model and the wind power model is developed and implemented in the MATLAB software. The focus of the work is to develop a short term wind speed prediction model. The wind speed model is implemented using the Auto Regressive Moving Average (ARMA) model and the Kalman filter and the Unscented Kalman filter. The Kalman filter is used for the linear model and the input to the Unscented Kalman filter is the non linear model. The difficulties were involved in developing and implementing the non linear model. To develop the wind farm power model, the physical factors that affect the wind turbine rotor disc are studied that takes into account the wake effect and the transmission loss due to the power transmission in the cables. The developed model is implemented for the Fermeuse wind farm located in the Newfoundland and the Cedar Creek Colorado wind farm located in the United States. The input wind data is in time series order to the wind speed model and the wind power model. The output is the processed and forecasted wind speed data in the time series order from the wind speed model. For the wind power model, the input is the wind data such as the wind speed, the pressure, the temperature, the air density, the wind direction in the time series order and the output is the wind power in the time series order. Detailed overview of the methods and the techniques has been proposed in this chapter for the wind speed model and the wind power model. From the proposed wind speed model and the wind power model, the

algorithm is designed and implemented in the MATLAB. The results are simulated in the MATLAB and are presented in the thesis in the next section.

## **1.2 Summary of the Research Papers**

**Below is a brief review on some of the research papers studied relevant to the wind speed and the wind power forecasting.**

### **Wind Shear, Vertical Wind Shear and Horizontal Wind Shear:**

Wind shear refers [10] to the variation of the wind speed either horizontal or vertical distance. Small changes in the wind speed will change the power significantly. The wind speed shear is given by the power law equation of shear at two different heights with the shear exponent ' $\alpha$ '. Increase in the wind velocity will increase the power generated significantly. Vertical wind shear is the rate of change of the wind with respect to altitude. Horizontal wind shear is the rate of change of the wind on a horizontal plane. Both the factors affect the power output, and results in a scatter larger than expected in the power curve if no additional information to the wind speeds at the hub height is taken into account. Therefore wind shear is a very important factor in predicting the wind power of a wind turbine.

**Direction Shear:** The direction shear is the component of the wind shear [4] which is due to the change in the wind direction with the height. In the speed shear and the directional shear, both the angle and the length of the wind vectors are changing with the height. A small clockwise direction shear increases the performance of the wind turbine resulting in a higher local tangential force, whereas an anticlockwise direction shear decreases the performance. The main difference with the speed shear effect is

that the direction shear implies a variation of the horizontal component of the wind orthogonal to the wind turbine axis. The direction shear has a smaller effect on the wind turbine power output than the speed shear. There is a greater effect when both the phenomena are combined.

**Turbulence:** An average power curve [4] of various turbulence intensities are shown in Figure 1.1. The effect of turbulence is more complex than that for shear and is therefore more difficult to account for in the power curve. Increasing the turbulence intensities will increase the power in the concave region and will decrease the wind power in the convex region of the power curve. Reduction in the energy production starts beyond 15% increase in the turbulence intensity. Thus turbulence is considered as a very important factor in predicting the wind power of a wind turbine.

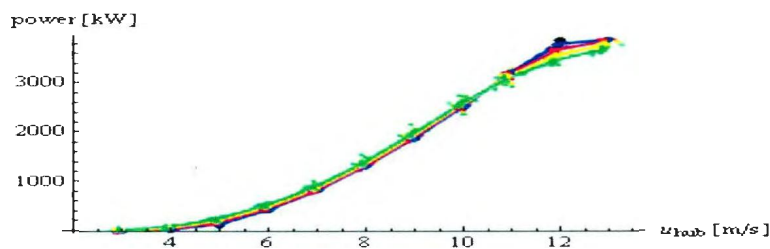


Figure 1.1: Average power curves for various turbulence intensities (5% (red), 10%(blue), 15%(green), 20%(yellow)) [4].

Icing [6] has a major effect on the power production and the wind turbine can stop operating under severe icing condition. Lift reduces and drag increases along the wind turbine blade following the power law. During icing events, ice accumulates on the wind turbine rotor blades, thus reducing the aerodynamic efficiency and torque, resulting in the power loss. Torque drops to zero under severe icing event and the wind

turbine stops operating and there is a complete loss in the power production. Therefore icing is considered as an important factor in predicting the wind power of a wind turbine.

#### **Wake Effect:**

The wake effect has a major effect on the power production in the wind farm when many wind turbines are operating at the same time [5]. The wind direction and the distance between the neighboring wind turbines has a significant influence on the wake effect. Due to the compact arrangement of the wind turbines in a wind farm, a wind turbine is operating in the wake of another wind turbine. The wind turbines extract energy from the wind and downstream there is a wake from the upstream or neighboring wind turbine, and the wind speed is reduced. The wake effect has the aggregated influence on the energy production in the wind farm, which results from the changes in the wind speed caused by the impact of the wind turbines. The wake effect is considered as an important factor in the power production of a wind farm.

#### **Air Density:**

An air density ' $\rho$ ' is an important factor affecting the output power of a wind turbine [3]. The power curve of the variable speed wind turbines with different air density is shown in Figure 1.2. From the figure, we see that the wind turbines output power will increase with increase in air density. An air density is closely related with the humidity, the temperature, and the pressure. Therefore, the pressure factor is considered in the wind power prediction. The density of air decreases with increase in temperature and altitude. The denser the air, the higher is the wind power density and vice versa. The wind power is directly proportional to the air density and any change

in the air density will change the output wind power of a wind turbine proportionately. The major factor affecting the power generation of the wind turbine is the wind speed and the atmospheric pressure. An air density plays an important factor in predicting the wind power.

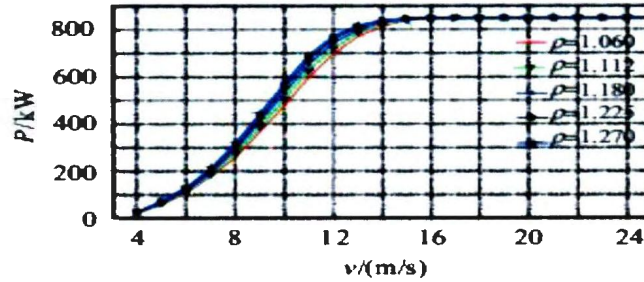


Figure 1.2: Wind turbine power curve with different air density [3]

### Temperature:

The temperature [6] is a very important factor in predicting the wind power.

If the temperature is too low and if ice accumulates on the wind turbine rotor disc, the wind turbine stops working. Therefore the temperature is considered as an important factor in predicting the wind power of a wind turbine.

**Dust:** The wind turbine blade [7] surface roughness has a significant influence on the aerodynamic load and the wind power production. Therefore, increasing the wind turbine operation period without cleaning the dust from the blade surface results in increase of the blade surface roughness, and consequently, there is increases in the loss in the wind turbine output power. The blade surface roughness reduces the effectiveness of the airfoil to extract the useful power from the wind and also results in reduced output power of the wind turbine. The accumulation of dust after years of



operation will affect the wind power production. Therefore dust accumulation has a smaller effect in predicting the wind power of a wind turbine.

#### **Complex Terrain:**

The wind farms [12] are generally situated in a more complex terrain. If there are severe up flow conditions induced by the terrain, there can be significant reduction in the performance of the wind turbine. The wind turbine experiencing a constant up flow angle of 10 degree at the hub height would have energy production approximately by 5% lower than that of an equivalent site with the horizontal flow. Therefore topography is an important role in the wind farm power production.

### **1.3 The Wind Speed Forecasting Models**

**Below is the list of some of the forecasting models used in predicting the wind speed and the corresponding wind power:**

Persistence Model

Auto Regressive Model (AR Model)

Auto Regressive and Moving Average (ARMA Model)

Autoregressive Integral and Moving Average (ARIMA)

Artificial Neural Network

Neural Network

Numerical Weather Prediction Model

Hybrid Model

**Numeric Weather Prediction (NWP) Model:** Numeric Weather Prediction model

[8] corresponds to the weather variables, mainly hourly mean wind speed, wind

direction, pressure, and temperature. In statistical approach, the forecasted value is based on the last known data for the power production. NWP obtain good result for the forecast horizon of about 72 hours up till 7 days in advance.

**Auto-regressive Moving-average (ARMA):** Auto Regressive Moving Average models are the mathematical models of the persistence, or the autocorrelation [11] in a time series. The ARMA models can effectively be used to predict the behavior of a time series from the past values alone. The ARMA models have an advantage that they can provide very accurate results for short term wind power prediction if data have fairly smooth trend and stationary. If the data are not stationary and there are quite high variations and change trend suddenly they may result in very inaccurate results. The autoregressive model includes lagged terms on the time series itself, and the moving average model includes lagged terms on the noise or the residuals. Combining the lagged terms gives the auto regressive moving average (ARMA), models. Therefore ARMA models can be used for short term wind power prediction and should not be used for long term wind power prediction.

**Artificial Neural Networks (ANNs):** Artificial Neural Network depends on the training data [11] and takes less amount of time in learning. The best network is chosen by trial and error method. It does not require very large amount of historical data but may require use of manual input in the training data.

**Hybrid Model:** Hybrid model is a combination of two or more forecasting model [9]. The forecasting models are classified as physical or statistical or a combination of both the models. Artificial Neural Networks have been developed to predict the wind power of a wind farm located in a complex terrain. The neural network has been used as a

statistic model based on the time series of the wind power. It has been integrated with numerical weather predictions and has a greater performance, with the longer time horizons. The pressure and the temperature have a significant influence in improving the forecasting models. The optimal model is a combination of both the models, physical considerations is used to capture the airflow in the region of the wind turbines and advanced statistical model is used to supplement the information given by the physical models. The errors are reduced with the combination of a hybrid model. Thus hybrid model gives accurate result to predict the wind power of a wind turbine.

#### **1.4 Design Overview of the Wind Power Physical Model**

The wind power is the conversion of the wind energy to produce electricity using the wind turbines. It is considered as an alternate source of the renewable energy. Various factors are considered in predicting the wind power of a wind turbine. These factors determine the actual production of the wind power using the wind turbine. The physical factors determine the wind power produced in real time and the wind turbine manufacturer power curve assumes ideal condition. The wind farm consists of many wind turbines and various physical factors are taken into account to predict the wind power of a wind turbine. Forecasting the wind power is essential for utility operators. The forecasting time horizon ranges from 10min, hour ahead, and 5 hours ahead up till seven days in advance. The physical factors considered predict the actual wind power in advance.

## **1.5 Research Goals**

The research involves finding a simulation model of a wind farm that could be used for the development of the wind power prediction software. The wind power model includes a simple individual wind turbine dynamic model, variation in the wind speed with height, variation in the wind speed over the site area and the wake interaction between the wind turbines. Detailed Computational Fluid Dynamics (CFD) based flow models of a wind farm including dynamic model of a wind turbine are too complex and are not suitable for the real time power prediction and it requires supercomputer for calculation. The main challenge for this work is to find a simple model that will take a topographical map, a wind farm layout and the long term site wind and the atmospheric data and uses this information to calculate the wind speed at all the wind turbines. A wind turbine corrected power curve that takes into account wind turbulence can be used as a simple model of a wind turbine. Using the wind turbine simple model the output power of each individual wind turbine in a wind farm can be established and the wake effects can be calculated. The work should focus on a method to determine or predict the output power of a wind farm. The resulting simple model of a wind farm will be used to develop a computer program that is fast and can be used in real time. The code will effectively employ real time wind and weather data to predict the expected short term and the long term output power of a wind farm.

## **1.6 Typical Method or Technique Applied in Predicting the Wind Power of a Wind Turbine**

The wind turbine manufacturer supplied power curve [1] is digitized by plotting power vs. wind speed characteristics and fitting a polynomial in MATLAB for an accurate estimation. Weather Research and Forecasting (WRF) has a wind data i.e. average wind speed, wind direction, pressure, temperature as input to the wind power physical model. WRF has pressure levels known as eta levels which intersect the wind turbine rotor disc. The height of these model levels which intersect the wind turbine rotor disc needs to be determined for the wind power physical model. The wind data is given in every ten minutes time series order. From the given wind data, the turbulence intensity, the turbulence adjusted wind speed, the equivalent disc wind speed can be calculated at the given model levels. The turbulence intensity is determined from the ratio of the average wind speed and the standard deviation value of the wind speed data. The turbulence adjusted wind speed is determined at the given model levels or heights of the wind turbine rotor disc. The wind shear exponent ' $\alpha$ ' is calculated from the power law equation of shear using the turbulence adjusted wind speed at the given model levels. The wind speed data is evaluated for the entire wind turbine rotor disc by numerically integrating the wind speed data from the lower wind turbine rotor tip to the upper wind turbine rotor tip and evaluating the wind data values using the designed algorithm. This value is assumed to be at the hub height of a wind turbine. From the evaluated disc speed, the uncorrected power can be determined which is subsequently adjusted for air density. The wind power physical model is implemented in the MATLAB software to evaluate the disc speed and the corresponding wind power.

Using this approach, the wind power is predicted for one wind turbine. For predicting the wind power of the wind farm, the wind power is determined for each of the wind turbines and influence of the wind direction and the wake effect is considered. The implemented wind power model in MATLAB software is tested for accuracy with different wind data sets in every 10 minutes time series order of the wind data.

## **1.7 Thesis Outline**

This thesis has five chapters. Concise information about the chapters is given below:

The first chapter gives the outline of the research work. It discusses the proposed models and research methods or techniques applicable to the research work.

The second chapter discusses the short term wind speed prediction model. It discusses the wind speed estimation and accuracy for the selected range of the wind speed. It discusses the work related to the ARMA modeling of the wind speed, the Kalman filter and the Unscented Kalman filter.

The third chapter discusses the wind farm power model, and the wake power model and the power loss due to the power transmission in the Fermeuse wind farm.

The fourth chapter discusses the wind farm power model, and the wake power model and the power loss due to the power transmission in the Cedar Creek Colorado wind farm.

The fifth chapter presents the conclusion of the research work. It also presents the research outcome and the future work.

## **Chapter 2**

### **Short Term Wind Speed Prediction**

#### **2.1 Background Information on the Wind Speed Prediction**

The wind is the mass movement of air due to the difference in pressure between the two sections on the earth. It is characterized by its speed, direction, time of occurrence. The wind energy is infinite and inexhaustible and its use in energy production does not lead to any pollution and is a better way to produce energy without being against the environment. Better techniques need to be adopted for efficient usage of the wind energy. The most important factor which influences the wind energy production is the local wind speed [13] and there is a great need of development of the improved forecasting methods which will directly improve the resource allocation and will determine the reliability of the energy producing company and the operation of the energy production systems and the energy distribution [14]. Various models have been investigated for accurate prediction. The forecast of hourly average wind speed of few hours in advance is required for the power plant operators. Predicting the output power of the wind farm is essential for the operation of the conventional electric power plants that are connected to the same power grid as those conversion systems. The wind speed in near future depends on the values of other meteorological variables, such as atmospheric pressure, moisture content, humidity, rainfall etc.

This chapter includes the following sub topics on the wind speed prediction:

Design of Five Hours In-advance Wind Speed Predictor and, An Hour Ahead Wind Speed Prediction Using the Kalman Filter and the Unscented Kalman Filter

The details are provided below.

## **2.2 Design of Five Hours In-advance the Wind Speed Predictor**

### **2.2.1 Introduction**

In this section wind speed prediction five hours in advance using Auto Regressive and Moving Average (ARMA) model is described. Various models have been investigated and ARMA model is chosen for predicting the wind speed. The ARMA has autoregressive and the moving average parameter and the computation is performed based on the past data. The aim of this work is to evaluate the applicability of the ARMA model to the time series of the hourly average wind speed, and assess the predictive behavior of the obtained model. The input to the wind speed model is the per hour time series wind speed data and the processing is done by the ARMA model. The parameters are estimated and prediction is computed for the specified duration and further testing is done on the predicted data to test accuracy and the error between expected and the predicted output should be zero. The application of ARMA models requires the time series to be stationary, i.e. the method assumes that the process remains in equilibrium about a constant mean level [13].

## **2.3 Detail Overview of the Wind Speed Prediction Models**

Various models have been investigated for predicting the wind speed in advance and some details are given below.



**Numeric Weather Prediction Model:** Numeric Weather Prediction is accurate for long term forecast. Time horizon for this model ranges from a day ahead up to 7 days in advance. It gives inaccurate results for the short term prediction and requires supercomputer for wind speed estimation [24].

**Persistence Model:** Persistence model [11] gives accurate result for very short term wind speed prediction and ranges from few minutes till 2 hrs in advance, the estimation is inaccurate for more than 2 hours and is not considered.

**ARIMA Model:** The popularity of the ARIMA model is due to its statistical properties as well as to the well-known Box–Jenkins methodology in the model building process [15]. ARIMA models assume that future values of a time series have a linear relationship with current and past values as well as with the white noise. Real time physical systems are often nonlinear so approximations by ARIMA models may not be adequate for complex nonlinear problems and they require a large amount of historical data in order to produce accurate results and are not considered for predicting the wind speed in advance.

**Neural Network:** The major advantage of neural networks is their flexible nonlinear modeling capability and high accuracy [16]. ANNs are data-driven, self-adaptive methods in that there are few a priori assumptions made about the models for problems under study. ANNs, models have data limitation. The amount of data for network training

depends on the network structure, the training method, the complexity of the particular problem or the amount of noise in the data; it requires supercomputer for computation and thus is not considered.

**Fuzzy forecasting:** These methods are suitable under incomplete data conditions and require fewer observations than other forecasting models. Although fuzzy forecasting methods can be applied to situations with scant available data and have no data limitation, their performance is not always satisfactory [24].

**Hybrid forecasting:** These models have been proposed using ARIMA, Artificial Neural Networks (ANNs), and Fuzzy logic and applied to financial time series forecasting with good prediction performance. They require super computers for forecast prediction [24]. These methods are usually quite complex in nature and are difficult to implement, furthermore these methods cannot guarantee the optimal solution for all real time forecasting problems.

**ARMA Model:** The Autoregressive and Moving Average Model [13] gives very accurate result for the short term wind speed prediction for few hours in advance, it does not require very large amount of historical data for accurate prediction as compared to ARIMA and does not require super computers for computation, it can be implemented on a simple desktop provided data have stationary values. It gives inaccurate result for the non linear data.

**Kalman Filter:** The Kalman filter is an algorithm that provides an efficient computational or recursive mean to estimate the state of a process and minimizes the mean of the square error [23]. It supports estimations of the past, present, and future states without knowing the precise nature of the modeled system. It is a tool for

filtering, smoothing, and prediction applied to the continuous models and the discrete models.

Thus theoretical part of the Kalman filtering is studied in this course and the model will be developed to predict the wind speed from the actual wind speed data.

**Auto Regressive Model:** The Auto Regressive is an appropriate method to simulate the hidden correlation between the data. A second order autoregressive model considers the effect of the relationship between the consecutive values in a series as well as the correlation between values two periods apart. The estimation of the model's parameters based on the historical data of the wind speed is an important role in modeling, and they determine the precision, reliability and efficiency of the model. Therefore, the best approximation is by least squares error method [25].

**Unscented Kalman Filter:** Unscented Kalman Filter (UKF) is an extension of Unscented Transform to the recursive estimation. The Unscented transformation (UT) is a method for calculating the statistics of a random variable which undergoes a non linear transformation. It is used for the non linear system [28].

**Non Linear ARX:** The Non linear ARX model is nonlinear auto regressive model with external input. The nonlinear arx model is implemented by one of the following nonlinearity estimators such as sigmoid net, wavelet, tree partition, custom net, neural net, linear [29]. It is used for the non linear system. From the literature search of the investigated models, the work is focused on the AR model, the nonlinear ARX model, the Kalman Filter and the Unscented Kalman for an hour ahead wind speed estimation.

### 2.3.1 Detailed Overview of the ARMA Model

The Auto Regressive Moving Average (ARMA) models are the mathematical models of the persistence, or the autocorrelation in a time series. There are several possible reasons for fitting the ARMA models to the data. The wind speed modeling contributes to the understanding of the physical system by revealing about the physical process that builds persistence into the series. ARMA models can also be used to predict the behavior of a time series from the past values.

### 2.4 The Mathematical Model of the ARMA Model

The ARMA models can be described by a series of equations [19] and is given in the equation (2.1).

$$y(t) = Y(t) - \bar{Y} \quad \text{where } t = 1, 2 \dots N \quad (2.1)$$

Where  $y(t)$  is the original time series,  $\bar{Y}$  is its sample mean, and  $Y(t)$  is the mean adjusted series. One subset of the ARMA models is the autoregressive or the AR models. An AR model expresses a time series as a linear function of its past values. The order of the AR model determines the number of the lagged past values. The simplest AR model is the first order autoregressive model, given by the equation (2.2).

$$y(t) + a_1 * y(t - 1) = e(t) \quad (2.2)$$

where  $y(t)$  is the mean-adjusted series in time  $t$ ,  $y(t-1)$  is the series in the previous time,  $a_1$  is the lag-1 autoregressive coefficient, and  $e(t)$  is the noise. The noise or the residuals  $e(t)$  is assumed to be random in time i.e. not auto correlated and normally distributed.

The equation for the AR (1) model is given in the equation (2.3).

$$y(t) = -a_1 * y(t-1) + e(t) \quad (2.3)$$

The AR (1) model has the form of a regression model in which  $y(t)$  is regressed on its previous value. In this form,  $a_1$  is analogous to the regression coefficient and  $e(t)$  to the regression residuals. The autoregressive refers to the regression on self. Higher order autoregressive models include more lagged  $y(t)$  terms as predictors. The moving average (MA) model is a form of ARMA model in which the time series is regarded as a moving average or unevenly weighted random series  $e(t)$ . The first order moving average or MA (1) model is given by the equation (2.4)

$$y(t) = e(t) + c_1 e(t-1) \quad (2.4)$$

where  $e(t)$ ,  $e(t-1)$  are the residuals at times  $t$  and  $t-1$ , and  $c_1$  is the first order moving average coefficient. Higher order MA models include higher order lagged terms. The autoregressive model includes lagged terms on the time series itself and that the moving average model include lagged terms on the noise or the residuals. Both the AR and MA models together are called the autoregressive moving average or the ARMA models. The order of the ARMA model is included in parentheses as ARMA ( $p, q$ ), where  $p$  is the autoregressive order and  $q$  is the moving average order and is given in the equation (2.5).

$$y(t) + a_1 y(t-1) = e(t) + c_1 e(t-1) \quad (2.5)$$

## 2.5 The Wind Speed Modeling Using ARMA Model

The first step is to identify the model [19, 11]. Identification consists of specifying the appropriate structure (AR, MA or ARMA) and order of the model. Identification is sometimes done from the plots of the autocorrelation (acf) and partial autocorrelation function (pacf) or by an automated iterative procedure. The second step is to estimate the coefficients of the model. Estimation of the parameters of MA and ARMA models usually requires a more complicated iteration procedure. It is accomplished automatically by a computer program with little or no user interaction. The third step is to check the model and is called diagnostic checking or verification. Checking is required to ensure that the residuals of the model are random, and to ensure that the estimated parameters are statistically significant. The classical method of the model identification as described by the Box and Jenkins [19] is to determine the appropriate model structure and order from the appearance of the plotted acf and pacf.

The partial autocorrelation function (pacf) at lag  $k$  is the autocorrelation at lag  $k$  after first removing the autocorrelation with an AR ( $k - 1$ ) model. The identification of ARMA models from the acf and pacf plots is difficult.

The acf and pacf for an AR (1) model is:

Acf: Declines in geometric progression from its highest value at lag 1

Pacf: Cuts off abruptly after lag 1

The opposite types of patterns apply to an MA (1) process:

Acf: Cuts off abruptly after lag 1

Pacf: Declines in geometric progression from its highest value at lag 1

Prediction differs from simulation in that the objective of the prediction is to estimate the future value of the time series as accurately as possible from the current and past values. Prediction utilize past values of the observed time series. A prediction form of the AR (1) model is given in the equation (2.6).

$$\tilde{y}(t) = -a_1\tilde{y}(t-1) \quad (2.6)$$

Where the  $\sim$  indicates an estimate

The equation can be applied one step ahead to get estimate  $\tilde{y}(t)$  from observed  $\tilde{y}(t-1)$ , for k step ahead AR (1). Prediction can be made by recursive application of equation (2.6). In recursive application, the observed y at time 1 is used to generate the estimated  $\tilde{y}$  at time 2. That estimate is then substituted as  $\tilde{y}(t-1)$  to get the estimated  $\tilde{y}$  at time 3; the k-step-ahead predictions eventually converge to zero as the prediction horizon k increases.

## 2.6 MATLAB Implementation of the ARMA Model

The designed algorithm is implemented in MATLAB for predicting the wind speed five hours in advance and is compared with actual wind data [11]. Hourly wind speed data from the Environmental Canada website, St John's is downloaded. The acf and pacf lag is determined and prediction is computed. For the ARMA model, the order chosen is armax (1 1) and if the data is in time series order, it is written as [1 1]. Using this order we get the Autoregressive and Moving Average parameters and are given below [20]. A copy of the MATLAB code is given in Appendix A.

Discrete-time IDPOLY model of armax (1, 1) is given by the equation (2.7):

$$A(q)y(t) = C(q)e(t) \quad (2.7)$$

$$A(q) = 1 - 0.9864 q^{-1}$$

$$C(q) = 1 - 0.2986 q^{-1}$$

Estimated using ARMAX from the data set z

## 2.7 The MATLAB Simulation Results

Input for the ARMA model is hourly controlled wind data, output data after processing with the ARMA model should be predicted wind speed five hours in advance, and further testing has to be done to determine the accuracy by comparing the actual and the predicted wind data and the error should be zero. A copy of the partial autocorrelation of the MATLAB code for the hourly wind speed data is attached in the Appendix B and the autocorrelation of the MATLAB code for the hourly wind speed data is attached in Appendix C. Figure (2.1) and Figure (2.2) is the autocorrelation and partial autocorrelation plots of the hourly wind data showing lag of 20 hours.

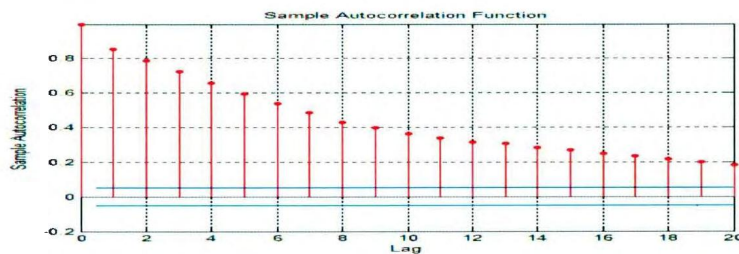


Figure 2.1: Autocorrelation of the input wind speed data.



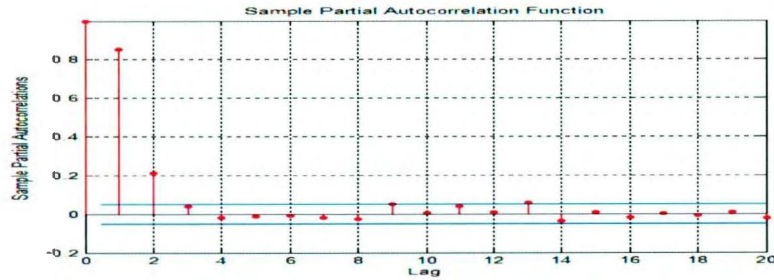


Figure 2.2: Partial autocorrelation of the input wind speed data.

Figure (2.3) is the plot of per hour 1600 time series wind speed data set. Figure (2.4) is the plot of predicted wind speed data five hour in advance using  $\text{armax}(1,1)$ . Figure (2.5) is the plot of predicted wind speed data five hour in advance using  $\text{armax}(1,1)$  for a time span of 500 hours.

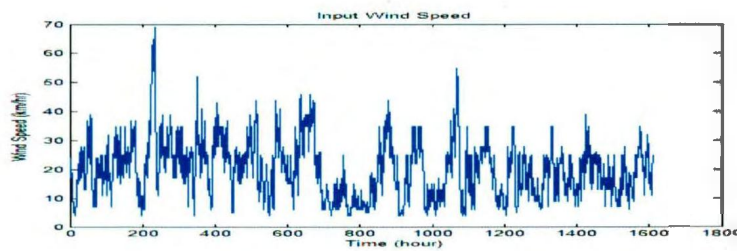


Figure 2.3: Input hourly wind speed data.

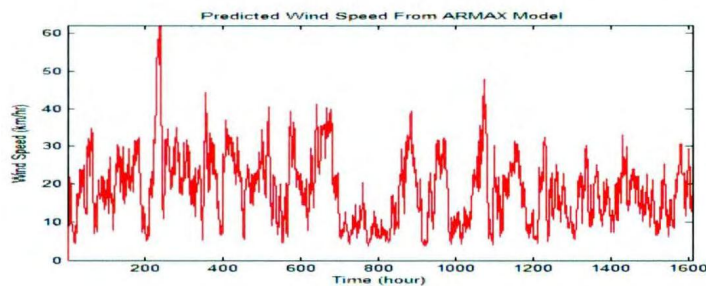


Figure 2.4: Predicted hourly five hours in advance wind speed data.

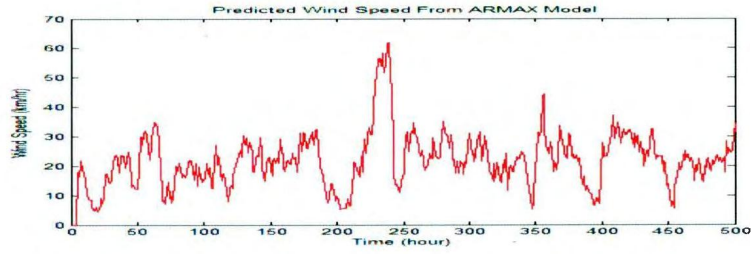


Figure 2.5: Predicted wind speed using armax (1, 1) for a time span of 500 hours.

Figure 2.6 is the comparison of the actual and the predicted wind speed data and there is a very less variation between the actual and the predicted wind data and the error is close to zero.

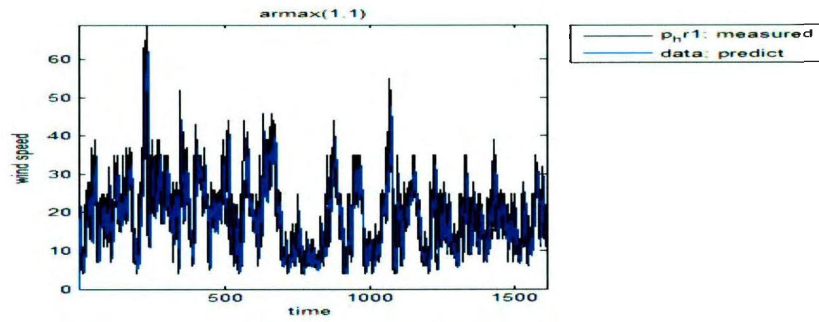


Figure 2.6: Comparison of the actual and the predicted wind speed data in km/hr and time in hours.

Table 2.1: Data Analysis of the Actual and the Predicted Wind Speed

Statistics	Actual wind speed data	Predicted wind speed data
Mean	5.12 m/s	5.52 m/s
Median	5.01 m/s	5.26 m/s
Standard Deviation	2.48 m/s	2.78 m/s

The above table 2.1 gives the data analysis results in detail and we can see that there is very less difference of mean, median and standard deviation between the actual and the predicted wind data and the prediction accuracy increases with large data and the error will be zero.

## **2.8 An Hour Ahead Wind Speed Prediction Using the Kalman Filter and the Unscented Kalman Filter**

### **2.8.1 Introduction**

This section reports an AR (Auto Regressive) model and a non linear Auto Regressive Exogenous model for a short term wind speed prediction to predict an hourly average wind speed up to 1 hour in advance. The Kalman filter and the Unscented Kalman Filter are used for filtering associated noise in the input wind speed for accurate estimation. The input to the wind speed model is an unprocessed wind speed. The input time series wind speed data is downloaded from the Environmental Canada website. The historic input wind speed data is in per hour time series order.

Autoregressive model is studied in detail, the raw wind speed data is processed using Autoregressive model of order 2. Further the Kalman filter is used for filtering unwanted noise parameter and for accurate estimation of the wind speed. The Unscented Kalman Filter is used for the nonlinear system. The non linear ARX model state space equation is determined in MATLAB and Unscented Kalman Filter is used for further correcting and estimating the wind speed. System identification toolbox in MATLAB is used to process the time series wind speed data. The input wind speed data is 1000 per hour time series data. The input per hour time series wind speed data

is stored in excel file and is imported into system identification toolbox GUI. The wind speed data is divided into the training data and the validation data. From the input wind speed data,  $2/3^{\text{rd}}$  of the input wind speed data is used for training the data and  $1/3^{\text{rd}}$  of the input wind speed data is used for the validation purpose. The linear and the non linear parametric model in the system identification toolbox GUI is used for wind speed estimation. The model structure used for the estimation is an AR model and a non linear ARX model of various model orders. The best fit data is tested by comparing actual wind speed data with the estimated data from the system identification toolbox GUI. From the best fitted data, the particular model structure of the best fit wind speed data is chosen for further wind speed processing. The Kalman Filter and the Unscented Kalman Filter are used for further wind speed processing. The state space equation of the particular model structure is determined from the model order. The parameters determined from the state space equation are used as input to the filter. The best fit model is estimated in the MATLAB System identification toolbox by comparing various model orders and estimating the best fitted model order. The code is written in MATLAB from the chosen best fit model order. The model parameters and the state space equation are determined for the chosen order. Further wind speed processing is done using the Kalman Filter and the Unscented Kalman Filter. The model output is estimated and the corrected wind speed data from the Kalman filter and the Unscented Kalman Filter is compared to test accuracy.

## 2.9 Part I: System Identification Toolbox GUI

### 2.9.1 Best fit estimation for the Auto Regressive Model

Figure 2.7 is the plot of the input wind speed data with respect to time. It is imported into system identification toolbox GUI [30] using “ident” command in MATLAB. The wind speed data is in 1000 per hour time series data.

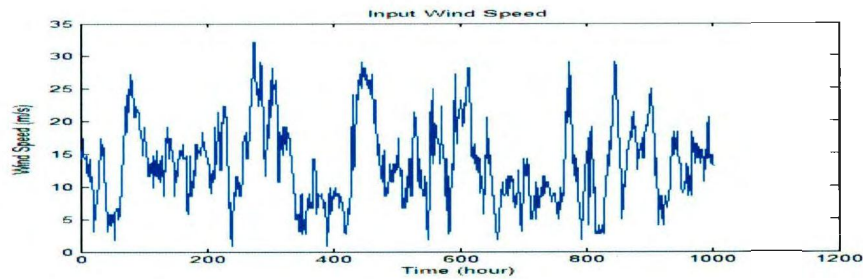


Figure 2.7: Input wind speed is plotted with respect to time.

The input wind speed data is divided into training data and the validation data. From the input wind speed data,  $2/3^{\text{rd}}$  of the input wind speed data is used for training the data and  $1/3^{\text{rd}}$  of the input wind speed data is used for validation purpose. The input wind speed data is divided into training data and the validation data and is shown in Figure 2.8.

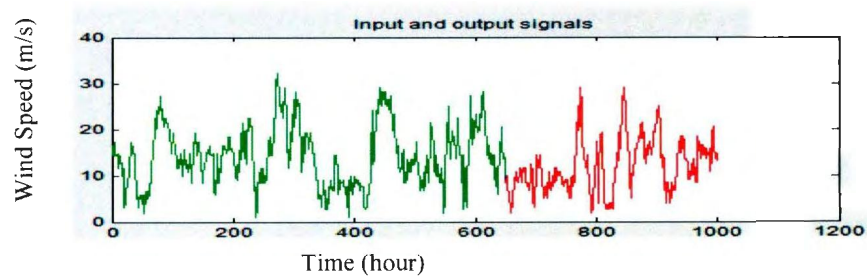


Figure 2.8 : Input wind speed has  $2/3^{\text{rd}}$  data as training data (green) and  $1/3^{\text{rd}}$  data as validation data (red).

In Figure 2.9 we see the input wind speed processing and estimation of linear parametric model using AR (Auto Regressive) model and ARMA (Auto Regressive and Moving Average) model in the system identification toolbox.

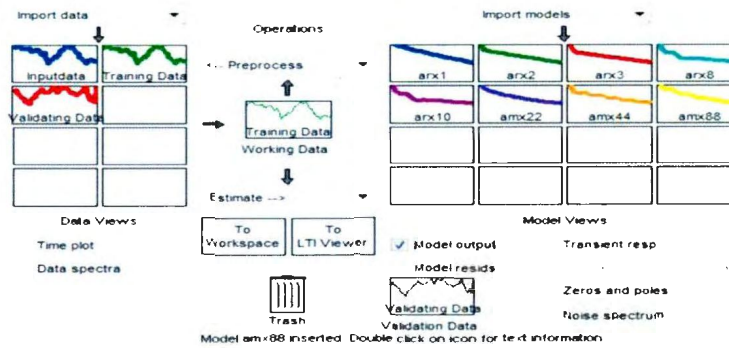


Figure 2.9: Wind speed data processing in the system identification.

In Figure 2.9, we see that the input wind speed is divided into training data and the validation data. The linear parametric model is used for the estimation purpose. For training the input wind speed data,  $2/3^{\text{rd}}$  of the wind speed data is used for training the data and  $1/3^{\text{rd}}$  of the wind speed data is used for validating the data in the System Identification toolbox. From the given model structure, Auto Regressive model of various order and Auto Regressive Moving Average model of various model order is tested with the actual validation data. In Figure 2.10 and Figure 2.11, we see that the best fitted data is compared with various model structures and model order. The measured and one step predicted output is shown in Figure 2.10 below. From Figure 2.10 we can conclude that the Auto Regressive model of order 2 is the best fitted model structure. The percentage of the best fitted data is 58.87%, as the model order is increased; the best fitted data has no significant improvement and remains the same.

As compared with the ARMA model, the best fitted data is nearly the same percentage as the AR model. This is the maximum best fitted data for one step predicted output from the available inbuilt model structure in the System Identification toolbox GUI [30]. As the model order is increased, the percentage of the best fitted data is almost the same and has no significant improvement with increase in the model order. For this reason the Auto Regressive model of order 2 is chosen as the best fitted model for the one step predicted output. With AR model order as 2, less number of parameters is estimated and the system is less complex.

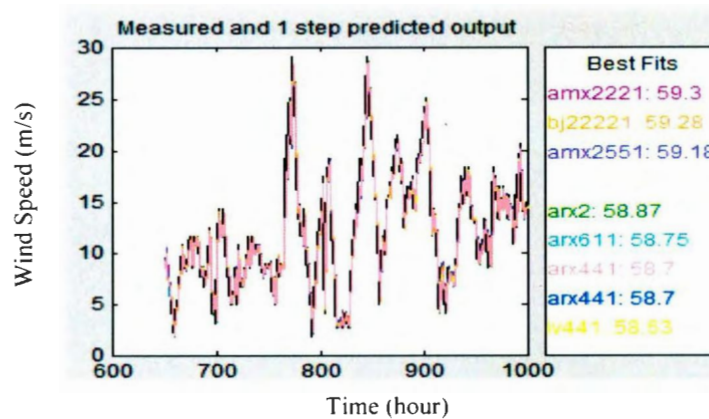


Figure 2.10: Best fitted one step ahead wind speed data tested with AR model and the ARMA model of different model order in the system identification toolbox.

In Figure 2.11, we see the best fitted Auto Regressive second order model for one step predicted output. Figure 2.12 is the plot of the autocorrelation of the residuals estimated from the AR 2<sup>nd</sup> order model.



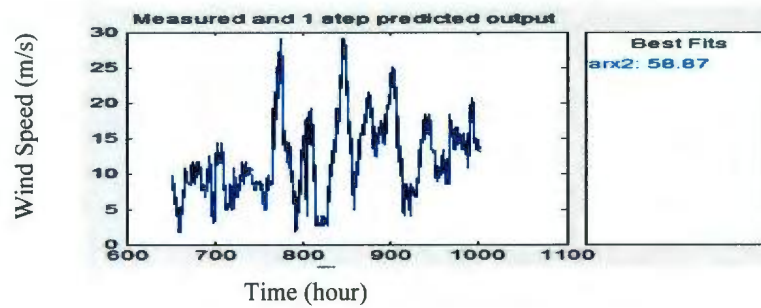


Figure 2.11: One step ahead estimated AR 2nd order model and percentage of the best fit estimate.

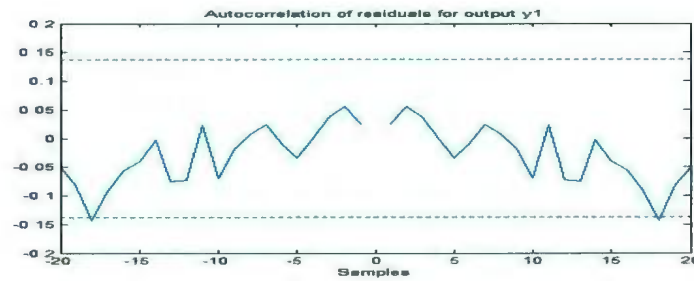


Figure 2.12: Autocorrelation of the residual estimated using AR, 2nd order model

## 2.10 The Kalman Filter Wind Speed Estimation Using Auto Regressive Model

### 2.10.1 Detail Overview of the Kalman Filter

The Kalman filter [26] is a tool for filtering, smoothing and prediction. This method can be applied to both continuous and discrete models. The Kalman filter is an algorithm that provides an efficient computational (recursive) mean to estimate the state of a process minimizing the mean of the square error. The filter supports estimations of the past, present, and future states, even when the precise nature of the



modeled system is not known. The Kalman filter provides a method for the recursive estimation of the unknown state based on all observation values up to time 't'. As such, the equations for the Kalman filter fall into two groups [26] 'time update' equations and 'measurement update'

equations. The former are responsible for projecting forward in time the current state and error covariance estimates to obtain a priori estimates for the next time step, while the latter are responsible for the feedback, i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate. The main goal is the simulation of the evolution in time of an unknown process or state vector, whose value at time 't' is denoted by 'x<sub>t</sub>'. The Kalman filter provides a method for the recursive estimation of the unknown state based on all observation values up to time t.

### 2.10.2 The Kalman Filter State Estimation

The input wind speed is assumed to have associated noise when estimated using Auto Regressive model. The Kalman filter is used to reduce the noise parameter associated with the input wind speed, estimated using Auto Regressive model of order 2 [26].

The Kalman filter estimates the state 'x' of a discrete-time controlled process that is governed by the linear stochastic difference equation and is given in the equation (2.8).

Here A and B are the matrix, u is the input, w is the process noise and, k and k-1 represents current step and previous step respectively.

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (2.8)$$

The measurement ' $z_k$ ' is given as shown in the equation (2.9). Here  $v$  is the measurement noise, and  $H$  is the matrix that relates the state to the measurement.

$$z_k = v_k + Hx_k \quad (2.9)$$

The random variables  $w(k)$  and  $v(k)$  represent the process noise and the measurement noise respectively. They are assumed to be independent of each other and with normal probability distributions as given in equation (2.10). Here  $Q$  is the process noise and  $R$  is the measurement noise.

$$p(w) \approx N(0, Q), \quad (2.10)$$

$$p(v) \approx N(0, R)$$

The process noise covariance and the measurement noise covariance matrices might change with each time step or the measurement. The matrix in the difference equation relates the state at the previous time step to the state at the current step, in the absence of either a driving function or process noise.

The a priori estimate error covariance is given in equation (2.11). Here  $E$  is the expected value,  $e_k^- e_k^{-T}$  is the priori error covariance, and  $P_k^-$  is the priori estimate.

$$P_k^- = E [e_k^- e_k^{-T}] \quad (2.11)$$

The posterior estimate error covariance is given in equation (2.12). Here  $e_k e_k^T$  is the posterior estimate error covariance, and  $P_k$  is the posterior estimate.

$$P_k = E [e_k e_k^T] \quad (2.12)$$

**Time Update Equation:** Time update equations project the state ( $\hat{x}_k^-$ ) and covariance ( $P_k^-$ ) estimates forward from time step  $k-1$  to step  $k$ . Equation (2.13)

and equation (2.14) gives the time update equation. Here A, B are the matrix and  $A^T$  is the matrix transpose.

$$\hat{x}_k^- = A * x_{k-1} + B * u_{k-1} \quad (2.13)$$

$$P_k^- = A^T A * P_{k-1} + Q \quad (2.14)$$

**Measurement Update Equation:** The first task during the measurement update is to compute the Kalman gain,  $K_k$ . The next step is to actually measure the process and then to generate an aposterior state estimate by incorporating the measurement. The final step is to obtain an aposterior error covariance estimate. The steps are given in equation (2.15). The recursive nature is one of the important features of the Kalman filter. Here  $K_k$  is the Kalman gain.  $H$  is the matrix,  $H^T$  is the matrix transpose.  $I$  is the identity matrix.

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \quad (2.15)$$

$$\hat{x}_k = \hat{x}_k^- + K_k (Z_k - H \hat{x}_k^-)$$

$$P_k = (I - K_k H) P_k^-$$

### 2.10.3 Filter Parameters and Tuning

In the actual implementation of the filter, the measurement noise covariance is usually measured prior to the operation of the filter [26]. Measuring the measurement error covariance is possible because we need to be able to measure the process while operating the filter, we should be able to take some off-line sample measurements in order to determine the variance of the measurement noise. The determination of the

process noise covariance is generally more difficult as we typically do not have the ability to directly observe the process we are estimating. In this case the process measurements are reliable. The filter performance can be obtained by tuning the filter parameters.

#### **2.10.4 MATLAB Implementation of the Designed Algorithm of the Kalman Filter**

The equation is written in the state space form as shown below. The parameters are estimated using 2<sup>nd</sup> order AR model determined in MATLAB and one step predicted output using hourly wind speed time series data given in the equation (2.16) and equation (2.17).

$$\begin{pmatrix} \hat{x}_1(t+1) \\ \hat{x}_2(t+1) \end{pmatrix} = \begin{pmatrix} a_1 & a_2 \\ 0 & 0 \end{pmatrix} * \begin{pmatrix} x_1(t+1) \\ x_2(t+1) \end{pmatrix} \quad (2.16)$$

Here  $a_1 = 0.8963$ ;  $a_2 = 0.09091$ ;

$$y(t) = (1 \ 0) * \begin{pmatrix} x_1(t) \\ x_2(t) \end{pmatrix} \quad (2.17)$$

#### **2.10.5 Observability and Controllability Test**

The observability and controllability test is performed on the estimated 2<sup>nd</sup> order, Auto Regressive model.

**Observability:** In order to see what is going on inside the system under observation, the system must be observable.

Observability Test

$A = [0.8963 \ 0.09091; \ 0 \ 0];$

$B = [0; 0];$

$C = [1 \ 0];$

$D = [0];$

$T_s = 1;$

$\text{observe1} = [C; C \cdot A];$

$r1 = \text{rank}(\text{observe1})$

$D1 = \det(\text{observe1})$

Test Result

$\text{observe1} = \begin{bmatrix} 1.0000 & 0 \\ 0.8963 & 0.0909 \end{bmatrix}$

$r1 = \text{rank}(\text{observe1}) = 2;$

$D1 = \det(\text{observe1}) = 0.0909;$

The rank of the matrix is 2 and the determinant of the matrix  $\neq 0$ .

Therefore the system is observable.

**Controllability:** In order to be able to do whatever we want with the given dynamic system under control input, the system must be controllable.

Controllability Test

$A = [0.8963 \ 0.09091; \ 0 \ 0];$

$B = [0; 0];$

$C = [1 \ 0];$

$D = [0];$

$T_s = 1;$

$$C_o = [B \ A*B];$$

$$r2 = \text{rank}(co);$$

$$D2 = \det(co)$$

Test Result

$$C_o = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$r2 = \text{rank}(co) = 0$$

$$D2 = \det(co) = 0;$$

The rank of the matrix is 0 and the determinant of the matrix is 0. Therefore the system is not controllable.

## 2.11 MATLAB Simulated and Corrected Wind Speed Estimation Using Kalman Filter

Figure 2.13 shows the Kalman filter state estimation with properly tuned parameters. The filter parameters are properly tuned with the process noise and the measurement noise. Figures 2.13, Figure 2.14, Figure 2.15 show the Kalman filter state estimation for state  $x_1$ . The state  $x_1$  is the observed state; the actual and the measurement follow closely at properly tuned filter parameters. For the Kalman filter, the linear time series models were developed using historical data. It is estimated an hour ahead and the best fit is around 60% due to the non linear nature of the wind speed. Using the state space equation of the linear AR model as initial conditions to the Kalman filter, the Kalman filter is used to filter and correct the bias in prediction. The prediction is validated

using the real data. For the Kalman filter, the process noise and the measurement noise is tuned properly using the filter parameters. The testing is done by proper tuning of the filter, it is assumed that the actual and measurement follow each other by properly tuning the Kalman filter parameters. This is shown in Figure 2.13. It shows that the Kalman filter has good performance in noise rejection and the actual and measurement follows each other.

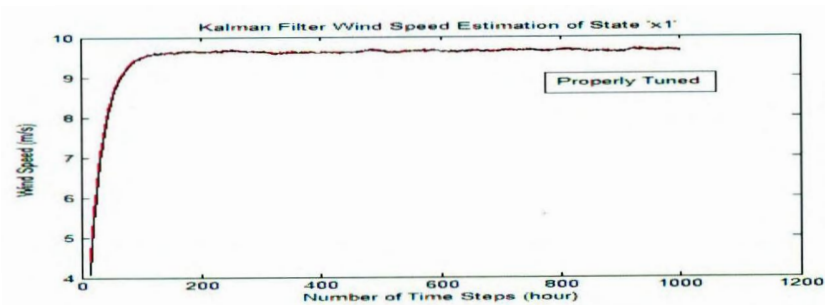


Figure 2.13: Properly tuned Kalman filter wind speed estimation.

Figure 2.14 shows the Kalman filter state estimation with the introduction of measurement noise. The state  $x_1$  is the observed state, the actual and the measurement are not following closely and there is a deviation. It means that we need to trust process more and measurement less.

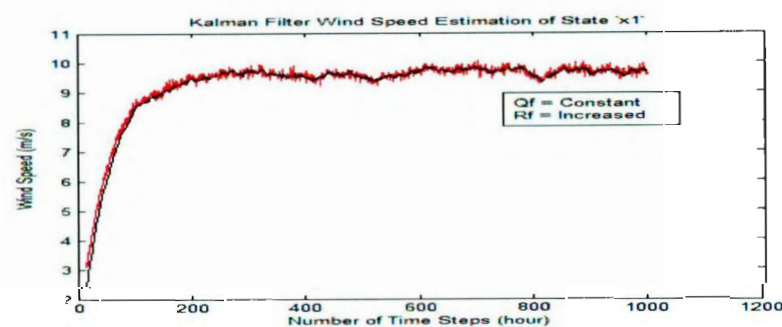


Figure 2.14: Kalman filter estimation with increase in measurement noise.

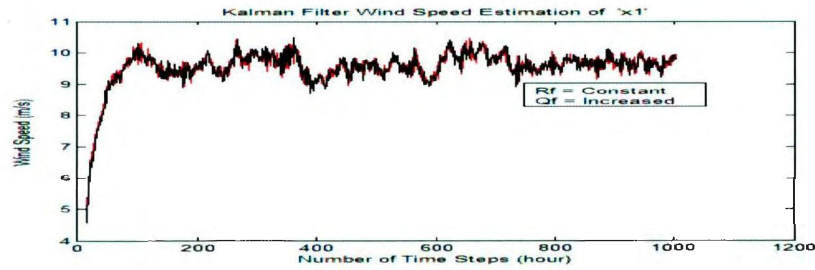


Figure 2.15: Kalman Filter estimation with increase in process noise ( $Q_f$ ) and the measurement noise ( $R_f$ ) is remaining constant.

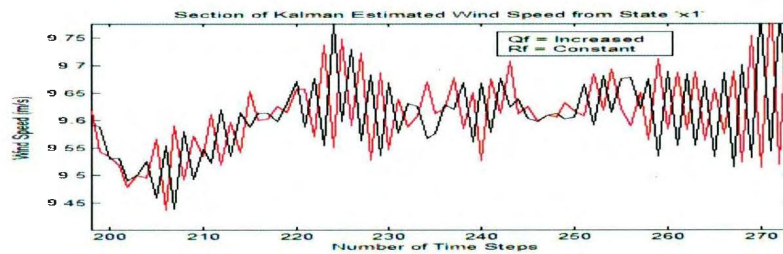


Figure 2.16: Section of Kalman filter with increase in process noise ( $Q_f$ ).

From the above figures we conclude that the Kalman filter performance is good. Appendix D gives the Auto Regressive code for determining the 'idpoly' model of the time series data for one step predicted output. The code for the Kalman filter is written in Appendix E. The code is implemented in MATLAB from the designed algorithm. The state space equation is determined and the model parameters are used in the Kalman Filter. State  $x_1$  is the observed state, Kalman filter performance is observed with the introduction of the noise parameters. We can conclude that the Kalman filter has good performance over noise rejection and its performance is



observed by minimizing the error. Tuning the filter parameters is understood and its effect on system performance is observed.

## 2.12 Wind Speed Estimation Using Unscented Kalman Filter:

### 2.12.1 Algorithm of the Unscented Kalman Filter

Unscented Kalman Filter is an extension of Unscented Transform to the recursive estimation. The Unscented transformation (UT) is a method for calculating the statistics of a random variable which undergoes a non linear transformation [28] and is given in equation (2.18).

$$y = f(x) \quad (2.18)$$

The variable 'x' is a random variable with mean  $\bar{x}$  and covariance  $P_{xx}$ . The variable y is related to the variable x through the non linear function ( $f(x)$ ). As seen in Figure 2.17, the nonlinear function is applied to each point to yield a cloud of transformed points. The mean  $\bar{y}$  and covariance  $P_{yy}$  are statistics of transformed points. We have to calculate the mean  $\bar{y}$  and covariance  $P_{yy}$ .

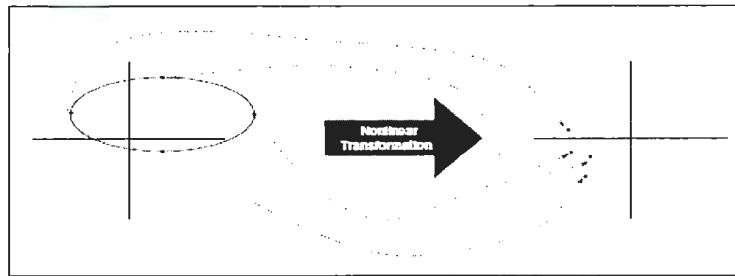


Figure 2.17: Principle of Unscented Transform [28].

A set of points or sigma points are chosen so that their mean and covariance are  $\bar{x}$  and  $P_{xx}$  respectively. The nonlinear function is applied to each point, the samples are not random points and follow an algorithm. The n-dimensional random variable  $x$  with mean  $\bar{x}$  and covariance  $P_{xx}$  is approximated by  $2n+1$  weighted points by the following [31]. Here  $n=2$  and  $k=1$ .

$$X_0 = \bar{x} \quad (2.19)$$

$$W_0 = k/(n+k) \quad (W \text{ is weight}) \quad (2.20)$$

$$X_i = \bar{x} + (\sqrt{(n+k)P_{xx}})_i \quad W_i = 1/2(n+k) \quad (2.21)$$

$$X_{i+n} = \bar{x} - (\sqrt{(n+k)P_{xx}})_i \quad W_{i+n} = 1/2(n+k) \quad (2.22)$$

Here  $k$  is the tuning parameter to fine tune higher order moments of approximation.

Here  $x(k)$  is assumed Gaussian, select  $n+k = 3$ . Instantiate each point through the function to yield set of transformed sigma points.

The transformed sigma points are:

$$Y_i = f[X_i] \quad (2.23)$$

$$\text{Mean is given by: } \bar{Y} = \sum_{i=0}^{2n} W_i Y_i \quad (2.24)$$

The associate covariance (  $P_{yy}$  ) is given by:

$$P_{yy} = \sum_{i=0}^{2n} W_i \{Y_i - \bar{Y}\} \{Y_i - \bar{Y}\}^T \quad (2.25)$$

The transformation process which occurs in the Kalman Filter consists of following steps [28].

Predict new state of the system or mean value.

Predict its associated covariance. It must take into account process noise.

Predict the expected observation and the innovation covariance.

The reduction should include effect of observation noise.

Predict the cross correlation matrix:

### 2.13 MATLAB Results of the Unscented Kalman Filter Using Autoregressive Model

In Figure 2.18, we see the properly tuned Unscented Kalman Filter response. The code is written in MATLAB from the steps of the Unscented Kalman Filter. The process noise and the measurement noise parameters are properly tuned. The state  $x_1$  is the observed state, the wind speed estimation of the actual and the measurement follow each other. Unscented Kalman Filter has good performance in state estimation.

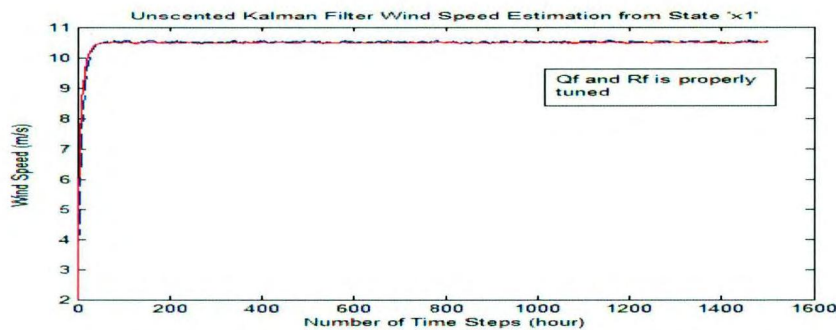


Figure 2.18: Unscented Kalman Filter response at properly tuned.

The UKF response is shown in Figure 2.19 and the measurement noise is introduced in the system. The measurement is trusted less and the process is trusted more. There is a deviation in the wind speed estimation of the actual and the measurement data.

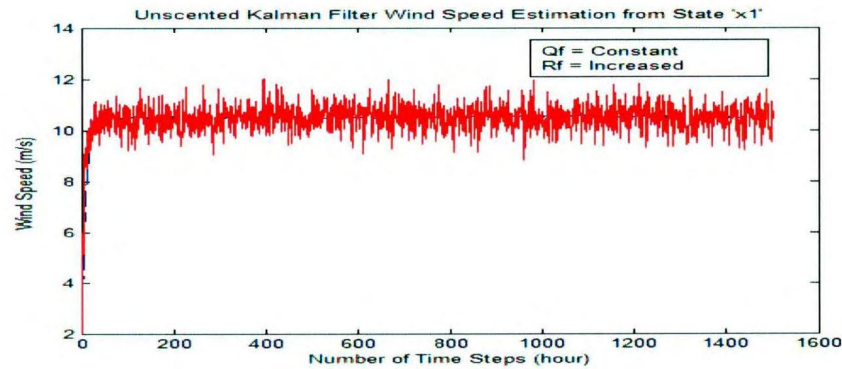


Figure 2.19: Unscented Kalman Filter response with the introduction of measurement noise.

The UKF response is shown in Figure 2.20 we see that the process noise is introduced in the system. The measurement is trusted more and the process is trusted less. There is a deviation in the wind speed estimation of the actual and the measurement data. The UKF has good performance by minimizing the noise effect.

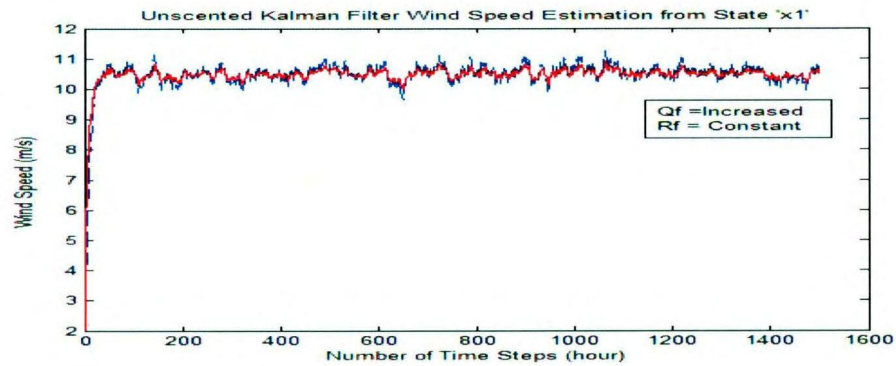


Figure 2.20: Unscented Kalman Filter response with the introduction of process noise.

From Figure 2.20, we conclude that the Unscented Kalman filter has good performance. The code for the filter is written in Appendix F. The code is implemented

in MATLAB from the designed algorithm of the UKF. State space equation determined from the model parameters is used in the Unscented Kalman Filter. State  $x_1$  is the observed state, the Unscented Kalman filter performance is observed with the introduction of noise parameters. Therefore, the Unscented Kalman filter has good performance over noise rejection and its performance is observed by minimizing the error.

## **2.14 PART II: System Identification Toolbox GUI**

### **2.14.1 Best fit estimation for the non linear Auto Regressive Exogenous Model**

The nonlinear ARX model is used in the system identification toolbox. The wind speed in the time series order is taken from the Environmental Canada website. The best fit estimation of the wind speed is performed in the System Identification toolbox. The wind speed is divided as training data and validation data and is shown in Figure 2.21. The wind speed data is 1000 per hour time series. The wind speed is divided as the training data for the wind speed range 1:650 and the validation data for the wind speed range 651:1000. The best fitted wind speed data is estimated by comparing non linear arx model with different model order. The comparison of the best fitted data is shown in Figure 2.22. From the comparison of the best fitted data, we conclude that the 2<sup>nd</sup> order 'arx' model is the best fitted data. As the model order is increased there is no further increase in the best fit estimation. With increase in model order, there is no

significant increase in the best fitted estimation of the wind speed and it remains the same which is about 58.08 %.

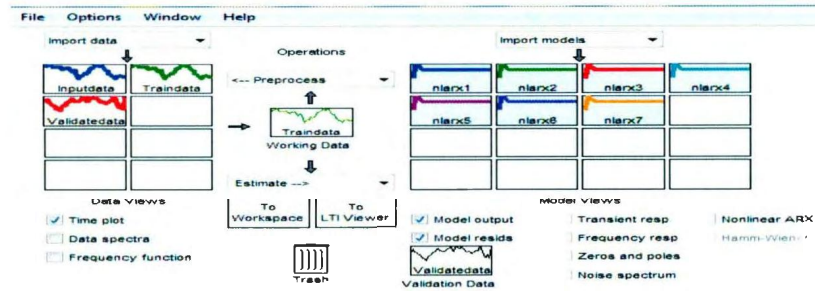


Figure 2.21: Non linear ARX model compared with various model orders

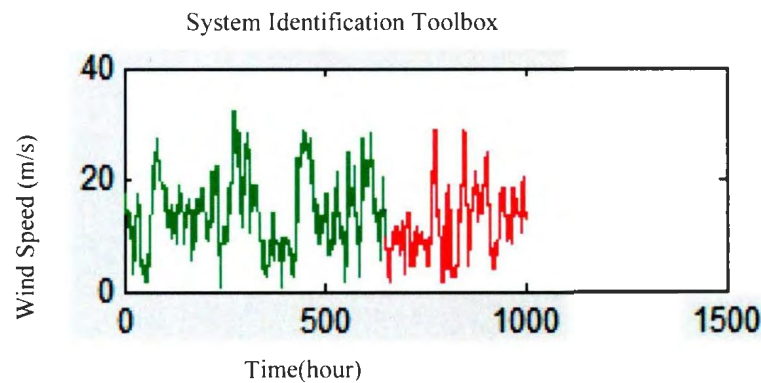


Figure 2.22: Training and Validation data for the wind speed in System Identification toolbox

Figure 2.23 and Figure 2.24 shows the best fit estimation of the non linear 'arx' model for various model orders. From the best fit estimation we see that the, 'nlarx2' is chosen as the best fitted data. The model chosen is nlarx2 with lower model orders for further estimation as less parameter are estimated and there is less complexity. With higher order model, more complexity arises as more parameters are estimated.

Figure 2.25 shows the autocorrelation of the residual for nlarx 2<sup>nd</sup> order model.

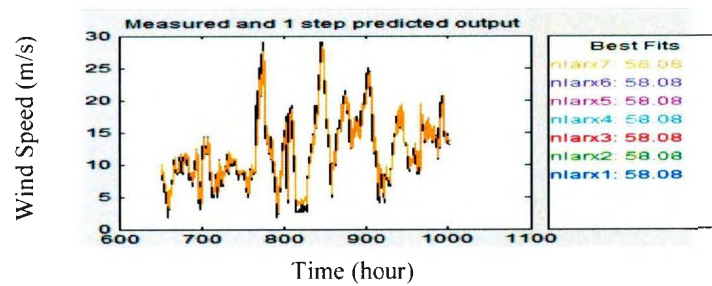


Figure 2.23: Comparison of the best fit nlarx model of various orders.

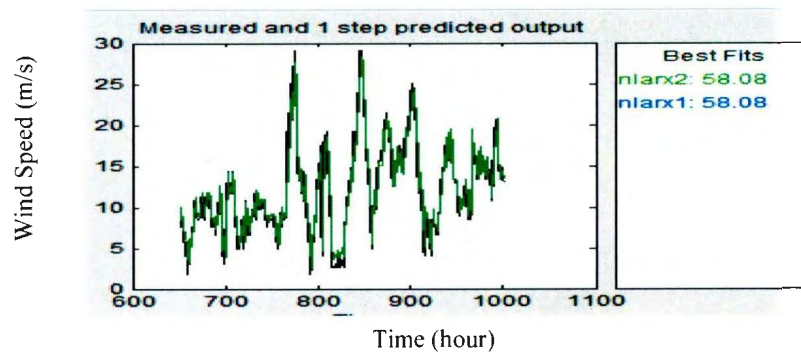


Figure 2.24: The nonlinear ARX best fitted 1st and 2nd order model.

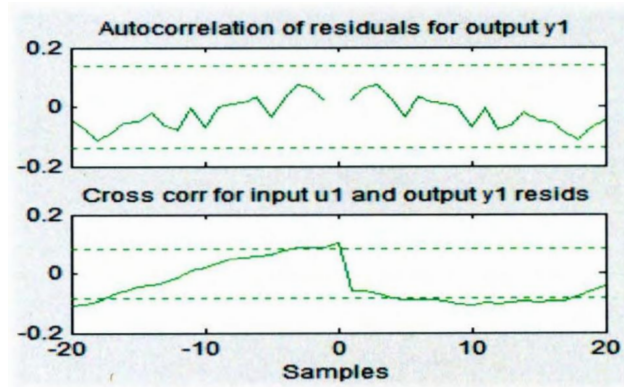


Figure 2.25: Autocorrelation of residuals for the nlarx model.

## 2.15 MATLAB Code analysis of the 2nd order non linear ARX Model

The state space model for the non linear 2<sup>nd</sup> order arx model is used in the Unscented Kalman Filter. The code is implemented in the MATLAB for second order nonlinear ARX model to estimate the best fitted data. A copy of the MATLAB code is attached in Appendix G. Figure 2.26 shows the best fitted data for 2<sup>nd</sup> order nlarx model.

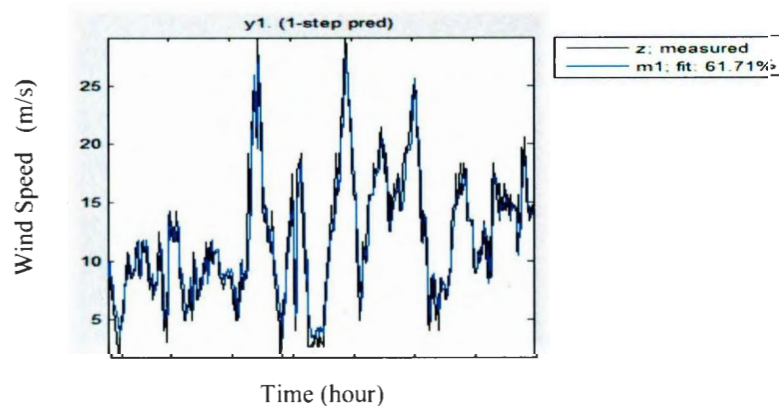


Figure 2.26: Nonlinear best fit estimation of the non linear arx 2nd order model.



MATLAB Code for 2<sup>nd</sup> order non linear ARX Model from the nonlinear parameters is estimated from the model. The wind speed is estimated using second order non linear arx model using sigmoid function. The following results are estimated from the implemented MATLAB code.

```
m1.nonlinearity.Parameters
```

```
Result = RegressorMean: [13.4477 13.448]
```

```
Nonlinear Subspace: [2x2] double
```

```
Linear Subspace: [2x2 double]
```

```
Dilation: [2x10 double]
```

```
Translation: [30.7162 -29.2601 6.0578 -9.3062 -1.4186 -0.4608 2.9542
```

```
2.7222 -8.6089 8.5297]
```

```
OutputCoef: [10x1 double]
```

```
Output Offset: 22.9998
```

```
m1.nonlinearity.Parameters.NonLinearSubspace
```

```
ans = 0.0825 -0.4050
```

```
0.0825 0.4050
```

```
m1.nonlinearity.Parameters.LinearSubspace
```

```
ans = 0.0825 -0.4050
```

```
0.0825 0.4050
```

The difficulty is in designing the state space model for the non linear ARX model. The state space of the nonlinear ARX model is determined using the non linear subspace parameters. The parameter for the non linear ARX model in state space form is assumed to be of the form given in equation 2.26:

$$A(q) y(t) = B(q) u(t) + e(t) \quad (2.26)$$

From this equation, we get:

$$a_1 = 0.0825 \quad a_2 = -0.4050$$

$$b_1 = 0.0825 \quad b_2 = 0.4050$$

or it is rewritten as given below

$$A = [0.0825 \ -0.4050; \ 0 \ 0];$$

$$B = [0.0825 \ -0.4050; \ 0 \ 0];$$

$$C = [1 \ 0];$$

Assuming that the nonlinear structure of the arx model is as given in equation (2.27)

$$\begin{pmatrix} a_1 & a_2 \\ 0 & 0 \end{pmatrix} * \begin{pmatrix} x_1(t+1) \\ x_2(t+1) \end{pmatrix} = \begin{pmatrix} b_1 & b_2 \\ 0 & 0 \end{pmatrix} * \begin{pmatrix} u_1(t+1) \\ u_2(t+1) \end{pmatrix} \quad (2.27)$$

$$y(t) = (1 \ 0) * \begin{pmatrix} x_1(t) \\ x_2(t) \end{pmatrix}$$

## 2.16 MATLAB simulated results of the Unscented Kalman filter using Non Linear Autoregressive Exogenous model

The state space determined in equation (2.27) is used in the Unscented Kalman Filter

from the non linear parameters estimated from the non linear ARX model. The

exogenous input is used in the Unscented Transform and the wind speed is estimated.

The code is written in MATLAB from the designed algorithm of the UKF and a copy

of code is attached in Appendix H. In Figure 2.27, we see that the state  $x_1$  is the

observed state. Both the process noise and the measurement noise is properly tuned,

the actual and the measurement estimation of the wind speed follow closely. The UKF

performance is observed at properly tuned filter parameters.

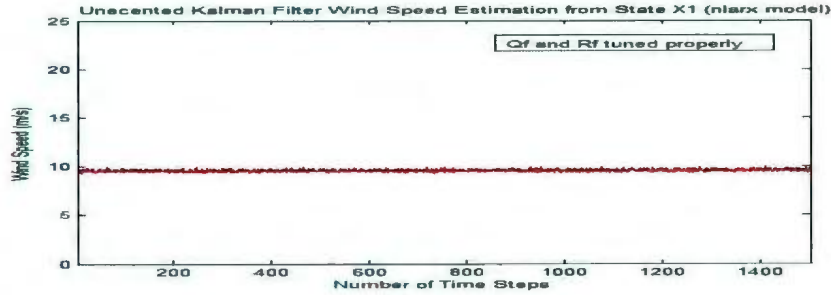


Figure 2.27: Process noise and measurement noise is reduced with UKF properly tuned.

Figure 2.28 and Figure 2.29 shows variation in the actual and the measurement data.

In Figure 2.28, we see process noise is increased and measurement noise is tuned at a very low value by the tuning parameters. We need to trust process less and measurement more. In Figure 2.29, we see process noise is low and measurement noise is increased by the tuning parameters. We need to trust process more and measurement less. We can conclude that the UKF performance is great with the associated noise, as it is minimizing the noise effect.

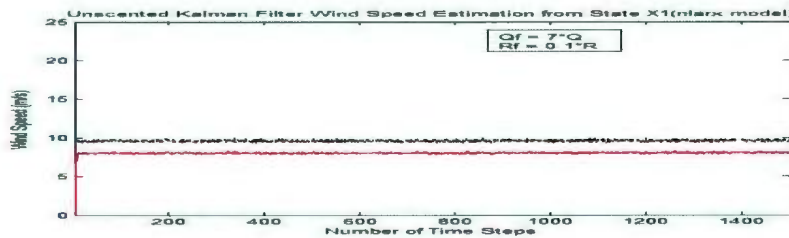


Figure 2.28: UKF performance with increase in process noise.

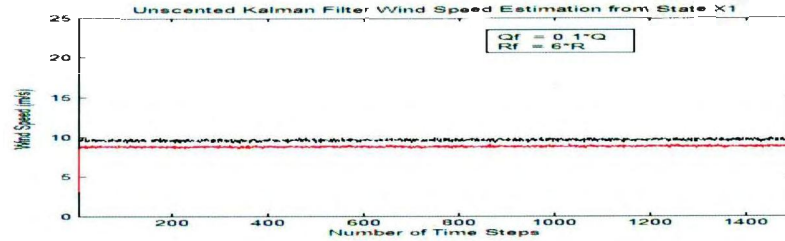


Figure 2.29: UKF performance with increase in measurement.

## 2.17 Conclusion

In this chapter, the short term wind speed predictor model is developed. From the analysis of the wind speed predictor model, it is concluded that an accurate estimation of the wind speed distribution is critical to the assessment of the wind energy potential. An hourly time series wind speed data gives accurate result for the short term wind speed prediction and the ARMA models have an advantage that they can provide very accurate results for the short term wind speed prediction. If the data are not stationary and there is a high variations and change trend suddenly it gives inaccurate results. The ARMA model gives accurate prediction for the range of the wind speed 4 m/s to 11 m/s. The wind speed data ranges from 1 m/s to 20 m/s for this predictor design. The MATLAB code works on different wind data file and is tested for accuracy. The wind speed is estimated an hour ahead using the Kalman filter and the Unscented Kalman Filter. From the models investigated for the short term wind speed prediction, AR model and Nonlinear ARX model is chosen for step or hour ahead prediction of the wind speed. System identification toolbox in MATLAB is used for estimating the best fitted data from the available model in the toolbox. From the literature review and the

available statistical model structure in system identification toolbox, Auto Regressive model and Auto Regressive Moving Average model is chosen for testing and estimating the best fitted data. The input wind speed is divided as training data set and validation data set. The AR model of various model orders and non linear ARX model of various model orders is tested by comparing the actual data with the estimated data from the selected model order. The best fitted data is of Auto Regressive, 2<sup>nd</sup> order model and for non linear system Autoregressive Exogenous, 2<sup>nd</sup> order model. For more accuracy the Kalman Filter and the Unscented Kalman Filter is used for further correction and estimating the states of the wind speed from the Auto Regressive model and nonlinear ARX model. Both the filter performance are observed and compared. The filter performance is observed when process noise and measurement noise is introduced in the system. From the results of Kalman filter for the AR model and UKF for AR model and non linear arx model, we see that for the case of Kalman filter the input is linear, as the wind speed is estimated from the linear AR model. The constraints in case of Kalman filter are both the functions  $h$  and  $y$  in MATLAB code are assumed to be linear with noise terms 'w' and 'v', uncorrelated and Gaussian. estimation using the Kalman filter is easier as it incorporates almost all linear calculation except a matrix inversion. In case of the Unscented Kalman Filter, we assume that some non linearity is present in the input because all real time physical system are non linear in nature. Comparing the UKF with the AR model and the non linear ARX model, we can see that more accurate estimation is with UKF for non linear ARX. Instead of linearising a nonlinear function it uses  $2N+1$  sigma points for  $N$  states and then propagates these points through the actual non-linear function,

eliminating linearization. It approximates the probability distribution. With this approach the computational complexities is reduced and at the same time there is improvement estimation accuracy. By comparing the results, it is concluded that almost similar results are estimated from the Kalman filter and the Unscented Kalman Filter. This shows that the developed and estimated results can be applied for short term wind speed prediction. The change in performance can be observed for long term wind speed prediction and very large historic data is taken as input to the system, and this introduces more non linearity in the system. At the same time it gives more accurate wind speed estimation for real time system. As Unscented Kalman Filter is used for non linearity and gives good performance for long term wind speed estimation. Thus the Kalman filter cannot be used under such condition. As the focus of the chapter is on short term or hour ahead wind speed estimation, both the Kalman filter and Unscented Kalman Filter has good performance.

## **Chapter 3**

### **Power Prediction of the Fermeuse, Newfoundland Wind Farm**

#### **3.1 Introduction**

The wind power is the conversion of the wind energy to produce electricity using wind turbines and is an alternate source of renewable energy. The wind power forecasting is essential for utility operators to plan shutdown of the thermal units in the system.

Physical factors such as vertical shear, turbulence intensity, turbulence adjusted wind speed, air density, pressure, and temperature are considered to predict the wind power of a wind turbine. The wind farm consists of many wind turbines. The physical factors determine the wind power estimation in real time. In this chapter, an algorithm is designed considering all physical factors affecting the wind power of the wind turbines in the wind farm. The code is written in MATLAB to estimate the wind power in real time. The wind turbine manufacturer supplied power curve assumes ideal conditions and in reality there is a variation in physical factors. The physical factors considered estimate of the wind power of the wind turbines in the wind farm. The Fermeuse wind farm is located in the community of the Fermeuse on the Southern Shore, Avalon Peninsula in Newfoundland [45]. The wind farm has nine wind turbines in an operating condition. The wind turbine used at the Fermeuse wind farm is the Vestas V90 3MW and the total capacity of the windfarm is 27MW. The main challenge for this work is to find a simple model that will take a topographical map, a wind farm layout, the long term site wind and atmospheric data. It utilizes this information to calculate the wind speed at all the wind turbines. The designed algorithm estimates the

wind speed adjusted for shear and turbulence for the wind turbine rotor disc from the lower hub height to the upper hub height. Air density is adjusted to predict the wind power of a wind turbine. For estimating power for the wind farm, speed and height for each wind turbine varies and depends on the distance between wind turbines, contour height, and layout information. The wake model is incorporated when wind turbines are placed at a closer distance and power of the wind farm is estimated from the input wake speed. The resulting simple model of a wind farm is used to develop a computer program that is fast and can be used on a windows computer.

### **3.2 Wind Turbine Power Estimation**

The detail of the Vestas V90 3MW wind turbine is required in the initial design stage. The supplied wind turbine power vs. wind speed characteristics is studied in detail. It is digitized from the power curve data. Thus the power curve of the Vestas V90 3 MW wind turbine is produced in the initial design stage. Figure 3.1 shows the Vestas V 90 3MW wind turbine at the Fermeuse.





Figure 3.1: Vestas V90 3MW wind turbine [46].

The Vestas V90 3MW wind turbine is designed to be light weight, making it easier to transport with lower installation and foundation cost. The tower is lighter and uses magnets instead of welding to attach the tower internals to the tower wall. Some technical specifications of the Vestas V90 3 MW wind turbine are given below.

#### Technical Specifications of the Vestas V90 3MW wind turbine

##### Operational data:

Rated power: 3,000 kW

Cut-in wind speed: 3.5 m/s

Rated wind speed: 15 m/s

Cut-out wind speed: 25 m/s

Re-cut in wind speed: 20 m/s

Wind class: IEC IA and IEC IIA

Operating temperature range: standard range -20°C to 40°C, low temperature option - 30°C to 40°C

Rotor diameter: 90 m

Swept area: 6,362 m<sup>2</sup>

Nominal revolutions: 16.1 rpm

Operational interval: 8.6 - 18.4 rpm

Air brake: full blade feathering with three pitch cylinders

Frequency: 50 Hz/60 Hz

Generator type: 4-pole doubly fed generator

Gearbox: Two planetary stages and one helical stage

Power regulation: Pitch regulated with variable speed [43]

The power curve supplied by the manufacturer assumes ideal conditions and in reality there is variation in physical parameters and variation in the output power. The wind turbine manufacturer supplied power curve can be digitized by extracting data from the power vs. speed characteristics. The Fermeuse wind farm has nine wind turbines. The actual height of a wind turbine rotor disc is determined by the hub height and wind turbine base elevation. The sensor height at the metrological (MET) tower is assumed to be at the height of 80m. The site measured and predicted wind speed of wind data are given at the sensor height. To determine a wind turbine output power, the wind

speed data should be known at the lower rotor tip of the wind turbine to the upper rotor tip of the wind turbine. The input wind data at unknown heights is determined using the power law equation of shear using  $1/7$  shear exponent value. The input wind speed data provided is typically sampled every second, averaged and stored every 10 minutes for 10000 time series. From a sensor measured input wind speed, pressure, temperature, and wind direction for every ten minutes, the wind turbine power is estimated. The turbulence adjusted wind speed is determined from the input wind speed and the turbulence intensity at the known model levels or height which intersects the wind turbine rotor disc. The wind shear exponent is calculated using the power law equation of shear from the turbulence adjusted wind speed data at known heights. The estimated disc wind speed, which is adjusted for turbulence and vertical shear, is evaluated for the entire rotor disc by numerically integrating the wind speed values from the lower rotor tip to the upper rotor tip of the wind turbine by solving the equation of the disc speed. The estimated disc speed value is assumed to be at the hub height. The uncorrected power curve function is determined from the digitized power curve supplied by the manufacturer. The disc speed is substituted in the uncorrected power curve function and is subsequently adjusted for the air density to estimate the power of a wind turbine. Thus the wind power is estimated for one wind turbine from the disc speed which is adjusted for turbulence and vertical shear.

### **3.3 The Fermeuse Wind Farm Power Estimation**

The Fermeuse wind farm has nine wind turbines in the wind farm. After a site visit to the Fermeuse wind farm and the information collected through extensive

research it was concluded that the wind farm has nine wind turbines all in operating condition. The contour height of the wind turbine is determined from the wind turbine base elevation and the assumed horizontal distance between wind turbines. The power of each wind turbine is estimated from the input time series wind data; therefore wind power for all the nine wind turbines is estimated. Implementation of the wind power model of the wind turbines in the Fermeuse wind farm is done in MATLAB. The wake model is implemented when the wind turbines operate in the wake of upstream and neighboring wind turbines. For a particular wind direction, a wind turbine may operate in the partial shadow or the complete shadow of upstream and neighboring wind turbines. This results in considerable reduction in the wind power. It is determined from the input predicted disc speed, radius of the shadow cone, nearest distance between wind turbines, radius of the rotor disc, area of the wind turbine rotor disc, and area of shadow region of the wind turbine. The output of the wake model is reduced wind speed due to the wake effect. The uncorrected power curve function has input wake speed and is subsequently adjusted for air density to determine corrected power of the wind turbine. The estimated power is the wake power of the wind turbine. The wake power of each wind turbine in the wind farm is added to determine the power of the wind farm. With the wake effect, there is a considerable reduction in the wind power of downstream wind turbines. For all other wind directions there is no reduction in the wind speed and the wind turbines operate at a maximum power.

### 3.3.1 Layout of the Fermeuse Wind Farm

After a site visit to the Fermeuse wind farm and after extensive research regarding the layout information, the wind farm layout is estimated [36] as shown in Figure 3.2.

Assumptions are made to the wind turbines placed in the wind farm, as the actual information is commercially sensitive.

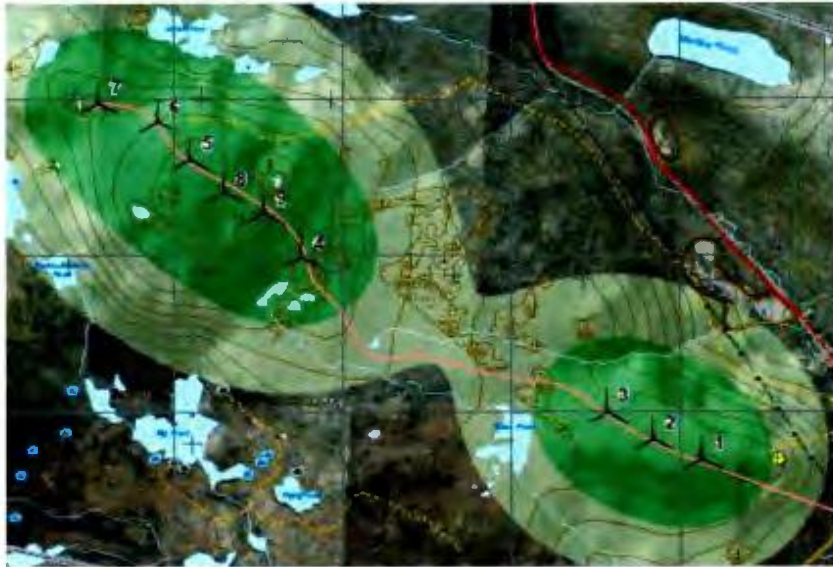


Figure 3.2: Fermeuse wind farm layout [36].

The contour height of the wind turbine is determined from the wind turbine base elevation. The horizontal distance between the wind turbines is obtained from the layout information. The wake effect is considered for the wind turbine for a particular wind direction in the wind farm and depending on the wind turbine placement available in the layout information. The wind speed for a wind turbine operating in the wake effect is reduced and therefore there is a considerable reduction of wind power. For a particular wind direction, the wind turbines operating in partial shadow or

complete shadow of upstream and neighboring wind turbines will result in a considerable low power. The estimated wind power of each wind turbine in the wind farm is added and the total power of the wind farm is determined. For all other wind direction there is no reduction of the wind speed and the wind turbines operate at a maximum power. Figure 3.3 below shows a flow chart of wind power physical model. Figure 3.4 below shows a flow chart of wake power model in the wind farm.

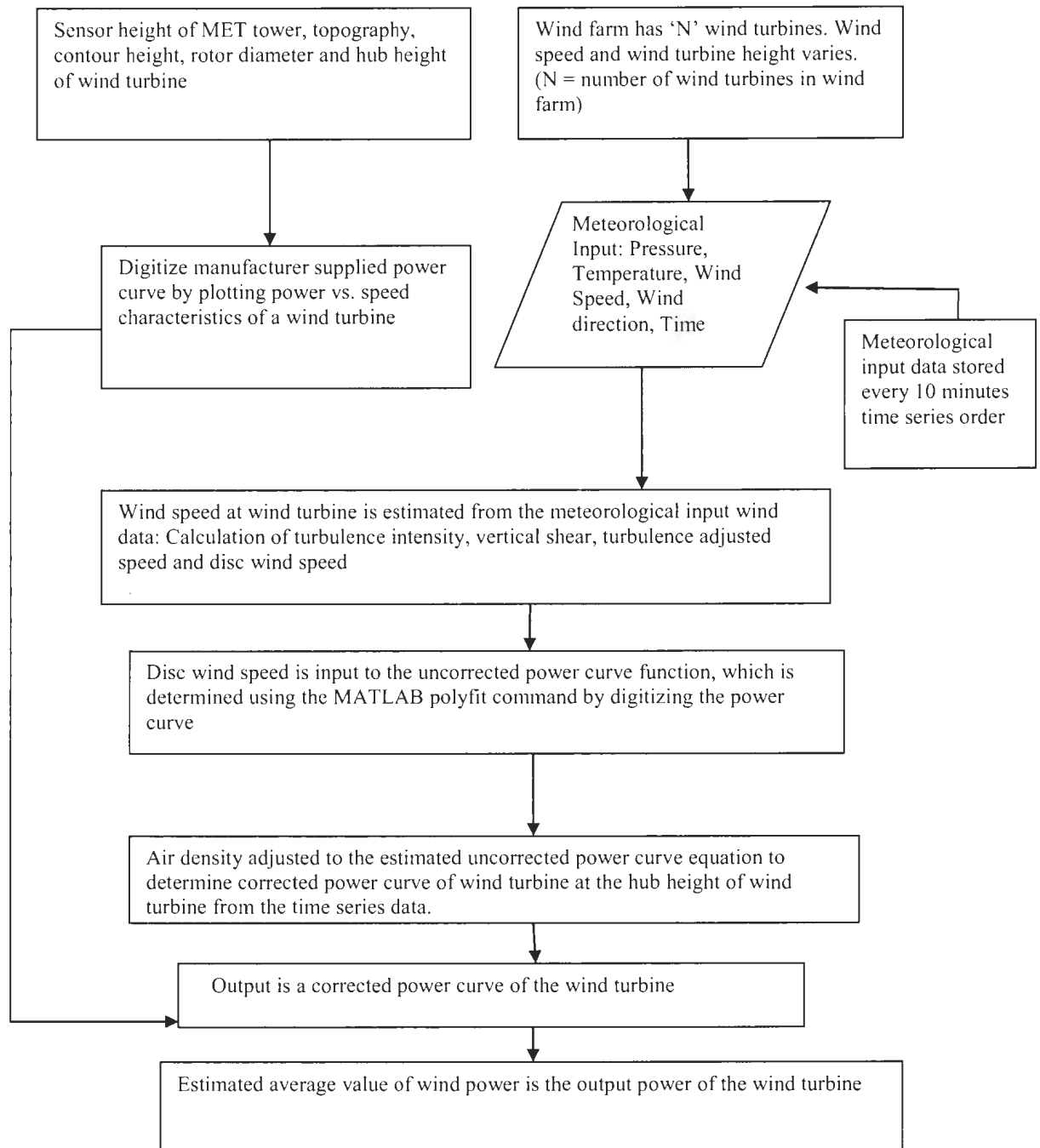


Figure 3.3: Flowchart of the wind power model.

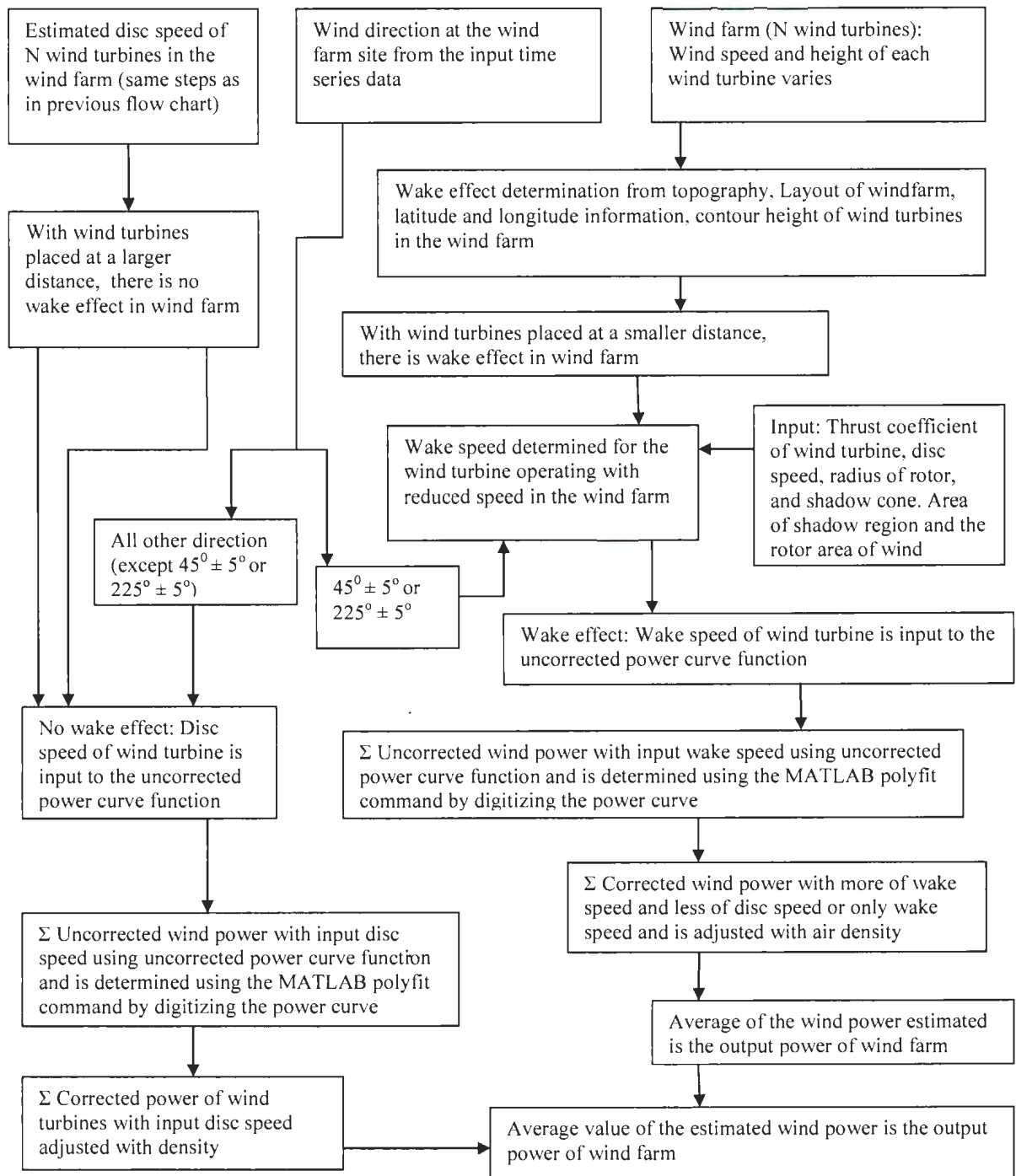


Figure 3.4: Flow chart of the wind farm wake model.



### 3.4 Methods/ Techniques Applied in Estimating Wind Turbine Power

The wind turbine manufacturer supplied power curve is digitized and the 8<sup>th</sup> order polynomial is fitted in the MATLAB for an accurate prediction. The curve fitted equation [32] of 8<sup>th</sup> degree is uncorrected power curve. The curve fitting equation is valid for the wind speed range below the rated wind speed till the rated wind speed of the wind turbine. Weather Research and Forecasting (WRF) forecasts metrological data i.e. wind speed, pressure, temperature, and wind direction which is used as input to the Wind Power Physical Model (WPPM). WRF has pressure levels, known as eta levels which intersect the wind turbine rotor disc. The height of these model levels that intersect the rotor disc of the wind turbine is determined. The Fermeuse wind farm has nine wind turbines; the height of each wind turbines is determined by considering its base elevation. The input wind speed is given at the sensor height. The input wind speed data should be determined at the lower rotor tip of the wind turbine to the upper rotor tip of the wind turbine. The wind speed at unknown height is determined from the power law equation of shear. The input wind data is sampled every 10 minutes and has 10000 data points. From the given input wind data, the physical factors considered such as turbulence intensity, turbulence adjusted speed and wind shear exponent can be calculated at the given input model levels. Turbulence intensity is determined from the average wind speed and standard deviation value of wind data. Turbulence adjusted wind speed is determined from the input wind speed and turbulence intensity at the known model levels or height which intersect with the wind turbine rotor disc. Wind shear exponent ' $\alpha$ ' is calculated using the power law equation of shear from the turbulence adjusted wind speed data at the given model levels. Final disc wind speed

which is adjusted for turbulence and vertical shear is evaluated for the entire rotor disc by numerically integrating in the range H-R (hub height – rotor radius) to H+R (hub height + rotor radius) or the lower rotor tip of the wind turbine to the upper rotor tip of the wind turbine by solving the equation of the disc speed. The estimated value of the disc speed is assumed to be at the hub height. The uncorrected power function is determined from the fitted equation. The disc wind speed substituted in the uncorrected power curve function is subsequently adjusted for air density to estimate the power of the wind turbine.

### 3.5 Designed Algorithm of the Wind Power Model

#### 3.5.1 Wind power of a wind turbine with no-wake effect

The manufacturer supplied power curve of the Vestas V90 3MW wind turbine is power vs. wind speed characteristics [43]. The uncorrected power curve function is determined using the MATLAB polyfit command from the curve fitting toolbox [32]. In the curve fitted equation the variable  $x$ , for the Vestas V90, 3 MW wind turbine is replaced by the wind turbine rotor disc speed ( $\bar{U}_{Disk}$ ) estimated from the algorithm adjusted for turbulence and shear.

The uncorrected power  $P1(uncorr)$  is determined from the disc wind speed, substituted in the polyfit equation as given in the equation (3.1).

$$P1(uncorr) = q(9) + q(8) * x + q(7) * x^2 + q(6) * x^3 + q(5) * x^4 + q(4) * x^5 + q(3) * x^6 + q(2) * x^7 + q(1) * x^8$$

Here  $x = \bar{U}_{Disk}$  = Estimated disc speed value of Vestas V90, 3 MW

wind turbine (3.1)

Wind speed is calculated at the hub height ( $H_{hub}$ ) of the wind turbine using a power law equation of shear from the input sensor speed ( $U_1$ ) at the sensor height ( $H_1$ ) and is given in equation (3.2).

$$U_{hub} = U_1 * \left(\frac{H_{hub}}{H_1}\right)^{0.143} \quad (3.2)$$

Turbulence Intensity ( $I_u$ ) at known heights is calculated using equation (3.3) from the input wind speed ( $U$ ) and standard deviation data ( $\sigma$ ) at the hub height of the Vestas V90 3 MW wind turbine.

$$I_u = \frac{\sigma}{U} \quad (3.3)$$

Turbulence adjusted wind speed  $U'(TI)$  is calculated from the input wind speed and turbulence intensity ( $I_u$ ) at the hub height of the Vestas V90, 3 MW wind turbine as given in equation (3.4).

$$U'(TI) = \sqrt[3]{U^3 * (1 + 3I_u^2)}. \quad (3.4)$$

Wind shear exponent ( $\alpha$ ) is calculated [37] from the above turbulence adjusted wind speed  $U'_2(TI)$  and  $U'_1(TI)$  at various model levels or heights  $H_2$  and  $H_1$  of the wind turbine rotor disc. It is given by the power law equation of shear as in equation (3.5).

$$\alpha = \frac{\log\left(\frac{U'_2(TI)}{U'_1(TI)}\right)}{\log\left(\frac{H_2}{H_1}\right)} \quad (3.5)$$

Wind velocity across the wind turbine rotor disc [1] which is adjusted for turbulence and vertical shear, is calculated using equation (3.6) from the lower rotor tip ( $H-R$ ) to the upper rotor tip ( $H+R$ ) of a wind turbine.

$$\bar{U}_{Disk} = \frac{2}{A} \int_{H-R}^{H+R} U_z \sqrt{R^2 - H^2 + 2HZ - Z^2} dz \quad (3.6)$$

Here H is the wind turbine hub height, R is the radius of the wind turbine rotor disc and A is the area of wind turbine rotor disc.

Air density ( $\rho$ ) [32] correction is applied to the disc power using the input pressure (P) and the temperature (T) as given below using equation (3.7).

$$\rho = 3.4837 * \frac{P}{T} \quad (3.7)$$

Corrected power P1(corr) of a wind turbine [32] is determined from the actual air density at Standard Temperature Pressure (STP) and the uncorrected power P1(uncorr) from the curve fitting equation, using the equation (3.8).

$$P1(corr) = P1(uncorr) * \frac{\rho}{\rho \text{ at STP}} \quad (3.8)$$

### 3.5.2 Wind power of a wind farm with no-wake effect

Below is the general equation to determine the wind power of the wind turbines with no-wake effect. For the Fermeuse wind farm, details of the wind farm layout, number of wind turbines, contour height of wind turbine, and distance between nearest wind turbines are studied. These values are considered to estimate the power of the wind turbines in the wind farm. For a particular wind direction, the wake effect is considerable when the wind turbines are placed at a distance less than four times the rotor diameter. For all the other wind directions, the wind turbines operate in free wind speed. The wind turbines operate at a maximum power and power of the wind farm is determined by adding power of each wind turbine with no-wake effect. The Fermeuse wind farm has nine wind turbines and the total power of the wind farm is the sum of

the power of each wind turbine in the wind farm and it is calculated using equation (3.9), where the number of wind turbines is denoted by n.

$$\sum_{n=1}^n P1(\text{corr}) = \text{Total Windfarm No\_wake Power} \quad (3.9)$$

### 3.5.3 Wind power of a wind turbine with the wake effect

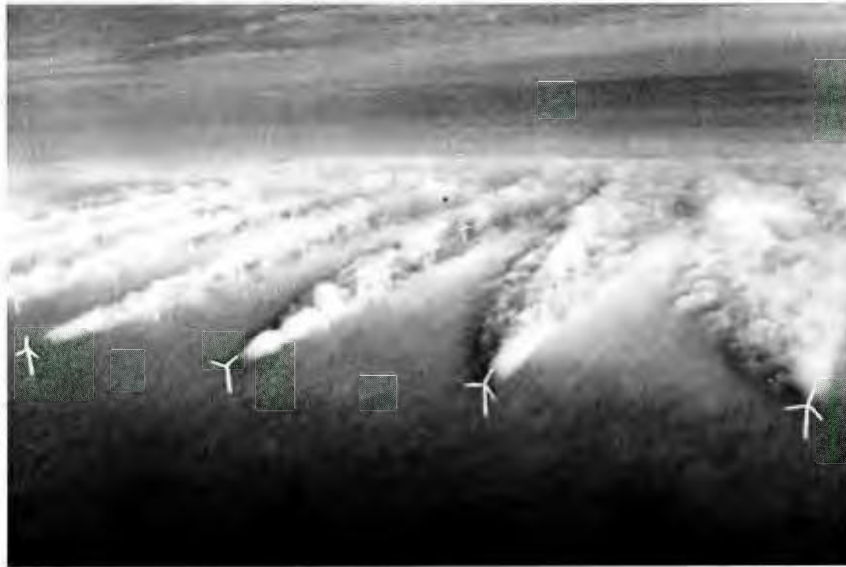


Figure 3.5: Wake effect in a wind farm [44].

Figure 3.5 shows [44] the wake effect in a wind farm. Below is the general equation to determine the wind power of the wind turbines with the wake effect. With the wake effect, the wind speed for downstream wind turbine reduces depending on the shadow area of the rotor disc, the radius of the shadow cone, the thrust coefficient of the wind turbine and this result in a reduction of the wind power. The wake speed of the wind turbine is determined from the free disc speed at the rotor disc and correspondingly the wake power is determined. Depending on the distance between the wind turbines (X),

the radius of the shadow cone ( $R_x$ ) [33] of upstream turbine is calculated using equation (3.10) from the radius of rotor ( $R$ ) and  $\tan\alpha$ . The value of  $\tan\alpha$  is 0.04 under free stream and 0.08 under wake stream.

$$R_x = R + X * \tan\alpha \quad (3.10)$$

The thrust coefficient ( $C_t$ ) of the wind turbine [34] is calculated from the disc speed adjusted for vertical shear and turbulence using equation (3.11) and is given below.

The disc speed is assumed to be at the hub height of the wind turbine.

$$C_t = 3.5 * \frac{(2 * \bar{U}_{Disc} - 3.5)}{(\bar{U}_{Disc})} \quad (3.11)$$

The wake speed ( $U_{wake}$ ) of a wind turbine [38] is calculated from the disc speed, the thrust coefficient, the radius of rotor disc, the radius of the shadow cone ( $R_x$ ) of the rotor disc, the area of shadow region (AS) of rotor disc and the area of the wind turbine rotor (A) using equation (3.12).

$$U_{wake} = \bar{U}_{Disc} * [1 - \sqrt{(1 - C_t)} * \left(\frac{R}{R_x}\right)^2 * \left(\frac{AS}{A}\right)] \quad (3.12)$$

The supplied power curve is used to determine the uncorrected power curve function.

The variable in the polyfit equation is replaced by the wake speed. The uncorrected wake power  $P2(uncorr\_wake)$  of the wind turbine is calculated using equation (3.13)

for the Vestas V 90, 3MW wind turbine.

$$P2(uncorr\_wake) = q(9) + q(8) * U_{wake} + q(7) * U_{wake}^2 + q(6) * U_{wake}^3 + q(5) * U_{wake}^4 + q(4) * U_{wake}^5 + q(3) * U_{wake}^6 + q(2) * U_{wake}^7 + q(1) * U_{wake}^8. \quad (3.13)$$

The actual air density is determined from the input pressure (P) and the temperature (T) using equation (3.7). Air density correction is applied and the corrected wake

power,  $P2(\text{corr\_wake})$  of the wind turbine [32] with the wake effect is determined from the actual density, the density at STP and the uncorrected wake power from the curve fitting equation of MATLAB using equation (3.14).

$$P2(\text{corr\_wake}) = P2(\text{uncorr\_wake}) * \frac{\rho}{\rho \text{ at STP}} \quad (3.14)$$

#### 3.5.4 Wind power of a wind farm with the wake effect

The Fermeuse wind farm has nine wind turbines and the corrected power ( $P2(\text{corr\_wake})$ ) of each wind turbine with the wake effect is summed using equation (3.15) and the total power of the wind farm with the wake effect is determined. Table 3.1 gives the details of the wind turbines of the Fermeuse wind farm operating in the wake effect and the area of shadow region of the rotor disc for a particular wind direction.

$$\sum_{n=1}^n P2(\text{corr\_wake}) = \text{Total Windfarm Wake Power} \quad (3.15)$$

#### 3.5.5 Wake coefficient of the wind turbines in the wind farm

The wake coefficient (WC) [33] of the wind turbines in the wind farm is calculated using equation (3.16) by the ratio of the summation of the total output power of the wind farm with the wake effect to the summation of the total output power of the wind farm neglecting the wake effect.

$$WC = \frac{\sum_{n=1}^n P2(\text{corr\_wake})}{\sum_{n=1}^n P1(\text{corr})} \quad (3.16)$$

### 3.6 Detail Overview of the Fermeuse Wind farm

The Fermeuse wind farm has nine Vestas V90, 3MW wind turbines. The wind turbine specifications are given in detail in Table 3.1 [43]. The sensors at the MET tower are assumed to be located at a height of 80m to record the wind speed.

Table 3.1: Specification of the Vestas V90 3 MW Wind Turbine.

Specifications of the Wind Turbine	Vestas V90 3MW Wind Turbine
Cut in wind speed	3.5 m/s
Rated wind speed	15 m/s
Rotor Diameter	90 m
Rated Power	3.0 MW
Hub Height	80m
Cut out wind speed	25 m/s

The details of the wind turbines of the Fermeuse wind farm are given in Table 3.2. The wind turbine hub height is determined from the turbine base elevation. The lower rotor tip and the upper rotor tip height of the wind turbine are determined from the radius of the wind turbine and its hub height. The nearest distance between the neighboring wind turbines is determined from the wind farm layout and is given in Table 3.3.



Table 3.2: Wind Turbines Details in the Fermeuse Wind farm.

Number of Wind Turbine	Contour Height of Wind Turbine + Hub Height (m)	Lower Rotor Tip (H-R) (m)	Upper Rotor Tip (m)	Hub Height (m)
WT1	95	50	140	80
WT2	95	50	140	80
WT3	95	50	140	80
WT4	127	82	172	112
WT5	153	108	198	138
WT6	140	95	185	125
WT7	128	83	173	113
WT8	148	103	193	133
WT9	120	75	165	105

Table 3.3: Nearest Distance between the Neighboring Wind Turbines.

Wind Turbines	Nearest Distance Between Wind Turbines (m)
WT1_WT2	250
WT2_WT3	250
WT3_WT4	1000
WT4_WT9	250
WT5_WT9	250
WT5_WT6	250
WT6_WT8	250
WT8_WT7	250

Table 3.4: Wind direction and shadow region of the wind turbines (WT\_Ash) in the Fermeuse wind farm.

Shadow Region of Wind Turbine	$45^{\circ} \pm 5^{\circ}$ or $225^{\circ} \pm 5^{\circ}$	All Other Wind Direction
WT1	3181 m <sup>2</sup>	0.0 m <sup>2</sup>
WT2	3181 m <sup>2</sup>	0.0 m <sup>2</sup>
WT3	0.0 m <sup>2</sup>	0.0 m <sup>2</sup>
WT4	3181 m <sup>2</sup>	0.0 m <sup>2</sup>
WT5	4772 m <sup>2</sup>	0.0 m <sup>2</sup>
WT6	3181 m <sup>2</sup>	0.0 m <sup>2</sup>
WT7	0.0 m <sup>2</sup>	0.0 m <sup>2</sup>
WT8	4772 m <sup>2</sup>	0.0 m <sup>2</sup>
WT9	3181 m <sup>2</sup>	0.0 m <sup>2</sup>

Table 3.4 gives the details of the shadow region of the wind turbines operating at the influence of the wake effect. From the layout information of the Fermeuse wind farm, the area of the shadow region of the wind turbines at the Fermeuse wind farm is assumed. It depends on the wind direction at the Fermeuse wind farm site and the nearest distance between the wind turbines. MATLAB simulated and estimated results of the wind turbine-2 tested with different input wind speed data files is given in Table 3.5, Table 3.6, Table 3.7, and Table 3.8. For all the individual physical factors considered, its contribution to the wind speed estimation is determined from the designed algorithm using average value of the wind speed for the Vestas V90 3MW wind turbine -2 from the input 10,000 time series wind data set.

Table 3.5: Wind speed estimation of the physical factors affecting wind turbine-2 in the Fermeuse wind farm determined from the input wind speed data file1.

Physical Factors of the Wind Power Model	Vestas V90, 3MW Wind Turbine -2 (Mean Value at the Hub Height)
Sensor Height Wind Speed (Mean Wind Speed)	9.21 m/s
Vertical Wind Speed Shear	9.45 m/s
Turbulence Adjusted Wind Speed	11.32 m/s
Disc Speed of Wind Turbine	10.57 m/s
Wake Speed of Wind Turbine	9.86 m/s

Table 3.6: Wind speed estimation of the physical factors affecting wind turbine-2 in the Fermeuse wind farm from the input wind speed data file2.

Physical Factors of Wind Power Model	Vestas V90 3MW Wind Turbine -2 (Mean Value at the Hub Height)
Sensor Height Wind Speed (Mean Wind Speed)	9.96 m/s
Vertical Wind Speed Shear	10.21 m/s
Turbulence Adjusted Wind Speed	12.13 m/s
Disc Speed of Wind Turbine	11.31 m/s
Wake Speed of Wind Turbine	10.55 m/s

Table 3.7: Wind speed estimation of the physical factors affecting wind turbine 2 in the Fermeuse wind farm from the input wind speed data file3.

Physical Factors of Wind Power Model	Vestas V90 3MW Wind Turbine-2 (Mean Value at Hub Height)
Sensor Height Wind Speed (Mean of Wind Speed)	8.72 m/s
Vertical Wind Speed Shear	8.94 m/s
Turbulence Adjusted Wind Speed	11.05 m/s
Disc Speed of Wind Turbine	10.30 m/s
Wake Speed of Wind Turbine	9.64 m/s

Table 3.8: Wind speed estimation of the physical factors affecting wind turbine-2 in the Fermeuse wind farm from the input wind speed data file4.

Physical Factors of Wind Power Model	Vestas V90 3MW Wind Turbine-2 (Mean Value at Hub Height)
Sensor Height Wind Speed (Mean of Wind Speed)	7.00 m/s
Vertical Wind Speed Shear	7.18 m/s
Turbulence Adjusted Wind Speed	8.81 m/s
Disc Speed of Wind Turbine	8.23 m/s
Wake Speed of Wind Turbine	7.74 m/s

The wind power of the wind turbine -2 placed in the Fermeuse windfarm is determined from the designed algorithm. For the physical factor considered, the average value of the wind speed is substituted in the equation of the uncorrected power curve function and the corresponding wind power is determined. The estimated result of the wind turbine-2 in MATLAB is tested with different input wind speed data files and is given in Table 3.9, Table 3.10, Table 3.11 and Table 3.12. The effect of individual physical factor considered and its contribution in estimating the wind power of a wind turbine-2 is determined.

Table 3.9: The wind power of the wind turbine -2 showing the effect of the individual physical factors considered from the input wind speed data file1.

Physical Factors of Wind Power Model Considered from the Designed Algorithm	Vestas V90 3MW Wind Turbine
Average value of the estimated speed of the vertical shear at hub height	1.43 MW (Estimated power using average value of speed of vertical shear)
Average value of the estimated turbulence adjusted speed at hub height	2.15 MW (Estimated power using average value of turbulence adjusted speed)
Average value of the estimated disc speed at hub height	1.86 MW (Estimated power using average value of disc speed)
Average value of the estimated air density adjusted disc speed	1.91 MW (Estimated power using average value of air density adjusted disc speed)

Table 3.10: The wind power of the wind turbine -2 showing the effect of the individual physical factors considered from the input wind speed data file2.

Physical Factors of Wind Power Model considered from the Designed Algorithm	Vestas V90 3MW Wind Turbine
Average value of the estimated speed of vertical shear at hub height	1.73 MW (Estimated power using average value of speed of vertical shear)
Average value of the estimated turbulence adjusted speed at hub height	2.41 MW (Estimated power using average value of turbulence adjusted speed)
Average value of the estimated disc speed at hub height	2.14 MW (Estimated power using average value of disc speed)
Average value of the estimated air density adjusted disc speed	2.19 MW (Estimated power using average value of air density adjusted disc speed)

Table 3.11: The wind power of the wind turbine -2 showing the effect of the individual physical factors considered from the input wind speed data file3.

Physical Factors of Wind Power Model considered from the Designed Algorithm	Vestas V90 3 MW Wind Turbine
Average value of the estimated speed of vertical shear at hub height	1.24 MW (Estimated power using average value of speed of vertical shear)
Average value of the estimated turbulence adjusted speed at hub height	2.05 MW (Estimated power using average value of turbulence adjusted speed)
Average value of the estimated disc speed at hub height	1.77 MW (Estimated power using average value of disc speed)
Average value of the estimated air density adjusted disc speed	1.81 MW (Estimated power using average value of air density adjusted disc speed)

Table 3.12: The wind power of the wind turbine -2 showing the effect of the individual physical factors considered from the input wind speed data file4.

Physical Factors of Wind Power Model considered from the Designed Algorithm	Vestas 3.0 MW Wind Turbine
Average value of the estimated speed of vertical shear at hub height	626.69 KW (Estimated power using average value of speed of vertical shear)
Average value of the estimated turbulence adjusted speed at hub height	1.18 MW (Estimated power using average value of turbulence adjusted speed)
Average value of the estimated disc speed at hub height	960.98 KW (Estimated power using average value of disc speed)
Average value of the estimated air density adjusted disc speed	983.10 KW (Estimated power using average value of air density adjusted disc speed)

Table 3.13: The Wake coefficient data determined from the wind direction and the shadow effect of the wind turbines in the wind farm.

Time Series Wind Speed Data of Equal Length (10 min)	Wake Coefficient for a Wind Direction ( $45^{\circ} \pm 5^{\circ}$ ; $225^{\circ} \pm 5^{\circ}$ )	Wake Coefficient for all other Wind Direction (except $45^{\circ} \pm 5^{\circ}$ and $225^{\circ} \pm 5^{\circ}$ )
Wake_Coefficient of Wind Data 1	0.84	1.00
Wake_Coefficient of Wind Data 2	0.85	1.00
Wake_Coefficient of Wind Data 3	0.83	1.00
Wake_Coefficient of Wind Data 4	0.80	1.00

Estimated wake coefficient results of the wind farm power model are given in Table 3.13. Layout information of the wind farm and the wind direction at the wind farm site is a major contributing factor when estimating wind farm power. The wake effect takes place for a particular wind direction when wind turbines are placed at a closer distance due to the shadow effect of a neighboring wind turbine. It results in the reduction of the wind speed, and correspondingly, the wind power. The wake coefficient is determined using equation 16 and a value of 1 indicates that the wind turbines operate at a maximum power and a value less than 1 indicates that the wind turbines operate at a reduced power due to the wake effect or the shadow effect of the neighboring wind turbines. The results are estimated and tested for different input wind data files.



Table 3.14 Estimated average value of the wind power of the wind turbine-2 operating at the disc speed in the Fermeuse wind farm.

Time Series Wind Speed Data of Equal Length (10 min)	Wind Turbine-2 Power of Vestas V 90 - 3 MW Wind Turbine (No Wake Effect)
Wind Data 1	1.75 MW
Wind Data 2	1.92 MW
Wind Data 3	1.63 MW
Wind Data 4	1.06 MW

The estimated power of the Vestas V90 3 MW wind turbine -2 is given in Table 3.14. It gives the average value of power of the 10,000 time series of the Vestas V90 3 MW wind turbine -2, operating at the disc speed and is tested with different input wind data set.

Table. 3.15 Estimated average value of the wind power of the wind turbine-2 operating at the wake speed in the Fermeuse wind farm.

Time Series Wind Speed Data of Equal Length (10 min)	Wind Turbine-2 Power of Vestas V 90 3 MW Wind Turbine (Wake Effect)
Wind Data 1	1.41 MW
Wind Data 2	1.58 MW
Wind Data 3	1.31 MW
Wind Data 4	805.82 KW

The estimated power of the Vestas V90 3 MW wind turbine -2 is given in Table 3.15. It gives the average value of power of 10,000 time series of the Vestas V90 3 MW wind turbine -2, operating at the wake speed.. MATLAB code is tested with different input wind speed data files.

Table 3.16: Estimated average value of the wind farm power of the Fermeuse wind farm, with the wind turbines operating at the disc speed.

Time Series Wind Speed Data of Equal Length (10 min)	Wind farm Power Vestas V90 3MW Wind Turbines (3 MW- 9 WT)
Wind Data 1	17.34 MW
Wind Data 2	18.76 MW
Wind Data 3	16.26 MW
Wind Data 4	11.16 MW

The Fermeuse wind farm has nine Vestas V90 3MW, wind turbines. Table 3.16 gives the estimated average value of the wind farm power of the input 10,000 time series wind data set. The average value of the wind farm power is determined with the wind turbines in the wind farm operating at the disc speed. The estimated results are tested with different input wind data set.

### **3.7 Transmission Loss in the Wind Farm**

The transmission loss occurs due to the flow of current in a cable and it results in a reduction of power. When the current flows through the wires, a voltage drop occurs and a corresponding power loss occurs in the cable. These losses are the copper loss and the induction loss [42], as follows:

- i) Copper loss occurs due to heating of the material.
- ii) Induction loss occurs when the metallic object absorbs the power due to the electromagnetic field generated by the current carrying conductors.

After extensive research on power loss, it is concluded that power loss within a wind farm is about 1% due to the transmission of current through cables [40, 41]. Actual transmission details and parameters of the Fermeuse wind farm were not available. Therefore, the wind farm power loss of the Fermeuse wind farm is assumed to have a transmission loss of 1%. The power loss factor of 0.99 is multiplied to estimate the wind farm power in real time.

Table 3.17: The Fermeuse wind farm power estimated before and after a constant transmission loss (TL) of 1% in the wind farm with and without wake effect.

Time Series Wind Speed Data of Equal Length (10 min)	TL	Average Wind farm Power before TL (No-wake effect)	Average Wind farm Power after TL (No-wake effect)	Average Wind farm Power before TL (Wake effect)	Average Wind farm Power after TL (Wake effect)
Wind Data 1	1.0%	17.34 MW	17.16 MW	16.37 MW	16.20 MW
Wind Data 2	1.0%	18.76 MW	18.57 MW	17.84 MW	17.66 MW
Wind Data 3	1.0%	16.26 MW	16.10 MW	15.32 MW	15.16 MW
Wind Data 4	1.0%	11.16 MW	11.04 MW	10.29 MW	10.18 MW

Above, Table 3.17 gives the average value of the wind farm power before and after transmission loss. The average value of the wind farm power is estimated considering that the wind turbines are operating with the wake effect and with no wake effect with a constant transmission loss factor of 1%. The results are estimated and tested with different input wind speed data files.

Table 3.18: The estimated average value of the loss in power, given a constant transmission loss of 1%, with the wake effect and without wake effect.

Time Series Input Wind Speed Data of Equal Length (10 min)	TL	Loss in Power (No wake effect)	Loss in Power (Wake effect)
Wind Data 1	1.0%	0.17 MW	0.16 MW
Wind Data 2	1.0%	0.19 MW	0.18 MW
Wind Data 3	1.0%	0.16 MW	0.15 MW
Wind Data 4	1.0%	0.12 MW	0.10 MW

Above, table 3.18 gives the estimated average value of the loss in power due to the transmission of power. The loss in power is determined from the difference in power when the wind turbines operate at the disc wind speed with no transmission loss and when the wind turbines operate at the disc wind speed with the transmission loss. Similarly loss in power is determined from the difference in power when the wind turbines operate at the wake speed with no transmission loss and when the wind turbines operate at the wake speed with the transmission loss. The estimated results are tested with different input wind speed data files.

### 3.8 Wind Farm Power Calculation Results

#### 3.8.1 Simulated MATLAB results using the designed algorithm to estimate the wind farm power

Using the Fermeuse wind farm layout information [39], the designed algorithm is implemented in the MATLAB. A copy of the MATLAB code is found in the Appendix I and Appendix J. Figure 3.6 is the manufacturer supplied power curve of

the Vestas V90 3MW wind turbine [52]. The supplied power curves are used to estimate the actual power curves. MATLAB software has curve fitting toolbox and after exploring various curve fitting techniques, it is concluded that the best fit polynomial curve is of order 9 for the Vestas V90 3MW wind turbine and is shown in Figure 3.7.

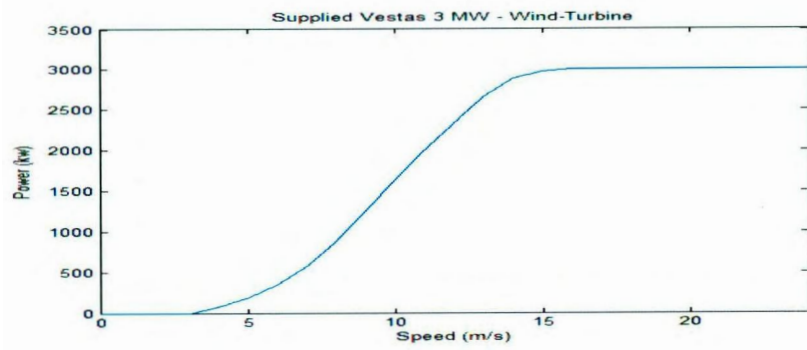


Figure 3.6: Power vs. Wind Speed characteristics of the Vestas V90 3 MW wind turbine (supplied power curve).

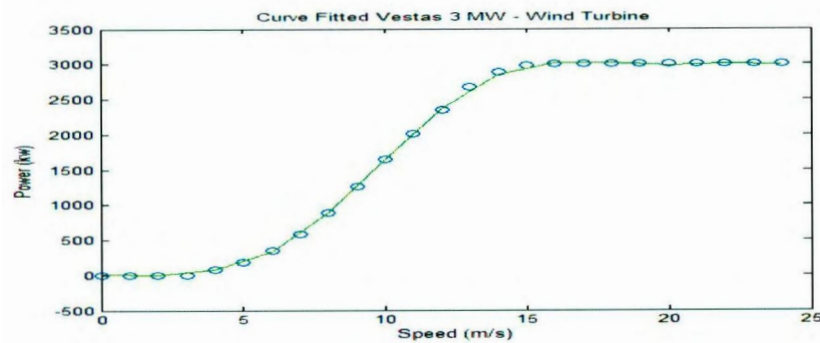


Figure 3.7: Power vs. Wind Speed characteristics of the Vestas V90 3 MW wind turbine (digitized and curve fitted).

The input wind speed data file 2 is recorded from the anemometer at a MET tower. It is assumed that the Fermeuse wind farm has a MET tower with the sensor located at a height of 80 m. The recorded wind speed is shown in Figure 3.8 for the Vestas V90 3MW wind turbine for a time range of 10,000 minutes. The average value of the wind speed data shown in Figure 3.8 is 9.96 m/s.

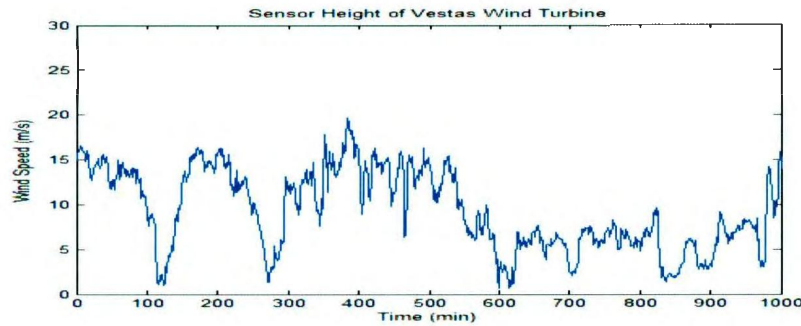


Figure 3.8: Recorded sensor height wind speed data for the Vestas V90 3MW wind turbine-2. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

The Fermeuse wind farm has 9 wind turbines. The hub height wind speed of the wind turbine is calculated from the input wind speed at the sensor height using the power law equation of shear with the shear exponent of  $1/7$  for each wind turbine hub height using equation (3.2). The hub height of each wind turbine is determined from the wind turbine base elevation. Figure 3.9 shows the estimated hub height wind speed for the Vestas V90 3MW wind turbine-2. The average value of the wind speed in Figure 3.9 is 10.21 m/s.

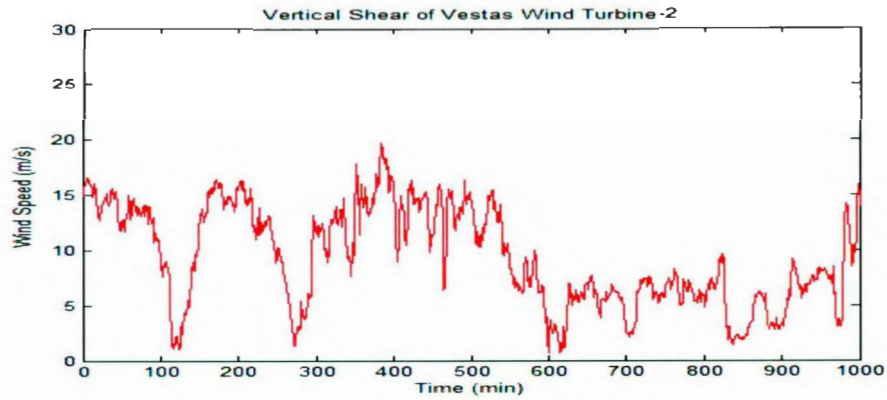


Figure 3.9: Hub height wind speed is estimated for the Vestas V90 3MW wind turbine-2 at the hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

The turbulence adjusted wind speed is estimated for the Vestas V90 3MW wind turbine-2 at the hub height. It is calculated using equation (3.4) from the input wind speed and the estimated turbulence intensity at the hub height. The resulting wind speed is shown in Figure 3.10 for the Vestas V90 3MW wind turbine. The average value of the wind speed in Figure 3.10 is 12.13 m/s.

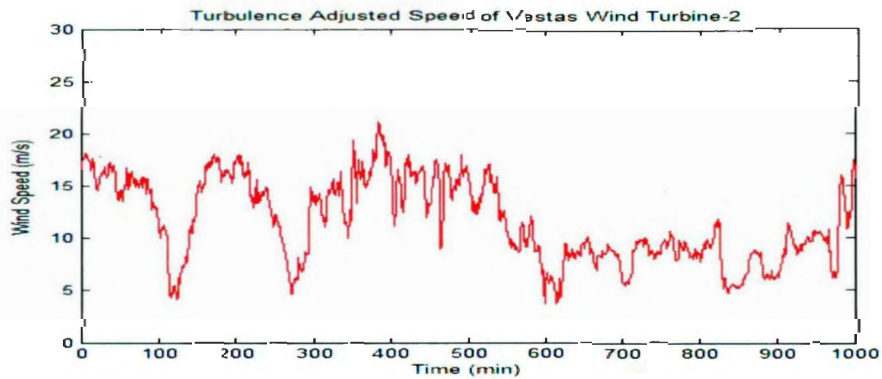


Figure. 3.10: Turbulence adjusted wind speed estimated for the Vestas V90 3MW wind turbine-2 at the hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).



The disc wind speed adjusted for vertical shear and turbulence adjusted speed, is calculated using equation (3.6) from the lower rotor tip to the upper rotor tip of the wind turbine. The resulting wind speed is assumed to be at the hub height and is plotted in Figure 3.11 for the Vestas V90 3MW wind turbine-2. The average value of the wind speed in Figure 3.11 is 11.31m/s.

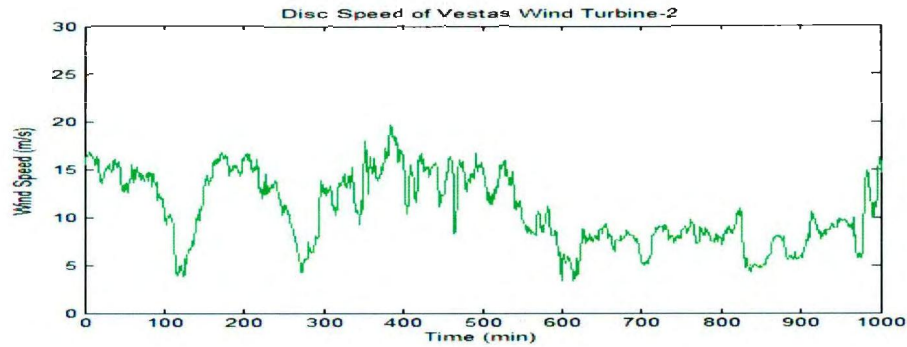


Figure 3.11: Estimated disc speed adjusted for turbulence and shear for the Vestas V90 3 MW wind turbine-2 at the hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

The estimated wake wind speed is shown in Figure 3.12 for the Vestas V90 3MW wind turbine-2. The wind speed is reduced due to the wake effect from the upstream turbines. The wind direction is a major contributing factor in estimating the wake effect. The wake effect is estimated from the thrust coefficient of the wind turbine and is influenced by the nearest distance between the neighboring wind turbines. It is calculated using equation (3.10), equation (3.11) and equation (3.12). The average value of the wind speed in Figure 3.12 is 10.55 m/s.

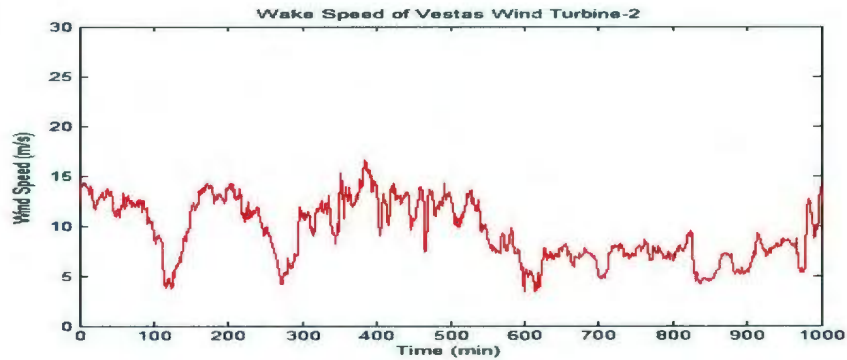


Figure 3.12: Wake speed estimated for Vestas 3 MW wind turbine-2 at hub height (Note: Time Scale: X axis: 1 unit=10 minute; 1000 unit = 10000 minutes).

Using the polynomial curve fitted supplied power curve, the actual power curve of the Vestas V90 3MW wind turbine is estimated from the uncorrected power curve function adjusted with air density using equation (3.8). There is an increase in the estimated power with air density adjustment as given in Table 3.6 for the wind turbine-2. The power curves are estimated for nine wind turbines of the Fermeuse wind farm. A simulated result of the power curve for one of the wind turbine is shown in Figure3.13.

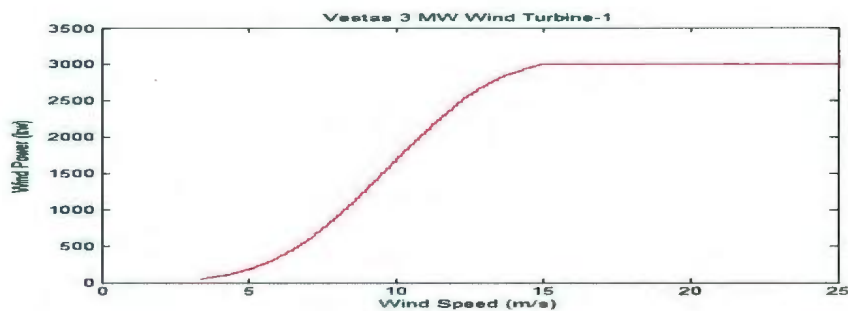


Figure 3.13: Estimated power curve of the Vestas 3MW wind turbine adjusted with air density.

The wake power model is developed in this chapter and the wake power is determined from the estimated wake speed. There is a reduction in power with the wake effect (black) as shown in Figure 3.14 for the Vestas V90 3MW wind turbine-2. The estimated wind power of the wind turbine-2 is compared with the wake effect (black) and without wake (red) effect and is plotted with respect to time as shown in Figure 3.14. The wind power remains constant after rated wind speed of the wind turbine is reached and the corresponding power is called rated power. With further increase in wind speed beyond rated wind speed, there is no significant improvement in the power and is shown in Figure 3.14 and Figure 3.15.

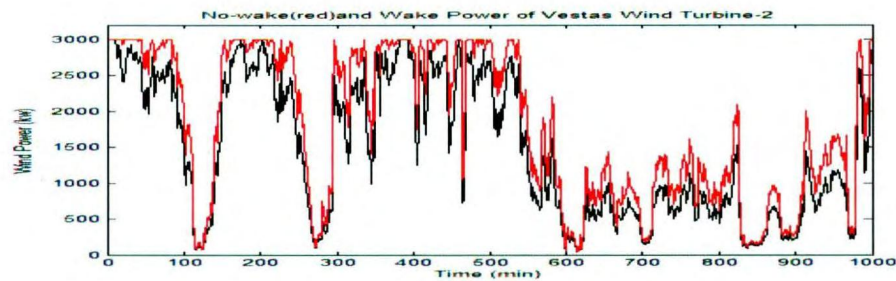


Figure 3.14: Comparison of the wind power of the wind turbine -2 operating at the wake effect (black) and no wake effect (red).

As shown in Figure 3.15, the wind farm power is determined from the wind turbines operating at the free disc speed and is plotted with respect to time. The wind farm power is estimated from the Vestas V90 3MW wind turbines. The total power of the wind turbines in the wind farm is added and is the estimated wind farm power. The average value of the wind farm power in Figure. 3.15 is 18.76 MW.

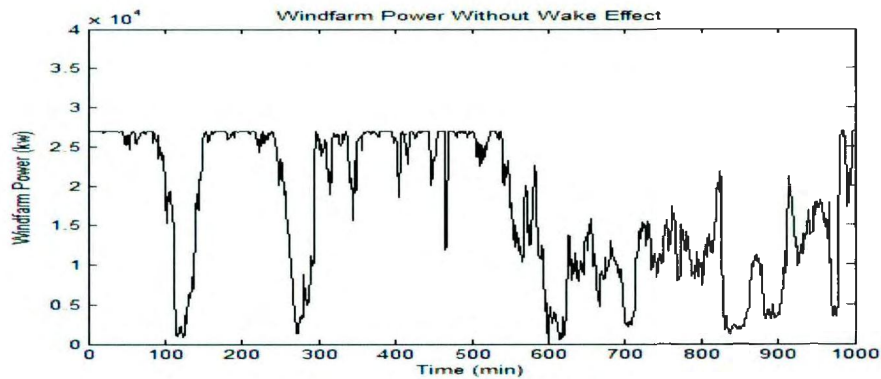


Figure 3.15: Estimated wind farm no-wake power with respect to time (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

In Figure 3.16, the wind farm power is determined at the wake wind speed and is plotted with respect to time. The wind farm power is estimated from the Vestas V90 3MW wind turbines. The total power of the wind turbines in the wind farm is the estimated wind farm power. The average value of the wind farm power in Figure 3.16 is 17.84 MW.

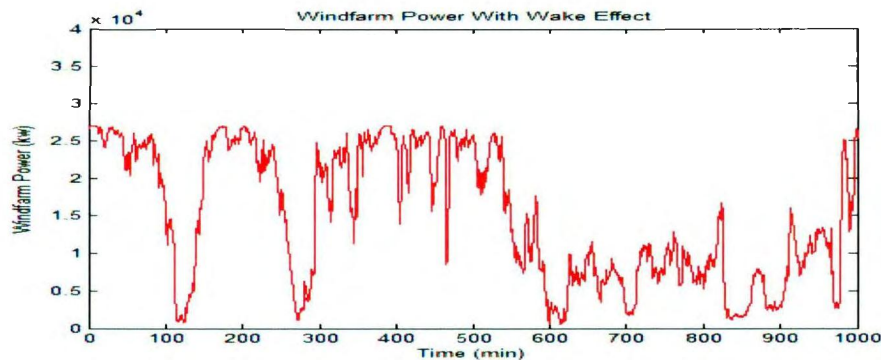


Figure 3.16: Estimated wind farm wake power with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

The wind farm power is estimated from the Vestas V90 3MW, wind turbines with the wake effect (red) and without wake effect (black) as shown in Figure 3.17. The

estimated wind farm power at the free disc speed is compared with the estimated wind farm power at the wake speed and is plotted with respect to time.

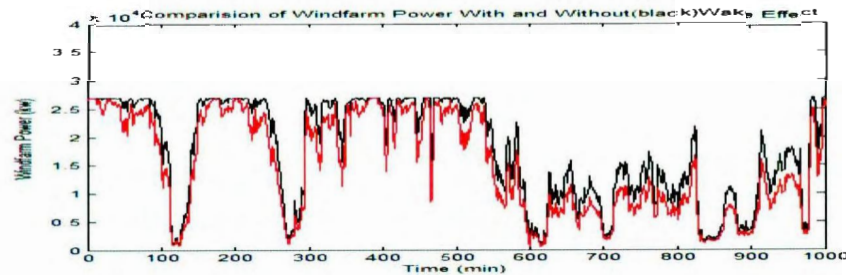


Figure 3.17: Comparison of estimated wind farm power with the wake effect (red) and without wake effect (black) is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

The wind farm power is determined from the wind direction and the shadow effect of the neighbouring wind turbines. The wake coefficient data determines the wind farm efficiency. Figure 3.18 is a plot of the wind direction at the wind farm site and Figure 3.19 is a plot of the wake coefficient. The wake coefficient of 1 indicates that the wind turbines operate at a maximum power and a value less than 1 indicates that the wind turbines operate at a reduced power or at the wake speed. In Figure 3.19, we see that at a wind direction of  $45^\circ \pm 5^\circ$  and  $225^\circ \pm 5^\circ$ , there is a wake effect and the wind speed is reduced as the wind turbines are placed at a closer distance. For all other wind direction, the wind turbines operate at a maximum power and this factor is determined from the wind farm layout and the distance between neighboring wind turbines.

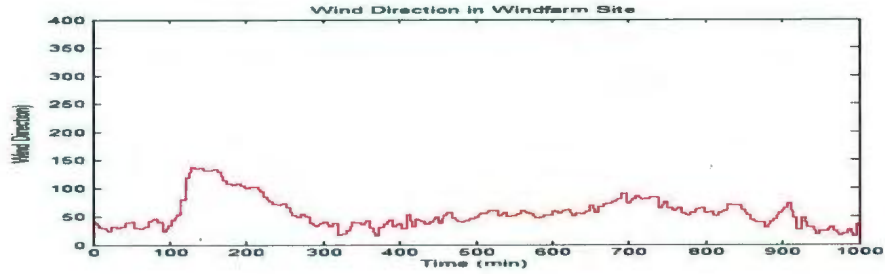


Figure 3.18: Wind direction (degrees) at the wind farm site for a time span of 10,000 minutes. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

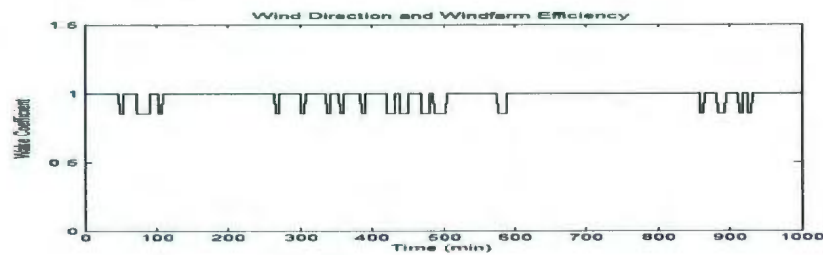


Figure 3.19: Wake coefficient determined from the wind direction is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

Figure 3.20 is a plot of the wind direction at the windfarm site for a time span of 5000 minutes and Figure 3.21 is a plot of wake coefficient for a time span of 5000 minutes.

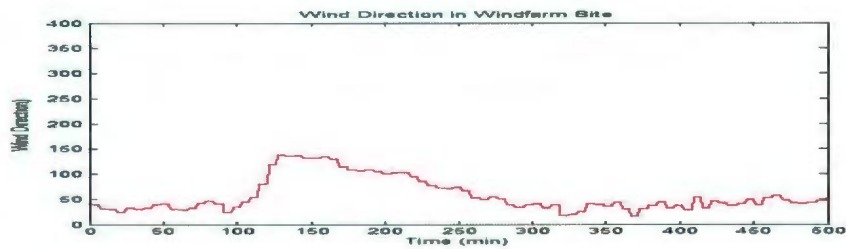


Figure 3.20: Wind direction (degrees) at the wind farm site for a time span of 5000 minutes. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).



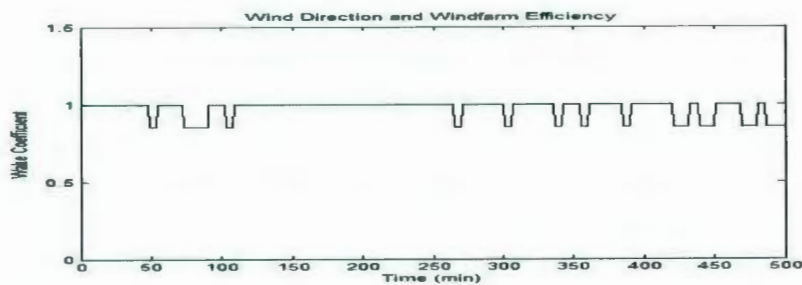


Figure 3.21: Wake coefficient determined from the wind direction is plotted with respect to time (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

With a transmission loss of 1%, there is a further reduction in the estimated wind farm power. Figure 3.22 and Figure 3.23 shows loss in power in the wind farm due to the transmission of power without the wake effect and with the wake effect respectively. The wind farm power loss due to the transmission of power is plotted with respect to time. With the wake effect there is a more reduction in power as compared to the power loss without the wake effect. The average value of power in Figure 3.22 is 18.57 MW and the average value of power in Figure 3.23 is 17.66 MW.

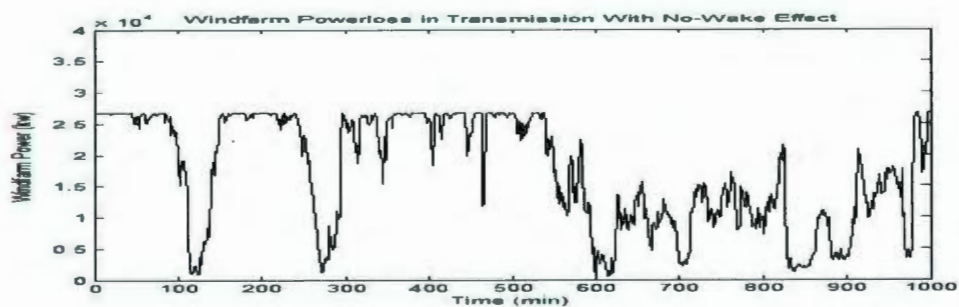


Figure 3.22: Wind farm output power with power loss (1%) in transmission with no wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

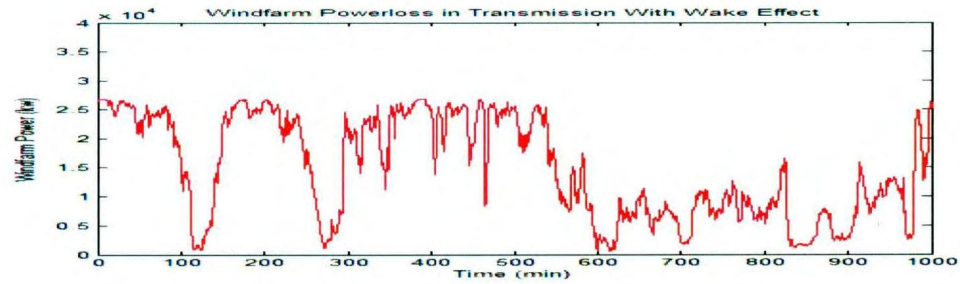


Figure 3.23: Wind farm output power with power loss in transmission (1%) and the wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

### 3.9 Conclusion

In this chapter, the working wind power model of the Fermeuse wind farm is developed, using the historic data of atmospheric parameters as input to the wind power model for the wind power estimation. The manufacturer supplied power curve assumes ideal conditions and the variation in atmospheric parameters results in the variation of the output power. In this chapter, details of the wind turbine characteristics and its specifications, wind farm layout, and the number of wind turbines are studied. The location of the MET tower and the sensor height is assumed from the layout information of the Fermeuse wind farm. The actual turbine power curves are produced when the power is plotted as a function of equivalent wind speed or disc speed instead of the hub height wind speed. This suggests that both vertical shear and turbulence are important factors in power production. Air density is an important factor in power production and the corrected power curve of the wind turbine is estimated from the equivalent wind speed adjusted with air density. The corrected power curves of the wind turbines are produced from the atmospheric parameters affecting the wind



turbine rotor disc and the wind farm output power is estimated. The wind direction and the wind farm layout have a significant influence upon the power output mainly due to the wake effect. The wake model is developed as the wind turbines are placed at a closer distance. The impact of the wake is to disturb the wind flow to the wind turbines and this result in power loss as compared to the wind turbines operating in undisturbed wind flow. This effect can be minimized by increasing the distance between the wind turbines. It is concluded that there is a reduction in the output power of the wind farm than if the ideal wind turbines layout in a wind farm is assumed. Thus, the MATLAB code is tested with different input time series wind speed data files. An accurate result is estimated and tested with every 10 minutes time series wind data file and is presented in this chapter.

## **Chapter 4**

### **Power Prediction of the Cedar Creek, Colorado Wind farm**

#### **4.1 Introduction**

The Cedar Creek wind farm is located in the United States [50]. The wind farm has 274 wind turbines in operating condition. The wind turbines of the Cedar Creek -I wind farm are the Mitsubishi 1MW and the GE 1.5MW wind turbines and the total capacity of the wind farm is 300MW. The wind turbine manufacturer supplied power curve assumes ideal conditions and in reality there is a significant variation in physical factors. Physical factors considered in this chapter are the vertical shear, the turbulence intensity, the turbulence adjusted wind speed, air density, pressure, and temperature to estimate the wind power of a wind turbine. The main challenge for this work is to find a simple model that will take a topographical map, a wind farm layout and the long term site wind and atmospheric data and uses this information to calculate the wind speed at all the wind turbines. The designed algorithm estimates the wind speed adjusted for shear and turbulence for the wind turbine rotor disc from the lower rotor tip to the upper rotor tip of the wind turbine. The value estimated is the effective wind speed and is assumed to be at the hub height. Air density is adjusted to predict the wind power of each wind turbine. The speed and height for each wind turbine varies when estimating power for the wind farm. It depends on the distance between the wind turbines, the contour height and the layout information. The wake model is incorporated when wind turbines are located less than four times the rotor diameter of upstream turbines or at a very closer distance from the neighboring wind turbines. The

wake power of the wind farm is estimated considering the wind direction, the wind farm layout information, the thrust coefficient of the wind turbine, and the free disc speed. The resulting simple model of a wind farm is simulated in the MATLAB software. The simulation results for a number of wind speed data sets are presented in this chapter.

## **4.2 Wind Turbine Power Estimation**

The wind turbine details of the Mitsubishi 1MW and the GE 1.5 MW are given below and are required in the initial design. The wind turbine power vs. wind speed characteristics is studied. It is digitized from the power curve data. Thus power curve of the Mitsubishi 1 MW and the GE 1.5 MW wind turbine is produced in the initial design stage. Figure 4.1 gives details and some specifications of the Mitsubishi 1MW wind turbine. The GE 's 1.5-77 wind turbine is a three blade, upwind, horizontal axis wind turbine and has a rotor diameter of 77 meters. This series of wind turbines has hub height of 65m and 80 m. The specifications of a wind turbine are given below. The wind turbine operates at a variable speed. It uses asynchronous generator. The power curve in the initial design stage is the supplied power curve of the GE 1.5 MW wind turbine. Below is the list of some of its features.

GE 1.5 MW Wind Turbine Technical Specification

Designed to IEC 61400-1

TC Ib: 10 m/s average wind speed; B turbulence intensity

Standard and cold weather extreme options

Rotational direction: Clockwise viewed from an upwind location

Speed regulation: Electric drive pitch control with battery backup

Aerodynamic brake: Full feathering of blade pitch

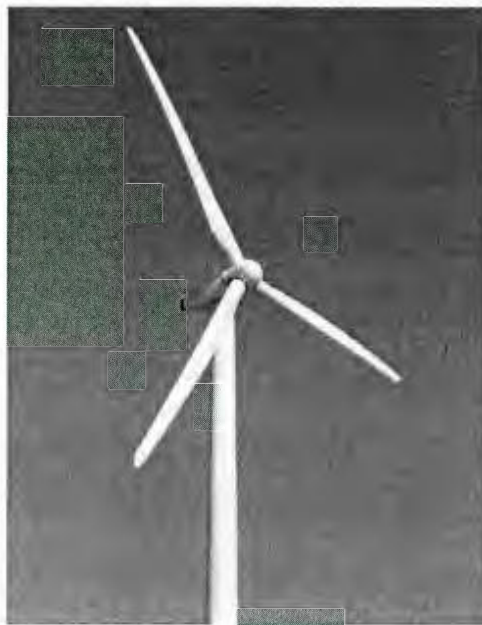
Cut in wind speed: 3.5 m/s

Cut out wind speed: 25 m/s

Rated power: 1.5 MW [48]

## MITSUBISHI WIND TURBINE GENERATOR

# MWT62/1.0 *(MWT-1000A)*



### Technical Data

#### Operation Data

Cut-in	3.0 m/s
Rated	12.5 m/s
Cut-out	25.0 m/s
Wind Class	IEC Class IIA

#### Rotor

Diameter	61.4 m
Swept Area	2,960 m <sup>2</sup>
Rotational Speed	19.8 rpm
Blade Length	29.5 m
Aerodynamic Brake	Blade Feathering

#### Generator

Type	Induction Generator (4 Pole Type)
Rated Power	1,000 kW
Voltage	690 V/600 V (50 Hz/60 Hz)
Frequency	50 Hz/60 Hz

#### Tower

Hub Height	50 m/60 m/69 m
------------	----------------

Figure 4.1: Mitsubishi Wind Turbine [48].

As mentioned above the Cedar Creek –I wind farm has the Mitsubishi 1MW and the GE 1.5MW wind turbines. Some specifications [49] of these wind turbines are shown in Figure 4.1. Recently, 123 more wind turbines have been added to the site in the second phase of the project called Cedar Creek –II [50]. This chapter only covers the first phase of the Cedar Creek wind farm. The wind turbine manufacturer supplied power curve assumes ideal condition and in reality there is a variation in physical parameters and a variation in the output power. The wind turbine manufacturer supplied power curve can be digitized by extracting data from power vs. wind speed characteristics. The Cedar Creek wind farm has 274 wind turbines. The actual height of the wind turbine rotor disc is determined by considering its contour height i.e. hub height and the wind turbine base elevation. The site measured wind speeds are given at the sensor heights. To determine a wind turbine output power, the wind speed data should be known at the lower rotor tip of the wind turbine to the upper rotor tip of the wind turbine. The input wind data at unknown heights is determined using the power law equation of shear using  $1/7$  shear exponent value. The input wind speed data provided is typically every 10 minutes, 45000 time series. Using live measured wind speed data AMEC can produce a predicted wind speed data. From a given predicted input wind speed data measured from the sensor; the turbulence intensity, the turbulence adjusted wind speed, the wind shear exponent, and the free disc speed of the wind turbine is determined. The turbulence adjusted wind speed is determined from the input wind speed and the turbulence intensity at the known model levels or heights which intersect the wind turbine rotor disc. The wind shear exponent is calculated using the power law equation of shear from the turbulence adjusted wind

speed data at known heights. The disc wind speed which is adjusted for turbulence and vertical shear is evaluated for the entire rotor disc by numerically integrating the wind speed values from the lower rotor tip to the upper rotor tip of the wind turbine by solving the equation of disc speed. The estimated value of the disc speed is assumed to be at the hub height. The uncorrected power is determined from the designed algorithm of the physical factors considered and the digitized and curve fitted wind turbine power curve supplied by the manufacturer. The disc speed is substituted in the uncorrected power curve function and is subsequently adjusted for air density to estimate the corrected power of a wind turbine. Thus wind power is estimated for one wind turbine from the estimated disc speed, adjusted for turbulence and vertical shear.

### **4.3 The Cedar Creek Wind Farm Power Estimation**

#### **4.3.1 Layout of the Cedar Creek Colorado Wind farm**

The wind farm layout [47] is plotted using Arc Geographic Information System (GIS) software available at Queen Elizabeth II, Memorial University of Newfoundland as shown in Figure 4.2 below using the latitude and longitude data of all the wind turbines and metrological tower (MET) tower locations. Figure 4.3 shows a section of the wind farm layout.

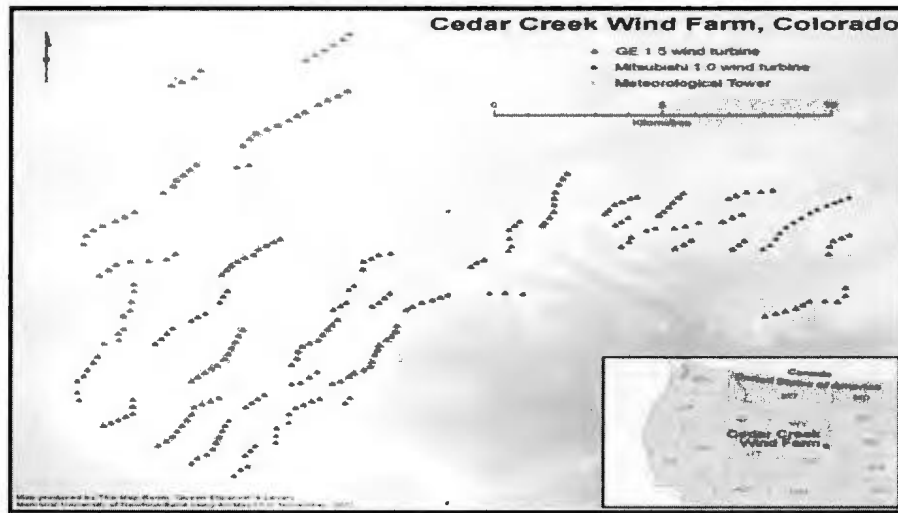


Figure 4.2: Cedar Creek- I Wind farm Layout [47].

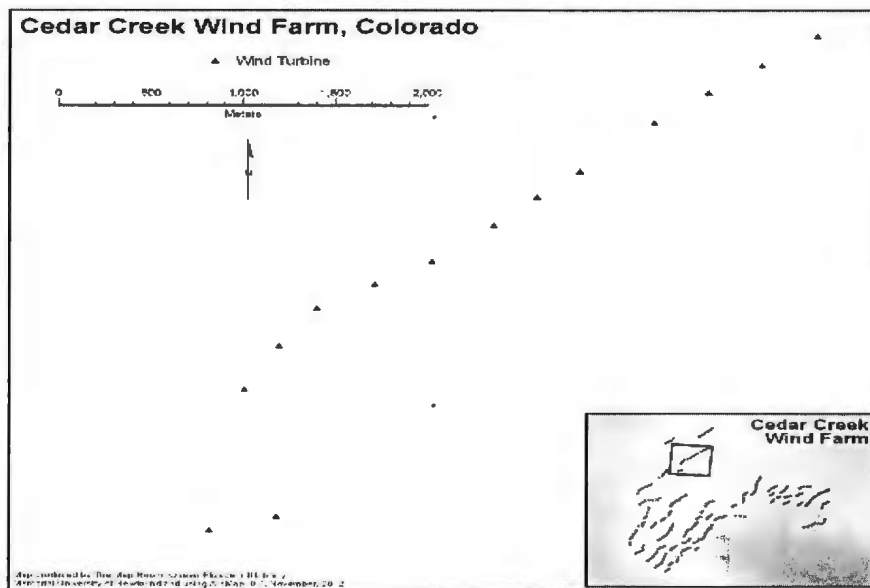


Figure 4.3: A section of the Cedar Creek Wind farm Layout [47].

The contour height of the wind turbine is determined from its layout information and the horizontal distance between the nearest wind turbines and is estimated

from the map. The wake effect is considered for the wind turbines for a particular wind direction in the wind farm. The wake effect arises when the wind turbines are located at a closer distance. The wind speed for the wind turbines operating in the wake is reduced and therefore there is a considerable reduction of the wind power. For a particular wind direction, the wind turbines operating in a partial shadow or a complete shadow of the upstream or the neighboring wind turbines will produce a considerable low power. The wake speed of all the wind turbines operating due the wake effect is determined from the thrust coefficient of the wind turbine, the free disc speed, and the wind farm layout information. The wind power is estimated for all the wind turbines operating due to the wake effect. Finally, the output power of each wind turbine in the wind farm is added to determine the total power of the wind farm. Figure 4.2 indicates that the wind farm will have some reduced power when wind is from north-east or from south west. For all other wind direction there will be negligible reduction of the wind speed and the wind turbines will operate at a maximum power.



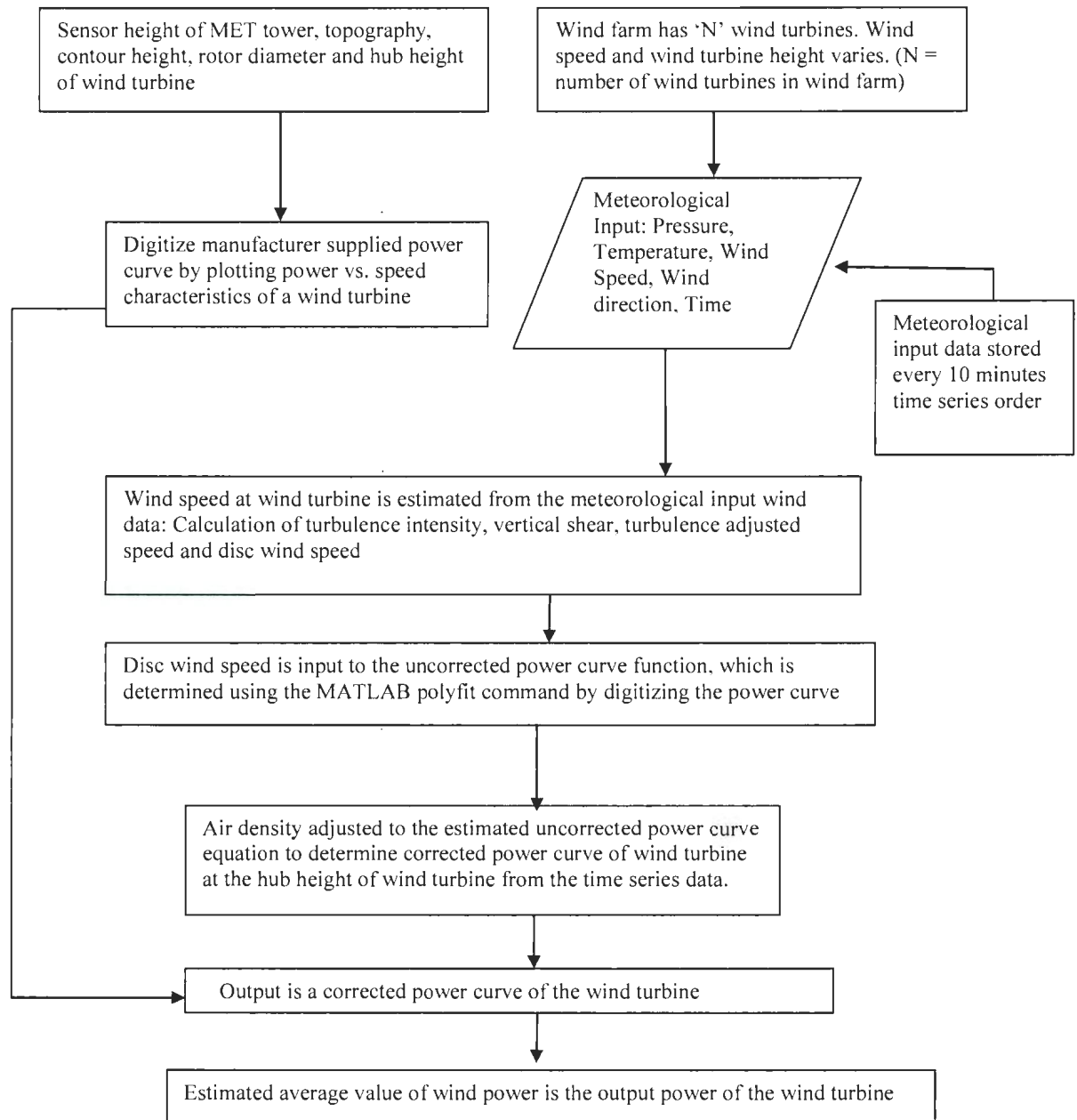


Figure 4.4: Flowchart of the wind power model.

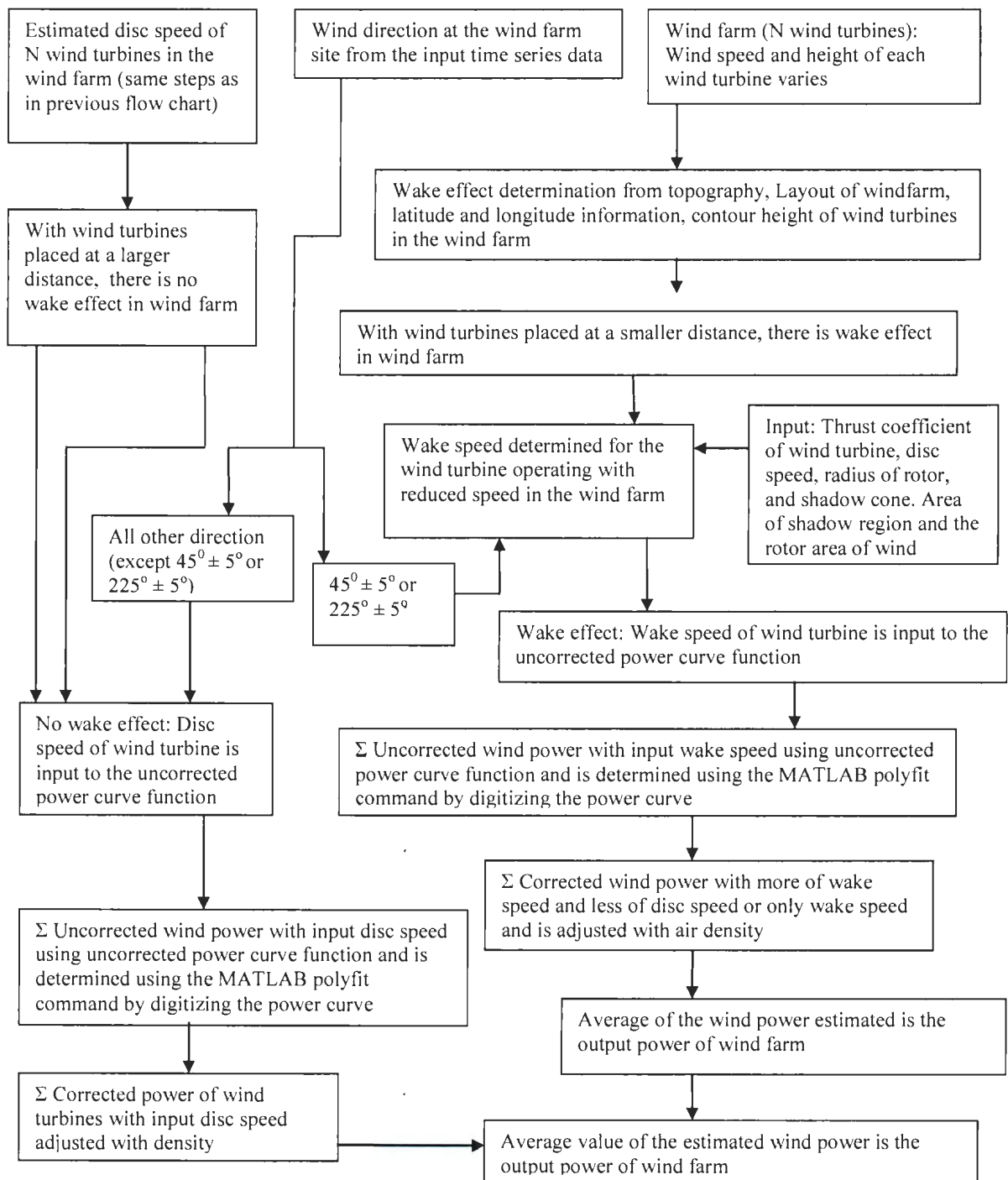


Figure 4.5: Flow chart of the wind farm wake model.

#### 4.4 Wind power of a wind turbine with no-wake effect

The manufacturer supplied power curve of the GE 1.5MW wind turbine and the Mitsubishi 1MW wind turbine is digitized by plotting power vs. wind speed characteristics. The uncorrected power curve function is determined using the polyfit command by the curve fitting toolbox [32] in the MATLAB software. In the curve fitted equation the variable 's' for the GE 1.5MW wind turbine and the variable 'r' for the Mitsubishi 1MW wind turbine is replaced by the wind turbine rotor disc speed ( $\bar{U}_{Disk}$ ) estimated from the algorithm adjusted for turbulence and shear for the GE 1.5MW and the Mitsubishi 1MW wind turbine. The uncorrected power is determined from the disc wind speed substituted in the polyfit equation and is given in equation (4.1) and equation (4.2).

For the GE 1.5MW wind turbine

$$\begin{aligned} GP_{uncor} = & q1(18) + q1(17).*(s)^1 + q1(16).*(s)^2 + q1(15).*(s)^3 + q1(14). \\ & *(s)^4 + q1(13).*(s)^5 + q1(12).*(s)^6 + q1(11).*(s)^7 + q1(10). \\ & *(s)^8 + q1(9).*(s)^9 + q1(8).*(s)^{10} + q1(7).*(s)^{11} + q1(6).*(s)^{12} \\ & + q1(5).*(s)^{13} + q1(4).*(s)^{14} + q1(3).*(s)^{15} + q1(2).*(s)^{16} \\ & + q1(1).*(s)^{17} \end{aligned}$$

Here s = Estimated disc speed value of the GE 1.5 MW wind turbine (4.1)

For the Mitsubishi 1MW wind turbine

$$\begin{aligned} MP_{uncor} = & q2(19) + q2(18) \cdot (r)^1 + q2(17) \cdot (r)^2 + q2(16) \cdot (r)^3 + q2(15) \cdot \\ & (r)^4 + q2(14) \cdot (r)^5 + q2(13) \cdot (r)^6 + q2(12) \cdot (r)^7 + q2(11) \cdot (r)^8 + q2(10) \cdot \\ & (r)^9 + q2(9) \cdot (r)^{10} + q2(8) \cdot (r)^{11} + q2(7) \cdot (r)^{12} + q2(6) \cdot (r)^{13} + q2(5) \cdot \\ & (r)^{14} + q2(4) \cdot (r)^{15} + q2(3) \cdot (r)^{16} + q2(2) \cdot (r)^{17} + q2(1) \cdot (r)^{18} \end{aligned}$$

Here  $r$  = Estimated disc speed value of the Mitsubishi 1MW wind turbine (4.2)

The wind speed at the hub height of the wind turbine is calculated using the power law equation of shear from the input sensor wind speed at known height and wind speed, and is given in equation (4.3).

$$U_{hub} = U_1 \cdot \left( \frac{H_{hub}}{H_1} \right)^{0.143} \quad (4.3)$$

The turbulence intensity ( $I_u$ ) at a known heights is calculated using equation (4.4) from an input wind speed ( $U$ ) at a MET tower height of 69m and 80m for Mitsubishi 1MW and GE 1.5MW wind turbine respectively and using standard deviation data ( $\sigma$ ) of the input wind speed.

$$I_u = \frac{\sigma}{U} \quad (4.4)$$

The turbulence adjusted wind speed ( $U' (TI)$ ) is calculated using equation (4.5) from the input wind speed and the turbulence intensity ( $I_u$ ) for the Mitsubishi 1MW and the GE 1.5MW wind turbine.

$$U' (TI) = \sqrt[3]{U^3 \cdot (1 + 3I_u^2)} \quad (4.5)$$

The wind shear exponent ( $\alpha$ ) is calculated [37] from the above turbulence adjusted wind speed  $U'2 (TI)$  and  $U'1 (TI)$  at various model level or heights  $H_2$  and  $H_1$  of a

wind turbine rotor disc. It is given by the power law equation of shear as in equation (4.6).

$$\alpha = \frac{\log \left( \frac{U'_{2(TI)}}{U'_{1(TI)}} \right)}{\log \left( \frac{H_2}{H_1} \right)} \quad (4.6)$$

The wind velocity across the wind turbine rotor disc [1] which is adjusted for turbulence and vertical shear, is calculated using equation (4.7) from the lower rotor tip (H-R) to the upper rotor tip (H+R) of the wind turbine. Here H is the wind turbine hub height and R is the radius of the wind turbine rotor disc and A is the area of wind turbine rotor disc.

$$\bar{U}_{Disk} = \frac{2}{A} \int_{H-R}^{H+R} U_Z \sqrt{R^2 - H^2 + 2HZ - Z^2} dZ \quad (4.7)$$

Actual air density is determined from the input pressure and the temperature as given in equation (4.8).

$$\rho = 3.4837 * \frac{P}{T} \quad (4.8)$$

Air density ( $\rho$ ) [32] correction is applied to the estimated disc speed and the corrected power  $P1(\text{corr})$  of a wind turbine [32] is determined from the actual air density, the air density at the Standard Temperature Pressure (STP), and the estimated uncorrected power  $P1(\text{uncorr})$  from the curve fitting equation and is given in equation (4.9) for the GE 1.5MW wind turbine and the Mitsubishi 1MW wind turbine.

$$P1(\text{corr}) = P1(\text{uncorr}) * \frac{\rho}{\rho \text{ at STP}} \quad (4.9)$$

Where  $P1(\text{uncorr}) = GP(\text{uncorr})$  for the GE wind turbine and  $MP(\text{uncorr})$  for the Mitsubishi wind turbine.  $P1(\text{corr}) = GP(\text{corr})$  for the GE wind turbine and  $MP(\text{corr})$  for the Mitsubishi wind turbine

#### 4.5 Wind power of a wind farm with no-wake effect

Below is the general equation to determine the wind power of a wind farm with no-wake effect. For the Colorado wind farm, detail study of the wind farm layout, the number of wind turbines, the contour height of the wind turbine and the distance between the wind turbines are studied. These values are considered to estimate the power of wind turbines in the wind farm. For a particular wind direction, the wake effect is considerable when the wind turbines are placed at a closer distance. For all other wind direction, the wind turbines operate in free wind speed. With no-wake effect, the wind turbines operate at a maximum power if the wind speed is above the rated value and the wind farm power is

determined by adding power of each wind turbine. The Colorado wind farm has 274 wind turbines and the total power of the wind farm is sum of the power of each wind turbine in the wind farm and is calculated using equation (4.10), where number of wind turbines is denoted by  $n=274$ .

$$\sum_{n=1}^n P1(\text{corr}) = \text{Total Windfarm No\_wake Power} \quad (4.10)$$

#### 4.6.1 Wind power of a wind turbine with the wake effect

Figure 4.6 shows [51] the wake effect in a wind farm. Below is the general equation to determine the wind power of a wind turbine with the wake effect. The wind speed for the downstream wind turbine reduces due to the wake effect depending on the shadow area of the rotor disc, the radius of the shadow cone, the thrust coefficient of the wind turbine resulting in a reduction in the wind power. The wake speed of the wind turbine

is determined from the free disc speed at the rotor disc and correspondingly the wake power is determined.

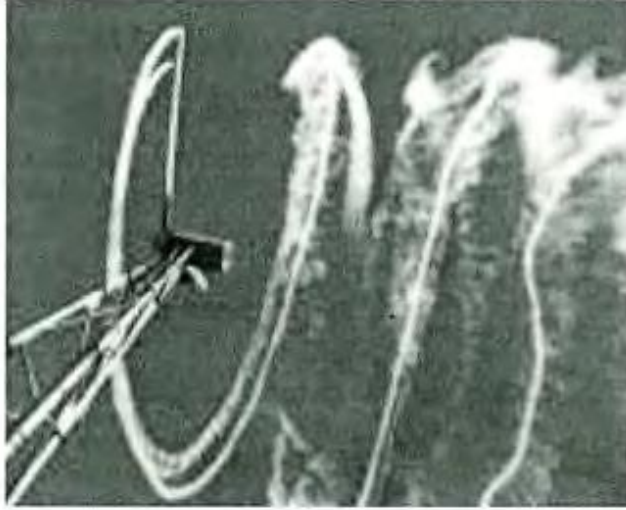


Figure 4.6: Wake Effect in a Wind farm [51].

Depending on the distance between the wind turbines ( $X$ ), the radius of the shadow cone  $R_x$  [33] of the upstream turbine is calculated using equation (4.11) from the radius of rotor ( $R$ ) and  $\tan\alpha$ . The value of  $\tan\alpha$  is 0.04 under the free stream and 0.08 under the wake stream.

$$R_x = R + X * \tan\alpha \quad (4.11)$$

The thrust coefficient ( $C_t$ ) of the wind turbine [34] is calculated from the disc speed adjusted for vertical shear and turbulence using equation (4.12) and is given below.

The disc speed is assumed to be at the hub height of the wind turbine.

$$C_t = 3.5 * \frac{(2 * \bar{U}_{Disk} - 3.5)}{(\bar{U}_{Disk})^2} \quad (4.12)$$

The wake speed ( $U_{wake}$ ) of a wind turbine [38] is calculated from the disc speed, the thrust coefficient, the radius of the rotor disc, the radius of the shadow cone ( $R_x$ ) of

rotor disc, the area of shadow region (AS) of rotor disc and the area of the wind turbine rotor (A) using equation (4.13).

$$U_{wake} = \bar{U}_{Disc} * [1 - \sqrt{(1 - Ct)} * \left(\frac{R}{R_x}\right)^2 * \left(\frac{AS}{A}\right)] \quad (4.13)$$

The supplied power curve is digitized by plotting power vs. wind speed characteristics and the uncorrected power is determined. The variable from the polyfit equation is replaced by the wake speed. The uncorrected wake power of the wind turbine is calculated using equation (4.14) and equation (4.15) for the GE 1.5MW and the Mitsubishi 1 MW wind turbine respectively

For the GE 1.5MW Wind Turbine

GP(uncorr\_wake)

$$\begin{aligned} &= q1(18) + q1(17).*(U_{wake1})^1 + q1(16).*(U_{wake1})^2 + q1(15). \\ &*(U_{wake1})^3 + q1(14).*(U_{wake1})^4 + q1(13).*(U_{wake1})^5 \\ &+ q1(12).*(U_{wake1})^6 + q1(11).*(U_{wake1})^7 + q1(10). \\ &*(U_{wake1})^8 + q1(9).*(U_{wake1})^9 + q1(8).*(U_{wake1})^{10} \\ &+ q1(7).*(U_{wake1})^{11} + q1(6).*(U_{wake1})^{12} + q1(5).*(U_{wake1})^{13} \\ &+ q1(4).*(U_{wake1})^{14} + q1(3).*(U_{wake1})^{15} + q1(2).*(U_{wake1})^{16} \\ &+ q1(1).*(U_{wake1})^{17} \end{aligned}$$

Here  $U_{wake1}$  = The wake speed determined using equation (4.13). (4.14)



For the Mitsubishi 1MW Wind Turbine

$$\begin{aligned}
 MP(uncorr_{wake}) = & q2(19) + q2(18).*(Uwake2)^1 + q2(17).*(Uwake2)^2 + \\
 & q2(16).*(Uwake2)^3 + q2(15).*(Uwake2)^4 + q2(14).*(Uwake2)^5 + q2(13).*( \\
 & (Uwake2)^6 + q2(12).*(Uwake2)^7 + q2(11).*(Uwake2)^8 + q2(10).*( \\
 & (Uwake2)^9 + q2(9).*(Uwake2)^{10} + q2(8).*(Uwake2)^{11} + q2(7).*( \\
 & Uwake2^{12} + q26.*Uwake2^{13} + q25. \\
 & *(Uwake2)^{14} + q2(4).*(Uwake2)^{15} + q2(3).*(Uwake2)^{16} + q2(2).*( \\
 & Uwake2^{17} + q21.*Uwake2^{18}
 \end{aligned}$$

Here  $Uwake2$  = The wake speed determined using equation (4.13) (4.15)

Actual air density is determined from the input pressure (P) and the temperature (T), using equation (8). Air density correction is applied and the corrected wake power,  $P1(corr\_wake)$  of the wind turbine [32] with the wake effect is determined from the actual density, the density at STP and the uncorrected wake power from the curve fitting equation of MATLAB using equation (4.16)

$$P1(corr\_wake) = P1(uncorr\_wake) * \frac{\rho}{\rho \text{ at STP}} \quad (4.16)$$

Here  $P1(uncorr\_wake) = GP(uncorr\_wake)$  for the GE wind turbine and

$MP(uncorr\_wake)$  for the Mitsubishi wind turbine determined using equation (4.16).

$P1(corr\_wake) = GP(corr\_wake)$  for the GE wind turbine and  $MP(corr\_wake)$

for the Mitsubishi wind turbine using equation (4.16).

#### 4.6.2 Wind power of a wind farm with the wake effect

The Cedar Creek wind farm has 274 wind turbines and the corrected wake power of each wind turbine with the wake effect is added using equation (4.17) and the total power of the wind farm with the wake effect is determined. Table 4-2 gives the details of the wind turbines of the Cedar Creek wind farm. From the layout data and the details of the wind turbine in Table 4-2, shadow effect of the wind turbines in the wind farm is estimated for a particular wind direction. Equation (4.17) determines the total wind farm wake power.

$$\sum_{n=1}^{n=n} P1(\text{corr\_wake}) = \text{Total Windfarm Wake Power} \quad (4.17)$$

#### 4.6.3 Wake coefficient of a wind turbines in the wind farm

The wake coefficient (WC) [33] of a wind turbine in the wind farm is calculated using equation (4.18) by the ratio of total output power of the wind farm with the wake effect to the total output power of the wind farm neglecting the wake effect.

$$WC = \frac{\sum_{n=1}^{n=n} P1(\text{corr\_wake})}{\sum_{n=1}^{n=n} P1(\text{corr})} \quad (4.18)$$

#### 4.7 The Cedar Creek Wind Farm Data

The Cedar Creek –I wind farm [50] has 53, G.E 1.5MW wind turbines and 221, Mitsubishi 1MW wind turbines. The wind turbine specifications are given in detail for the two wind turbines. There are two MET towers and the sensors are located at a

height of 80m and 69m for the GE 1.5 MW and the Mitsubishi 1 MW wind turbines to record the wind speed.

Table 4.1: Specifications of the Wind Turbines.

Specifications of Wind Turbine	GE 1.5 MW Wind Turbine	Mitsubishi 1 MW Wind Turbine
Cut in wind speed	3.5 m/s	3.5 m/s
Rated wind speed	12.5 m/s	12 m/s
Rotor Diameter	77 m	61.4 m
Rated Power	1.5 MW	1.0 MW
Hub Height	80 m	69 m
Cut out wind speed	25 m/s	25 m/s

Table 4.2: Layout data of wind turbines of Colorado wind farm [9]. Here FID is nearest feature identity.

Wind Turbine	Name of Wind Turbine	Near FID	Contour Height + Hub Height(m)	H+R (m)	H-R (m)
A01	GE 1.5	0	146.02	184.52	107.52
A02	GE 1.5	1	152.52	191.02	114.02
A03	GE 1.5	2	152.19	190.69	113.69
A04	GE 1.5	3	158.62	197.12	120.12
A05	GE 1.5	4	154.34	192.84	115.84
A06	GE 1.5	5	156.12	194.62	117.62
A07	GE 1.5	6	169.4	207.9	130.9
A08	GE 1.5	7	167.54	206.04	129.04
A09	GE 1.5	8	170.62	209.12	132.12
A10	GE 1.5	9	167.1	205.6	128.6
B01	GE 1.5	10	152.83	191.33	114.33

B02	GE 1.5	11	154.89	193.39	116.39
B03	GE 1.5	12	153.98	192.48	115.4
B04	GE 1.5	13	158.88	197.38	120.38
B05	GE 1.5	14	163.49	201.99	124.99
B06	GE 1.5	15	163.2	201.7	124.7
B07	GE 1.5	16	168.37	206.87	129.87
B08	GE 1.5	17	168.34	206.84	129.84
B09	GE 1.5	18	167.74	206.24	129.24
B10	GE 1.5	19	170.66	209.16	132.16
B11	GE 1.5	20	171.48	209.98	132.98
B12	GE 1.5	21	165.2	203.7	126.7
B13	GE 1.5	22	158.99	197.49	120.49
B14	GE 1.5	23	164.03	202.53	125.53
B15	GE 1.5	24	170.06	208.56	131.56
B16	GE 1.5	25	168.6	207.11	130.11
B17	GE 1.5	26	170.8	209.3	132.3
B18	GE 1.5	27	181.33	219.83	142.83
B19	GE 1.5	28	178.04	216.54	139.54
B20	GE 1.5	29	184.59	223.09	146.09
B21	GE 1.5	30	177.1	215.6	138.6
B22	GE 1.5	31	179.77	218.27	141.27
B23	GE 1.5	32	176.34	214.84	137.84
B24	GE 1.5	33	180.58	219.08	142.08
B25	GE 1.5	34	183.08	221.58	144.58
B26	GE 1.5	35	180.35	218.85	141.85
B27	GE 1.5	36	179	217.5	140.5
C01	GE 1.5	37	165.3	203.85	126.85
C02	GE 1.5	38	170.89	209.39	132.39
C03	GE 1.5	39	170.8	209.33	132.33
C04	GE 1.5	40	173.85	212.35	135.35
C05	GE 1.5	41	179.35	217.85	140.85
C06	GE 1.5	42	178.49	216.99	139.99
C07	GE 1.5	43	176.8	215.36	138.36
C08	GE 1.5	44	164.32	202.82	125.82
C09	GE 1.5	45	167.44	205.94	128.94
C10	GE 1.5	46	170.73	209.23	132.23
C11	GE 1.5	47	167.69	206.19	129.19
C12	GE 1.5	48	167.09	205.59	128.59
C13	GE 1.5	49	164.38	202.88	125.88
C14	GE 1.5	50	164.1	202.6	125.6
C15	GE 1.5	51	163.76	202.26	125.26
C16	GE 1.5	52	164.1	202.6	125.6
D00	Mitsubishi 1.0	53	137.84	168.84	106.84

D01	Mitsubishi 1.0	54	141	172	110
D02	Mitsubishi 1.0	55	143.6	174.65	112.65
D03	Mitsubishi 1.0	56	150.86	181.86	119.86
D04	Mitsubishi 1.0	57	150.35	181.35	119.35
D05	Mitsubishi 1.0	58	150.6	181.6	119.6
D06	Mitsubishi 1.0	59	150.14	181.14	119.14
D07	Mitsubishi 1.0	60	151.23	182.23	120.23
D08	Mitsubishi 1.0	61	156.42	187.42	125.42
D09	Mitsubishi 1.0	62	160.16	191.16	129.16
D10	Mitsubishi 1.0	63	146.8	177.83	115.83
D11	Mitsubishi 1.0	64	144.73	175.73	113.73
D12	Mitsubishi 1.0	65	145.06	176	114
D13	Mitsubishi 1.0	66	141.49	172.4	110.49
D14	Mitsubishi 1.0	67	143.32	174.32	112.32
D15	Mitsubishi 1.0	68	145.6	176.6	114.6
D16	Mitsubishi 1.0	69	147.99	178.9	116.9
D17	Mitsubishi 1.0	70	148.71	179.7	117.71
D18	Mitsubishi 1.0	71	150.4	181.4	119.4
D19	Mitsubishi 1.0	72	148.8	179.8	117.8
D20	Mitsubishi 1.0	73	153.5	184.56	122.56
D21	Mitsubishi 1.0	74	154.91	185.91	123.91
D22	Mitsubishi 1.0	75	155.86	186.86	124.86
D23	Mitsubishi 1.0	76	155.38	186.38	124.38
D24	Mitsubishi 1.0	77	157.91	188.92	126.91
D25	Mitsubishi 1.0	78	159.23	190.23	128.23
D26	Mitsubishi 1.0	79	156.62	187.62	125.62
E01	Mitsubishi 1.0	80	140.74	171.74	109.74
E02	Mitsubishi 1.0	81	140.2	171.2	109.2
E03	Mitsubishi 1.0	82	144.44	175.44	113.44
E04	Mitsubishi 1.0	83	140.42	171.42	109.42
E05	Mitsubishi 1.0	84	140.74	171.74	109.74
E06	Mitsubishi 1.0	85	143.6	174.6	112.6
E07	Mitsubishi 1.0	86	149.33	180.33	118.3
E08	Mitsubishi 1.0	87	151.84	182.84	120.84
E09	Mitsubishi 1.0	88	153.06	184	122.06
E10	Mitsubishi 1.0	89	155.6	186.67	124.67
E11	Mitsubishi 1.0	90	155.41	186.41	124.4
E12	Mitsubishi 1.0	91	156.42	187.42	125.42
E13	Mitsubishi 1.0	92	158.91	189.91	127.91
E14	Mitsubishi 1.0	93	160.15	191.15	129.15
E15	Mitsubishi 1.0	94	160.71	191.71	129.71
E16	Mitsubishi 1.0	95	160.95	191.95	129.9
E17	Mitsubishi 1.0	96	161.2	192.2	130.2

E18	Mitsubishi 1.0	97	161.73	192.73	130.73
F01	Mitsubishi 1.0	98	165.21	196.21	134.21
F02	Mitsubishi 1.0	99	163.59	194.59	132.59
F03	Mitsubishi 1.0	100	165.57	196.57	134.57
F04	Mitsubishi 1.0	101	164.93	195.93	133.93
F05	Mitsubishi 1.0	102	163.66	194.66	132.66
F06	Mitsubishi 1.0	103	165.4	196.4	134.4
F07	Mitsubishi 1.0	104	164.49	195.49	133.49
F08	Mitsubishi 1.0	105	164.63	195.63	133.63
F09	Mitsubishi 1.0	106	166.08	197.08	135.08
F10	Mitsubishi 1.0	107	168.71	199.71	137.71
F11	Mitsubishi 1.0	108	165.93	196.93	134.93
G01	Mitsubishi 1.0	109	126.07	157.07	95.07
G02	Mitsubishi 1.0	110	132.03	163.03	101.03
G03	Mitsubishi 1.0	111	130.84	161.84	99.84
G04	Mitsubishi 1.0	112	132.09	163.09	101.09
G05	Mitsubishi 1.0	113	129.79	160.79	98.79
G06	Mitsubishi 1.0	114	134.27	165.27	103.27
G07	Mitsubishi 1.0	115	135.26	166.26	104.26
G08	Mitsubishi 1.0	116	141.19	172.19	110.19
G09	Mitsubishi 1.0	117	139.79	170.79	108.79
G10	Mitsubishi 1.0	118	139.38	170.38	108.38
G11	Mitsubishi 1.0	119	141.12	172.12	110.12
G12	Mitsubishi 1.0	120	142.89	173.89	111.89
G13	Mitsubishi 1.0	121	144.94	175.94	113.94
G14	Mitsubishi 1.0	122	147.24	178.24	116.24
G15	Mitsubishi 1.0	123	153.88	184.88	122.88
G16	Mitsubishi 1.0	124	154.56	185.56	123.56
G17	Mitsubishi 1.0	125	153.17	184.17	122.17
G18	Mitsubishi 1.0	126	156.4	187.4	125.4
G19	Mitsubishi 1.0	127	155.92	186.92	124.92
G20	Mitsubishi 1.0	128	156.56	187.56	125.56
G21	Mitsubishi 1.0	129	147.21	178.21	116.2
G22	Mitsubishi 1.0	130	149.2	180.2	118.2
G23	Mitsubishi 1.0	131	150.18	181.18	119.18
G24	Mitsubishi 1.0	132	151.16	182.16	120.16
G25	Mitsubishi 1.0	133	150.89	181.89	119.89
G26	Mitsubishi 1.0	134	153.01	184.01	122.01
G27	Mitsubishi 1.0	135	153.19	184.19	122.19
G28	Mitsubishi 1.0	136	155.02	186.02	124.02
G29	Mitsubishi 1.0	137	159.2	190.2	128.2
G30	Mitsubishi 1.0	138	159.65	190.65	128.65
G31	Mitsubishi 1.0	139	162.33	193.33	131.33

G32	Mitsubishi 1.0	140	162.51	193.51	131.51
G33	Mitsubishi 1.0	141	164.47	195.47	133.47
G34	Mitsubishi 1.0	142	163.47	194.47	132.47
G35	Mitsubishi 1.0	143	162.09	193.09	131.09
G36	Mitsubishi 1.0	144	159.69	190.69	128.69
G37	Mitsubishi 1.0	145	162.67	193.67	131.67
H01	Mitsubishi 1.0	146	113.65	144.65	82.65
H02	Mitsubishi 1.0	147	116	147	85
H03	Mitsubishi 1.0	148	118.59	149.59	87.59
H04	Mitsubishi 1.0	149	125.6	156.6	94.6
H05	Mitsubishi 1.0	150	120.56	151.56	89.56
H06	Mitsubishi 1.0	151	118.94	149.94	87.94
H07	Mitsubishi 1.0	152	122.8	153.89	91.89
H08	Mitsubishi 1.0	153	123.53	154.53	92.53
H09	Mitsubishi 1.0	154	138.23	169.23	107.23
H10	Mitsubishi 1.0	155	139.44	170.44	108.44
H11	Mitsubishi 1.0	156	135.39	166.39	104.39
H12	Mitsubishi 1.0	157	134.78	165.78	103.78
H13	Mitsubishi 1.0	158	133.14	164.14	102.14
H14	Mitsubishi 1.0	159	128.83	159.83	97.83
H15	Mitsubishi 1.0	160	133	164	102
H16	Mitsubishi 1.0	161	141.82	172.82	110.82
H17	Mitsubishi 1.0	162	128.11	159.11	97.11
H18	Mitsubishi 1.0	163	127.12	158.12	96.12
H19	Mitsubishi 1.0	164	125.7	156.7	94.7
H20	Mitsubishi 1.0	165	127.84	158.84	96.8
H21	Mitsubishi 1.0	166	132.25	163.25	101.25
H22	Mitsubishi 1.0	167	128.8	159.8	97.8
H23	Mitsubishi 1.0	168	126.82	157.82	95.82
H24	Mitsubishi 1.0	169	125.61	156.61	94.61
H25	Mitsubishi 1.0	170	129.1	160.1	98.1
H26	Mitsubishi 1.0	171	122.99	153.99	91.99
H27	Mitsubishi 1.0	172	123.88	154.88	92.88
H28	Mitsubishi 1.0	173	126	157	95
H29	Mitsubishi 1.0	174	135.02	166.02	104.02
H30	Mitsubishi 1.0	175	135.38	166.38	104.38
H31	Mitsubishi 1.0	176	135.2	166.25	104.25
H32	Mitsubishi 1.0	177	135.43	166.43	104.43
H34	Mitsubishi 1.0	178	129.81	160.81	98.8
H35	Mitsubishi 1.0	179	132.59	163.59	101.5
H36	Mitsubishi 1.0	180	135.85	166.85	104.85
H37	Mitsubishi 1.0	181	135.78	166.78	104.78
H38	Mitsubishi 1.0	182	135.7	166.7	104.7

H39	Mitsubishi 1.0	183	137.06	168.06	106.06
H40	Mitsubishi 1.0	184	137.91	168.91	106.91
H41	Mitsubishi 1.0	185	144.8	175.8	113.8
H42	Mitsubishi 1.0	186	140.82	171.82	109.82
H43	Mitsubishi 1.0	187	143.93	174.93	112.93
H44	Mitsubishi 1.0	188	145.17	176.17	114.17
H45	Mitsubishi 1.0	189	144.79	175.79	113.79
H46	Mitsubishi 1.0	190	147.35	178.35	116.35
H47	Mitsubishi 1.0	191	145.9	176.9	114.9
H48	Mitsubishi 1.0	192	139.95	170.95	108.95
H49	Mitsubishi 1.0	193	140.1	171.1	109.1
H50	Mitsubishi 1.0	194	153.46	184.46	122.4
H51	Mitsubishi 1.0	195	153.71	184.71	122.71
H52	Mitsubishi 1.0	196	156.68	187.68	125.68
H53	Mitsubishi 1.0	197	152.1	183.1	121.1
H54	Mitsubishi 1.0	198	153.32	184.32	122.32
H55	Mitsubishi 1.0	199	155.22	186.22	124.22
H56	Mitsubishi 1.0	200	159.2	190.2	128.2
H57	Mitsubishi 1.0	201	159.35	190.35	128.35
H58	Mitsubishi 1.0	202	159.3	190.3	128.3
H59	Mitsubishi 1.0	203	162.75	193.75	131.75
H60	Mitsubishi 1.0	204	164.28	195.28	133.28
H61	Mitsubishi 1.0	205	162.88	193.88	131.88
H62	Mitsubishi 1.0	206	156.9	187.9	125.9
H63	Mitsubishi 1.0	207	159.8	190.8	128.8
H64	Mitsubishi 1.0	208	152.7	183.7	121.7
J01	Mitsubishi 1.0	209	123.74	154.74	92.74
J02	Mitsubishi 1.0	210	126.16	157.16	95.16
J03	Mitsubishi 1.0	211	129.33	160.33	98.33
J04	Mitsubishi 1.0	212	130.07	161.07	99.07
J05	Mitsubishi 1.0	213	132.23	163.23	101.23
J06	Mitsubishi 1.0	214	134.89	165.89	103.89
J07	Mitsubishi 1.0	215	129.27	160.27	98.27
J08	Mitsubishi 1.0	216	132.27	163.27	101.27
J09	Mitsubishi 1.0	217	132.66	163.66	101.66
K01	Mitsubishi 1.0	218	116.58	147.58	85.58
K02	Mitsubishi 1.0	219	109.4	140.4	78.4
K03	Mitsubishi 1.0	220	106.98	137.98	75.98
K04	Mitsubishi 1.0	221	112.58	143.58	81.58
K05	Mitsubishi 1.0	222	123.4	154.4	92.4
K06	Mitsubishi 1.0	223	122.37	153.37	91.3
K07	Mitsubishi 1.0	224	123.28	154.28	92.28
K08	Mitsubishi 1.0	225	122.75	153.75	91.75



K09	Mitsubishi 1.0	226	127.1	158.1	96
K10	Mitsubishi 1.0	227	119.87	150.87	88.87
K11	Mitsubishi 1.0	228	113.79	144.79	82.79
L01	Mitsubishi 1.0	229	92.4	123.44	61.44
L02	Mitsubishi 1.0	230	93.48	124.48	62.48
L03	Mitsubishi 1.0	231	95.8	126.89	64.89
L04	Mitsubishi 1.0	232	98.6	129.62	67.62
L05	Mitsubishi 1.0	233	98.6	129.64	67.64
L06	Mitsubishi 1.0	234	89.8	120.8	58.8
L07	Mitsubishi 1.0	235	91.03	122.03	60.03
L08	Mitsubishi 1.0	236	91.59	122.59	60.59
L09	Mitsubishi 1.0	237	101.34	132.34	70.34
L10	Mitsubishi 1.0	238	106.2	137.2	75.2
L11	Mitsubishi 1.0	239	110.64	141.64	79.64
L12	Mitsubishi 1.0	240	95.7	126.7	64.7
L13	Mitsubishi 1.0	241	97.38	128.38	66.38
L14	Mitsubishi 1.0	242	98.78	129.78	67.78
M01	Mitsubishi 1.0	243	87.84	118.84	56.84
M02	Mitsubishi 1.0	244	89.91	120.91	58.9
M03	Mitsubishi 1.0	245	89.83	120.83	58.83
M04	Mitsubishi 1.0	246	89.87	120.87	58.87
M05	Mitsubishi 1.0	247	92.33	123.33	61.33
M06	Mitsubishi 1.0	248	95.59	126.59	64.59
M07	Mitsubishi 1.0	249	98.85	129.85	67.85
M08	Mitsubishi 1.0	250	93.83	124.83	62.83
M09	Mitsubishi 1.0	251	98.64	129.64	67
M10	Mitsubishi 1.0	252	97.26	128.26	64.24
M11	Mitsubishi 1.0	253	95.24	126.2	61.97
M12	Mitsubishi 1.0	254	92.97	123.97	62.11
M13	Mitsubishi 1.0	255	93.11	124.11	64.02
M14	Mitsubishi 1.0	256	95.02	126.02	65.4
M15	Mitsubishi 1.0	257	96.4	127.4	67.79
M16	Mitsubishi 1.0	258	98.79	129.79	74.04
P01	Mitsubishi 1.0	259	105.04	136.04	66.43
P02	Mitsubishi 1.0	260	97.43	128.43	74.16
P03	Mitsubishi 1.0	261	105.16	136.16	64.81
P04	Mitsubishi 1.0	262	95.81	126.81	61.2
P05	Mitsubishi 1.0	263	92.24	123.24	54.96
P06	Mitsubishi 1.0	264	85.96	116.96	55.71
P07	Mitsubishi 1.0	265	86.71	117.71	67.07
P08	Mitsubishi 1.0	266	98.07	129.07	63.45
P09	Mitsubishi 1.0	267	94.45	125.45	39.9
P10	Mitsubishi 1.0	268	70.9	101.99	38.12

P11	Mitsubishi 1.0	269	69.12	100.12	44.39
P12	Mitsubishi 1.0	270	75.39	106.39	40.9
P13	Mitsubishi 1.0	271	71.9	102.9	42.02
P14	Mitsubishi 1.0	272	73.02	104.02	55.47
P15	Mitsubishi 1.0	273	86.47	117.47	126.58

The layout information is supplied from the AMEC, St John's. From the latitude and longitude information of the wind turbines, the nearest distance between the wind turbines is estimated. The Arc GIS software is used to estimate the nearest feature identity for a particular wind turbine in the wind farm.

Table 4.3: Wind Direction and Area of Shadow of the Wind Turbines in the Wind farm.

Wind Turbines in the Wind farm	Area of Shadow of Wind Turbine in (m <sup>2</sup> ) at $45^{\circ}\pm 5^{\circ}/225^{\circ}\pm 5^{\circ}$	For all Other Wind Direction (m <sup>2</sup> )
GEWT1	2500.0	0
GEWT2	2500.0	0
GEWT3	2500.0	0
GEWT4	2500.0	0
GEWT5	1900.0	0
GEWT6	2100.0	0
GEWT7	2500.0	0
GEWT8	2500.0	0
GEWT9	2400.0	0
GEWT10	1500.0	0
GEWT11	2500.0	0
GEWT12	2100.0	0
GEWT13	2100.0	0
GEWT14	2100.0	0
GEWT15	2500.0	0
GEWT16	2500.0	0
GEWT17	2500.0	0
GEWT18	2100.0	0
GEWT19	2100.0	0
GEWT20	2400.0	0
GEWT21	2400.0	0

GEWT22	2100.0	0
GEWT23	0.0000	0
GEWT24	0.0000	0
GEWT25	2500.0	0
GEWT26	2500.0	0
GEWT27	2500.0	0
GEWT28	2000.0	0
GEWT29	2000.0	0
GEWT30	0.0000	0
GEWT31	0.0000	0
GEWT32	2000.0	0
GEWT33	2000.0	0
GEWT34	2000.0	0
GEWT35	2500.0	0
GEWT36	2500.0	0
GEWT37	2200.0	0
GEWT38	0.0000	0
GEWT39	2200.0	0
GEWT40	0.000	0
GEWT41	0.000	0
GEWT42	2200.0	0
GEWT43	2200.0	0
GEWT44	0.000	0
GEWT45	0.000	0
GEWT46	2000.0	0
GEWT47	1000.0	0
GEWT48	2400.0	0
GEWT49	2400.0	0
GEWT50	0.0000	0
GEWT51	2000.0	0
GEWT52	2000.0	0
GEWT53	2000.0	0
MITWT1	0.0000	0
MITWT2	1952.85	0
MITWT3	650.95	0
MITWT4	741.52	0
MITWT5	1741.52	0
MITWT6	1741.52	0
MITWT7	1801.9	0
MITWT8	1952.85	0
MITWT9	1952.85	0
MITWT10	1952.85	0
MITWT11	0	0

MITWT12	1862.28	0
MITWT13	1801.9	0
MITWT14	0	0
MITWT15	1043.42	0
MITWT16	1043.42	0
MITWT17	0	0
MITWT18	1741.52	0
MITWT19	1650.95	0
MITWT20	1741.52	0
MITWT21	741.52	0
MITWT22	1741.52	0
MITWT23	741.52	0
MITWT24	741.52	0
MITWT25	681.14	0
MITWT26	0	0
MITWT27	0	0
MITWT28	0	0
MITWT29	1801.9	0
MITWT30	2801.9	0
MITWT31	2801.9	0
MITWT32	1862.28	0
MITWT33	1862.28	0
MITWT34	1254.75	0
MITWT35	1254.75	0
MITWT36	1801.9	0
MITWT37	1862.28	0
MITWT38	1862.28	0
MITWT39	0	0
MITWT40	1650.95	0
MITWT41	1862.28	0
MITWT42	1862.28	0
MITWT43	1801.9	0
MITWT44	1801.9	0
MITWT45	1801.9	0
MITWT46	0	0
MITWT47	1590.57	0
MITWT48	1590.57	0
MITWT49	1590.57	0
MITWT50	1801.9	0
MITWT51	801.9	0
MITWT52	801.9	0
MITWT53	801.9	0
MITWT54	801.9	0

MITWT55	1650.95	0
MITWT56	2560.38	0
MITWT57	0	0
MITWT58	2650.95	0
MITWT59	681.14	0
MITWT60	681.14	0
MITWT61	0	0
MITWT62	0	0
MITWT63	862.28	0
MITWT64	0	0
MITWT65	952.85	0
MITWT66	801.9	0
MITWT67	0	0
MITWT68	1043.42	0
MITWT69	1043.42	0
MITWT70	952.85	0
MITWT71	801.9	0
MITWT72	650.95	0
MITWT73	952.85	0
MITWT74	952.85	0
MITWT75	801.9	0
MITWT76	590.57	0
MITWT77	0	0
MITWT78	0	0
MITWT79	650.95	0
MITWT80	650.95	0
MITWT81	0	0
MITWT82	801.9	0
MITWT83	801.9	0
MITWT84	1801.9	0
MITWT85	0	0
MITWT86	952.85	0
MITWT87	952.85	0
MITWT88	801.9	0
MITWT89	801.9	0
MITWT90	801.9	0
MITWT91	560.38	0
MITWT92	590.57	0
MITWT93	590.57	0
MITWT94	0	0
MITWT95	862.28	0
MITWT96	650.95	0
MITWT97	801.9	0

MITWT98	801.9	0
MITWT99	650.95	0
MITWT100	650.95	0
MITWT101	650.95	0
MITWT102	801.9	0
MITWT103	801.9	0
MITWT104	0	0
MITWT105	862.28	0
MITWT106	862.28	0
MITWT107	0	0
MITWT108	1405.7	0
MITWT109	1405.7	0
MITWT110	0	0
MITWT111	862.28	0
MITWT112	1862.28	0
MITWT113	0	0
MITWT114	0	0
MITWT115	0	0
MITWT116	0	0
MITWT117	741.52	0
MITWT118	650.95	0
MITWT119	0	0
MITWT120	1254.75	0
MITWT121	1254.75	0
MITWT122	0	0
MITWT123	1741.52	0
MITWT124	1741.52	0
MITWT125	1741.52	0
MITWT126	1103.80	0
MITWT127	1103.80	0
MITWT128	1405.70	0
MITWT129	1405.70	0
MITWT130	1405.70	0
MITWT131	1405.70	0
MITWT132	1405.70	0
MITWT133	1405.70	0
MITWT134	1405.70	0
MITWT135	741.52	0
MITWT136	862.28	0
MITWT137	862.28	0
MITWT138	560.38	0
MITWT139	1560.38	0
MITWT140	741.52	0

MITWT141	741.52	0
MITWT142	0	0
MITWT143	650.95	0
MITWT144	650.95	0
MITWT145	650.95	0
MITWT146	0	0
MITWT147	0	0
MITWT148	0	0
MITWT149	741.52	0
MITWT150	741.52	0
MITWT151	801.9	0
MITWT152	801.9	0
MITWT153	3801.9	0
MITWT154	801.9	0
MITWT155	801.9	0
MITWT156	0	0
MITWT157	0	0
MITWT158	862.28	0
MITWT159	741.52	0
MITWT160	741.52	0
MITWT161	1556.65	0
MITWT162	1556.65	0
MITWT163	741.52	0
MITWT164	862.28	0
MITWT165	862.28	0
MITWT166	0	0
MITWT167	862.28	0
MITWT168	1862.28	0
MITWT169	2952.85	0
MITWT170	1164.18	0
MITWT171	1164.18	0
MITWT172	0	0
MITWT173	0	0
MITWT174	1345.32	0
MITWT175	1345.32	0
MITWT176	0	0
MITWT177	0	0
MITWT178	0	0
MITWT179	0	0
MITWT180	741.52	0
MITWT181	741.52	0
MITWT182	0	0
MITWT183	0	0

MITWT184	0	0
MITWT185	0	0
MITWT186	0	0
MITWT187	0	0
MITWT188	0	0
MITWT189	0	0
MITWT190	0	0
MITWT191	650.95	0
MITWT192	952.85	0
MITWT193	952.85	0
MITWT194	862.28	0
MITWT195	862.28	0
MITWT196	862.28	0
MITWT197	0	0
MITWT198	0	0
MITWT199	0	0
MITWT200	801.90	0
MITWT201	801.90	0
MITWT202	650.95	0
MITWT203	650.95	0
MITWT204	0	0
MITWT205	1862.28	0
MITWT206	1801.90	0
MITWT207	0	0
MITWT208	1650.95	0
MITWT209	801.90	0
MITWT210	1801.90	0
MITWT211	0	0
MITWT212	0	0
MITWT213	0	0
MITWT214	0	0
MITWT215	0	0
MITWT216	862.28	0
MITWT217	1862.28	0
MITWT218	1650.95	0
MITWT219	0	0
MITWT220	0	0
MITWT221	0	0

MATLAB estimated results of the wind turbine-2. The average value of the wind speed data of the GE 1.5 MW wind turbine-2 and the Mitsubishi 1.0 MW wind turbine



is determined from the designed algorithm and the estimated results are tested with different input time series wind data files implemented in MATLAB software.

Table 4.4: Estimated results of the wind turbine-2 from the input wind data file 4.

Physical Factors of the Wind Power Model	GE 1.5MW Wind Turbine-2 (Mean Value at Hub Height)	Mitsubishi 1MW Wind Turbine-2 (Mean Value at Hub Height)
Sensor Height Wind Speed (Mean Value of the Wind Speed)	7.37 m/s	7.22 m/s
Vertical Wind Speed Shear	8.08 m/s	7.99 m/s
Turbulence Adjusted Wind Speed	9.71 m/s	9.59 m/s
Disc Speed of Wind Turbine	9.62 m/s	9.53 m/s
Wake Speed of Wind Turbine	8.25 m/s	7.80 m/s

Table 4.5: Estimated results of the wind turbine-2 for an input wind data file 3.

Physical Factors of Wind Power Model	GE 1.5 MW Wind Turbine-2 (Mean Value at Hub Height)	Mitsubishi 1.0 MW Wind Turbine -2 (Mean Value at Hub Height)
Sensor Height Wind Speed (Mean of Wind Speed)	7.37 m/s	7.22 m/s
Vertical Wind Speed Shear	8.09 m/s	7.99 m/s
Turbulence Adjusted Wind Speed	9.71 m/s	9.59 m/s
Disc Speed of Wind Turbine	9.62 m/s	9.54 m/s
Wake Speed of Wind Turbine	8.25 m/s	7.80 m/s

Table 4.6: MATLAB estimated results of wind turbine-2 for an input wind data file 2.

Physical Factors of Wind Power Model	GE 1.5 MW Wind Turbine-2 (Mean Value at Hub Height)	Mitsubishi 1.0 MW Wind Turbine -2 ( Mean Value at Hub Height)
Sensor Height Wind Speed (Mean of Wind Speed)	7.35 m/s	7.19 m/s
Vertical Wind Speed Shear	8.06 m/s	7.97 m/s
Turbulence Adjusted Wind Speed	9.71 m/s	9.59 m/s
Disc Speed of Wind Turbine	9.63 m/s	9.54 m/s
Wake Speed of Wind Turbine	8.25 m/s	7.80 m/s

Table 4.7: MATLAB estimated results of wind turbine-2 for an input wind data file 1

Physical Factors of Wind Power Model	GE 1.5 MW Wind Turbine-2 (Mean Value at Hub Height)	Mitsubishi 1.0 MW Wind Turbine-2 (Mean Value at Hub Height)
Sensor Height Wind Speed (Mean of Wind Speed)	7.33 m/s	7.18 m/s
Vertical Wind Speed Shear	8.04 m/s	7.95 m/s
Turbulence Adjusted Wind Speed	9.68 m/s	9.57 m/s
Disc Speed of Wind Turbine	9.59 m/s	9.50 m/s
Wake Speed of Wind Turbine	8.22 m/s	7.78 m/s

The estimated power of individual physical factors considered and its contribution in determining the wind power of a wind turbine is given in the table below. The change in wind power is determined from the physical factors considered. The uncorrected

power curve function determined from the curve fitting toolbox using the polyfit command in MATLAB is used to estimate the corresponding power. The average value of wind speed is substituted in the equation of uncorrected power curve function and corresponding wind power is determined for the physical factor considered.

Table 4.8: The wind power of a wind turbine -2 in the wind farm with the input time series data file 1.

Physical Factors of Wind Power Model Considered from the Designed Algorithm	GE 1.5 MW Wind Turbine	Mitsubishi 1MW Wind Turbine
Average value of the estimated speed of the vertical shear at hub height	635.92 KW (Estimated power using average value of speed of vertical shear)	275.89 KW (Estimated power using average value of speed of vertical shear)
Average value of the estimated turbulence adjusted speed at hub height	1.15 MW (Estimated power using average value of turbulence adjusted speed)	632.66 KW (Estimated power using average value of turbulence adjusted speed)
Average value of the estimated disc speed at hub height	1.12 MW (Estimated power using average value of disc speed)	617.44 KW (Estimated power using average value of disc speed)
Average value of the estimated air density adjusted disc speed	1.14 MW (Estimated power using average value of air density adjusted disc speed)	631.65 KW (Estimated power using average value of air density adjusted disc speed)

Table 4.9: Wind power of wind turbine -2 in the Colorado wind farm with the input wind data file 2.

Physical Factors of Wind Power Model considered from the Designed Algorithm	GE 1.5 MW Wind Turbine	Mitsubishi 1 MW Wind Turbine
Average value of the estimated speed of vertical shear at hub height	636.45 KW (Estimated power using average value of speed of vertical shear)	276.33 KW (Estimated power using average value of speed of vertical shear)
Average value of the estimated turbulence adjusted speed at hub height	1.15 MW (Estimated power using average value of turbulence adjusted speed)	633 KW (Estimated power using average value of turbulence adjusted speed)
Average value of the estimated disc speed at hub height	1.12 MW (Estimated power using average value of disc speed)	618 KW (Estimated power using average value of disc speed)
Average value of the estimated air density adjusted disc speed	1.15 MW (Estimated power using average value of air density adjusted disc speed)	632.14 KW (Estimated power using average value of air density adjusted disc speed)

Table 4.10: Wind power of a wind turbine -2 in the wind farm using the input wind data file 3.

Physical Factors of Wind Power Model considered from the Designed Algorithm	GE 1.5 MW Wind Turbine	Mitsubishi 1 MW Wind Turbine
Average value of the estimated speed of vertical shear at hub height	628.86 KW (Estimated power using average value of speed of vertical shear)	272 KW (Estimated power using average value of speed of vertical shear)
Average value of the estimated turbulence adjusted speed at hub height	1.148 MW (Estimated power using average value of turbulence adjusted speed)	633.09 KW (Estimated power using average value of turbulence adjusted speed)
Average value of the estimated disc speed at hub height	1.124 MW (Estimated power using average value of disc speed)	617.87 KW (Estimated power using average value of disc speed)
Average value of the estimated air density adjusted disc speed	1.15 MW (Estimated power using average value of air density adjusted disc speed)	632.1 KW (Estimated power using average value of air density adjusted disc speed)

Table 4.11: Wind power of a wind turbine -2 in the Colorado wind farm with the input wind data file 4.

Physical Factors of Wind Power Model considered from the Designed Algorithm	GE 1.5 MW Wind Turbine	Mitsubishi 1 MW Wind Turbine
Average value of the estimated speed of vertical shear at hub height	622 KW (Estimated power using average value of speed of vertical shear)	268.18 KW (Estimated power using average value of speed of vertical shear)
Average value of the estimated turbulence adjusted speed at hub height	1.139 MW (Estimated power using average value of turbulence adjusted speed)	625.34 KW (Estimated power using average value of turbulence adjusted speed)
Average value of the estimated disc speed at hub height	1.115 MW (Estimated power using average value of disc speed)	610.14 KW (Estimated power using average value of disc speed)
Average value of the estimated air density adjusted disc speed	1.1409 MW (Estimated power using average value of air density adjusted disc speed)	624.18 KW (Estimated power using average value of air density adjusted disc speed)

Results of Table 4-12 are estimated from the wind farm power model. The layout information of the wind farm and the wind direction at the wind farm site is a major contributing factor to estimate the wind farm power. The wake effect takes place for a particular wind direction when wind turbines are placed at a closer distance due to the shadow effect of neighboring wind turbines. It results in reduction in the wind speed and correspondingly the wind power. The wake coefficient is determined using equation (4.18). The wake coefficient of 1 indicates that the wind turbines operate at a

maximum power and a value less than 1 indicates that the wind turbines operate at reduced power due to the wake effect or the shadow effect of neighboring wind turbines. The results are estimated and tested with different input wind data files.

Table 4.12: Wake coefficient data determined from the wind direction and shadow effect of the wind turbines in the wind farm.

Time Series Wind Speed Data of Equal Length (10 min)	Wind Direction ( $45^{\circ} \pm 5^{\circ}$ ; $225^{\circ} \pm 5^{\circ}$ )	All other Wind Direction (except $45^{\circ} \pm 5^{\circ}$ and $225^{\circ} \pm 5^{\circ}$ )
Wake_Coefficient of Wind Data 1	0.8451	1.0
Wake_Coefficient of Wind Data 2	0.8452	1.0
Wake_Coefficient of Wind Data 3	0.8440	1.0
Wake_Coefficient of Wind Data 4	0.8439	1.0

Table 4.13: Estimated power output of the Colorado wind farm.

Time Series Wind Speed Data of Equal Length (10 min)	G.E Wind Turbines (1.5 MW- 53 WT)	Mitsubishi Wind Turbines (1MW-221 WT)	Average Wind farm (GE + Mitsubishi)
Wind Data 1	49.10 MW	111.4 MW	160.5 MW
Wind Data 2	49.34 MW	112.1 MW	161.3 MW
Wind Data 3	49.55 MW	112.29 MW	161.7 MW
Wind Data 4	49.50 MW	112.19 MW	161.6 MW

The Colorado wind farm has the Mitsubishi 1 MW, 221 wind turbines and the GE 1.5 MW, 53 wind turbines. Results of Table 4-13 are the estimated average value of power of the GE wind turbines and the Mitsubishi wind turbines, when the wind turbines are operating at the disc speed. The MATLAB code is tested with different input wind speed data files.

#### **4.8 Transmission Loss in the Wind farm**

Transmission losses occur due to the current flow in the cables and there is reduction in power. When current flows through wires, voltage drop occurs and thus correspondingly power loss occurs in the cable. The losses include copper loss and induction loss [42].

- i) Copper loss is as a consequence of heating of the material with a potential difference.
- ii) Induction losses occur when metallic object absorbs power due to electromagnetic field generated by current carrying conductors.

After an extensive research on power loss it is concluded that the power loss within a wind farm is about 1% due to transmission of current through cables [40, 41]. Actual transmission details and parameters of the Colorado wind farm were not available.

Therefore, wind farm power loss of the Colorado wind farm is assumed to have 1% transmission loss. The power loss factor of 0.99 is multiplied to estimate the wind farm power in real time.



Table 4.14: Estimated Colorado wind farm power before and after transmission loss (TL) in wind farm.

Input Time Series Wind Data of Equal Length (10 min)	TL	Average Wind Farm Power before TL. (No- wake effect)	Average Wind Farm Power after TL (No- wake effect)	Average Wind Farm Power before TL (Wake effect)	Average Wind Farm Power after TL (Wake effect)
Wind Data1	1.0%	160.51 MW	158.89 MW	135.63 MW	134.27 MW
Wind Data2	1.0%	161.31 MW	159.68 MW	136.33 MW	134.97 MW
Wind Data3	1.0%	161.71 MW	160.08 MW	136.49 MW	135.12 MW
Wind Data4	1.0%	161.64 MW	160.03 MW	136.41 MW	135.05 MW

Results of Table 4-14 are the average value of the wind farm power due to transmission loss of 1%. Actual power is the wind farm power after transmission loss. The actual power data is estimated when the wind turbines are operating at the disc speed with the transmission loss of 1% and when the wind turbines are operating at the wake speed with the transmission loss of 1%.

Table 4.15: Estimated Loss in the power of the Colorado wind farm due to power transmission.

Time Series Input Wind Speed Data of Equal Length (10 min)	Transmission Loss	Loss in Power (No wake effect)	Loss in Power (Wake effect)
Wind Data 1	1.0%	1.605 MW	1.356 MW
Wind Data 2	1.0%	1.613 MW	1.3633 MW
Wind Data 3	1.0%	1.6172 MW	1.3649 MW
Wind Data 4	1.0%	1.616 MW	1.364 MW

Results of Table 4-15 are the estimated net loss in power due to the power transmission. The transmission loss factor is 1%. Estimated net loss in power is determined from the difference in power when the wind turbines operate at the disc speed (no transmission loss factor) and when the wind turbines operate at the disc speed considering the transmission loss factor (1%). Similarly net loss in power is determined from the difference in power when the wind turbines operate at the wake speed (no transmission loss factor) and when the wind turbines operate at the wake speed considering transmission loss factor. The loss in power is estimated and tested with different input wind speed data files.

## 4.9 Wind Farm Power Calculation Results

### 4.9.1 Simulated MATLAB Results using the designed algorithm to estimate wind farm power

Using the Cedar Creek layout information [50], the designed algorithm was implemented in MATLAB. The Simulated results in MATLAB are shown in the figure below. A copy of MATLAB code is attached in Appendix K, Appendix L, and Appendix M. Figure 4.7 and Figure 4.8 are the manufacturer supplied power curve of the Mitsubishi 1MW wind turbine [49] and the GE 1.5 MW wind turbine [48] respectively. The supplied power curves are used to estimate the actual power curve. The first step is to digitize the power curves i.e. the curve is fitted to the supplied power curve of the Mitsubishi 1MW wind turbine and the GE 1.5MW wind turbine as shown in Figure 4.9 and Figure 4.10 respectively. The MATLAB has curve fitting toolbox and after exploring various curve fitting techniques, it is concluded that the best fit polynomial curve is of order 18 for the Mitsubishi 1MW wind turbine and of order 17 for the GE 1.5MW wind turbine.

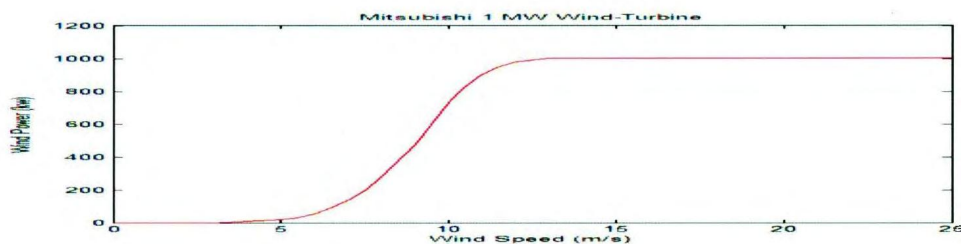


Figure 4.7: Power vs. Wind Speed characteristics of Mitsubishi 1 MW wind turbine (supplied power curve).

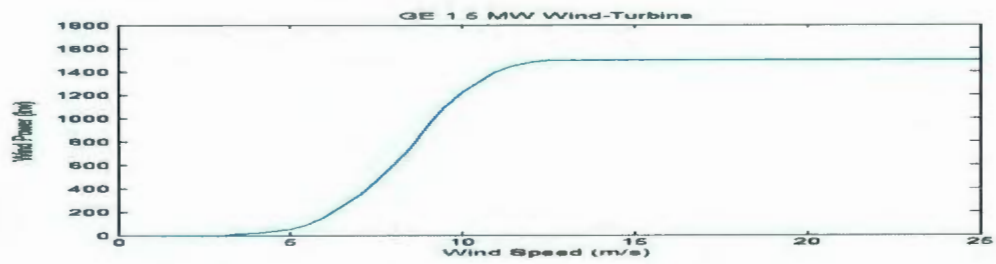


Figure 4.8: Power vs. Wind Speed characteristics of GE 1.5 MW wind turbine (supplied power curve).

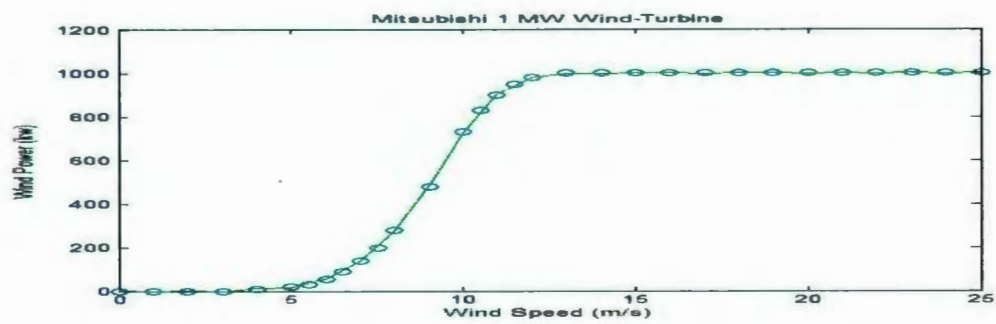


Figure 4.9: Power vs. Wind Speed characteristics of Mitsubishi 1 MW wind turbine (curve fitted).

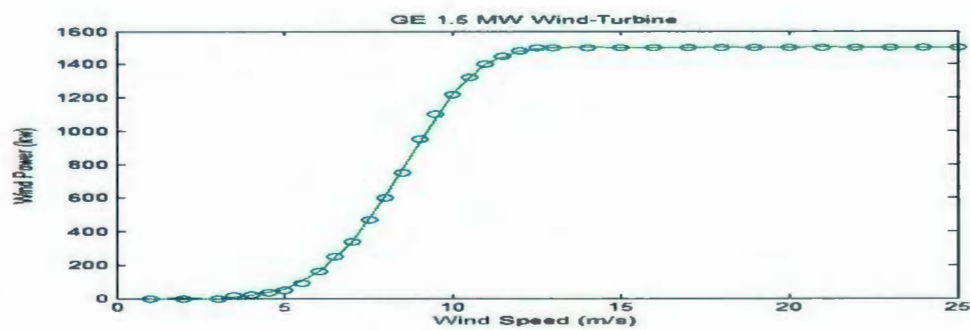


Figure 4.10: Power vs. Wind Speed characteristics of GE 1.5 MW wind turbine (curve fitted).

The input wind speed data file1 is recorded from the anemometer at the MET tower.

The Colorado wind farm has two MET tower. The MET tower 1 records the wind speed for the GE wind turbines at a height of 80m and the MET tower 2 records the wind speed of the Mitsubishi wind turbines at a height of 69m. The recorded wind speed is from the wind speed data file1 and correspondingly results are simulated in MATLAB. The recorded wind speed is shown in Figure 4.11 and Figure 4.12 for the GE 1.5 MW wind turbine and the Mitsubishi 1 MW wind turbine respectively for a time range of 45,000 minutes. The average value of the wind speed data in Figure 4.11 is 7.33 m/s and the average value of the wind speed data in Figure 4.12 is 7.18 m/s.

The average value of the wind speed data in Figure 4.11 is a bit higher than the average value of the wind speed data in Figure 4.12.



Figure 4.11: Sensor height wind speed data for the GE 1.5 MW wind turbine-2 recorded from MET tower1. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

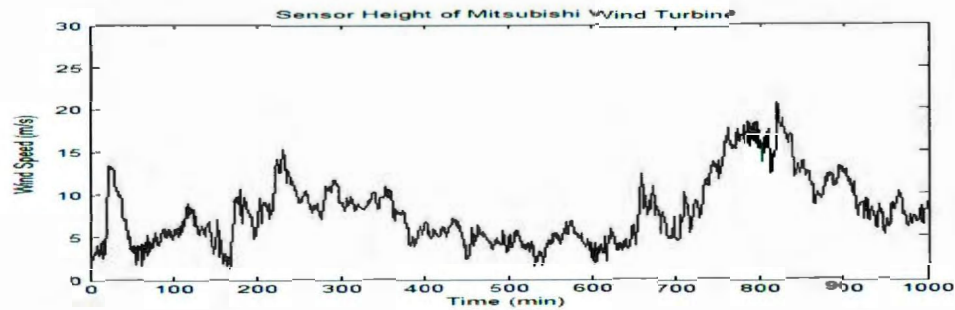


Figure 4.12: Sensor height wind speed data for the Mitsubishi 1.0 MW wind turbine-2 recorded from MET tower2. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

The Colorado wind farm has 274 wind turbines. The wind speed at the hub height is calculated from the input wind speed at the sensor height using the power law equation of shear with shear exponent of  $1/7$  for each wind turbine at the hub height using equation (4.3). The hub height of each wind turbine is calculated considering the turbine base elevation. Figure 4.13 and Figure 4.14 shows the estimated hub height wind speed for the GE 1.5MW wind turbine-2 and the Mitsubishi 1MW wind turbine-2 respectively. The average value of the wind speed data in Figure 4.13 is 8.04 m/s. The average value of the wind speed data in Figure 4.14 is 7.95 m/s. The average value of the wind speed data in Figure 4.13 is a bit higher than the average value of the wind speed data in Figure 4.14.

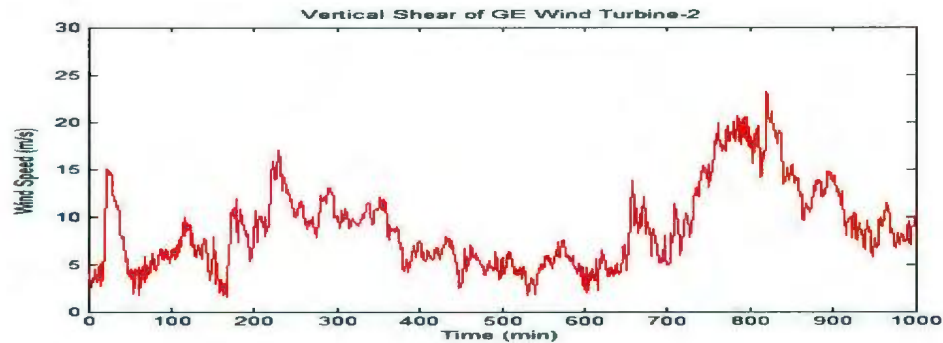


Figure 4.13: Hub height wind speed estimated for the GE 1.5 MW wind turbine-2. (Note: Time Scale: X axis: 1 unit=10 minute; 1000 unit = 10000 minutes).



Figure 4.14: Hub height wind speed estimated for the Mitsubishi 1MW wind turbine- 2. (Note: Time Scale: X axis: 1 unit=10 minute; 1000 unit = 10000 minutes).

The turbulence adjusted wind speed is estimated for the GE 1.5MW wind turbine-2 and the Mitsubishi 1MW wind turbine-2 at the hub height of the wind turbine. It is calculated using equation (4.5) from the input wind speed and the turbulence intensity at the hub height. The resulting wind speed is shown in Figure 4.15 and Figure 4.16 for the GE1.5 MW wind turbine and the Mitsubishi 1MW wind turbine respectively. The average value of the wind speed data in Figure 4.15 is 9.68 m/s. The average value of the wind speed data in Figure 4.16 is 9.57 m/s. The average value of the wind speed

data in Figure 4.15 is a bit higher than the average value of the wind speed data in Figure 4.16.

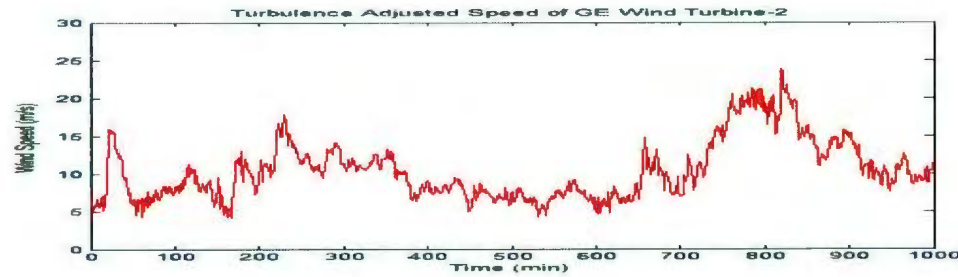


Figure 4.15: Turbulence adjusted wind speed estimated for GE 1.5 MW wind turbine- 2 at hub height.  
(Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

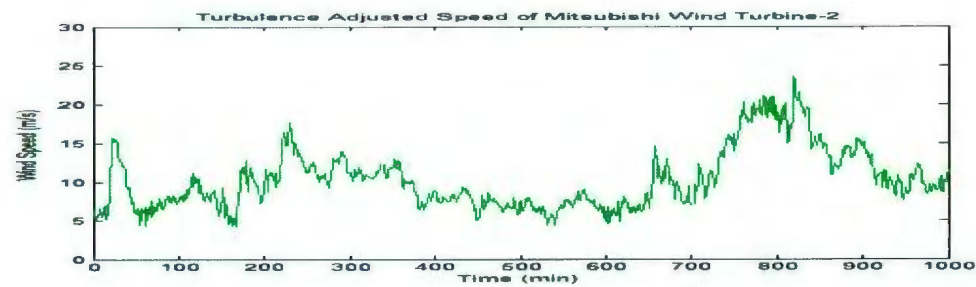


Figure 4.16: Turbulence adjusted wind speed estimated for Mitsubishi 1.0 MW wind turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

The disc speed adjusted for vertical shear and turbulence adjusted speed is calculated using equation (4.7) from the lower rotor tip to the upper rotor tip of the wind turbine. The resulting wind speed is assumed to be at the hub height of the wind turbine. The wind speed is plotted in Figure 4.17 for the GE 1.5 MW wind turbine-2 and in Figure 4.18 for the Mitsubishi 1MW wind turbine-2. The average value of the wind speed data in Figure 4.17 is 9.59 m/s. The average value of the wind speed data in Figure



4.18 is 9.50 m/s. The average value of the wind speed data in Figure 4.17 is a bit higher than the average value of the wind speed data in Figure 4.18.



Figure 4.17: Estimated disc Speed (adjusted for turbulence and shear) for GE 1.5 MW wind turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit=10 minute; 1000 unit = 10000 minutes).

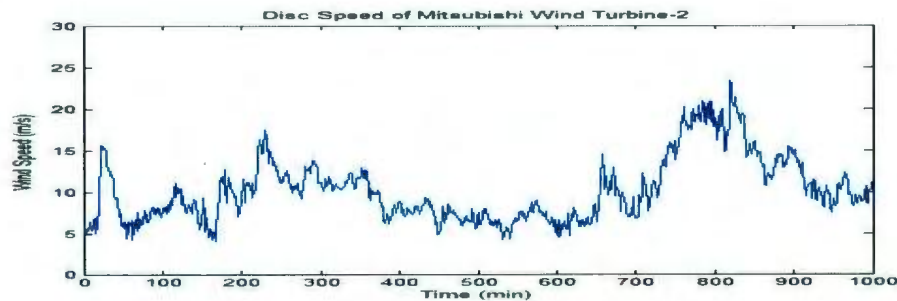


Figure 4.18: Estimated disc speed (adjusted for turbulence and shear) for Mitsubishi 1.0 MW wind turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit=10 minute; 1000 unit = 10000 minutes).

The wake speed is shown in Figure 4.19 for the GE wind turbine-2 and in Figure. 4.20 for the Mitsubishi wind turbine-2. The wind speed is reduced due to the wake effect from the upstream turbines. It is estimated from the thrust coefficient of the wind turbine and the closest distance from neighboring turbines using equation (4.11), equation (4.12) and equation (4.13). The average value of the wind speed data in

Figure 4.19 is 8.22 m/s. The average value of the wind speed data in Figure 4.20 is 7.78 m/s. The average value of the wind speed data in Figure 4.19 is a bit higher than the average value of the wind speed data in Figure 4.20.

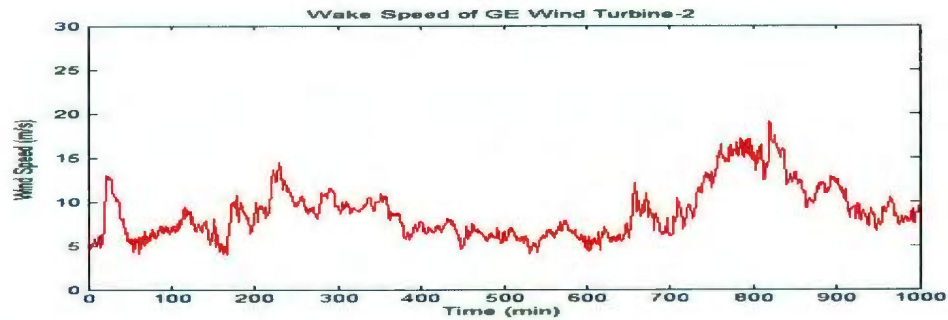


Figure 4.19: Wake speed estimated for GE 1.5 MW wind turbine-2 at hub height (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).



Figure 4.20: Wake speed estimated for Mitsubishi 1.0 MW wind turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

Using the curve fitted supplied power curve, the actual power curves of the wind turbine is estimated from the uncorrected power adjusted with air density using equation (4.9). The power curves are estimated from the designed algorithm for 274 wind turbines of the Colorado wind farm. The estimated power curves are shown in Figure 4.21 for the GE 1.5 MW wind turbine-1 and in Figure 4.22 for the GE 1.5 MW

turbine-2. Figure 4.23 and Figure 4.24 are the estimated power curves for the Mitsubishi 1MW wind turbine-1 and the Mitsubishi 1MW wind turbine-2 respectively.

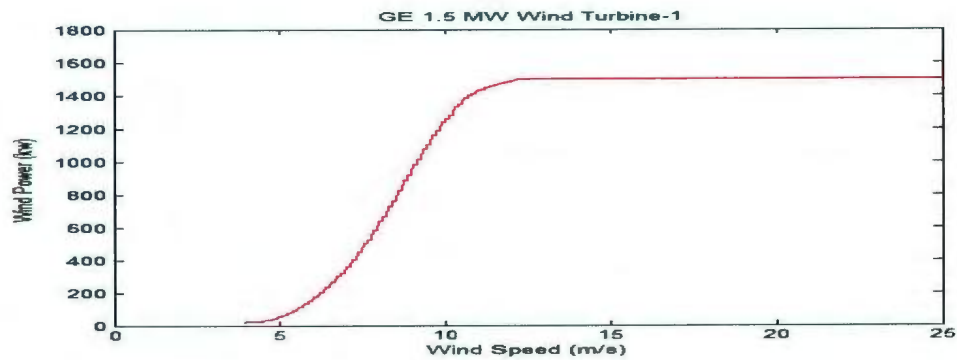


Figure 4.21: Estimated power curve of GE 1.5 MW wind turbine-1 adjusted with air density.

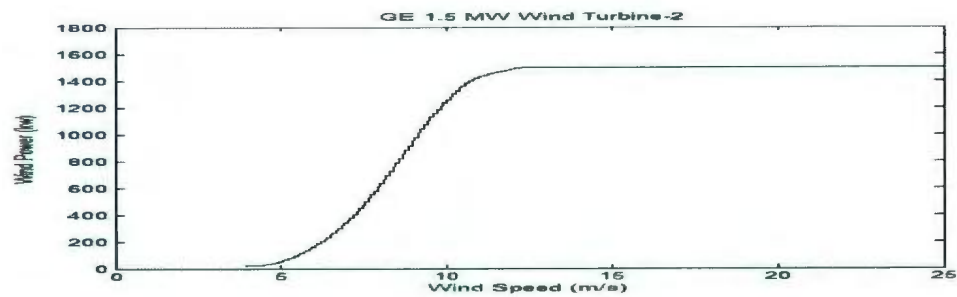


Figure 4.22: Estimated power curve of the GE 1.5MW wind turbine-2 adjusted with air density.

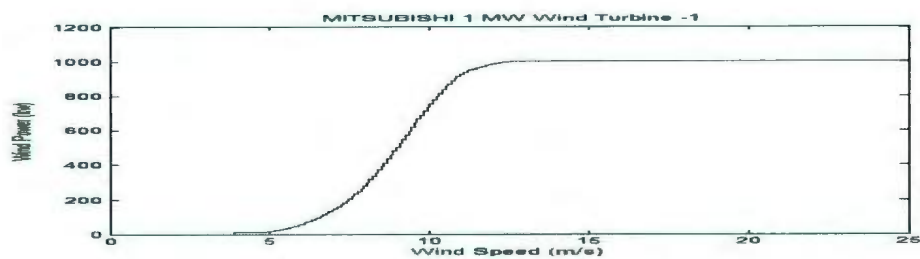


Figure 4.23: Estimated power curve of the Mitsubishi 1MW wind turbine-1 adjusted with air density.

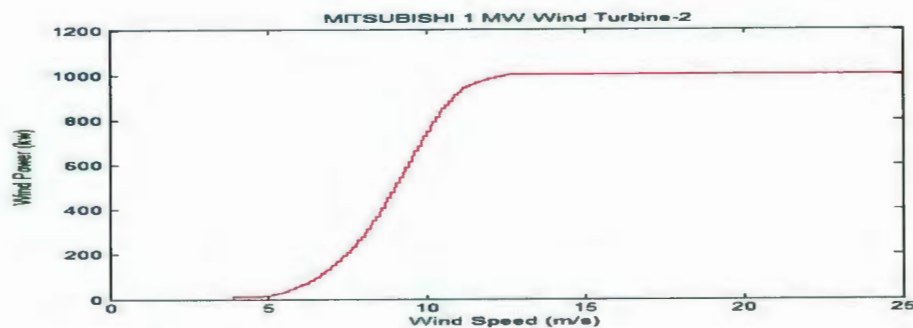


Figure 4.24: Estimated power curve of the Mitsubishi 1.0 MW wind turbine-2 adjusted with air density.

The wake model is developed in this chapter and the wake power is determined from the estimated wake speed. There is reduction in power with the wake effect (black) as shown in Figure 4.25 for the GE wind turbine-2 and in Figure 4.26 for the Mitsubishi wind turbine-2. The estimated wind power of the wind turbine-2 is compared with the wake effect and without wake effect. When there is no wake effect, the power is not reduced (red). The wind power of the wind turbine-2 is plotted with respect to time.

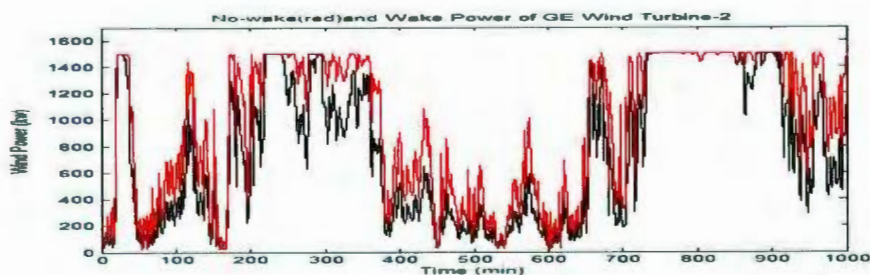


Figure 4.25: Comparison of power estimated with wake (black) and without wake (red) effect for GE 1.5 MW wind turbine-2. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

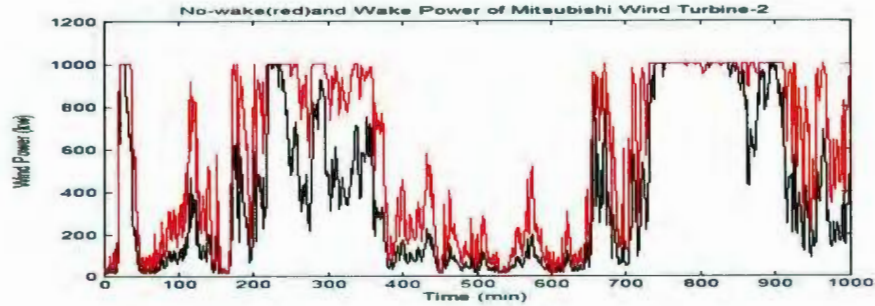


Figure 4.26: Comparison of power estimated with wake (black) and without wake (red) effect for Mitsubishi 1.0 MW wind turbine-2. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

As shown in Figure 4.27, the wind farm power is determined at the free disc speed and is plotted with respect to time. The wind farm power is estimated from the GE 1.5 MW and the Mitsubishi 1 MW wind turbines. The total power of the wind turbines in the wind farm is added and is the estimated wind farm power.

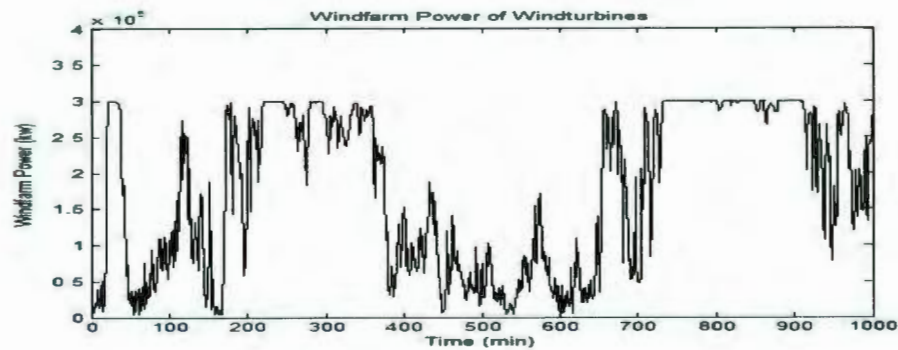


Figure 4.27: Estimated wind farm no-wake power with respect to time. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

As shown in Figure 4.28, the wind farm power is estimated at the free disc speed and is compared with the wake power of the wind farm. The wind farm power is plotted

with respect to time. The wind farm power is estimated from the GE and the Mitsubishi wind turbines with the wake effect (red) and without wake effect (black).

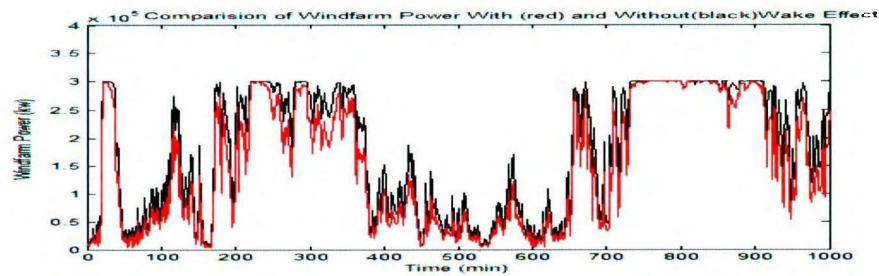


Figure 4.28: Comparison of estimated wind farm power with wake effect (red) and no-wake effect (black) with respect to time. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

The wind farm output power is determined from the wind direction and shadow effect of the neighboring wind turbines. Figure 4.29 is a plot of a wind direction at the wind farm site. As shown in Figure 4.30, the wake coefficient of 1 indicates that the wind turbines operate at a maximum power and a value less than 1 indicates that the wind turbines operating at reduced power or at the wake speed. In Figure 4.30, we see that at a wind direction of  $45^\circ \pm 5^\circ$  and  $225^\circ \pm 5^\circ$ , there is a wake effect and the wind speed is reduced as the wind turbines are placed at a closer distance. For all other wind direction, the wind turbines operate at a maximum power and this factor is determined from the wind farm layout and the distance between neighboring wind turbines.



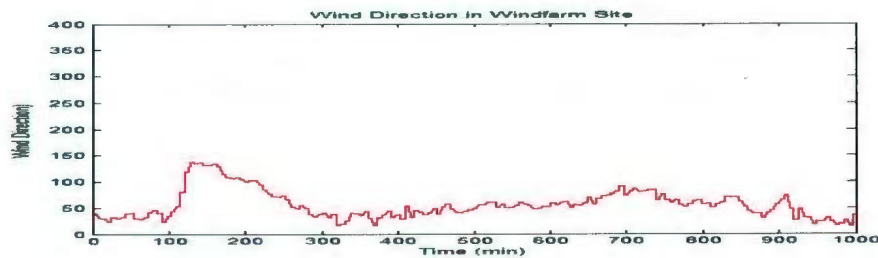


Figure 4.29: Wind direction (degrees) at the wind farm site for a time span of 10000 minutes. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

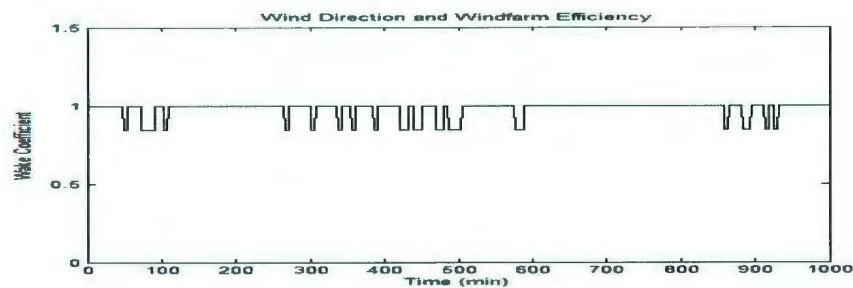


Figure 4.30: Wake coefficient determined from wind direction is plotted with respect to time. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

Figure 4.31 is a plot of the wind direction at the wind farm site for a time span of 5000 minutes and Figure 4.32 is a plot of the wake coefficient determined from the wind direction for a time span of 5000 minutes.

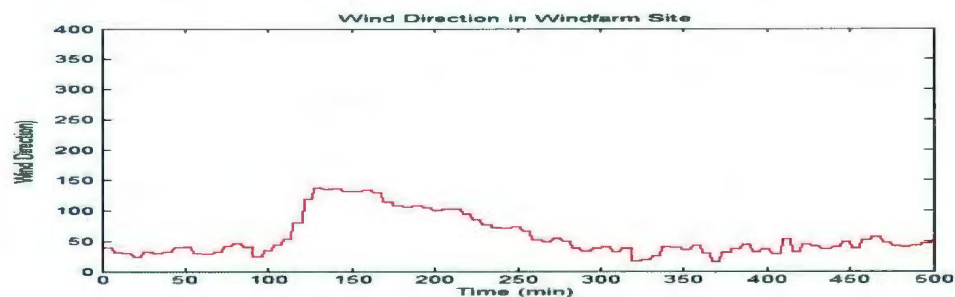


Figure 4.31: Wind direction (degrees) at the wind farm site for a time span of 5000 minutes. (Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

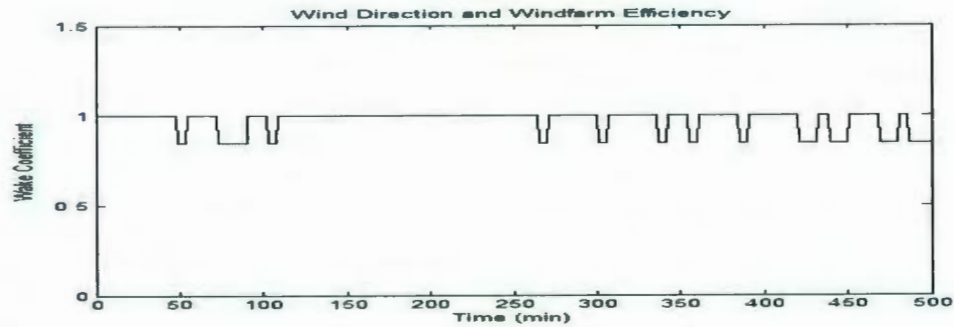


Figure 4.32: Wake coefficient determined from wind direction is plotted with respect to time (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

With the transmission loss of 1%, there is a further reduction in the estimated wind farm power. Figure 4.33 and Figure 4.34 gives loss in power of the wind farm due to the power transmission without the wake effect and with the wake effect respectively. The wind farm power loss due to the transmission is plotted with respect to time. Due to the wake effect there is more reduction in power as compared to power loss with no wake effect.

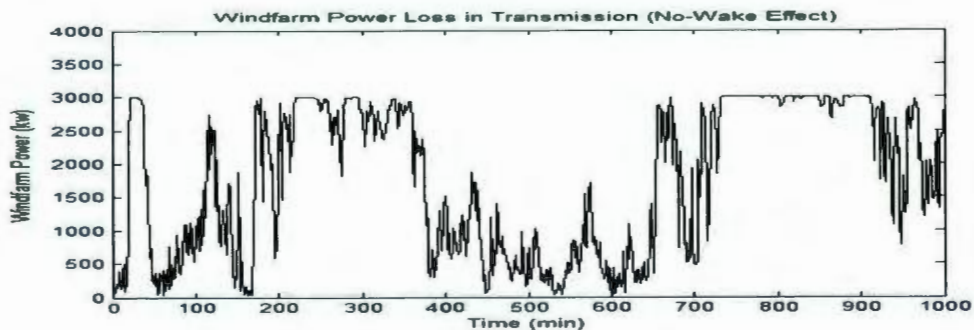


Figure 4.33: Wind farm output power with power loss (1%) in transmission with no wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).



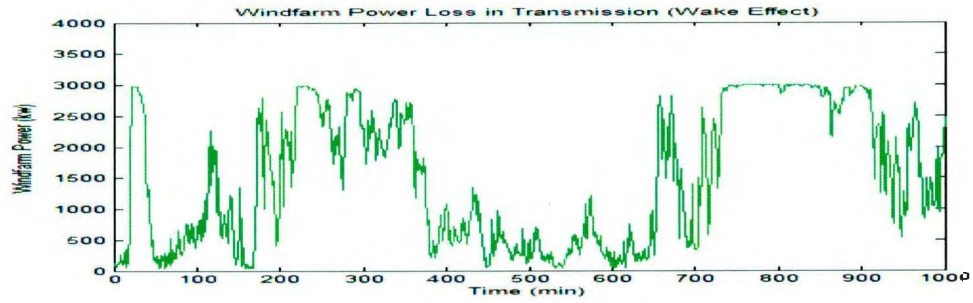


Figure 4.34: Wind farm output power with power loss (1%) in transmission and wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

Figure 4.35 and Figure 4.36 gives actual wind farm power considering the transmission loss due to the wake effect and no wake effect respectively. The actual wind farm power is plotted with respect to time. Due to transmission loss there is a reduction in power. There is more reduction in power due to the wake effect as compared to power loss without wake effect. The actual power is plotted considering the transmission loss. Net loss in power due to transmission of power is estimated with transmission loss of 1%.

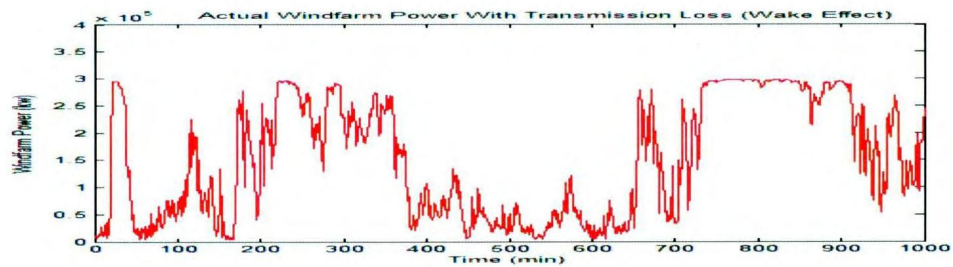


Figure 4.35: Actual estimated wind farm power with transmission loss of 1% due to wake effect is plotted with respect to time. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

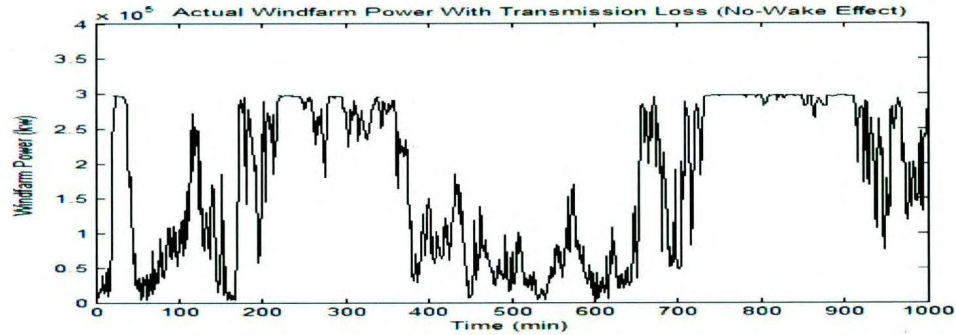


Figure 4.36: Actual estimated wind farm power with transmission loss of 1% with no wake effect is plotted with respect to time (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

#### 4.10 Conclusion

In this chapter working power model of the Cedar Creek -I, Colorado wind farm is developed with the historic data of atmospheric parameters as input to the wind power model for power estimation. The manufacturer supplied power curve assumes ideal condition and a variation of the atmospheric parameters results in a variation in the output power. In this chapter detail of the wind turbine characteristics, its specifications, wind farm layout and the number of wind turbines is studied. The location of met tower and the sensor height is known. The actual turbine power curves are produced when the power is plotted as a function of equivalent wind speed or disc speed instead of the hub height wind speed. This suggests that both vertical shear and the turbulence are important factors in power production. Air density has a major effect in power production and the corrected power curve of the wind turbine is estimated from the equivalent wind speed adjusted with air density. The corrected power curves of the wind turbines are produced from the atmospheric parameters

effecting wind turbine rotor disc and the wind farm output power is estimated and presented in the chapter. This chapter shows that the wind direction and the wind farm layout have a significant influence upon the power output mainly due to the wake effect. The wake model is developed as wind turbines are placed at a closer distance. The impact of wake is to disturb wind flow to the wind turbines and as a result it results in power loss as compared to the wind turbines operating in undisturbed wind. This effect can be minimized by increasing the distance between the wind turbines. It is concluded that there is a reduction in the output power of the wind farm than if the ideal wind turbines are assumed. The MATLAB code is tested with different input wind data files. An accurate result is estimated with every 10 minutes wind data file and is presented in this chapter.

## **Chapter 5**

### **Conclusion and Future Work**

#### **5.1 Research Overview**

In this research the wind speed forecasting models and the physical factors of the atmospheric parameters were studied that affects the wind turbine power production and a working wind speed models and a wind farm power model were implemented in the MATLAB. Major contributing factors in the wind power production are analyzed and their effect on the wind power estimation is understood. Some of the factors such as wind speed, topography, pressure, temperature, wind direction, air density and their contribution to the wind power generation are studied and the simulated results are presented that shows the effect of the individual physical factor in estimating the wind power of a wind turbine. The physical factors such as vertical shear, turbulence intensity, air density has a major effect on the energy production. The wind farm layout, the influence of the wind direction, the thrust coefficient of the wind turbine, and the wind turbine placements in the wind farm have a greater influence in determining the wake coefficient data in the wind farm. The transmission loss in the wind farm which results in the power loss is determined and the results are estimated for the Farceuse wind farm located in the Newfoundland and the Cedar Creek Colorado wind farm located in the United States. The physical model of the wind power combined with the statistical forecasting model is required for the effective use of the generated wind power for the utility operators. The designed algorithm takes into account the physical factors affecting the wind turbine rotor disc is implemented

in the MATLAB software, which is fast and accurate and can take any number of wind turbines as input to the power model with huge data set of historic time series wind data. It is tested for accuracy for every 10 minutes time series data set.

The wind speed forecasting models are studied in this research work and some of the models are designed and implemented in the MATLAB software and are tested for accuracy using the input time series wind speed data. The wind speed models studied and implemented in these projects are the Auto Regressive Moving Average model, the Kaman Filter, the Unscented Kaman Filter, and the Non Linear Auto Regressive Exogenous model. Accurate forecast of the wind speed is obtained for the selected range of the wind speed. The designed model on the wind speed estimation gives accurate result for the short term wind speed prediction for the time series wind speed data. The Kaman filter and the Unscented Kaman filter have a greater impact in minimizing the noise effect associated with the input wind speed data, and are crucial for accurate estimation for the wind speed forecasters. The noise associated in the wind speed can result in errors in the actual wind speed estimation. The working model of both the filters is implemented in the MATLAB and its performance is tested for accurate estimation of the forecasted wind speed.

## **5.2 Research Contribution**

The research contributions are:

Short term wind speed prediction using the Auto Regressive Moving Average model for five hours in advance is developed and implemented in the MATLAB software.

The designed algorithm using Auto Regressive Moving Average model implemented in the MATLAB software is fast, accurate and is tested with different input wind speed data sets. An hour ahead wind speed model using the Kalman filter is implemented in the MATLAB software using linear parametric model or Auto Regressive model as input to the Kalman filter. The developed hybrid model has the advantage of accurate estimation of the wind speed and the error is minimised. An hour ahead wind speed model using Unscented Kalman filter is developed in the MATLAB software using non linear Auto Regressive Exogenous (ARX) model as input to the Unscented Kalman filter. It gives accurate estimation of the wind speed and the performance is compared with the linear Auto Regressive model as input to the Unscented Kalman filter. It is proved from the wind speed prediction model that the Kalman filter gives accurate estimation for the linear models and the Unscented Kalman filter gives accurate estimation for the non linear model. The challenges and difficulties involved in developing a non linear model are studied and understood and one such model is developed in this research in estimating the wind speed. One of the major components of the research is predicting the wind power in real time considering the time varying atmospheric physical factors that affect the wind turbine rotor disc. The algorithm is designed considering the atmospheric parameters, and the results simulated in the MATLAB software. The wake effect and its impact on the wind farm power production is implemented in the wake power model. It research shows the influence of the wind direction and the wind farm layout in the power estimation in the wind farm. The power loss occurs due to the wind power transmission in the cables and this

research shows the amount of estimated loss for the Colorado wind farm and the Fermeuse wind farm.

### **5.3 Future Work on the Wind Speed and the Wind Power Forecasting**

In this research work, the wind power of a wind farm that takes into account the estimation of the wind speed, and the wind farm power model is developed and implemented in the MATLAB software. Below there are few suggestions for further improvement of the developed wind speed model and the wind power model. The future research work on the wind speed forecasting requires forecasting days ahead or a week ahead wind speed forecasting from Numerical Weather Prediction model. It requires use of High Performance Computer Cluster. It has faster computational speed. The forecast of days ahead wind speed is useful for power utility operators and they can shut down the power unit and use the alternate source of power generated from the wind turbine [8].

The use of hybrid models in the wind speed forecasting is essential for accurate estimation, the use of such models has a benefit from each of the model and the errors are reduced. The hybrid models will obtain a globally optimal forecasting performance. In such a forecast the combination of the forecasting models are given below.

- Combination of physical and statistical approaches.
- Combination of models for the short term and for the medium term or the long term [14].

The research on short term wind speed forecasting using Artificial Neural Network (ANN) is required and has the advantage of learning the relationship between the inputs and the outputs by a non statistical approach. They do not require any mathematical models and can provide results with minimum errors [14]. In the wind power forecasting, the future work should focus on the effect of atmospheric humidity, and the effect of turbulent kinetic energy which has a major contribution in the wind power estimation from the wind turbines. The effect of the horizontal shear has not been considered in the implemented wind power model. More research is needed to consider the effect of the horizontal shear. It contributes to the wind power estimation. The dust accumulation on the wind turbine rotor disc and its effect on the wind power generation should also be considered. Although its effect is smaller but its contribution along with other physical factors will have a greater impact in wind power estimation [7]. The atmospheric temperature has a major influence on the wind power forecasting. The effect of icing conditions and the ice accumulation on the wind turbine rotor blades has a greater influence in the wind power generation. Under severe icing conditions, the wind turbines stop operating and there is a complete loss in the wind power generation. The future work should focus on de-icing techniques under severe icing conditions [6].



## **Bibliography**

- [1] S. Wharton, & J. Lundquist, (2010). "Atmospheric Stability Impacts on Power Curves of Tall. Wind Turbines - An Analysis of a West Coast North American Wind Farm".
- [2] J. Wiley, Nick Jenkins, David Sharpe, Ervin Bossanyi, (2004). "Wind Energy Handbook by Tony Burton".
- [3] Lingling Li, Minghui Wang, Fenfen Zhu, and Chengshan Wang (2009) –"Wind Power Forecasting Based on Time Series and Neural Network, School of Electrical Engineering and Automation , Tianjin University".
- [4] Ioannis Antoniou, Soeren Markkilde Pedersen, Peder Bay Enevoldsen,(2009), pp 449-468 : "Wind Shear and Uncertainties in Power Curve Measurements and Wind Resource". Renewable Energy and Wind Power, Journal Article in.
- [5] Hans Georg Beyer, Thomas Pahlke, Wolfgang Schmidt, Hans-Peter Waldl, Ubbo de Witt Beyer et al, (1994, May), pp 303–318: "Wake Effects in a Linear Wind Farm". Journal of Wind Engineering and Industrial.
- [6] Clement Hochart<sup>1</sup>, Guy Fortin<sup>1</sup>, Jean Perron<sup>1</sup>, Adrian Ilinca<sup>2</sup> (2007). " Wind Turbine Performance under Icing Conditions, Wind Energy"..Journal Article.
- [7] Mohammed G. Khalfallaha, Aboelyazied M. Koliub (2007). "Effect of dust on the performance of wind turbines". The Ninth Arab International Conference on Solar Energy (AICSE-9), Kingdom of Bahrain.

- [8] Ignacio J. Ramirez-Rosado<sup>a</sup>, L. Alfredo Fernandez-Jimenez<sup>b</sup>, Cláudio Monteiro<sup>c</sup>, d, João Sousa<sup>c</sup>, d, Ricardo Bessa<sup>a</sup> (2009). “ Comparison of Two New Short Term Wind Power Forecasting Systems.” Renewable.
- [9] Maria Grazia De Giorgi<sup>a</sup>Corresponding, Antonio Ficarella, Marco Tarantino (July 2011), pp 3968–3978. “Assessment of the Benefits of Numerical Weather Predictions in Wind Power Forecasting Based on Statistical Methods”.
- [10] Rozenn Wagner, Ioannis Antoniou, Søren M. Pedersen, Michael S. Courtney, Hans E. JørgensenRozenn Wagner, ( 2008. Sept). “ Influence of Local Wind Speed and Direction to Wind Turbine Performance”, Wind Energy Journal.
- [11] Munir Ahmad Nayak<sup>1</sup> and M C Deo<sup>2</sup> (2010, May). “ Wind Speed Prediction by Different Computing Techniques”. Balwois, Ohrid, Republic of Macedonia.
- [12 ] Andrew Tindal, Clint Johnson, Marc LeBlanc, Keir Harman, Elisabeth Raeshide, and Anne Marie Graves, Garrad Hassan America, Inc (2008, June). “Site-Specific Adjustments to Wind Turbine Power Curves”, Poster Presentation at the AWEA Wind Power Conference.
- [13] J.L. Torres<sup>a</sup>, A. Garcí'a<sup>a</sup>, M. De Blas<sup>a</sup>, A. De Francisco<sup>b</sup>. (2005, July), “Forecast of hourly average wind speed with ARMA model in Navarre (Spain)”.
- [14] K. Gnana Sheela (2011). “Computing Models for Wind Speed Prediction in Renewable Energy Systems by NCCSE”.
- [15] Mehdi Khashei, Mehdi Bijari, Gholam Ali Raissi Ardali; (2009, Jan), “ Improvement of Auto-Regressive Integrated Moving Average models using Fuzzy logic and Artificial Neural Networks (ANNs)”.
- [16] G. Zhang, B.E. Patuwo and M.Y. Hu; (1998), pp. 35–62. “Forecasting with

artificial neural networks: the state of the art, Int. J. Forecast”.

[17] B.K. Wong, S. Vincent and L. Jolie, 1994–1998, Comput. Oper. Res 27 2000, pp. 1023–1044. “A bibliography of neural network business applications research”.

[18] F. Lisi and R.A. Schiavo, (1999), pp. 87–102: “A comparison between neural networks and chaotic models for exchange rate prediction”.

[19] Autoregressive-Moving-Average Modeling, Notes\_5, GEOS 585 A. [Online].

[Available]:

[http://www.ltrr.arizona.edu/~dmeko/notes\\_5.pdf](http://www.ltrr.arizona.edu/~dmeko/notes_5.pdf).

[20] MATLAB programming: [Online]. [Available]:

<http://www.mathworks.com>

[21] Mehdi Khashei, Seyed Reza Hejazi, Mehdi Bijari, (2008). “A new hybrid artificial neural networks and fuzzy regression model for time series forecasting”.

[22] K. Sreelakshmi, P. Ramakanthkumar. (2008). “Neural Network for Short Term Wind Speed Prediction”.

[23] Federico Cassola a, Massimiliano Burlando: (2012, June). “Wind speed and Wind Energy Forecast through Kalman Filtering of Numerical Weather Prediction Model Output”.

[24] Soman, S.S. Zareipour, H. Malik, O. Mandal, P (2010). “A Review of Wind Power and Wind Speed Forecasting Methods With Different Time Horizons”.

[25] Auto Regressive Model. [Online]. [Available].

[http://google.ca:kovriguineda.ucoz.ru/VVAGS/-7052-autoregressive\\_models.ppt](http://google.ca:kovriguineda.ucoz.ru/VVAGS/-7052-autoregressive_models.ppt).

[26] Greg Welch and Gary Bishop, (2006, July). “An Introduction to the Kalman Filter”: Advanced Control System Lecture notes on Kalman filter for wind speed

prediction, Memorial University of Newfoundland.

[27] Hamed Babazadeh, Wenzhong Gao, Lin Cheng, Jin Lin (2012). “An Hour Ahead Wind Speed Prediction by Kalman Filter ”.

[28] Simon J, Julier, Jeffrey K, Uhlmann, IEEE: Vol. 92, No.3, ( 2004, March). “ Unscented Filtering and Nonlinear Estimation Proceedings of the IEEE ”.

[29] Non linear ARX model using MATLAB. [Available]. MATLAB Software

[30] System Identification toolbox. [Available]. MATLAB Software

[31] Unscented Kalman Filter; [Online]. [Available].

<http://signal.hut.fi/kurssit/s884221/ukf.pdf> S-88.4221 Postgraduate Seminar on Signal Processing.

[32] MATLAB Curve Fitting Techniques. [Online]. [Available].

<http://www.mathworks.com>

[33] F. Koch, M. Gresch, F. Shewarega, I. Erlich, and U. Bachmann, (2005), Institute of Electrical Power Systems and Automation. “Consideration of Wind Farm Wake Effect in Power System Dynamic Simulation”.

[34] Peter Frohboese, Christian Schmuck, (2010). “Thrust Coefficients used for Estimation of Wake Effects for Fatigue Load Calculation”. European Wind Energy Conference, Warsaw, Poland.

[35] GL Garrad Hassan, (2010). “Thrust Coefficients used for Estimation of Wake Effects for Fatigue Load Calculation”. European Wind Energy Conference, Warsaw, Poland.

[36] Fermeuse wind farm layout information. [Online]. [Available]:

<http://www.env.gov.nl.ca>.

[37] Giovanni Gualtieri a, Sauro Secci b (2010, May). “Wind Shear Coefficients, Roughness Length and Energy Yield Over Coastal Locations in Southern Italy”.

[38] F. González-Longatt, P. Wall, V. Terzija. (2011, Aug). “Wake effect in Wind Farm Performance: Steady-State and Dynamic Behavior”.

[39] Fermeuse wind farm details. [Online]. [Available]:

<http://www.canwea.ca>.

[40] N. Barberis Negra, J. Todorovic, and T. Ackermann,(2006). “Loss Evaluation of HVAC and HVDC Transmission Solutions for Large Offshore Wind Farms”.

[41] Fritz Santjer; DEWI GmbH Deutsches Windenergie-Institut, Wilhelmshaven, Germany: “Influence of Transmission Lines on Grid Connection”.

[Online].[Available]:

[http://www.dewi.de/dewi/fileadmin/pdf/publications/Publikations/15\\_4\\_Santjer.pdf](http://www.dewi.de/dewi/fileadmin/pdf/publications/Publikations/15_4_Santjer.pdf).

[42] Sumaira Tasnim, Amanullah Maung Than Oo, and Fakhrul Islam, (2012). “Wind Generated Electricity, A Review of Generation,Transmission and Power Loss”.

[43] The Vestas V90 3MW wind turbine details. [Online]. [Available]:

[http:// www.vestas.com](http://www.vestas.com)

[44] The wake effect. [Online]. [Available]:

<http://www.algonquinadventures.com/waywardwind/thewind.htm>.

[45] The Fermeuse wind farm location. [Online]. [Available]:

<http://www.poweryourknowledge.com/wind.htm>

[46] Vestas wind turbine picture taken after a site visit to the Fermeuse wind farm, Newfoundland.

[47] Arc Geographic Information System, Cedar Creek layout map: Map Room, Queen Elizabeth II Library, and Memorial University of Newfoundland.

[48] GE 1.5 MW wind turbine details. [Online]. [Available]:

<http://www.ge-energy.com>.

[49] Mitsubishi 1.0 MW wind turbine details. [Online]. [Available]:

<http://www.jnepower.com/pdf/mwt1000a.pdf>

[50] AMEC, St John's confidential information on Cedar Creek Colorado wind farm.

[51] Wake Effect figure: [Online]. [Available]:

<http://wiki.windpower.org/index.php/Wake>

[52] Vestas Wind turbine details. [Online]. [Available]:

<http://www.vestas.com>

## Appendices

### Appendix A

```
% MATLAB code for armax (1, 1) to predict wind speed in advance
p_hr1.txt contains hourly wind data
load
p_hr1.txt
plot(p_hr1)
figure(1)
z=importdata('p_hr1.txt')
data = armax(z,[1 1])
figure(2)
predict(data,p_hr1,5)
figure(3)
compare(p_hr1,data,5)
xlabel('time')
ylabel('wind speed')
title('armax(1,1)')
```

### Appendix B

```
% Partial autocorrelation of text file( p_hr1.txt)
load p_hr1.txt
x=importdata ('p_hr1.txt')
[pacf, lags, bounds] = parcorr(x)
figure (1)
parcorr(x)
```

### Appendix C

```
% Autocorrelation of text file( p_hr1.txt)
load p_hr1.txt
y=importdata ('p_hr1.txt')
[acf, lags, bound]=autocorr(y)
figure(1)
autocorr(y)
```

## Appendix D

```
% Auto Regressive Model MATLAB Code
array = dlmread('Control_speed.csv','');
% speed = array(:,1); % every 10 min wind speed
speed = array(:,4); % per hour wind speed
time = array(:,2); % Time
z = speed(1:1000);
data = AR(z,2,'ls');
M = idpoly(data);
zhat = predict(z,data,1); % Every hour wind data
% zhat = predict(z,data,6); % Every 10 min wind data
figure(1)
plot(time,z,'r')
ylabel('Wind Speed (m/s)')
xlabel('Time(hr)')
title('Input Wind Speed')
axis([0 1000 0 50])
pause
figure(2)
plot(time,zhat{1,1},'k',time,speed,'r')
ylabel('Wind Speed (m/s)')
xlabel('Time(hr)')
title('AR Estimated Wind Speed')
axis([0 1000 0 40])
pause
```

Result:

Discrete-time IDPOLY model:  $A(q)y(t) = e(t)$

$A(q) = 1 - 0.8963 q^{-1} - 0.09091 q^{-2}$

Estimated using AR ('ls'/'now') from data set z

Sampling interval: 1

Note: System Identification toolbox gives similar idpoly model of AR 2nd order model.



## Appendix E

```
% Kalman Filter MATLAB Code Using AR Model Parameter
A=[0.8963 0.09091;0 0];
B= [0 0;0 0];
C=[1 0];
D =[0];
N = 1000; %Data Generation Steps
x_initial=[1;1]*0;
h(:,2)=[x_initial];
x(:,2)=[x_initial];
y(:,2)=C*x(:,2);
Q= 0.015*eye(2); % Covariance of process noise
R= 0.02; % Covariance of measurement noise
% Tuning Parameters
Qf=0.05*Q;
Rf=0.05*R;
% Initialisation Block
Pu= [1 0;0 1]; % Error Covariance of initial states
P=Pu;
for i = 1:N
L=chol(Q);
h(:,i+1)=A*x(:,i)+L*randn(2,1);
LL=chol(R); % Gaussian Noise
y(:,i)=C*h(:,i)+LL*randn(1,1); % Accurate Measurement
%-----Predict-----
x(:,i+1)=A*x(:,i)+L; % Prediction of State
P_apri=A*P*A'+Qf; % Prediction of Covariance
%-----Update-----
K=P_apri*C'*inv((C*P_apri*C')+Rf); % Obtaining Kalman Gain
innov = y(:,i)-(C*x(:,i)); % Obtaining the Innovations (Apriori Residuals)
x(:,i+1)=x(:,i)+K*(y(:,i)-(C*x(:,i))); % Updating the State (Aposteriori)
resid = y(:,i) - (C*x(:,i)); % Obtaining the Residuals (Aposteriori Residuals)
P= P_apri-(P_apri*K*C); % Obtaining Aposteriori Covariance
end
figure(3)
%subplot(2,1,1),plot([1:N+1]', h(1,:), 'r-', [1:N+1]', x(1,:), 'k-')
plot([1:N+1]', h(1,:), 'r-', [1:N+1]', x(1,:), 'k-')
title('X1')
figure(4)
subplot(2,1,2),plot([1:N+1]', h(2,:), 'k-', [1:N+1]', x(2,:), 'r-');
title('X2')
```

## Appendix F

% Unscented Kalman Filter MATLAB Code Using AR model Parameters

A = [0.8963 0.09091;0 0]; %System in State Space form

B = [0 0]';

C = [1 0];

D = 0;

H = C;

Ts = 0.2; %Sampling Time

Ad= A;

Bd= B;

delta\_t = 0.2; %Time steps

length = 300;

N=length/delta\_t;

Q=0.0001\*eye(1); %Covariance Matrix

R=1;

%Tunning Parameters

Qf= 0.001\*Q; % Process Noise

Rf=0.001\*R; % Measurement Noise

Po = 5\*eye(2);

P\_apost = Po;

h(:,1) = [2 2]'; % Initialize State

y(:,1) = H\*h(:,1);

LL = chol(Q); % Cholesky Factorization Data generation

for i = 1:N

h(:,i+1) = Ad \* h(:,i)+1+LL\*randn(2,1);

L = chol(R);

y(:,i+1) = H\*h(:,i+1)+8+L\*randn(1,1);

end

x\_initial = h(:,1)\*3;

x(:,1) = x\_initial';

n = 2;

%% Prediction and Update

% Prediction Step

for i = 1:N

Pred = [chol(n\*P\_apost)]';

x1 = x(:,i) + Pred(:,1);

x2 = x(:,i) + Pred(:,2);

Tx1 = Ad \* x1;

Tx2 = Ad \* x2;

Tx = (Tx1 + Tx2)/(2\*n);

P\_apri = (((Tx1 - Tx)\*(Tx1 - Tx)' + (Tx2 - Tx)\*(Tx2 - Tx)')/(2\*n)) + Qf);

```

UTran = [chol(n*P_apri)]';
Ux1 = Tx1 + UTran(:,1);
Ux2 = Tx2 + UTran(:,2);
Y1 = H*Ux1;
Y2 = H*Ux2;
Y = (Y1 + Y2)/(2*n);
Py = (((Y1 - Y)*(Y1 - Y)' + (Y2 - Y)*(Y2 - Y)'/(2*n)) + Rf);
Pxy = (((Tx1 - Tx)*(Y1 - Y)' + (Tx2 - Tx)*(Y2 - Y)'/(2*n)));
% Update Step
K = Pxy*(1/Py);
x(:,i+1) = (Tx + K*(y(:,i) - Y));
P_apost = P_apri - K*Py*K';
end

%Plotting of Graphs
figure(1)
plot([1:N+1],h(1,:), '--',[1:N+1],x(1,:), 'r-')
title('Unscented Kalman Filter Wind Speed Estimation from State X1')
ylabel('Wind Speed (m/s)')
xlabel('Number of Time Steps')
figure(2)
plot([1:N+1],h(2,:), '--',[1:N+1],x(2,:), 'r-')
title('Unscented Kalman Filter Wind Speed Estimation from State X2')
ylabel('Wind Speed (m/s)')
xlabel('Number of Time Steps')

```

## Appendix G

Non linear ARX model estimated from input hourly wind speed

```

array = dlmread('Control_speed.csv','');
speed = array(:,4);
time = array(:,2);
z = iddata(speed(651:1000),[ ],0.1);
m1 = nlarx(z(651:1001),2,'sigmoid')
figure(1)
compare(z,m1,1)

```

## Appendix H

Unscented Kalman Filter wind speed estimation using input non linear ARX model

%% Unscented Kalman Filter For Non Linear System

A = [0.0825 -0.4050;0 0]; %System in State Space form

B = [0.0825 -0.4050;0 0];

C = [1 0];

D = 0;

H = C;

delta\_t = 0.2; %Time steps

length = 1500;

N=length/delta\_t;

Q=0.01\*eye(1); %Covariance Matrix

R=0.01;

%Tunning Parameters

Qf = 0.1\*Q; % Process Noise

Rf=0.1\*R; % Measurement Noise

Po = 6\*eye(2);

P\_apost = Po;

u(2,:)= [1\*ones(N,1);3.5\*ones(N,1);3\*ones(N,1);1\*ones(N,1)]\*1 ; % External Input

h(:,1) = [2 2]'; % Initialize State

y(:,1) = H\*h(:,1);

LL = chol(Q); % Cholesky Factorization

h(:,1)= [1 1]';

y(:,1)=H\*h(:,1);

%Data generation

for i = 1:N

h(:,i+1)= A\*h(:,i)+ B\*u(:,i)+15.5+LL\*randn(2,1);

L = chol(R);

y(:,i+1)=H\*h(:,i+1)+10+L\*randn(1,1);

end

x\_initial = [1 1]\*1 ;

x = x\_initial';

n = 2;

%% Prediction and Update

% Prediction Step

for i = 1:N

Pred = [chol(n\*P\_apost)]';

x1 = x(:,i) + Pred(:,1);

x2 = x(:,i) + Pred(:,2);

Dx1 = A \* x1;

Dx2 = A \* x2;

```

Dx = (Dx1 + Dx2)/(2*n);
P_apri = (((Dx1 - Dx)*(Dx1 - Dx)' + (Dx2 - Dx)*(Dx2 - Dx)')/(2*n)) + Qf);
UTran = [chol(n*P_apri)]';
Ux1 = Dx1 + UTran(:,1);
Ux2 = Dx2 + UTran(:,2);
Y1 = H*Ux1;
Y2 = H*Ux2;
Y = (Y1 + Y2)/(2*n);
Py = (((Y1 - Y)*(Y1 - Y)' + (Y2 - Y)*(Y2 - Y)')/(2*n)) + Rf);
Pxy = (((Dx1 - Dx)*(Y1 - Y)' + (Dx2 - Dx)*(Y2 - Y)')/(2*n));

% Update Step
K = Pxy*(1/Py);
x(:,i+1) = (Dx + K*(y(:,i) - Y));
P_apost = P_apri - K*Py*K';
End

%Plotting of Graphs
figure(1)
plot([5:N+1],h(1,5:end),'k--',[5:N+1],x(1,5:end),'r-')
title('Unscented Kalman Filter Wind Speed Estimation from State X1')
ylabel('Wind Speed (m/s)')
xlabel('Number of Time Steps')
axis([5 1500 0 25 5 1500 0 25])
figure(2)
plot([1:N+1],h(2,:), '--',[1:N+1],x(2,:), 'r-')
title('Unscented Kalman Filter Wind Speed Estimation from State X2')
ylabel('Wind Speed (m/s)')
xlabel('Number of Time Steps')

```

## Appendix I

```
%% FERMEUSE WINDFARM IMPLEMENTATION
%% Vestas 3 MW,-9 WIND TURBINES;
%% IMPLEMENTATION OF 9 WIND TURBINES USING FUNCTION %%
%array = dlmread('file.csv',''); % Accessing Input 10 Minute Wind Data File
array = dlmread('file2.csv',''); % Accessing Input 10 Minute Wind Data File
%array = dlmread('file3.csv',''); % Accessing Input 10 Minute Wind Data File
%array = dlmread('file4.csv',''); % Accessing Input 10 Minute Wind Data File
global Wt N Y y H
hour = array(:,5); % Accessing 10 Minutes Data in Time Series Order
WS_80 = array(:,1);
% Accessing Input Wind Speed at 80m Sensor Height for
% Vestas 3 MW Wind turbine
N = numel(hour); % Accessing Total Number of Time Series Data
TK = array(:,2); % Accessing Temperature
act_density = array(:,4); % Accessing act_density 3.4837*Pressure/Temperature;
wd = array(:,6); % Accessing Wind Direction time series data

%% SOLVING FOUR EQUATIONS OF DESIGNED ALGORITHM %%
% Vestas 3 MW 9,Windturbines
% WS and WS1 = Verical Shear using shear exponent 0.143;
%% [Equation:  $U2/U1 = (H2/H1)^{0.143}$ ]
% sd and sd1= standard deviation of wind speed data;
%% [Equation: sd = standard deviation of wind speed]
% lu and lu1 = Turbulence Intensity;
%% [Equation: lu = Standard deviation of WS/ Mean (WS)]
% u and u1 = Turbulence Adjusted Speed;
%% [Equation:  $U(TI)=\text{cuberoor}[(U)^3*(1+3lu^2 )]$ ]
i2 = 1;
for Y = [50,80,95,120,127,140,148,153,170,195] % Y = Height Range at the wind
% turbine rotor disc
WS(:,i2) = WS_80.*(Y/80).^(0.143); % Wind Speed for Vestas 3 MW Wind turbine
sd(:,i2)=std(WS(:,i2)); % Standard Deviation for Vestas 3 MW Wind turbine
lu(:,i2) = std(WS(:,i2))./(WS(:,i2)); % Turbulence Intensity for Vestas 3 MW Wind
turbine
u(:,i2)=nthroot((power(WS(:,i2),3).*(1+power(lu(:,i2),2).*3)),3);
% Turbulence %Adjusted Speed for
i2 = i2+1;
% Vestas 3 MW Wind Turbine
end
%% END %
```

```

%% Mean Data of Turbulence Intensity
TI_ge = mean(Iu(:,2)); % Vestas 3 MW WT

%% Assigning Turbulence Adjusted Speed at the corresponding height level of rotor
disc %%
u_50 = u(:,1); u_80=u(:,2); u_95=u(:,3); u_120=u(:,4); u_127=u(:,5); u_140 = u(:,6);
u_148= u(:,7); u_153 = u(:,8); u_170 = u(:,9);u_195= u(:,10); % Vestas 3 MW Wind
Turbine

%% Calculation of Shear Exponent of Vestas 3 MW Wind Turbine %%%
a50to80 = log(u_80.\u_50)./log(80\50);
%alpha50to80 = (log(u_80.\u_50)./log(80\50));
a80to100 = log(u_95.\u_80)./log(95\80);
%alpha80to100 = (log(u_95.\u_80)./log(95\80));
a100to120 = log(u_127.\u_95)./log(127\95);
%alpha100to120 = (log(u_127.\u_95)./log(127\95));
a120to140 = log(u_140.\u_127)./log(140\127);
%alpha120to140 = (log(u_140.\u_127)./(log(140\127)));
a140to160 = log(u_170.\u_140)./log(170\140);
%alpha170to140 = log(u_170.\u_140)./log(170\140);
a160to195 = log(u_195.\u_170)./log(195\170);
%alpha195to160 = log(u_195.\u_170)./log(195\170);

% Digitize Manufacturer Supplied Power Curve Vestas V90, 3MW Wind Turbine
% Vestas 3MW Wind Turbine is Digitised by Plotting power vs speed
Characteristics
% START %%%
spd = [ 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24];
pw = [0 0 0 0 81 190 353 581 885 1258 1641 2004 2353 2671 2888 2976 3000 3000
3000 3000 3000 3000 3000 3000 3000];
figure(1)
plot(spd,pw,'b-','MarkerSize',3)
xlabel('Speed (m/s)'); ylabel('Power (kw)')
title('Supplied Vestas 3 MW-Wind Turbine')
axis([0 24 0 3500])
pause
q = polyfit(spd,pw,8);
xp= 0:2:25;
yp = polyval(q,xp);
figure(2)
plot(spd,pw,'o',xp,yp);
xlabel('Speed (m/s)'); ylabel('Power (kw)');
title('Curve Fitted Vestas-Wind Turbine');
pause

```

```

%% DISC SPEED ESTIMATION FOR Vestas 3MW, 9 WIND TURBINES %%
%% Equation;  $U_{Disk} = 2/A * \int [U_Z * \sqrt{R^2 - H^2 + 2HZ - Z^2}] dZ$  (Integral limits H-R to H+R)
%% Solving using function the disc speed equation adjusted for turbulence and shear for wind turbines
%% Initialising Height Range for Vestas 3MW, 9 Wind Turbines %%
Wt = zeros(2,2,9);
% Creating Array of 9 Wind turbines; Last Value = 9, Vestas 3MW wind turbines
Wt(:,:,1) = [50 95.1; 95 140]; Wt(:,:,6) = [95 140.1; 140 185];

% Assign height range for 9 wind turbines to solve integral equation
Wt(:,:,2) = [50 95.1; 95 140]; Wt(:,:,7) = [83 128.1; 128 173];
Wt(:,:,3) = [50 95.1; 95 140]; Wt(:,:,8) = [103 148.1; 148 193];
Wt(:,:,4) = [82 127.1; 127 172]; Wt(:,:,9) = [75 120.1; 120 165];
Wt(:,:,5) = [108 153.1; 153 198];

%% Initializing Wind turbine Hub Height (varies due to contour height) H=9, Vestas 3MW wind turbines;
%% H = Vestas 3MW Wind Turbines
H = [95; 95; 95; 127; 153; 140; 128; 148; 120];

%% SOLVING NUMERIC INTEGRATION USING FUNCTION; [Y,y are variables of Vestas 3MW wind turbines] %%
Y = [u_50, u_80, u_95, u_120, u_127, u_140, u_148, u_153, u_170, u_195, a50to80, a80to100, a100to120, a120to140, a140to160, a160to195]; % Vestas 3MW Wind Turbine; Assign variables to solve equation
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% Vestas 3MW Wind Turbine; Assign variables to solve equation
y = [1,11,3,13; 1,11,3,13; 1,11,3,13; 2,13,5,15; 3,15,8,16; 3,14,8,15; 2,13,5,15; 3,14,8,16; 2,13,5,15]; % To access the variable that is assigned (Eg; 3 = u_95; 4 = u_120; 10 = u_195; 11 = a50to80)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%% Calling Vestas 3MW Wind Turbine Using Function
v = zeros(N,1,9); % last value = 9 -Vestas 3MW, Wind Turbines; Area of
% Vestas 3MW Wind Turbine = 6362;
for i1 = 1:9 % last value = 9 -Vestas 3MW Wind Turbines
v2 = ft_v(i1); % Calling using functions for 9 -Vestas 3MW Wind Turbines
% v2 ; v
v(:,i1) = (2/6363).* v2(:,:,); % Result of Disc Speed is stored in variable v; or
% Equation = (2/ A) *( Udisc)
end
x1 = v(:,,1); % 1 = First WT disc speed
x2 = v(:,,2); % 2 = second WT disc speed

```



```

x3 = v(:,3); % 1 = First WT disc speed
x4 = v(:,4); % 2 = second WT disc speed
x5 = v(:,5); % 1 = First WT disc speed
%% END OF DISC SPEED      %%%%%%%%%%%

%% POWER PREDICTION FROM DISC SPEED FOR Vestas 3MW; 9 WIND
TURBINES %
for il =1:9 % Last value = 9 WT; VPuncor = Uncorrected Power of Vestas 3 MW
Wind Turbine
Vpuncor(:,il) =
q(9)+(q(8).*(v(:,il))) + (q(7).*(v(:,il)).^2) + (q(6).*(v(:,il)).^3) + (q(5).*(v(:,il)).^4)
+ (q(4).*(v(:,il)).^5) + (q(3).*(v(:,il)).^6) + (q(2).*(v(:,il)).^7) + (q(1).*(v(:,il)).^8);
Vpcor(:,il) = Vpuncor(:,il).*(act_density./1.225);
end
%% POWER REMAINS CONSTANT AFTER RATED WIND SPEED FOR Vestas
3MW WIND TURBINE; %%
nn2 = length(v(:,il));
for il = 1:9
AA1 = find(Vpcor(:,il) >= 3000); % Rated power is equal to 3000 KW
nn3 = length(AA1);
for j2 = 1:nn3
Vpcor(nn2*(il-1) + AA1(j2)) = 3000; % Power remains constant after rated wind
speed
end;
end

% WAKE MODEL FOR Vestas 3 MW WIND TURBINE
% WAKE SPEED ESTIMATION FOR Vestas 3 MW, 9 WIND TURBINES %
% Rrot = Radius of GE Wind Turbine; x = Distance between nearest wind turbine;
% Ashad = Area of shadow region of wind turbines
% Arot = Area of GE wind turbine rotor; Ct = Thrust coefficient of wind turbine; tana
% = 0.04(no-wake)/0.08(wake); Rx = Radius of shadow cone
% v(:,il) = Disc Speed; Uwake(:,il) = Wake Speed of Wind Turbine

x = [250;250;1000;250;250;250;0;250;250;];
Ashad = [2500;2500;0;3181;3772;2181;0;3772;3181];
% Equation : Thrust Coefficient (Ct) and Wake Speed Calculation (Uwake) for WT-
Wind Turbine
% Ct = 3.5*(2*Vhub - 3.5)/(Vhub)^2;
% R(x) = Rrot + x.tana ; tana = 0.04 (free speed) or tana = 0.08 (wake)%
% Uwake = Vi[1 - sqrt(1 - Ct)*(Rrot/R(x))^2*(Ashad / Arot)]
for il=1:9      % 9, Vestas 3MW Wind Turbines
Rrot = 45;
Ct(:,il) = 3.5.*((2.*v(:,il)) - 3.5)./(v(:,il)).^2;
tana = 0.08;

```

```

Rx(i1) = Rrot + x(i1)*tana;
Arot = 6362;
Uwake(:,i1) = v(:,i1).*(1- sqrt(1 - Ct(:,i1))).*(Rrot/Rx(i1))^2.*(Ashad(i1)/Arot));
end

%% POWER PREDICTION FROM DISC SPEED FOR Vestas 3MW; 9 WIND
TURBINES %
for i1 =1:9 % Last value = 9 WT; VPuncor = Uncorrected Power of Vestas 3MW
Wind Turbine
Vpuncorw(:,i1) =
q(9)+(q(8).*(Uwake(:,i1)))+(q(7).*(Uwake(:,i1)).^2)+(q(6).*(Uwake(:,i1)).^3)+(
q(5).*(Uwake(:,i1)).^4)+(q(4).*(Uwake(:,i1)).^5)+(q(3).*(Uwake(:,i1)).^6)+(q(2).
*(Uwake(:,i1)).^7)+(q(1).*(Uwake(:,i1)).^8);
Vpcorw(:,i1)=Vpuncorw(:,i1).*(act_density./1.225);
end

% POWER REMAINS CONSTANT AFTER RATED WIND SPEED FOR Vestas
3MW WIND TURBINE
nn4 = length(Uwake(:,i1));
for i1 = 1:9
AA3 = find(Vpcorw(:,i1)>=3000); % Rated power is equal to 3000 kw
nn5 = length(AA3);
for j2 = 1:nn5
Vpcorw(nn4*(i1-1)+ AA3(j2))=3000; % Power remains constant after rated speed
end
end

%%%%%%%% START OF WAKE COEFFICIENT At 45 and 225 degree
% Sum of No-wake power of windfarm = VE_cpw
% Sum of wake power of windfarm = VE_wpw
% Wake Coefficient = Sum of No-wake power/Sum of Wake power

VE_cpw = Vpcor(:,1) + Vpcor(:,2)+ Vpcor(:,3)+ Vpcor(:,4)+ Vpcor(:,5) +
Vpcor(:,6)+ Vpcor(:,7)+ Vpcor(:,8)+ Vpcor(:,9);
VE_wpw = Vpcorw(:,1) + Vpcorw(:,2)+ Vpcorw(:,3)+ Vpcorw(:,4)+
Vpcorw(:,5) + Vpcorw(:,6)+ Vpcorw(:,7)+ Vpcorw(:,8)+ Vpcorw(:,9);
Total1 = sum(VE_cpw); % No-wake windfarm power
Total2 = sum(VE_wpw); % Wake windfarm power
wc = Total2/Total1; % Wake coefficient

%%%%%%%% Wind Direction and Wake Coefficient Evaluation
wd = array(:,6); % Accessing Wind Direction time series data
Wake_Coeff =
wc*(wd<=50).*(wd>=40)+wc*(wd<=230).*(wd>=220)+(wd>50).*(wd<220)+(wd<40

```

```
)+(wd>230); % Equation determining the wake and Nowake data depending on the
wind direction
```

```
%% %%%%%%%%%%% END %%%%%%%%%%% %%%%%%%%%%% %%%%%%%%%%%
```

```
%%AVERAGE WINDFARM POWER - Vestas 3MW, 9 WIND TURBINES
```

```
Avg_VE = mean(Vpcor(:,1))+ mean(Vpcor(:,2))+ mean(Vpcor(:,3))+
mean(Vpcor(:,4))+ mean(Vpcor(:,5))+ mean(Vpcor(:,6))+ mean(Vpcor(:,7))+
mean(Vpcor(:,8))+ mean(Vpcor(:,9));
Avg_VE_wake = mean(Vpcorw(:,1))+ mean(Vpcorw(:,2))+ mean(Vpcorw(:,3))+
mean(Vpcorw(:,4))+ mean(Vpcorw(:,5))+ mean(Vpcorw(:,6))+
mean(Vpcorw(:,7))+ mean(Vpcorw(:,8))+ mean(Vpcorw(:,9));
```

```
% FERMEUSE WIND FARM AVERAGE POWER
```

```
Avg_farm = Avg_VE;
```

```
% AVERAGE WINDFARM POWER WITH TRANSMISSION LOSS OF 1 %%
```

```
VE_loss = VE_cpw*0.99;
VE_wakeloss = VE_wpw*0.99;
Actual_power = VE_cpw - VE_loss;
Actual_power_wake = VE_wpw - VE_wakeloss;
%%%%%%%%%
```

```
% PLOTTING FIGURES FROM THE SIMULATED RESULT
```

```
%% SENSOR HEIGHT WIND SPEED Vestas 3MW WIND TURBINE %
```

```
figure(3)
plot(hour,WS_80,'b-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Sensor Height of Vestas Wind Turbine');
pause
% Mean value of wind speed data at 80m %
Sensor_80m = mean(WS_80);
std_sensor = std('Sensor_80m');
```

```
% DISC SPEED OF Vestas 3MW WIND TURBINE-2 %
```

```
figure(4)
plot(hour,v(:,2),'g-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Disc Speed of Vestas Wind Turbine-2');
pause
```

```

% Mean value of wind speed data at 80m %
disc_80m = mean(v(:,2));
%% VERTICAL SHEAR OF Vestas 3MW WIND TURBINE-2 %
% Vestas 3MW WIND TURBINE %
figure(5)
plot(hour,WS(:,2),'r-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Vertical Shear of Vestas Wind Turbine-2');
pause
% Mean value of wind speed data at 80m %
vs_80m = mean(WS(:,3));

%% TURBULENCE ADJUSTED SPEED OF Vestas 3MW WIND TURBINE-2%
% Vestas 3MW WIND TURBINE %
figure(6)
plot(hour,u_95,'r-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Turbulence Adjusted Speed of Vestas Wind Turbine-2');
pause
% Mean value of wind speed data at 80m %
ts_80m = mean(u_95);

%% WAKE SPEED OF Vestas 3MW WIND TURBINE-2%
% Vestas 3MW WIND TURBINE %
figure(7)
plot(hour,Uwake(:,2),'r-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Wake Speed of Vestas Wind Turbine-2');
pause
% Mean value of wind speed data at 80m %
wk_80m = mean(Uwake(:,2));

%% NO-WAKE AND WAKE POWER OF WIND TURBINE WITH RESPECT TO
TIME %
% Vestas 3MW WIND TURBINE %
figure(8)
plot(hour,Vpcorw(:,2),'k-',hour,Vpcor(:,2),'r-')
axis([0 1000 0 3200])
xlabel('Time (min)');

```

```

ylabel('Wind Power (kw)');
title('No-wake(red)and Wake Power of Vestas Wind Turbine-2');
pause
% Mean value of windpower data at 80m %
wkp1_80m = mean(Vpcorw(:,2));
nowk_80m = mean(Vpcor(:,2));
uncorr_pogewt = mean(Vpuncor(:,2));

%% WINDFARM POWER WITH RESPECT TO TIME
% Vestas 3MW WIND TURBINES
figure(9)
plot(hour,VE_cpw,'k-')
axis([0 1000 0 40000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Windfarm Power of Windturbines');
pause
% Mean value of windfarm power data %
wfnwkpowl = mean(VE_cpw);

% COMPARISION OF WINDFARM POWER WITH AND WITHOUT WAKE
EFFECT %
% Vestas 3MW WIND TURBINES
figure(10)
plot(hour,VE_cpw,'k-',hour,VE_wpw,'r-')
axis([0 1000 0 40000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Comparision of Windfarm Power With and Without(black)Wake Effect');
pause
% Mean value of wakefarm power data %
wfwkpowerl = mean(VE_wpw);

%% WIND DIRECTION AND WAKE COEFFICIENT OF WINDFARM
% Wind direction @45 degree and @225 degree, the wake coefficient is 0.84
figure(11)
plot(hour,Wake_Coeff,'k-')
axis([0 500 0 1.5])
xlabel('Time (min)');
ylabel('Wake Coefficient');
title('Wind Direction and Windfarm Efficiency');
pause

```

```

%% WINDFARM POWER WITH TRANSMISSION LOSS OF 1%
% TRANSMISSION LOSS POWER OF Vestas 3MW WIND TURBINES WITH
NO-WAKE EFFECT
figure(12)
plot(hour,VE_loss,'k-')
axis([0 1000 0 40000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Windfarm Powerloss in Transmission With No-Wake Effect');
pause
% Mean value of no-wake wind power transmission loss data %
tlnowkpGE_MIT = mean(VE_loss);

% TRANSMISSION LOSS POWER OF Vestas 3MW WIND TURBINES WITH
WAKE EFFECT
figure(13)
plot(hour,VE_wakeloss,'r-')
axis([0 1000 0 40000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Windfarm Powerloss in Transmission With Wake Effect');
pause

% Mean value of wake wind power transmission loss data %
tlwkpGE_MIT = mean(VE_wakeloss);
% ACTUAL POWER OF Vestas 3MW WIND TURBINES(NO-WAKE-EFFECT)%
figure(14)
plot(hour,VE_loss,'k-')
axis([0 1000 0 40000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Transmission Loss Power(No-Wake Effect)');
pause

% Mean value of wind power transmission loss data %
actpwGE_MIT = mean(Actual_power);
% ACTUAL POWER OF Vestas 3MW WIND TURBINES(WAKE EFFECT)%
figure(15)
plot(hour,VE_wakeloss,'g-')
axis([0 1000 0 40000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Transmission Loss(Wake Effect)');
pause

```

```
% Mean value of wake wind power transmission loss data %
actwkpwGE_MIT = mean(Actual_power_wake);
```

```
% WIND DIRECTION PLOT
```

```
figure(16)
plot(hour,wd,'r-')
axis([0 1000 0 400])
xlabel('Time (min)');
ylabel('Wind Direction');
title('Wind Direction in Windfarm Site');
```

```
pause
figure(17)
plot(hour,wd,'r-')
axis([0 500 0 400])
xlabel('Time (min)');
ylabel('Wind Direction');
title('Wind Direction in Windfarm Site');
```

```
pause
figure(18)
plot(hour,Wake_Coeff,'k-')
axis([0 1000 0 1.5])
xlabel('Time (min)');
ylabel('Wake Coefficient');
title('Wind Direction and Windfarm Efficiency');
```

```
figure(19)
v8(:,1) = sort(v(:,1));
Vp1cor = sort(Vpcor(:,1));
plot(v8(:,1),Vp1cor,'r-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Vestas 3 MW Wind Turbine-1');
axis([0 25 0 3500]);
pause
```

```
figure(20)
v8(:,2) = sort(v(:,2));
Vp2cor = sort(Vpcor(:,2));
plot(v8(:,2),Vp2cor,'k-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Vestas 3 MW Wind Turbine-2');
```

```
axis([0 25 0 3500]);
pause
figure(21)
v8(:,3) = sort(v(:,3));
Vp3cor = sort(Vpcor(:,3));
```

```

plot(v8(:,3),Vp3cor,'r-');
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Disc Speed of Vestas Wind Turbine-3');
pause
figure(22)
v8(:,4)= sort(v(:,4));
Vp4cor = sort(Vpcor(:,4));
plot(v8(:,4),Vp4cor,'r-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Vestas 3 MW Wind Turbine-4');
axis([0 25 0 3500]);
pause
figure(23)
v8(:,5)= sort(v(:,5));
Vp5cor = sort(Vpcor(:,5));
plot(v8(:,5),Vp5cor,'k-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Vestas 3 MW Wind Turbine-5');
axis([0 25 0 3500]);
pause
figure(24)
v8(:,6)= sort(v(:,6));
Vp6cor = sort(Vpcor(:,6));
plot(v8(:,6),Vp6cor,'r-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Vestas 3 MW Wind Turbine-6');
axis([0 25 0 3500]);
pause
figure(25)
v8(:,7)= sort(v(:,7));
Vp7cor = sort(Vpcor(:,7));
plot(v8(:,7),Vp7cor,'k-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Vestas 3 MW Wind Turbine-7');
axis([0 25 0 3500]);
pause
figure(26)
v8(:,8)= sort(v(:,8));
Vp8cor = sort(Vpcor(:,8));

```



```

plot(v8(:,8),Vp8cor,'r-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Vestas 3 MW Wind Turbine-8');
axis([0 25 0 3500]);
pause
figure(27)
v8(:,9)= sort(v(:,9));
Vp9cor = sort(Vpcor(:,9));
plot(v8(:,9),Vp9cor,'k-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Vestas 3 MW Wind Turbine-9');
axis([0 25 0 3500]);

```

## Appendix J

```
% Vestas 3 MW WIND TURBINE FUNCTION %
%% Calling function from main program to solve disc speed equation %%
%% Sub program %%
%% START %%
function v = ft_v(i1) % Function is called from main program and contains result of
disc speed
global Wt Y y N H
z7 = Wt(1,1,i1); % Lower Half of Rotor Disc (Minimum Height Limit)
z7max = Wt(2,1,i1); % Lower Half of Rotor Disc (Maximum Height Limit)
R = 45; % Radius of Wind Turbine
H7 = H(i1); % Hub height is varying for each wind turbine
dz = 0.1; % dz is from disc equation and signifies height range in steps of 0.1
i = 1;
v7 = zeros(N,1); % Creating Array for time series data
while z7 <= z7max % Lower rotor disc (Height limits from minimum to maximum
value)
v7(:,1) = v7(:,1) + abs(Y(:,y(i1,1))).*power((z7/80),Y(:,y(i1,2))).*sqrt((R.^2)-
(H7.^2)+(2.*H7.*z7)-(z7.^2)).*dz); % Udisc Equation
i = i+1;
z7 = z7+0.1;
end
z7 = Wt(1,2,i1); % Upper Half of Rotor Disc (Minimum Height Limit)
z7max = Wt(2,2,i1); % Upper Half of Rotor Disc (Maximum Height Limit)
i = 1;
while z7 <= z7max % Upper rotor disc (Height limits from minimum to maximum
value)
v7(:,1) = v7(:,1) + abs(Y(:,y(i1,3))).*power((z7/150),Y(:,y(i1,4))).*sqrt((R.^2)-
(H7.^2)+(2.*H7.*z7)-(z7.^2)).*dz); % Udisc Equation % "It adds all the results from
H-R to H+R of rotor disc "
i = i+1;
z7 = z7+0.1;
end
v = v7;
end
```

## Appendix K

Main Program: MATLAB Code of Cedar Creek Colorado Wind farm  
%% CEDAR CREEK COLORADO WINDFARM IMPLEMENTATION  
%% GE 1.5 MW, 53 WIND TURBINES; MITSUBISHI 1 MW, 221 WIND  
TURBINES

```
%% IMPLEMENTATION OF 274 WIND TURBINES USING FUNCTION %%  
%array = dlmread('Inputdata12.csv',''); % Accessing Input 10 Minute Wind Data  
from the file  
%array = dlmread('Inputdata13.csv',''); % Accessing Input 10 Minute Wind Data  
from the file  
%array = dlmread('Inputdata14.csv',''); % Accessing Input 10 Minute Wind Data from  
the file  
array = dlmread('Inputdata15.csv',''); % Accessing Input 10 Minute Wind Data from  
the file  
global Wt N Y y H H2 Wt Y2 y2  
hour = array(:,5); % Accessing Minutes/Seconds Data in Time Series Order  
WS_80 = array(:,6); % Accessing Input Wind Speed at 80m Sensor Height for GE 1.5  
MW Wind turbine  
WS1_69 = array(:,1); % Accessing Input Wind Speed at 69m Sensor Height for  
%Mitsubishi 1 MW Wind turbine  
N = numel(hour); % Accessing Total Number of Time Series Data  
TK = array(:,2); % Accessing Temperature  
act_density = array(:,4); % Accessing act_density = 3.4837*Pressure/Temperature;  
wd = array(:,7); % Accessing Wind Direction time series data  
  
%% SOLVING FOUR EQUATIONS OF DESIGNED ALGORITHM %%  
% There are two different wind turbines GE and Mitsubishi  
% WS and WS1 = Verical Shear using shear exponent 0.143;  
%% [Equation:  $U2/U1 = (H2/H1)^{0.143}$ ]  
% sd and sd1= standard deviation of wind speed data;  
%% [Equation: sd = standard deviation of wind speed]  
% Iu and Iu1 = Turbulence Intensity;  
%% [Equation: Iu = Standard deviation of WS/ Mean (WS)]  
% u and u1 = Turbulence Adjusted Speed;  
  
%% [Equation:  $U(TI)=\text{cuberoor}[(U)^3*(1+3Iu^2 )]$ ]  
i2 = 1;  
for Y = [69,80,100,120,160,200,220,153,141]  
% Y = Height Range at the wind turbine rotor disc  
WS(:,i2) = WS_80.*(Y/80).^(0.143);  
% 80m Height for GE 1.5 MW Wind turbine  
WS1(:,i2) = WS1_69.*(Y/69).^(0.143);
```

```

% 69m Height for Mitsubishi 1.0 MW Wind Turbine
sd(:,i2)=std(WS(:,i2));
% 80m Height for GE 1.5 MW Wind turbine
sd1(:,i2)=std(WS1(:,i2));
% 69m Height for Mitsubishi 1.0 MW Wind Turbine
lu(:,i2) = std(WS(:,i2))./(WS(:,i2)); % 80m Height for GE 1.5 MW Wind turbine
lu1(:,i2) = std(WS1(:,i2))./(WS1(:,i2)); % 69m Height for Mitsubishi 1.0 MW Wind
Turbine
u(:,i2)=nthroot((power(WS(:,i2),3).*(1+power(lu(:,i2),2).*3)),3);
% 80m Height for GE 1.5 MW Wind Turbine
u1(:,i2)=nthroot((power(WS1(:,i2),3).*(1+power(lu1(:,i2),2).*3)),3);
% 69m Height for Mitsubishi 1.0 MW Wind Turbine
i2 = i2+1;
end
%% END

```

```

%% Assigning Turbulence Adjusted Speed at the corresponding height level of rotor
disc %%

```

```

% GE 1.5 MW Wind Turbine
u_69 = u(:,1); u_80=u(:,2); u_100=u(:,3); u_120=u(:,4); u_160=u(:,5); u_200 =
u(:,6); u_220 = u(:,7); u_153 = u(:,8); u_141 = u(:,9);

```

```

% Mitsubishi 1 MW Wind Turbine
u1_69 = u1(:,1); u1_80=u1(:,2); u1_100=u1(:,3); u1_120=u1(:,4); u1_160=u1(:,5);
u1_200 = u1(:,6); u1_220 = u1(:,7); u1_153 = u1(:,8); u1_141 = u1(:,9);

```

```

%% Calculation of Shear Exponent of GE Wind Turbine %%

```

```

a69to80 = log(u_80.\u_69)./log(80\69);
% [Equation] %alpha69to80 = (log(u_80.\u_69)./log(80\69));
a80to100 = log(u_100.\u_80)./log(100\80);
%alpha80to100 = (log(u_100.\u_80)./log(100\80));
a100to120 = log(u_120.\u_100)./log(120\100); %alpha100to120 =
(log(u_120.\u_100)./log(120\100));
a120to160 = log(u_160.\u_120)./log(160\120); %alpha120to160 =
(log(u_160.\u_120)./log(160\120));
a160to200 = log(u_200.\u_160)./log(200\160); %alpha160to200 =
(log(u_200.\u_160)./log(200\160));
a200to220 = log(u_220.\u_200)./log(220\200); %alpha200to220 =
(log(u_220.\u_200)./log(220\200));

```

```

% Calculation of Shear Exponent of Mitsubishi Wind Turbine %%

```

```

a169to80=log(u1_80.\u1_69)./log(80\69);% Equation]
%alpha169to80 = (log(u1_80.\u1_69)./log(80\69));
a180to100 = log(u1_100.\u1_80)./log(100\80);
%alpha180to100 = (log(u1_100.\u1_80)./log(100\80));
a1100to120=log(u1_120.\u1_100)./log(120\100);

```

```

%alpha1100to120 = (log(u1_120.\u1_100)./log(120\100));
a1120to160 = log(u1_160.\u1_120)./log(160\120);
%alpha1120to160 = (log(u1_160.\u1_120)./(log(160\120)));
a1160to200 = log(u1_200.\u1_160)./log(200\160);
%alpha1160to200 = (log(u1_200.\u1_160)./(log(200\160)));
a1200to220 = log(u1_220.\u1_200)./log(220\200);
%alpha1200to220 = (log(u1_220.\u1_200)./(log(220\200)));

```

#### %% DIGITIZE MITSUBISHI 1 MW WIND TURBINE POWER VS SPEED CHARACTERISTICS

```

spd1 = [0 1 2 3 4.0 5.0 5.5 6.0 6.5 7.0 7.5 8.0 9.0 10 10.5 11 11.5 12 13 14 15 16 17 18
19 20 21 22 23 24 25];
pw1 = [0 0 0 0 10 20 30 55 90 140 200 280 480 730 830 900 950 980 1000 1000 1000
1000 1000 1000 1000 1000 1000 1000 1000 1000 1000];
figure(1)
plot(spd1,pw1,'r-','MarkerSize',3)
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Mitsubishi 1 MW Wind-Turbine');
axis([0 25 0 1200])
q1 = polyfit(spd1,pw1,18);
% Curve Fitted to 18th degree
xp= 0:1:25;
yp = polyval(q1,xp);
figure(2)
plot(spd1,pw1,'o',xp,yp);
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('Mitsubishi 1 MW Wind-Turbine');
axis([0 25 0 1200])

```

#### %DIGITIZE GE 1.5MW WIND TURBINE POWER VS SPEED CHARACTERISTICS

```

spd2 = [1 2 3 3.5 4.0 4.5 5.0 5.5 6.0 6.5 7.0 7.5 8.0 8.5 9.0 9.5 10 10.5 11 11.5 12 12.5
13 14 15 16 17 18 19 20 21 22 23 24 25];
pw2 = [0 0 0 15 20 35 50 90 160 250 340 470 600 750 950 1100 1220 1320 1400 1450
1480 1500 1500 1500 1500 1500 1500 1500 1500 1500 1500 1500 1500];
figure(3)
plot(spd2,pw2,'b-','MarkerSize',3)
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)')
title('GE 1.5 MW Wind-Turbine')
axis([0 25 0 1800])

```

```

pause
q2 = polyfit(sp2,pw2,17);
%Curve Fitted to 17th degree
xp= 0:1:25;
yp = polyval(q2,xp);
f = polyval(sp2,q2);
figure(4)
plot(sp2,pw2,'o',xp,yp);
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title('GE 1.5 MW Wind-Turbine');
axis([0 25 0 1600])
pause

```

```

%% DISC SPEED ESTIMATION FOR GE 1.5 MW, 53 WIND TURBINES %%
%% Equation;  $\bar{U}_{Disk} = 2/A * \int [UZ * \sqrt{R^2 - H^2 + 2HZ - Z^2}] dZ$ 
(Integral limits H-R to H+R)
%% Solving using function the disc speed equation adjusted for turbulence and shear
for wind turbines
% Initialising Height Range for GE 1.5 MW, 53 Wind Turbines %%
Wt = zeros(2,2,53); %Creating Array of 53 Wind turbines; Last Value = 53 GE 1.5
%MW wind turbines
% Assign height range for 53 wind turbines to solve integral equation
Wt(:,:,1) = [108 150.1; 150 185]; Wt(:,:,2) = [114 150.1; 150 191]; Wt(:,:,3) = [114
150.1; 150 191]; Wt(:,:,4) = [120 160.1; 160 197]; Wt(:,:,5) = [116 160.1; 160 193];
Wt(:,:,6) = [118 150.1; 150 195]; Wt(:,:,7) = [131 160.1; 160 208]; Wt(:,:,8) = [129
160.1; 160 206]; Wt(:,:,9) = [132 160.1; 160 209]; Wt(:,:,10) = [129 160.1; 160
206]; Wt(:,:,11) = [114 150.1; 150 191]; Wt(:,:,12) = [116 150.1; 150
193]; Wt(:,:,13) = [116 150.1; 150 193]; Wt(:,:,14) = [120 160.1; 160 197];
Wt(:,:,15) = [125 160.1; 160 202];
Wt(:,:,16) = [125 160.1; 160 202]; Wt(:,:,17) = [130 160.1; 160 207];
Wt(:,:,18) = [130 160.1; 160 207]; Wt(:,:,19) = [129 160.1; 160 206];
Wt(:,:,20) = [132 160.1; 160 209]; Wt(:,:,21) = [133 160.1; 160 210];
Wt(:,:,22) = [127 160.1; 160 204]; Wt(:,:,23) = [121 160.1; 160 198];
Wt(:,:,24) = [126 160.1; 160 203]; Wt(:,:,25) = [132 160.1; 160 209];
Wt(:,:,26) = [130 160.1; 160 207]; Wt(:,:,27) = [132 160.1; 160 209];
Wt(:,:,28) = [143 160.1; 160 200]; Wt(:,:,29) = [140 160.1; 160 217];
Wt(:,:,30) = [146 200.1; 200 223]; Wt(:,:,31) = [139 160.1; 160 216];
Wt(:,:,32) = [141 160.1; 160 218]; Wt(:,:,33) = [137 160.1; 160 215];
Wt(:,:,34) = [142 160.1; 160 219]; Wt(:,:,35) = [145 200.1; 200 222];
Wt(:,:,36) = [142 200.1; 200 219]; Wt(:,:,37) = [141 200.1; 200 218];
Wt(:,:,38) = [127 160.1; 160 204]; Wt(:,:,39) = [132 160.1; 160 209];
Wt(:,:,40) = [132 160.1; 160 209]; Wt(:,:,41) = [135 160.1; 160 212];
Wt(:,:,42) = [141 160.1; 160 218]; Wt(:,:,43) = [140 160.1; 160 217];
Wt(:,:,44) = [138 160.1; 160 215]; Wt(:,:,45) = [126 160.1; 160 203];

```

```

Wt(:,46) = [129 160.1; 160 206]; Wt(:,47) = [132 160.1; 160 209];
Wt(:,48) = [129 160.1; 160 206]; Wt(:,49) = [129 160.1; 160 206];
Wt(:,50) = [126 160.1; 160 203]; Wt(:,51) = [126 160.1; 160 203];
Wt(:,52) = [125 160.1; 160 202]; Wt(:,53) = [126 160.1; 160 203];

```

```

%% DISC SPEED ESTIMATION FOR MITSUBISHI 1 MW, 221 WIND
TURBINES %%

```

```

%% Solving using function the disc speed equation adjusted for turbulence and shear
using functions for wind turbines

```

```

% Initialising Height Range for MITSUBISHI 1 MW, 221 Wind Turbine

```

```

Wtt = zeros(2,2,221); % Creating Array of 221 Wind turbines; Last Value = 221
MITSUBISHI Wind Turbines

```

```

% Assign height range for 221 wind turbines to solve integral equation

```

```

Wtt(:,1) = [107 140.1; 140 169]; Wtt(:,2) = [110 140.1; 140 172];
Wtt(:,3) = [113 140.1; 140 175]; Wtt(:,4) = [120 160.1; 160 182];
Wtt(:,5) = [119 160.1; 160 181]; Wtt(:,6) = [120 160.1; 160 182];
Wtt(:,7) = [119 160.1; 160 181]; Wtt(:,8) = [120 160.1; 160 182];
Wtt(:,9) = [125 160.1; 160 187]; Wtt(:,10) = [129 160.1; 160 191];
Wtt(:,11) = [116 140.1; 140 178]; Wtt(:,12) = [114 140.1; 140 176];
Wtt(:,13) = [114 140.1; 140 176]; Wtt(:,14) = [110 140.1; 140 173];
Wtt(:,15) = [112 140.1; 140 174]; Wtt(:,16) = [115 140.1; 140 177];
Wtt(:,17) = [117 140.1; 140 179]; Wtt(:,18) = [118 140.1; 140 180];
Wtt(:,19) = [119 160.1; 160 181]; Wtt(:,20) = [118 140.1; 140 180];
Wtt(:,21) = [123 160.1; 160 185]; Wtt(:,22) = [124 160.1; 160 186];
Wtt(:,23) = [125 160.1; 160 187]; Wtt(:,24) = [124 160.1; 160 186];
Wtt(:,25) = [127 160.1; 160 189]; Wtt(:,26) = [128 160.1; 160 190];
Wtt(:,27) = [126 160.1; 160 188]; Wtt(:,28) = [110 140.1; 140 172];
Wtt(:,29) = [109 140.1; 140 171]; Wtt(:,30) = [113 140.1; 140 175];
Wtt(:,31) = [109 140.1; 140 171]; Wtt(:,32) = [110 140.1; 140 172];
Wtt(:,33) = [113 140.1; 140 175]; Wtt(:,34) = [118 140.1; 140 180];
Wtt(:,35) = [121 160.1; 160 183]; Wtt(:,36) = [122 160.1; 160 184];
Wtt(:,37) = [125 160.1; 160 187]; Wtt(:,38) = [124 160.1; 160 186];
Wtt(:,39) = [125 160.1; 160 187]; Wtt(:,40) = [128 160.1; 160 190];
Wtt(:,41) = [129 160.1; 160 191]; Wtt(:,42) = [130 160.1; 160 192];
Wtt(:,43) = [130 160.1; 160 192]; Wtt(:,44) = [130 160.1; 160 192];
Wtt(:,45) = [131 160.1; 160 193]; Wtt(:,46) = [134 160.1; 160 196];
Wtt(:,47) = [133 160.1; 160 195]; Wtt(:,48) = [135 160.1; 160 197];
Wtt(:,49) = [134 160.1; 160 196]; Wtt(:,50) = [133 160.1; 160 195];
Wtt(:,51) = [134 160.1; 160 196]; Wtt(:,52) = [133 160.1; 160 195];
Wtt(:,53) = [134 160.1; 160 196]; Wtt(:,54) = [135 160.1; 160 197];
Wtt(:,55) = [138 160.1; 160 200]; Wtt(:,56) = [135 160.1; 160 197];
Wtt(:,57) = [95 140.1; 140 157]; Wtt(:,58) = [101 140.1; 140 163];

```

Wtt(:,59)=[100 140.1; 140 162]; Wtt(:,60)=[101 140.1; 140 163];  
 Wtt(:,61)=[99 140.1; 140 161]; Wtt(:,62)=[103 140.1; 140 165];  
 Wtt(:,63)=[104 140.1; 140 166]; Wtt(:,64)=[110 140.1; 140 172];  
 Wtt(:,65)=[109 140.1; 140 171]; Wtt(:,66)=[108 140.1; 140 170];  
 Wtt(:,67)=[110 140.1; 140 172]; Wtt(:,68)=[112 140.1; 140 174];  
 Wtt(:,69)=[114 140.1; 140 176]; Wtt(:,70)=[116 140.1; 140 178];  
 Wtt(:,71)=[123 160.1; 160 185]; Wtt(:,72)=[124 160.1; 160 186];  
 Wtt(:,73)=[122 160.1; 160 184]; Wtt(:,74)=[125 160.1; 160 187];  
 Wtt(:,75)=[125 160.1; 160 187]; Wtt(:,76)=[126 160.1; 160 188];  
 Wtt(:,77)=[116 140.1; 140 178]; Wtt(:,78)=[118 140.1; 140 180];  
 Wtt(:,79)=[119 140.1; 140 181]; Wtt(:,80)=[120 160.1; 160 182];  
 Wtt(:,81)=[120 160.1; 160 182]; Wtt(:,82)=[122 160.1; 160 184];  
 Wtt(:,83)=[122 160.1; 160 184]; Wtt(:,84)=[124 160.1; 160 186];  
 Wtt(:,85)=[128 160.1; 160 190]; Wtt(:,86)=[129 160.1; 160 191];  
 Wtt(:,87)=[131 160.1; 160 193]; Wtt(:,88)=[132 160.1; 160 194];  
 Wtt(:,89)=[133 160.1; 160 195]; Wtt(:,90)=[132 160.1; 160 194];  
 Wtt(:,91)=[131 160.1; 160 193]; Wtt(:,92)=[129 160.1; 160 191];  
 Wtt(:,93)=[132 160.1; 160 194]; Wtt(:,94)=[83 120.1; 120 145];  
 Wtt(:,95)=[85 120.1; 120 147]; Wtt(:,96)=[88 120.1; 120 150];  
 Wtt(:,97)=[95 120.1; 120 157]; Wtt(:,98)=[90 120.1; 120 152];  
 Wtt(:,99)=[88 120.1; 120 150]; Wtt(:,100)=[92 120.1; 120 154];  
 Wtt(:,101)=[93 140.1; 140 155]; Wtt(:,102)=[107 140.1; 140 169];  
 Wtt(:,103)=[108 140.1; 140 170]; Wtt(:,104)=[104 140.1; 140 166];  
 Wtt(:,105)=[104 140.1; 140 166]; Wtt(:,106)=[102 140.1; 140 164];  
 Wtt(:,107)=[98 140.1; 140 160]; Wtt(:,108)=[102 140.1; 140 164];  
 Wtt(:,109)=[111 140.1; 140 173]; Wtt(:,110)=[97 120.1; 120 159];  
 Wtt(:,111)=[96 120.1; 120 158]; Wtt(:,112)=[95 120.1; 120 157];  
 Wtt(:,113)=[97 120.1; 120 159]; Wtt(:,114)=[101 140.1; 140 163];  
 Wtt(:,115)=[98 120.1; 120 160]; Wtt(:,116)=[96 120.1; 120 158];  
 Wtt(:,117)=[95 120.1; 120 157]; Wtt(:,118)=[98 120.1; 120 160];  
 Wtt(:,119)=[92 120.1; 120 154]; Wtt(:,120)=[93 120.1; 120 155];  
 Wtt(:,121)=[95 150.1; 150 157]; Wtt(:,122)=[104 140.1; 140 166];  
 Wtt(:,123)=[104 140.1; 140 166]; Wtt(:,124)=[104 140.1; 140 166];  
 Wtt(:,125)=[104 140.1; 140 166]; Wtt(:,126)=[99 140.1; 140 161];  
 Wtt(:,127)=[102 140.1; 140 164]; Wtt(:,128)=[105 140.1; 140 167];  
 Wtt(:,129)=[105 140.1; 140 167]; Wtt(:,130)=[105 140.1; 140 167];  
 Wtt(:,131)=[106 140.1; 140 168]; Wtt(:,132)=[107 140.1; 140 169];  
 Wtt(:,133)=[114 140.1; 140 176]; Wtt(:,134)=[110 140.1; 140 172];  
 Wtt(:,135)=[113 140.1; 140 175]; Wtt(:,136)=[114 140.1; 140 176];  
 Wtt(:,137)=[114 140.1; 140 176]; Wtt(:,138)=[116 140.1; 140 178];  
 Wtt(:,139)=[115 140.1; 140 177]; Wtt(:,140)=[109 140.1; 140 171];  
 Wtt(:,141)=[109 140.1; 140 171]; Wtt(:,142)=[122 160.1; 160 184];  
 Wtt(:,143)=[123 160.1; 160 185]; Wtt(:,144)=[126 160.1; 160 188];  
 Wtt(:,145)=[121 160.1; 160 183]; Wtt(:,146)=[122 160.1; 140 184];  
 Wtt(:,147)=[124 160.1; 160 186]; Wtt(:,148)=[128 160.1; 160 190];



```

Wtt(:,149) = [128 160.1; 160 190]; Wtt(:,150) = [128 160.1; 160 190];
Wtt(:,151) = [131 160.1; 160 194]; Wtt(:,152) = [133 160.1; 160 195];
Wtt(:,153) = [132 160.1; 160 194]; Wtt(:,154) = [126 160.1; 160 188];
Wtt(:,155) = [129 160.1; 160 191]; Wtt(:,156) = [122 160.1; 160 184];
Wtt(:,157) = [93 120.1; 120 155]; Wtt(:,158) = [95 120.1; 120 157];
Wtt(:,159) = [98 120.1; 120 160]; Wtt(:,160) = [99 120.1; 120 161];
Wtt(:,161) = [101 140.1; 140 163]; Wtt(:,162) = [104 140.1; 140 166];
Wtt(:,163) = [98 140.1; 140 160]; Wtt(:,164) = [101 140.1; 140 163];
Wtt(:,165) = [102 140.1; 140 164]; Wtt(:,166) = [86 120.1; 120 148];
Wtt(:,167) = [78 120.1; 120 140]; Wtt(:,168) = [76 120.1; 120 138];
Wtt(:,169) = [82 120.1; 120 144]; Wtt(:,170) = [92 120.1; 120 154];
Wtt(:,171) = [91 120.1; 120 153]; Wtt(:,172) = [92 120.1; 120 154];
Wtt(:,173) = [92 120.1; 120 154]; Wtt(:,174) = [96 120.1; 120 158];
Wtt(:,175) = [89 120.1; 120 151]; Wtt(:,176) = [83 120.1; 120 145];
Wtt(:,177) = [61 120.1; 120 123]; Wtt(:,178) = [62 120.1; 120 124];
Wtt(:,179) = [65 120.1; 120 127]; Wtt(:,180) = [68 120.1; 120 130];
Wtt(:,181) = [68 100.1; 100 130]; Wtt(:,182) = [59 100.1; 100 120];
Wtt(:,183) = [60 100.1; 100 122]; Wtt(:,184) = [61 100.1; 100 123];
Wtt(:,185) = [70 100.1; 100 132]; Wtt(:,186) = [75 100.1; 100 137];
Wtt(:,187) = [80 120.1; 120 142]; Wtt(:,188) = [65 100.1; 100 127];
Wtt(:,189) = [66 100.1; 100 128]; Wtt(:,190) = [68 100.1; 100 130];
Wtt(:,191) = [57 100.1; 100 119]; Wtt(:,192) = [59 100.1; 100 121];
Wtt(:,193) = [59 100.1; 100 121]; Wtt(:,194) = [59 100.1; 100 121];
Wtt(:,195) = [61 100.1; 100 123]; Wtt(:,196) = [65 100.1; 100 127];
Wtt(:,197) = [68 100.1; 100 130]; Wtt(:,198) = [63 100.1; 100 125];
Wtt(:,199) = [68 100.1; 100 130]; Wtt(:,200) = [66 100.1; 100 128];
Wtt(:,201) = [64 100.1; 100 126]; Wtt(:,202) = [62 100.1; 100 124];
Wtt(:,203) = [62 100.1; 100 124]; Wtt(:,204) = [64 100.1; 100 126];
Wtt(:,205) = [65 100.1; 100 127]; Wtt(:,206) = [68 100.1; 100 130];
Wtt(:,207) = [74 100.1; 100 136]; Wtt(:,208) = [66 100.1; 100 128];
Wtt(:,209) = [74 100.1; 100 136]; Wtt(:,210) = [65 100.1; 100 127];
Wtt(:,211) = [61 100.1; 100 123]; Wtt(:,212) = [55 100.1; 100 117];
Wtt(:,213) = [56 100.1; 100 118]; Wtt(:,214) = [67 100.1; 100 129];
Wtt(:,215) = [63 100.1; 100 125]; Wtt(:,216) = [40 80.1; 80 102];
Wtt(:,217) = [38 80.1; 80 100]; Wtt(:,218) = [44 80.1; 80 106];
Wtt(:,219) = [41 80.1; 80 103]; Wtt(:,220) = [42 80.1; 80 104];
Wtt(:,221) = [55 80.1; 80 117];

```

%% Initializing Wind turbine Hub Height (varies due to contour height) H=53, GE  
wind turbines; H2=221 Mitsubishi wind turbines;

%% H = GE Wind Turbines

```

H = [146; 153; 152; 159; 154; 156; 169; 168; 171; 167; 153; 155; 154; 159; 163; 163;
168; 168; 168; 171; 171; 165; 159; 164; 170; 169; 171; 181; 178; 185; 177; 180;
176; 181; 183; 180; 179; 165; 171; 171; 174; 179; 178; 177; 164; 167; 171; 168; 167;
164; 164; 164; 164];

```

% H2 = Mitsubishi Wind Turbines

```
H2 = [138; 141; 144; 151; 150; 151; 150; 151; 156; 160; 147; 145; 145; 141; 143; 146;
148; 149; 150; 149; 154; 155; 156; 155; 158; 159; 157; 141; 140; 144; 140; 141; 144;
149; 152; 153; 156; 155; 156; 159; 160; 161; 161; 161; 162; 165; 164; 166; 165; 164;
165; 164; 165; 166; 169; 166; 126; 132; 131; 132; 130; 134; 135; 141; 140; 139; 141;
143; 145; 147; 154; 155; 153; 156; 156; 157; 147; 149; 150; 151; 151; 153; 153; 155;
159; 160; 162; 163; 164; 163; 162; 160; 163; 114; 116; 119; 126; 121; 119; 123; 124;
138; 139; 135; 135; 133; 129; 133; 142; 128; 127; 125; 128; 132; 129; 127; 126; 129;
123; 124; 126; 135; 135; 135; 135; 130; 133; 136; 136; 136; 137; 140; 145; 141;
144; 145; 145; 147; 146; 140; 140; 153; 154; 157; 152; 153; 155; 159; 159; 159; 163;
164; 162; 157; 160; 153; 124; 126; 129; 130; 132; 135; 129; 132; 133; 117; 109; 107;
113; 123; 122; 123; 123; 127; 120; 114; 92; 93; 96; 99; 99; 90; 91; 92; 101; 106;
111; 96; 97; 99; 88; 90; 90; 90; 92; 96; 99; 94; 99; 97; 95; 93; 93; 95; 96; 99; 105; 97;
105; 96; 92; 86; 87; 98; 94; 71; 69; 75; 72; 73; 86];
```

%% SOLVING NUMERIC INTEGRATION USING FUNCTION;[Y,y and Y2,y2 are variables of GE and Mitsubishi wind turbines]

%%

```
Y = [u_69, u_80, u_100, u_120, u_160, u_200, u_220, a69to80, a80to100, a100to120,
a120to160, a160to200, a200to220]; % GE Wind Turbine; Assign variables to solve
equation
```

```
Y2 = [u1_69, u1_80, u1_100, u1_120, u1_160, u1_200, u1_220, a169to80, a180to100,
a1100to120, a1120to160, a1160to200, a1200to220]; % Mitsubishi Wind Turbine;
Assign variables to solve equation
```

GE Wind Turbine; Assign variables to solve equation

```
y = [3,10,4,11; 3,10,4,11; 3,10,4,11; 4,11,5,12; 3,10,4,11; 3,10,4,11; 4,11,5,12;
4,11,5,12; 4,11,5,12; 4,11,5,12; 3,10,4,11; 3,10,4,11; 3,10,4,11; 4,11,5,12;
4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
4,11,5,12; 4,11,6,13; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,6,13;
4,11,6,13; 4,11,6,13; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12]; % To access the variable that is
%assigned(Eg; 3 = u_100; 4 = u_120; 10 = a100to120; 11 = a120to160)
```

% Mitsubishi Wind Turbine; Assign variables to solve equation

```
y2 = [3,10,4,11; 3,10,4,11; 3,10,4,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11;
4,10,5,11; 4,10,5,11; 4,10,5,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11;
3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 4,10,5,11; 3,10,4,11; 4,10,5,11;
4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 3,11,5,12;
3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 4,10,5,11;
```

```

4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
2,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11;
3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11;
4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 3,10,4,11;
3,10,4,11; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12; 4,11,5,12;
4,11,5,12; 4,11,5,12; 2,9,4,10; 2,9,4,10; 2,9,4,11; 2,9,4,11; 2,9,4,11; 2,10,4,11;
2,10,4,11; 2,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11;
3,10,4,11; 3,10,4,11; 3,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11;
3,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11;
2,10,4,11; 2,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11;
3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11;
3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11; 3,10,4,11;
3,10,4,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11;
4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11; 4,10,5,11;
4,10,5,11; 4,10,5,11; 2,9,4,10; 2,9,4,10; 2,9,4,10; 2,9,4,10; 3,10,4,11; 3,10,4,11;
3,10,4,11; 3,10,4,11; 3,10,4,11; 2,10,4,11; 1,9,4,10; 1,9,4,10; 2,10,4,11;
2,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11; 2,10,4,11;
1,9,4,10; 1,9,4,10; 1,9,4,10; 1,9,4,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10;
1,9,3,10; 1,9,3,10; 2,10,4,11; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10;
1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10;
1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10;
1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,9,3,10; 1,8,2,9;
1,8,2,9; 1,8,2,9; 1,8,2,9; 1,8,2,9; 1,8,2,10]; % To access the variable that is
assigned(Eg; 3 = u1_100; 4 = u1_120; 10 = a1100to120; 11 = a1120to160)

```

```

%%%%%%%%%% Calling GE Wind Turbine Using Function
v = zeros(N,1,53);
% last value = 53 GE Wind Turbines; Area of GE Wind Turbine = 4657;
for il = 1:53 % last value = 53 GE Wind Turbines
v2 = gt_v(il); % Calling using functions for 53 GE Wind Turbines %v2 ; v
v(:,il)=(2/4657).* v2(:,:); % Result of Disc Speed is stored in variable v; or
Equation = (2/ A) *( Udisc)
end
x1 = v(:,1); % 1 = First WT disc speed
x2 = v(:,2); % 2 = Second WT disc speed
x3 = v(:,3); % 3 = Third WT disc speed
x4 = v(:,4); % 4 = Fourth WT disc speed
x5 = v(:,5); % 5 = Fifth WT disc speed

```

```

%% Calling Mitsubishi Wind Turbine Using Function
v4 = zeros(N,1,221);
for i3 = 1:221 % last value = 221 Mitsubishi Wind Turbines; Area of Mitsubishi
Wind Turbine = 3019; v4 = gtt_v(i3); % Calling using functions for 221 Mitsubishi
%Wind Turbines %v4; v4
v5(:,i3)=(2/3019).* v4(:,i3);% Disc Speed is stored in variable v5; or Equation = (2/
A) *( U_disc)
end
x11 = v5(:,1); % 1 = First WT disc speed
x12 = v5(:,2); % 2 = Second WT disc speed
x13 = v5(:,3); % 3 = Third WT disc speed
x14 = v5(:,4); % 4 = Fourth WT disc speed
x15 = v5(:,5); % 5= Fifth WT disc speed

%% END OF DISC SPEED
%% POWER PREDICTION FROM DISC SPEED FOR GE 1.5 MW; 53 WIND
TURBINES %
for i1 = 1:53 % Last value = 53 WT; GPuncor = Uncorrected Power of GE Wind
Turbine
gpuncor(:,i1) =
q2(18)+(q2(17).*(v(:,i1)))+(q2(16).*(v(:,i1)).^2)+(q2(15).*(v(:,i1)).^3)+(q2(14).*(v
(:,i1)).^4)+(q2(13).*(v(:,i1)).^5)+(q2(12).*(v(:,i1)).^6)+(q2(11).*(v(:,i1)).^7)
+(q2(10).*(v(:,i1)).^8)
+(q2(9).*(v(:,i1)).^9)+(q2(8).*(v(:,i1)).^10)+(q2(7).*(v(:,i1)).^11)
+(q2(6).*(v(:,i1)).^12)+(q2(5).*(v(:,i1)).^13)+(q2(4).*(v(:,i1)).^14)+(q2(3).*(v(:,i
1)).^15)+(q2(2).*(v(:,i1)).^16)+(q2(1).*(v(:,i1)).^17));
gpcor(:,i1)=gpuncor(:,i1).*(act_density./1.225);
end

%% POWER REMAINS CONSTANT AFTER RATED WIND SPEED FOR GE
WIND TURBINE;%%
nn2 = length(v(:,i1));
for i1 = 1:53
AA1 = find(gpcor(:,i1)>=1500); % Rated power is equal to 1500 KW
nn3 = length(AA1);
for j2 = 1:nn3
gpcor(nn2*(i1-1)+ AA1(j2))=1500; % Power remains constant after rated wind
speed
end
end
end
figure(5)
v8(:,1)= sort(v(:,1));
gplcor = sort(gpcor(:,1));
plot(v8(:,1),gplcor,'r-');
xlabel('Wind Speed (m/s)');

```

```

ylabel('Wind Power (kw)');
title(' GE 1.5 MW Wind Turbine');
axis([0 25 0 1800]);
pause
figure(6)
v8(:,2)= sort(v(:,2));
gp2cor = sort(gpcor(:,2));
plot(v8(:,2),gp2cor,'k-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title(' GE 1.5 MW Wind Turbine');
axis([0 25 0 1800]);
pause

```

```

%% POWER PREDICTION FROM DISC SPEED FOR MITSUBISHI 1 MW; 221
WIND TURBINES %
for i3 =1:221 % Last value = 221 Mitsubishi WT ; MPuncor = Uncorrected Power of
Mitsubishi Wind Turbine
mpuncor(:,i3) =q1(19)+ (q1(18).*(v5(:,i3)))+(q1(17).*(v5(:,i3)).^2)+
(q1(16).*(v5(:,i3)).^3)+(q1(15).*(v5(:,i3)).^4)+(q1(14).*(v5(:,i3)).^5)+(q1(13).*(v5
(:,i3)).^6)+(q1(12).*(v5(:,i3)).^7)+
(q1(11).*(v5(:,i3)).^8) +(q1(10).*(v5(:,i3)).^9)+ (q1(9).*(v5(:,i3)).^10)+
(q1(8).*(v5(:,i3)).^11)+(q1(7).*(v5(:,i3)).^12)+(q1(6).*(v5(:,i3)).^13)+
(q1(5).*(v5(:,i3)).^14)+(q1(4).*(v5(:,i3)).^15)+
(q1(3).*(v5(:,i3)).^16)+(q1(2).*(v5(:,i3)).^17)+(q1(1).*(v5(:,i3)).^18);
mpcor(:,i3)=mpuncor(:,i3).*(act_density./1.225);
end
%%
%% POWER REMAINS CONSTANT AFTER RATED WIND SPEED FOR
MITSUBISHI WIND TURBINE;%%
nn = length(v5(:,i3));
for i3 = 1:221
AA = find(mpcor(:,i3)>=1000); % Rated power is equal to 1000 KW
nn1 = length(AA);
for j1 = 1:nn1
mpcor(nn*(i3-1)+ AA(j1))=1000; % Power remains constant after rated wind speed
end
end
%%
figure(7)
Mv(:,1)= sort(v5(:,1));
mpcor11 = sort(mpcor(:,1));
plot(Mv(:,1),mpcor11,'k-');
xlabel('Wind Speed (m/s)');

```

```

ylabel('Wind Power (kw)');
title(' MITSUBISHI 1 MW Wind Turbine');
axis([0 25 0 1200]);
pause
figure(8)
Mv(:,2)= sort(v5(:,2));
mpcor12 = sort(mpcor(:,2));
plot(Mv(:,2),mpcor12,'r-');
xlabel('Wind Speed (m/s)');
ylabel('Wind Power (kw)');
title(' MITSUBISHI 1 MW Wind Turbine');
axis([0 25 0 1200]);
%% WAKE MODEL FOR GE WIND TURBINE
%% WAKE SPEED ESTIMATION FOR GE 1.5 MW, 53 WIND TURBINES %
% Rrot = Radius of GE Wind Turbine; x = Distance between nearest wind turbine;
Ashad = Area of shadow region of wind turbines
% Arot = Area of GE wind turbine rotor; Ct = Thrust coefficient of wind turbine; tana
= 0.04(no-wake)/0.08(wake); Rx = Radius of shadow cone
% v(:,il) = Disc Speed; Uwake(:,il)= Wake Speed of Wind Turbine
x=[262;262;292;296;306;0;301;201;259;0;298;298;302;246;246;258;302;302;269
;269;282;0;335;0;248;248;209;209;344;0;293;293;283;266;266;288;0;299;0;0;264;264
;325;0;229;298;255;255;0;226;226;408];
Ashad=[2500;2500.0;2500.0;2500.0;1900.0;2100.0;2500.0;2500.0;2400.0;1500.0;250
0.0;2100.0;2100.0;2100.0;2500.0;2500.0;2500.0;2100.0;2100.0;2400.0;2400.0;
2100.0;0.0000; 0.0000;2500.0;2500.0;2500.0; 2000.0;2000.0;0.0000; 0.0000;
2000.0;2000.0;2000.0;2500.0;2500.0;2200.0;0.0000;2200.0;0.000; 0.000;
2200.0;2200.0;0.00;0.00;2000.0;1000.0;2400.0;2400.0;0.0000;2000.0;2000.0;
0.2000];

% Equation : Thrust Coefficient (Ct) and Wake Speed Calculation (Uwake) for
% WT- Wind Turbine
% Ct = 3.5*(2*Vhub - 3.5)/(Vhub)^2;
% R(x) = Rrot + x.tana ; tana = 0.04 (free speed) or tana = 0.08 (wake)%
% Uwake = Vi[1- sqrt(1 - Ct)*(Rrot/R(x))^2*(Ashad / Arot)]
for il=1:53 % 53, GE 1.5 MW Wind Turbines
Rrot =38.5;
Ct(:,il) = 3.5.*((2.*v(:,il)) - 3.5)./(v(:,il)).^2;
tana=0.08;
Rx(il) = Rrot + x(il)*tana;
Arot = 4657;
Uwake(:,il) = v(:,il).*(1- sqrt(1 - Ct(:,il)).*(Rrot/Rx(il))^2.*(Ashad(il)/Arot));
end
%%
%% POWER PREDICTION FROM WAKE SPEED FOR GE 1.5 MW, 53 WIND
TURBINES %

```

```

for i1 = 1:53      % 53 GE 1.5 MW Wind Turbines; gpuncorw = Uncorrected Wake
Power of GE Wind Turbine; gpcorw = Corrected Wake Power of GE Wind Turbine
gpuncorw(:,i1) = q2(18)+(q2(17).*(Uwake(:,i1))+(q2(16).*(Uwake(:,i1)).^2)+
(q2(15).*(Uwake(:,i1)).^3)+
(q2(14).*(Uwake(:,i1)).^4)+(q2(13).*(Uwake(:,i1)).^5)+
(q2(12).*(Uwake(:,i1)).^6)+(q2(11).*(Uwake(:,i1)).^7)+
(q2(10).*(Uwake(:,i1)).^8)+(q2(9).*(Uwake(:,i1)).^9)+
(q2(8).*(Uwake(:,i1)).^10)+(q2(7).*(Uwake(:,i1)).^11)+
(q2(6).*(Uwake(:,i1)).^12)+(q2(5).*(Uwake(:,i1)).^13)+
(q2(4).*(Uwake(:,i1)).^14)+(q2(3).*(Uwake(:,i1)).^15)+
(q2(2).*(Uwake(:,i1)).^16)+(q2(1).*(Uwake(:,i1)).^17));
gpcorw(:,i1) = gpuncorw(:,i1).*(act_density./1.225);
end

```

```

%% POWER REMAINS CONSTANT AFTER RATED WIND SPEED FOR GE
WIND TURBINE %%%%%%%%%%

```

```

nn4 = length(Uwake(:,i1));
for i1 = 1:53
    AA3 = find(gpcorw(:,i1)>=1500); % Rated power is equal to 1500 kw
    nn5 = length(AA3);
    for j2 = 1:nn5
        gpcorw(nn4*(i1-1)+ AA3(j2))=1500; % Power remains constant after rated speed
    end
end

```

```

%% WAKE MODEL FOR MITSUBISHI WIND TURBINE%%

```

```

%% WAKE SPEED ESTIMATION FOR MITSUBISHI 1 MW, 221 WIND
TURBINES %

```

```

% R2 = Radius of Mitsubishi Wind Turbine; x2 = distance between nearest wind
turbine; Ashad2 = Area of shadow region of wind turbines

```

```

% Ct2 = Thrust Coefficient of Wind turbine; Rx2 = Radius of shadow cone;

```

```

tana = 0.04(no-wake)/ 0.08(wake);

```

```

% Uwake2 = Wake Speed ; v5(:,i3) = Disc Speed ;

```

```

Arot2 = Area of wind turbine rotor disc (3019)

```

```

R2= 31;

```

```

x2=[194;194;234;230;230;232;223;193;193;195;214;214;222;237;206;206;232;232;23
6;232;234;234;235;240;258;258;221;221;220;220;212;212;194;194;220;210;210;231;
231;215;215;217;217;219;248;242;241;241;225;225;226;225;225;235;244;324;231;22
9;229;264;204;204;199;199;220;211;204;204;214;224;235;218;218;227;241;
271;271;227;227;227;213;211;211;198;197;197;216;216;218;242;236;236;201;201;22
7;207;207;223;225;224;116;116;202;202;202;274;164;164;222;205;205;461;437;
437;214;214;220;291;188;188;215;213;213;214;195;195;173;173;168;168;177;171;17
1;214;198;198;240;240;222;222;236;231;231;236;281;281;258;221;221;213;211;211;
209;209;271;198;198;215;215;150;150;223;192;192;205;205;203;197;187;187;

```



```
254;254;172;172;250;317;317;300;220;220;287;287;304;377;300;300;248;246;246;23
0;190;190;213;215;218;218;258;252;252;212;212;229;229;213;213;220;226;226;207;
207;254;256;256;294;335;208;208;223;274;274;307];
```

```
NE = numel(x2); % Counting wind turbines
```

```
Ashad2=[0;1952.85;650.95;741.52;1741.52;1741.52;1801.9;1952.85;1952.85;1952.85
;0;1862.28;1801.9;0;1043.42;1043.42;0;1741.52;1650.95;1741.52;741.52;1741.52;741
.52;741.52;681.14;0;0;0;1801.9;2801.9;2801.9;1862.28;1862.28;1254.75;1254.75;180
1.9;1862.28;1862.28;0;1650.95;1862.28;1862.28;1801.9;1801.9;1801.9;0;1590.57;159
0.57;1590.57;1801.9;801.9;801.9;801.9;801.9;1650.95;2560.38;0;2650.95;681.14;681.
14;0;0;862.28;0;952.85;801.9;0;1043.42;1043.42;952.85;801.9;650.95;952.85;952.85;
801.9;590.57;0;0;650.95;650.95;0;801.9;801.9;1801.9;0;952.85;952.85;801.9;801.9;80
1.9;560.38;590.57;590.57;0;862.28;650.95;801.9;801.9;650.95;650.95;650.95;801.9;8
01.9;0;862.28;862.28;0;1405.7;1405.7;0;862.28;
1862.28;0;0;0;0;741.52;650.95;0;1254.75;1254.75;0;1741.52;1741.52;1741.52;1103.8;
1103.8;1405.7;1405.7;1405.7;1405.7;1405.7;1405.7;1405.7;741.52;862.28;
862.28;560.38;1560.38;741.52;741.52;0;650.95;650.95;650.95;0;0;0;741.52;741.52;80
1.9;801.9;3801.9;801.9;801.9;0;0;862.28;741.52;741.52;1556.65;1556.65;741.52;
862.28;862.28;0;862.28;1862.28;2952.85;1164.18;1164.18;0;0;1345.32;
1345.32;0;0;0;0;741.52;741.52;0;0;0;0;0;0;0;0;650.95;952.85;952.85;862.28;862.28;
862.28;0;0;0;801.9;801.9;650.95;650.95;0;1862.28;1801.9;0;1650.95;
801.9;1801.9;0;0;0;0;0;862.28;1862.28;1650.95;0;0;0];
```

```
% Equation : Thrust Coefficient (Ct) and Wake Speed Calculation (Uwake) for
```

```
% WT- Wind Turbine
```

```
%  $C_t = 3.5 \cdot (2 \cdot V_{hub} - 3.5) / (V_{hub})^2$ ;
```

```
%  $R(x) = R_{rot} + x \cdot \tan\alpha$  ;  $\tan\alpha = 0.04$  (free speed) or  $\tan\alpha = 0.08$  (wake)%
```

```
%  $U_{wake} = V_i [1 - \sqrt{1 - C_t} \cdot (R_{rot}/R(x))^2 \cdot (Ashad / A_{rot})]$ 
```

```
for i3=1:221 % Last value = 221 Mitsubishi WT
```

```
 $C_{t2}(:,i3) = 3.5 \cdot ((2 \cdot v5(:,i3)) - 3.5) / (v5(:,i3))^2$ ;
```

```
 $\tan\alpha = 0.08$ ;
```

```
 $R_{x2}(i3) = R_2 + x2(i3) \cdot \tan\alpha$ ;
```

```
 $A_{rot2} = 3019$ ;
```

```
 $U_{wake2}(:,i3) = v5(:,i3) \cdot (1 - \sqrt{1 -$ 
```

```
 $C_{t2}(:,i3)) \cdot (R_2/R_{x2}(i3))^2 \cdot (Ashad2(i3)/A_{rot2}))$ ;
```

```
end
```

```
%% POWER PREDICTION FROM WAKE SPEED FOR MITSUBISHI 1 MW, 221
WIND TURBINES %
```

```
 $xx1 = U_{wake2}(:,i3)$ ;
```

```
for i3 =1:221
```

```
%Last value = 221 Mitsubishi WT; MPuncorw = Uncorrected Wake Power of
```

```
%Mitsubishi Wind Turbine; mpcorw = Corrected Wake Power of Mitsubishi Wind
```

```
%Turbine
```



```

mpuncorw(:,i3) = q1(19)+(q1(18).*(Uwake2(:,i3)))+(q1(17).*(Uwake2(:,i3)).^2)+
(q1(16).*(Uwake2(:,i3)).^3)+(q1(15).*(Uwake2(:,i3)).^4)+(q1(14).*(Uwake2(:,i3)
).^5)+(q1(13).*(Uwake2(:,i3)).^6)+q1(12).*(Uwake2(:,i3)).^7)+(q1(11).*(Uwake2(
(:,i3)).^8)+(q1(10).*(Uwake2(:,i3)).^9)+(q1(9).*(Uwake2(:,i3)).^10)+(q1(8).*(Uwa
ke2(:,i3)).^11)+(q1(7).*(Uwake2(:,i3)).^12)+(q1(6).*(Uwake2(:,i3)).^13)+(q1(5).*
(Uwake2(:,i3)).^14)+(q1(4).*(Uwake2(:,i3)).^15)+(q1(3).*(Uwake2(:,i3)).^16)+
(q1(2).*(Uwake2(:,i3)).^17)+(q1(1).*(Uwake2(:,i3)).^18);
mpcorw(:,i3) = mpuncorw(:,i3).*(act_density./1.225);
end

```

```

%% POWER REMAINS CONSTANT AFTER RATED WIND SPEED FOR
MITSUBISHI WIND TURBINE;%%

```

```

nn6 = length(Uwake2(:,i3));
for i3 = 1:221
AA4 = find(mpcorw(:,i3)>=1000); % Rated power is equal to 1000 kw
nn7 = length(AA4);
for j1 = 1:nn7
mpcorw(nn6*(i3-1)+ AA4(j1))=1000; % Power remains constant after rated speed
end
end

```

```

%% START OF WAKE COEFFICIENT At 45 and 225 degree
% Sum of No-wake power of windfarm = GE_Mit_cpw
% Sum of wake power of windfarm = GE_Mit_wpw
% Wake Coefficient = Sum of No-wake power/Sum of Wake power

```

```

GE_Mit_cpw = mpcor(:,1) + mpcor(:,2)+ mpcor(:,3)+ mpcor(:,4)+ mpcor(:,5) +
mpcor(:,6)+ mpcor(:,7)+ mpcor(:,8)+ mpcor(:,9)+ mpcor(:,10)+ mpcor(:,11)+
mpcor(:,12)+ mpcor(:,13)+ mpcor(:,14)+ mpcor(:,15)+ mpcor(:,16)+
mpcor(:,17)+ mpcor(:,18)+ mpcor(:,19)+ mpcor(:,20)+ mpcor(:,21) +
mpcor(:,22)+ mpcor(:,23)+ mpcor(:,24)+ mpcor(:,25)+ mpcor(:,26)+
mpcor(:,27) + mpcor(:,28)+ mpcor(:,29) + mpcor(:,30)+ mpcor(:,31)+
mpcor(:,32)+ mpcor(:,33)+ mpcor(:,34)+ mpcor(:,35) + mpcor(:,36) +
mpcor(:,37)+ mpcor(:,38)+ mpcor(:,39)+ mpcor(:,40)+ mpcor(:,41)+
mpcor(:,42)+ mpcor(:,43)+ mpcor(:,44)+ mpcor(:,45)+ mpcor(:,46)+
mpcor(:,47)+ mpcor(:,48)+ mpcor(:,49)+ mpcor(:,50)+ mpcor(:,51)+
mpcor(:,52)+ mpcor(:,53)+ mpcor(:,54)+ mpcor(:,55)+ mpcor(:,56)+
mpcor(:,57)+ mpcor(:,58)+ mpcor(:,59)+ mpcor(:,60)+ mpcor(:,61)+
mpcor(:,62)+ mpcor(:,63)+ mpcor(:,64)+ mpcor(:,65) + mpcor(:,66) +
mpcor(:,67)+ mpcor(:,68)+ mpcor(:,69)+ mpcor(:,70)+ mpcor(:,71)+
mpcor(:,72) + mpcor(:,73)+ mpcor(:,74)+ mpcor(:,75)+ mpcor(:,76)+
mpcor(:,77)+ mpcor(:,78)+ mpcor(:,79)+ mpcor(:,80) + mpcor(:,81)+
mpcor(:,82)+ mpcor(:,83)+ mpcor(:,84)+ mpcor(:,85)+ mpcor(:,86)+
mpcor(:,87) + mpcor(:,88)+ mpcor(:,89)+ mpcor(:,90)+ mpcor(:,91) +

```

```

mpcor(:,92)+mpcor(:,93)+mpcor(:,94)+mpcor(:,95)+mpcor(:,96)+
mpcor(:,97)+mpcor(:,98)+mpcor(:,99)+mpcor(:,100)+mpcor(:,101)+
mpcor(:,102)+mpcor(:,103)+mpcor(:,104)+mpcor(:,105)+mpcor(:,106)+
mpcor(:,107)+mpcor(:,108)+mpcor(:,109)+mpcor(:,110)+mpcor(:,111)+
mpcor(:,112)+mpcor(:,113)+mpcor(:,114)+mpcor(:,115)+mpcor(:,116)+
mpcor(:,117)+mpcor(:,118)+mpcor(:,119)+mpcor(:,120)+mpcor(:,121)+
mpcor(:,122)+mpcor(:,123)+mpcor(:,124)+mpcor(:,125)+mpcor(:,126)+
mpcor(:,127)+mpcor(:,128)+mpcor(:,129)+mpcor(:,130)+mpcor(:,131)+
mpcor(:,132)+mpcor(:,133)+mpcor(:,134)+mpcor(:,135)+mpcor(:,136)+
mpcor(:,137)+mpcor(:,138)+mpcor(:,139)+mpcor(:,140)+mpcor(:,141)+
mpcor(:,142)+mpcor(:,143)+mpcor(:,144)+mpcor(:,145)+mpcor(:,146)+
mpcor(:,147)+mpcor(:,148)+mpcor(:,149)+mpcor(:,150)+mpcor(:,151)+
mpcor(:,152)+mpcor(:,153)+mpcor(:,154)+mpcor(:,155)+mpcor(:,156)+
mpcor(:,157)+mpcor(:,158)+mpcor(:,159)+mpcor(:,160)+mpcor(:,161)+
mpcor(:,162)+mpcor(:,163)+mpcor(:,164)+mpcor(:,165)+mpcor(:,166)+
mpcor(:,167)+mpcor(:,168)+mpcor(:,169)+mpcor(:,170)+mpcor(:,171)+
mpcor(:,172)+mpcor(:,173)+mpcor(:,174)+mpcor(:,175)+mpcor(:,176)+
mpcor(:,177)+mpcor(:,178)+mpcor(:,179)+mpcor(:,180)+mpcor(:,181)+
mpcor(:,182)+mpcor(:,183)+mpcor(:,184)+mpcor(:,185)+mpcor(:,186)+
mpcor(:,187)+mpcor(:,188)+mpcor(:,189)+mpcor(:,190)+mpcor(:,191)+
mpcor(:,192)+mpcor(:,193)+mpcor(:,194)+mpcor(:,195)+mpcor(:,196)+
mpcor(:,197)+mpcor(:,198)+mpcor(:,199)+mpcor(:,200)+mpcor(:,201)+
mpcor(:,202)+mpcor(:,203)+mpcor(:,204)+mpcor(:,205)+mpcor(:,206)+
mpcor(:,207)+mpcor(:,208)+mpcor(:,209)+mpcor(:,210)+mpcor(:,211)+
mpcor(:,212)+mpcor(:,213)+mpcor(:,214)+mpcor(:,215)+mpcor(:,216)+
mpcor(:,217)+mpcor(:,218)+mpcor(:,219)+mpcor(:,220)+mpcor(:,221)+
gpcor(:,1)+gpcor(:,2)+gpcor(:,3)+gpcor(:,4)+gpcor(:,5)+gpcor(:,6)+gpcor(:,7)+
gpcor(:,8)+gpcor(:,9)+gpcor(:,10)+gpcor(:,11)+gpcor(:,12)+
gpcor(:,13)+gpcor(:,14)+gpcor(:,15)+gpcor(:,16)+gpcor(:,17)+gpcor(:,18)+gpcor(
(:,19)+gpcor(:,20)+gpcor(:,21)+gpcor(:,22)+gpcor(:,23)+gpcor(:,24)+
gpcor(:,25)+gpcor(:,26)+gpcor(:,27)+gpcor(:,28)+gpcor(:,29)+gpcor(:,30)+gpc
or(:,31)+gpcor(:,32)+gpcor(:,33)+gpcor(:,34)+gpcor(:,35)+gpcor(:,36)+
gpcor(:,37)+gpcor(:,38)+gpcor(:,39)+gpcor(:,40)+gpcor(:,41)+gpcor(:,42)+gpc
or(:,43)+gpcor(:,44)+gpcor(:,45)+gpcor(:,46)+gpcor(:,47)+gpcor(:,48)+
gpcor(:,49)+gpcor(:,50)+gpcor(:,51)+gpcor(:,52)+gpcor(:,53);

```

```

GE_Mit_wpw = mpcorw(:,1) + mpcorw(:,2)+ mpcorw(:,3)+ mpcorw(:,4)+
mpcorw(:,5) + mpcorw(:,6)+ mpcorw(:,7)+mpcorw(:,8)+ mpcorw(:,9)+
mpcorw(:,10)+ mpcorw(:,11)+ mpcorw(:,12)+ mpcorw(:,13)+ mpcorw(:,14)+
mpcorw(:,15)+ mpcorw(:,16)+ mpcorw(:,17)+ mpcorw(:,18)+ mpcorw(:,19)+
mpcorw(:,20)+ mpcorw(:,21) + mpcorw(:,22)+ mpcorw(:,23)+ mpcorw(:,24)+
mpcorw(:,25)+ mpcorw(:,26)+ mpcorw(:,27) +mpcorw(:,28)+ mpcorw(:,29) +
mpcorw(:,30)+ mpcorw(:,31)+ mpcorw(:,32)+ mpcorw(:,33)+ mpcorw(:,34)+
mpcorw(:,35) +mpcorw(:,36) + mpcorw(:,37)+ mpcorw(:,38)+ mpcorw(:,39)+
mpcorw(:,40)+ mpcorw(:,41)+ mpcorw(:,42)+ mpcorw(:,43)+ mpcorw(:,44)+

```

mpcorw(:,45)+ mpcorw(:,46)+ mpcorw(:,47)+mpcorw(:,48)+ mpcorw(:,49)+  
 mpcorw(:,50)+ mpcorw(:,51)+ mpcorw(:,52)+ mpcorw(:,53)+ mpcorw(:,54)+  
 mpcorw(:,55)+mpcorw(:,56)+ mpcorw(:,57)+ mpcorw(:,58)+ mpcorw(:,59)+  
 mpcorw(:,60)+ mpcorw(:,61)+ mpcorw(:,62)+ mpcorw(:,63)+ mpcorw(:,64)+  
 mpcorw(:,65)+ mpcorw(:,66)+ mpcorw(:,67)+ mpcorw(:,68)+ mpcorw(:,69)+  
 mpcorw(:,70)+ mpcorw(:,71)+ mpcorw(:,72)+ mpcorw(:,73)+ mpcorw(:,74)+  
 mpcorw(:,75)+ mpcorw(:,76)+ mpcorw(:,77)+ mpcorw(:,78)+ mpcorw(:,79)+  
 mpcorw(:,80)+ mpcorw(:,81)+ mpcorw(:,82)+ mpcorw(:,83)+ mpcorw(:,84)+  
 mpcorw(:,85)+ mpcorw(:,86)+ mpcorw(:,87)+ mpcorw(:,88)+ mpcorw(:,89)+  
 mpcorw(:,90)+ mpcorw(:,91)+ mpcorw(:,92)+ mpcorw(:,93)+ mpcorw(:,94)+  
 mpcorw(:,95)+ mpcorw(:,96)+ mpcorw(:,97)+ mpcorw(:,98)+ mpcorw(:,99)+  
 mpcorw(:,100)+mpcorw(:,101)+mpcorw(:,102)+mpcorw(:,103)+  
 mpcorw(:,104)+mpcorw(:,105)+mpcorw(:,106)+mpcorw(:,107)+  
 mpcorw(:,108)+mpcorw(:,109)+mpcorw(:,110)+mpcorw(:,111)+  
 mpcorw(:,112)+mpcorw(:,113)+mpcorw(:,114)+mpcorw(:,115)+  
 mpcorw(:,116)+mpcorw(:,117)+mpcorw(:,118)+mpcorw(:,119)+  
 mpcorw(:,120)+mpcorw(:,121)+mpcorw(:,122)+mpcorw(:,123)+  
 mpcorw(:,124)+mpcorw(:,125)+mpcorw(:,126)+mpcorw(:,127)+  
 mpcorw(:,128)+ mpcorw(:,129)+mpcorw(:,130)+mpcorw(:,131)+  
 mpcorw(:,132)+ mpcorw(:,133)+mpcorw(:,134)+ mpcorw(:,135)+  
 mpcorw(:,136)+ mpcorw(:,137)+ mpcorw(:,138)+mpcorw(:,139)+  
 mpcorw(:,140)+mpcorw(:,141)+mpcorw(:,142)+mpcorw(:,143)+  
 mpcorw(:,144)+ mpcorw(:,145)+ mpcorw(:,146)+ mpcorw(:,147)+  
 mpcorw(:,148)+mpcorw(:,149)+ mpcorw(:,150)+ mpcorw(:,151)+  
 mpcorw(:,152)+ mpcorw(:,153)+mpcorw(:,154)+ mpcorw(:,155)+  
 mpcorw(:,156)+ mpcorw(:,157)+ mpcorw(:,158)+mpcorw(:,159)+  
 mpcorw(:,160)+mpcorw(:,161)+mpcorw(:,162)+mpcorw(:,163)+  
 mpcorw(:,164)+ mpcorw(:,165)+ mpcorw(:,166)+ mpcorw(:,167)+  
 mpcorw(:,168)+mpcorw(:,169)+ mpcorw(:,170)+ mpcorw(:,171)+  
 mpcorw(:,172)+mpcorw(:,173)+mpcorw(:,174)+mpcorw(:,175)+  
 mpcorw(:,176)+ mpcorw(:,177)+ mpcorw(:,178)+ mpcorw(:,179)+  
 mpcorw(:,180)+ mpcorw(:,181)+ mpcorw(:,182)+ mpcorw(:,183)+  
 mpcorw(:,184)+ mpcorw(:,185)+ mpcorw(:,186)+ mpcorw(:,187)+  
 mpcorw(:,188)+ mpcorw(:,189)+ mpcorw(:,190)+ mpcorw(:,191)+  
 mpcorw(:,192)+ mpcorw(:,193)+ mpcorw(:,194)+ mpcorw(:,195)+  
 mpcorw(:,196)+ mpcorw(:,197)+ mpcorw(:,198)+ mpcorw(:,199)+  
 mpcorw(:,200)+ mpcorw(:,201)+ mpcorw(:,202)+ mpcorw(:,203)+  
 mpcorw(:,204)+ mpcorw(:,205)+ mpcorw(:,206)+ mpcorw(:,207)+  
 mpcorw(:,208)+ mpcorw(:,209)+ mpcorw(:,210)+ mpcorw(:,211)+  
 mpcorw(:,212)+ mpcorw(:,213)+ mpcorw(:,214)+ mpcorw(:,215)+  
 mpcorw(:,216)+ mpcorw(:,217)+ mpcorw(:,218)+ mpcorw(:,219)+  
 mpcorw(:,220)+mpcorw(:,221)+gpcorw(:,1)+gpcorw(:,2)+gpcorw(:,3)+  
 gpcorw(:,4)+ gpcorw(:,5)+gpcorw(:,6)+gpcorw(:,7)+ gpcorw(:,8)+  
 gpcorw(:,9)+gpcorw(:,10)+gpcorw(:,11)+ gpcorw(:,12)+  
 gpcorw(:,13)+gpcorw(:,14)+gpcorw(:,15)+gpcorw(:,16)+

```

gpcorw(:,17)+gpcorw(:,18)+gpcorw(:,19)+ gpcorw(:,20) +
gpcorw(:,21)+gpcorw(:,22)+gpcorw(:,23)+ gpcorw(:,24)+
gpcorw(:,25)+gpcorw(:,26)+gpcorw(:,27)+gpcorw(:,28)+
gpcorw(:,29)+gpcorw(:,30)+gpcorw(:,31)+ gpcorw(:,32) +
gpcorw(:,33)+gpcorw(:,34)+gpcorw(:,35)+ gpcorw(:,36)+
gpcorw(:,37)+gpcorw(:,38)+gpcorw(:,39)+gpcorw(:,40)+
gpcorw(:,41)+gpcorw(:,42)+gpcorw(:,43)+ gpcorw(:,44) +
gpcorw(:,45)+gpcorw(:,46)+gpcorw(:,47)+ gpcorw(:,48)+
gpcorw(:,49)+gpcorw(:,50)+gpcorw(:,51)+gpcorw(:,52)+
gpcorw(:,53);
Total1 = sum(GE_Mit_cpw); % No-wake windfarm power
Total2 = sum(GE_Mit_wpw); % Wake windfarm power
wc = Total2/Total1;

% Wake coefficient
%% Wind Direction and Wake Coefficient Evaluation
wd = array(:,7); % Accessing Wind Direction time series data
Wake_Coeff = wc*(wd<=50).*(wd>=40)+ wc*(wd<=230).*(wd>=220)+
(wd>50).*(wd<220)+(wd<40)+(wd>230); % Equation determining the
wake and Nowake data depending on the wind direction

% AVERAGE WINDFARM POWER %
% MITSUBISHI 1 MW, 221 WIND TURBINES
Avg_MIT = mean(mpcor(:,1))+mean(mpcor(:,2))+mean(mpcor(:,3))+
mean(mpcor(:,4))+ mean(mpcor(:,5)) + mean(mpcor(:,6)) +
mean(mpcor(:,7)) + mean(mpcor(:,8))+ mean(mpcor(:,9))+
mean(mpcor(:,10))+mean(mpcor(:,11))
+ mean(mpcor(:,12)) + mean(mpcor(:,13)) + mean(mpcor(:,14)) +
mean(mpcor(:,15))+ ean(mpcor(:,16))+mean(mpcor(:,17))+
mean(mpcor(:,18))+ mean(mpcor(:,19))+ mean(mpcor(:,20)) +
mean(mpcor(:,21)) + mean(mpcor(:,22)) + mean(mpcor(:,23))+
mean(mpcor(:,24))+ mean(mpcor(:,25))+ mean(mpcor(:,26))+
mean(mpcor(:,27)) + mean(mpcor(:,28)) + mean(mpcor(:,29)) +
mean(mpcor(:,30))+ ean(mpcor(:,31))+mean(mpcor(:,32))+
mean(mpcor(:,33))+ mean(mpcor(:,34))+ mean(mpcor(:,35)) +
mean(mpcor(:,36)) + mean(mpcor(:,37)) + mean(mpcor(:,38))+
mean(mpcor(:,39))+ mean(mpcor(:,40))+ mean(mpcor(:,41))+
mean(mpcor(:,42)) + mean(mpcor(:,43)) + mean(mpcor(:,44)) +
mean(mpcor(:,45))+ ean(mpcor(:,46))+mean(mpcor(:,47))+
mean(mpcor(:,48))+ mean(mpcor(:,49))+ mean(mpcor(:,50)) +
mean(mpcor(:,51)) + mean(mpcor(:,52)) + mean(mpcor(:,53))+
mean(mpcor(:,54))+ mean(mpcor(:,55))+ mean(mpcor(:,56))+
mean(mpcor(:,57)) + mean(mpcor(:,58)) + mean(mpcor(:,59)) +
mean(mpcor(:,60))+ ean(mpcor(:,61))+mean(mpcor(:,62))+

```

mean(mpcor(:,63))+ mean(mpcor(:,64))+ mean(mpcor(:,65)) +  
 mean(mpcor(:,66)) + mean(mpcor(:,67)) + mean(mpcor(:,68))+  
 mean(mpcor(:,69))+mean(mpcor(:,70))+ mean(mpcor(:,71))+  
 mean(mpcor(:,72)) + mean(mpcor(:,73)) + mean(mpcor(:,74)) +  
 mean(mpcor(:,75))+mean(mpcor(:,76))+mean(mpcor(:,77))+  
 mean(mpcor(:,78))+ mean(mpcor(:,79))+ mean(mpcor(:,80)) +  
 mean(mpcor(:,81)) + mean(mpcor(:,82)) mean(mpcor(:,83))+  
 mean(mpcor(:,84))+ mean(mpcor(:,85))+ mean(mpcor(:,86))+  
 mean(mpcor(:,87)) + mean(mpcor(:,88)) + mean(mpcor(:,89)) +  
 mean(mpcor(:,90))+ ean(mpcor(:,91))+mean(mpcor(:,92))+  
 mean(mpcor(:,93))+ mean(mpcor(:,94))+ mean(mpcor(:,95)) +  
 mean(mpcor(:,96)) + mean(mpcor(:,97)) +  
 mean(mpcor(:,98))+mean(mpcor(:,99))+ mean(mpcor(:,100))+  
 mean(mpcor(:,101))+ mean(mpcor(:,102)) + mean(mpcor(:,103)) +  
 mean(mpcor(:,104)) + mean(mpcor(:,105))+  
 mean(mpcor(:,106))+mean(mpcor(:,107))+mean(mpcor(:,108))+  
 mean(mpcor(:,109))+ mean(mpcor(:,110)) + mean(mpcor(:,111)) +  
 mean(mpcor(:,112)) + mean(mpcor(:,113))+mean(mpcor(:,114))+  
 mean(mpcor(:,115))+ mean(mpcor(:,116))+ mean(mpcor(:,117)) +  
 mean(mpcor(:,118)) + mean(mpcor(:,119)) + mean(mpcor(:,120))+  
 mean(mpcor(:,121))+mean(mpcor(:,122))+mean(mpcor(:,123))+  
 mean(mpcor(:,124))+ mean(mpcor(:,125)) + mean(mpcor(:,126)) +  
 mean(mpcor(:,127)) + mean(mpcor(:,128))+mean(mpcor(:,129))+  
 mean(mpcor(:,130))+ mean(mpcor(:,131))+ mean(mpcor(:,132)) +  
 mean(mpcor(:,133)) + mean(mpcor(:,134)) + mean(mpcor(:,135))+  
 mean(mpcor(:,136))+mean(mpcor(:,137))+mean(mpcor(:,138))+  
 mean(mpcor(:,139))+ mean(mpcor(:,140)) + mean(mpcor(:,141)) +  
 mean(mpcor(:,142)) + mean(mpcor(:,143))+mean(mpcor(:,144))+  
 mean(mpcor(:,145))+ mean(mpcor(:,146))+ mean(mpcor(:,147)) +  
 mean(mpcor(:,148)) + mean(mpcor(:,149)) + mean(mpcor(:,150))+  
 mean(mpcor(:,151))+mean(mpcor(:,152))+mean(mpcor(:,153))+  
 mean(mpcor(:,154))+ mean(mpcor(:,155)) + mean(mpcor(:,156)) +  
 mean(mpcor(:,157)) + mean(mpcor(:,158))+mean(mpcor(:,159))+  
 mean(mpcor(:,160))+ mean(mpcor(:,161))+ mean(mpcor(:,162)) +  
 mean(mpcor(:,163)) + mean(mpcor(:,164)) + mean(mpcor(:,165))+  
 mean(mpcor(:,166))+mean(mpcor(:,167))+mean(mpcor(:,168))+  
 mean(mpcor(:,169))+ mean(mpcor(:,170)) + mean(mpcor(:,171)) +  
 mean(mpcor(:,172)) + mean(mpcor(:,173))+mean(mpcor(:,174))+  
 mean(mpcor(:,175))+ mean(mpcor(:,176))+ mean(mpcor(:,177)) +  
 mean(mpcor(:,178)) + mean(mpcor(:,179)) + mean(mpcor(:,180))+  
 mean(mpcor(:,181))+mean(mpcor(:,182))+mean(mpcor(:,183))+  
 mean(mpcor(:,184))+ mean(mpcor(:,185)) + mean(mpcor(:,186)) +  
 mean(mpcor(:,187)) + mean(mpcor(:,188))+mean(mpcor(:,189))+  
 mean(mpcor(:,190))+ mean(mpcor(:,191))+ mean(mpcor(:,192)) +  
 mean(mpcor(:,193)) + mean(mpcor(:,194)) + mean(mpcor(:,195))+

```

mean(mpcor(:,:,196))+mean(mpcor(:,:,197))+mean(mpcor(:,:,198))+
mean(mpcor(:,:,199))+ mean(mpcor(:,:,200)) + mean(mpcor(:,:,201)) +
mean(mpcor(:,:,202)) + mean(mpcor(:,:,203))+mean(mpcor(:,:,204))+
mean(mpcor(:,:,205))+ mean(mpcor(:,:,206))+ mean(mpcor(:,:,207)) +
mean(mpcor(:,:,208)) + mean(mpcor(:,:,209)) + mean(mpcor(:,:,210))+
mean(mpcor(:,:,211))+mean(mpcor(:,:,212))+mean(mpcor(:,:,213))+
mean(mpcor(:,:,214))+ mean(mpcor(:,:,215)) + mean(mpcor(:,:,216)) +
mean(mpcor(:,:,217)) + mean(mpcor(:,:,218))+mean(mpcor(:,:,219))+
mean(mpcor(:,:,220))+ mean(mpcor(:,:,221));

```

%GE 1.5 MW, 53 WIND TURBINES

```

Avg_GE = mean(gpcor(:,:,1))+ mean(gpcor(:,:,2))+ mean(gpcor(:,:,3))+
mean(gpcor(:,:,4))+ mean(gpcor(:,:,5))+ mean(gpcor(:,:,6))+ mean(gpcor(:,:,7))+
mean(gpcor(:,:,8))+ mean(gpcor(:,:,9)) + mean(gpcor(:,:,10))+ mean(gpcor(:,:,11))+
mean(gpcor(:,:,12))+ mean(gpcor(:,:,13))+ mean(gpcor(:,:,14))+ mean(gpcor(:,:,15))+
mean(gpcor(:,:,16))+ mean(gpcor(:,:,17))+ mean(gpcor(:,:,18))+ mean(gpcor(:,:,19))+
mean(gpcor(:,:,20))+ mean(gpcor(:,:,21))+ mean(gpcor(:,:,22))+ mean(gpcor(:,:,23))+
mean(gpcor(:,:,24)) + mean(gpcor(:,:,25))+ mean(gpcor(:,:,26))+ mean(gpcor(:,:,27))+
mean(gpcor(:,:,28))+ mean(gpcor(:,:,29))+ mean(gpcor(:,:,30))+ mean(gpcor(:,:,31))+
mean(gpcor(:,:,32))+ mean(gpcor(:,:,33))+ mean(gpcor(:,:,34))+ mean(gpcor(:,:,35))+
mean(gpcor(:,:,36))+ mean(gpcor(:,:,37))+ mean(gpcor(:,:,38))+
mean(gpcor(:,:,39)) + mean(gpcor(:,:,40))+ mean(gpcor(:,:,41))+ mean(gpcor(:,:,42))+
mean(gpcor(:,:,43))+ mean(gpcor(:,:,44))+ mean(gpcor(:,:,45))+ mean(gpcor(:,:,46))+
mean(gpcor(:,:,47))+ mean(gpcor(:,:,48))+ mean(gpcor(:,:,49))+ mean(gpcor(:,:,50))+
mean(gpcor(:,:,51))+ mean(gpcor(:,:,52))+ mean(gpcor(:,:,53));

```

%%%%% COLORADO WIND FARM AVERAGE POWER

```

Avg_farm = Avg_MIT + Avg_GE;
% AVERAGE WINDFARM POWER WITH TRANSMISSION LOSS OF 1%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
GE_Mit_loss = GE_Mit_cpw*0.99; %% Windfarm power lossof 1% (nowake Effect)
GE_Mit_wakeloss = GE_Mit_wpw*0.99; %% Windfarm power lossof 1% (wake
%Effect)
Actual_power = GE_Mit_cpw-GE_Mit_loss; %%Actual windfarm power(nowake
%Effect)
Actual_power_wake = GE_Mit_wpw-GE_Mit_wakeloss; %%Actual windfarm wake
%power)

```

%% PLOTTING FIGURES FROM THE RESULT

```

%% SENSOR HEIGHT WIND SPEED GE WIND TURBINE %
figure(9)
plot(hour, WS_80, 'b-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');

```

```

title('Sensor Height of GE Wind Turbine');
pause
%% Mean value of wind speed data at 80m %
Sensor_80m = mean(WS_80);

% SENSOR HEIGHT WIND SPEED MITSUBISHI WIND TURBINE %
figure(10)
plot(hour,WS1_69,'k-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Sensor Height of Mitsubishi Wind Turbine');
pause
%% Mean value of wind speed data at 69m %
Sensor_69m = mean(WS1_69);

%% DISC SPEED OF MITSUBISHI WIND TURBINE-2 %
figure(11)
plot(hour,v5(:,2),'b-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Disc Speed of Mitsubishi Wind Turbine-2');
pause
%% Mean value of wind speed data at 69m %
disc1_69m = mean(v5(:,2));

% DISC SPEED OF GE WIND TURBINE-2 %
figure(12)
plot(hour,v(:,2),'g-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Disc Speed of GE Wind Turbine-2');
pause

%% Mean value of wind speed data at 80m %
disc_80m = mean(v(:,2));
%% VERTICAL SHEAR OF GE AND MITSUBISHI WIND TURBINE-2 %
% GE WIND TURBINE %
figure(13)
plot(hour,WS(:,8),'r-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');

```

```

title('Vertical Shear of GE Wind Turbine-2');
pause
%% Mean value of wind speed data at 80m %
vs_80m = mean(WS(:,8));

% MITSUBISHI WIND TURBINE %
figure(14)
plot(hour,WS1(:,9),'k-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Vertical Shear of Mitsubishi Wind Turbine-2');
%% Mean value of wind speed data at 69m %
vs1_69m = mean(WS1(:,9));

%% TURBULENCE ADJUSTED SPEED OF GE AND MITSUBISHI WIND
TURBINE-2%
% GE WIND TURBINE %
figure(15)
plot(hour,u_153,'r-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Turbulence Adjusted Speed of GE Wind Turbine-2');
pause

%% Mean value of wind speed data at 80m %
ts_80m = mean(u_153);
% MITSUBISHI WIND TURBINE %
figure(16)
plot(hour,u_141,'g-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Turbulence Adjusted Speed of Mitsubishi Wind Turbine-2');
pause
%% Mean value of wind speed data at 69m %
ts1_69m = mean(u_141);

% WAKE SPEED OF GE AND MITSUBISHI WIND TURBINE-2%
% GE WIND TURBINE %
figure(17)
plot(hour,Uwake(:,2),'r-')
axis([0 1000 0 30])

```



```

xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Wake Speed of GE Wind Turbine-2');
pause
%% Mean value of wind speed data at 80m %
wk_80m = mean(Uwake(:,2));

% MITSUBISHI WIND TURBINE %
figure(18)
plot(hour,Uwake2(:,2),'g-')
axis([0 1000 0 30])
xlabel('Time (min)');
ylabel('Wind Speed (m/s)');
title('Wake Speed of Mitsubishi Wind Turbine-2');
pause
%% Mean value of wind speed data at 69m %
wk1_69m = mean(Uwake2(:,2));

%% NO-WAKE AND WAKE POWER OF WIND TURBINE WITH RESPECT TO
TIME %
% MITSUBISHI WIND TURBINE %
figure(19)
plot(hour,mpcorw(:,2),'k-',hour,mpcor(:,2),'r-')
axis([0 1000 0 1200])
xlabel('Time (min)');
ylabel('Wind Power (kw)');
title('No-wake(red)and Wake Power of Mitsubishi Wind Turbine-2');
pause
%% Mean value of wind speed data at 69m %
wkpwl_69m = mean(mpcorw(:,2));
nowk_69m = mean(mpcor(:,2));
uncorr_pomiwt = mean(mpuncor(:,2));

% GE WIND TURBINE %
figure(20)
plot(hour,gpcorw(:,2),'k-',hour,gpcor(:,2),'r-')
axis([0 1000 0 1700])
xlabel('Time (min)');
ylabel('Wind Power (kw)');
title('No-wake(red)and Wake Power of GE Wind Turbine-2');
pause
%% Mean value of windpower data at 80m %
wkp1_80m = mean(gpcorw(:,2));
nowk_80m = mean(gpcor(:,2));
uncorr_pogewt = mean(gpuncor(:,2));

```

```

%% WINDFARM POWER WITH RESPECT TO TIME
% GE WIND TURBINES + MITSUBISHI WIND TURBINES
figure(21)
plot(hour,GE_Mit_cpw,'k-')
axis([0 1000 0 400000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Windfarm Power of Windturbines');
pause
%% Mean value of windfarm power data %
wfnwkpowl = mean(GE_Mit_cpw);

% COMPARISION OF WINDFARM POWER WITH AND WITHOUT
WAKE EFFECT %
% GE WIND TURBINES + MITSUBISHI WIND TURBINES
figure(22)
plot(hour,GE_Mit_cpw,'k-',hour,GE_Mit_wpw,'r-')
axis([0 1000 0 400000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Comparision of Windfarm Power With and Without(black)Wake Effect');
pause
%% Mean value of wakefarm power data %
wfwkpowerl = mean(GE_Mit_wpw);
%% WIND DIRECTION AND WAKE COEFFICIENT OF WINDFARM
% Wind direction @45 degree and @225 degree, the wake coefficient is 0.84
figure(23)
plot(hour,Wake_Coeff,'k-')
axis([0 500 0 1.5])
xlabel('Time (min)');
ylabel('Wake Coefficient');
title('Wind Direction and Windfarm Efficiency');
pause

%% WINDFARM POWER WITH TRANSMISSION LOSS OF 1% %
% TRANSMISSION LOSS POWER OF GE WIND TURBINES
+ MITSUBISHI WIND TURBINES WITH NO-WAKE EFFECT
figure(24)
plot(hour,GE_Mit_loss,'k-')
axis([0 1000 0 4000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Windfarm Powerloss in Transmission With No-Wake Effect');
pause
%% Mean value of no-wake wind power transmission loss data %

```

```

tlnowkpwGE_MIT = mean(GE_Mit_loss);

% TRANSMISSION LOSS POWER OF GE WIND TURBINES
+ MITSUBISHI WIND TURBINES WITH WAKE EFFECT
figure(25)
plot(hour,GE_Mit_wakeloss,'r-')
axis([0 1000 0 4000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Windfarm Powerloss in Transmission With Wake Effect');
pause
%% Mean value of wake wind power transmission loss data %
tlwkpGE_MIT = mean(GE_Mit_wakeloss);

% ACTUAL POWER OF GE WIND TURBINES + MITSUBISHI WIND
TURBINES(NO-WAKE-EFFECT)%
figure(26)
plot(hour,Actual_power,'k-')
axis([0 1000 0 400000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Actual Windfarm Power With Transmission Loss(No-Wake Effect)');
pause
%% Mean value of wind power transmission loss data %
actpwGE_MIT = mean(Actual_power)

% ACTUAL POWER OF GE WIND TURBINES + MITSUBISHI WIND
TURBINES(WAKE EFFECT)%
figure(27)
plot(hour,Actual_power_wake,'g-')
axis([0 1000 0 400000])
xlabel('Time (min)');
ylabel('Windfarm Power (kw)');
title('Actual Windfarm Power With Transmission Loss(Wake Effect)');
pause
% Mean value of wake wind power transmission loss data %
actwkpGE_MIT = mean(Actual_power_wake);
%% END OF MAIN PROGRAM, %%%%%%%%%%%

```

## Appendix L

Main Program Calling GE 1.5 MW Wind Turbine

Sub-Program: Function

% GE WIND TURBINE FUNCTION %

%% Calling function from main program to solve disc speed equation %%

%% Sub program %%

%% START %%

function v = gt\_v(i1) % Function is called from main program and contains  
result of disc speed

global Wt Y y N H

z7 = Wt(1,1,i1); % Lower Half of Rotor Disc (Minimum Height Limit)

z7max = Wt(2,1,i1); % Lower Half of Rotor Disc (Maximum Height Limit)

R = 38.5; % Radius of Wind Turbine

H7 = H(i1); % Hub height is varying for each wind turbine

dz = 0.1; % dz is from disc equation and signifies height range in steps of 0.1

i = 1;

v7 = zeros(N,1); % Creating Array for time series data

while z7 <= z7max % Lower rotor disc (Height limits from minimum to maximum  
%value)

v7(:,1) = v7(:,1) + abs(Y(:,y(i1,1))).\*power((z7/80),Y(:,y(i1,2))).\*sqrt((R.^2)-  
(H7.^2)+(2.\*H7.\*z7)-(z7.^2)).\*dz); % Udisc Equation

i = i+1;

z7 = z7+0.1;

end

z7 = Wt(1,2,i1); % Upper Half of Rotor Disc (Minimum Height Limit)

z7max = Wt(2,2,i1); % Upper Half of Rotor Disc (Maximum Height Limit)

i = 1;

while z7 <= z7max % Upper rotor disc (Height limits from minimum to maximum  
%value)

v7(:,1) = v7(:,1) + abs(Y(:,y(i1,3))).\*power((z7/160),Y(:,y(i1,4))).\*sqrt((R.^2)-  
(H7.^2)+(2.\*H7.\*z7)-(z7.^2)).\*dz);

% Udisc Equation % "It adds all the results from H-R to H+R of rotor disc "

i = i+1;

z7 = z7+0.1;

end

v = v7;

end

## Appendix M

Main Program Calling Mitsubishi 1.0 MW Wind Turbine

Sub-Program: Function

% MITSUBISHI WIND TURBINE FUNCTION %

%% Calling function from main program to solve disc speed equation %%

%% Sub program %%

%% START %%

function v4 = gtt\_v(i3) % Function is called from main program and contains result of disc speed

global N H2 Wtt Y2 y2

z71 = Wtt(1,1,i3); % Lower Half of Rotor Disc (Minimum Height Limit)

z71max = Wtt(2,1,i3); % Lower Half of Rotor Disc (Maximum Height Limit)

R2 = 31; % Radius of Wind Turbine

H71 = H2(i3); % Hub height is varying for each wind turbine

dz = 0.1; % dz is from disc equation and signifies height range in steps of 0.1

i = 1;

v71 = zeros(N,1); % Creating Array for time series data

while z71 <= z71max % Lower rotor disc (Height limits from minimum to maximum value)

v71(i,1) = v71(i,1) + bs(Y2(:,y2(i3,1)).\*power((z71/80),Y2(:,y2(i3,2))).\*sqrt((R2.^2)-(H71.^2)+(2.\*H71.\*z71)-(z71.^2)).\*dz); % Udisc Equation

i = i + 1;

z71 = z71 + 0.1;

end

z71 = Wtt(1,2,i3); % Upper Half of Rotor Disc (Minimum Height Limit)

z71max = Wtt(2,2,i3); % Upper Half of Rotor Disc (Maximum Height Limit)

i = 1;

while z71 <= z71max

% Upper rotor disc (Height limits from minimum to maximum value)

v71(i,1) = v71(i,1) + abs(Y2(:,y2(i3,3)).\*power((z71/160),Y2(:,y2(i3,4))).\*sqrt((R2.^2)-(H71.^2)+(2.\*H71.\*z71)-(z71.^2)).\*dz);

% Udisc Equation % "It adds all the results from H-R to H+R of rotor disc "

i = i + 1;

z71 = z71 + 0.1;

end

v4 = v71;

end

%% END OF SUB PROGRAM %%%%%%%%%%

## Appendix N

**Wind power estimation with the wind turbines operating under the influence of wake effect and no wake effect in the wind farm depending on the wind direction.**

### Wake Model for GE 1.5 MW Wind Turbine

Wind direction has a major effect in estimating the wind power in the wind farm when the wind turbines are operating under the influence of wake effect. The wind speed and the wind power is estimated for GE 1.5 MW, 2<sup>nd</sup> wind turbine placed in the wind farm site operating under the influence of wake effect depending on the wind direction.

#### Symbols Used:

Rrot = Radius of GE wind turbine rotor;  
x = Distance between nearest wind turbine;  
Ashad = Area of shadow region of wind turbines  
Arot = Area of GE wind turbine rotor;  
Ct = Thrust coefficient of wind turbine;  
tana = 0.04(no-wake) / 0.08(wake);  
Rx = Radius of shadow cone  
v(:,il) = Disc speed; % il = 2 for second wind turbine and is called using function  
Uwake(:,il) = Wake speed of wind turbine  
x=[262];  
Ashad=[2500]; (Assumed for 2<sup>nd</sup> wind turbine)  
gpuncorw = Uncorrected Wake Power of GE Wind Turbine;  
gpcorw = Corrected Wake Power of GE Wind Turbine

#### Equation:

Thrust Coefficient (Ct) and Wake Speed Calculation (Uwake) for WT-2, (Wind Turbine-2)

$Ct = 3.5 \cdot (2 \cdot V_{hub} - 3.5) / (V_{hub})^2$ ;  
 $R(x) = R_{rot} + x \cdot tana$ ;  
tana = 0.04 (free speed) or tana = 0.08 (wake)  
 $Uwake = V_i \cdot [1 - \sqrt{1 - Ct} \cdot (R_{rot} / R(x))^2 \cdot (Ashad / Arot)]$

#### Calculation:

**Uwake = Wind speed estimated under influence of wake effect for 2<sup>nd</sup> wind turbine (taken from part of Matlab code).**

for il=1:53 % il = 2 for second wind turbine; There are 53 GE 1.5 MW Wind Turbines

Rrot=38.5; % Radius of rotor  
 $Ct(:,il) = 3.5 \cdot ((2 \cdot v(:,il)) - 3.5) / (v(:,il))^2$ ; % v(:,il) is called using function  
tana=0.08;  
 $Rx(il) = R_{rot} + x(il) \cdot tana$ ;  
Arot = 4657; (Area = 3.142\*38.5\*38.5) or  $A = \pi \cdot r \cdot r$

```

Uwake(:, :, i1) = v(:, :, i1).*(1- sqrt(1 - Ct(:, :, i1))).*(Rrot/Rx(i1))^2.*(Ashad(i1)/Arot));
% i1 = 2 for second wind turbine
end

```

**gpcorw = Wind power is estimated under wake effect from the input estimated wind speed for 2<sup>nd</sup> wind turbine (taken from part of Matlab code).**

```

for i1 = 1:53      % i1 = 2 for second wind turbine; there are 53 GE 1.5 MW wind turbines
gpcorw(:, :, i1) = q2(18)+(q2(17).*(Uwake(:, :, i1)))+(q2(16).*(Uwake(:, :, i1)).^2)+
q2(15).*(Uwake(:, :, i1)).^3)+(q2(14).*(Uwake(:, :, i1)).^4)+(q2(13).*(Uwake(:, :, i1)).^5)+
(q2(12).*(Uwake(:, :, i1)).^6)+(q2(11).*(Uwake(:, :, i1)).^7)+(q2(10).*(Uwake(:, :, i1)).^8)+
(q2(9).*(Uwake(:, :, i1)).^9)+(q2(8).*(Uwake(:, :, i1)).^10)+(q2(7).*(Uwake(:, :, i1)).^11)+
(q2(6).*(Uwake(:, :, i1)).^12)+(q2(5).*(Uwake(:, :, i1)).^13)+
q2(4).*(Uwake(:, :, i1)).^14)+(q2(3).*(Uwake(:, :, i1)).^15)+
(q2(2).*(Uwake(:, :, i1)).^16)+(q2(1).*(Uwake(:, :, i1)).^17));
gpcorw(:, :, i1) = gpcorw(:, :, i1).*(act_density./1.225);      % i1 = 2 for second wind turbine
end

```

### GE 1.5 MW wind turbine-2 operating at disc speed

Disc speed is estimated when the wind turbine operates at free flow of wind speed and correspondingly the wind power is estimated from the disc speed.

#### Equation:

Refer equations to determine disc speed of wind turbine: page 104 to 106

$P_{corr} = P_{uncorr} \cdot \text{actual density} / \text{density at STP}$  (Corrected Power/Power)

$P_{uncorr}$  = Uncorrected power estimated from curve fitting function from input disc speed (Uncorrected Power)

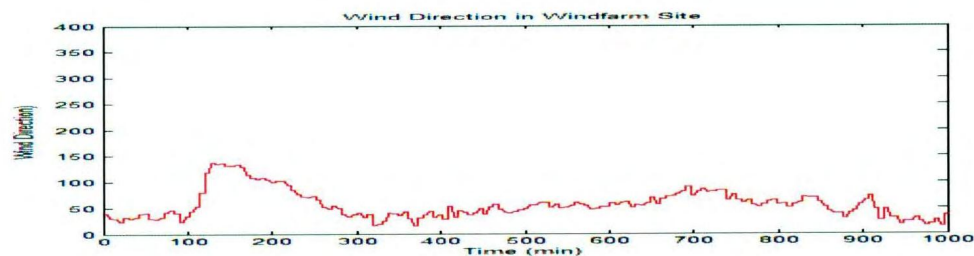


Figure N.1: Wind direction (degrees) at the wind farm site for a time span of 10000 minutes.

(Note: Time Scale: X axis: 1 unit = 10 minute; 1000 unit = 10000 minutes).

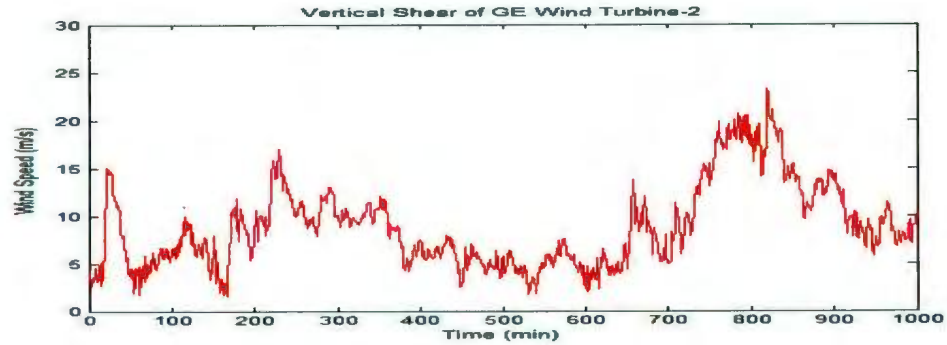


Figure N.2: Wind speed estimated for the GE 1.5 MW wind turbine- 2 at the hub height. (Note:

Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

Note: With wake effect, wake speed is estimated and is assumed to be at the hub height

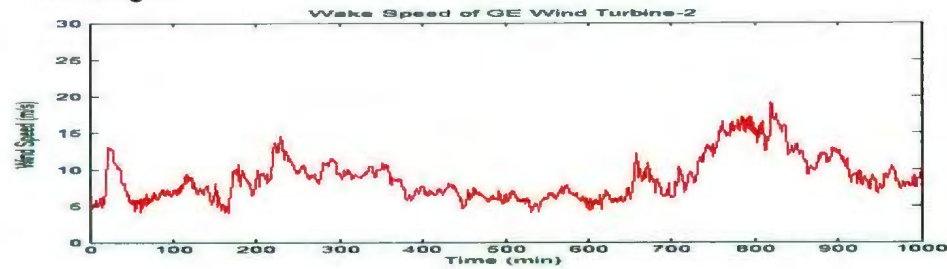


Figure N.3: Wake speed estimated for GE 1.5 MW wind turbine-2 at hub height (Note: Time

Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).

Note: With no- wake effect, disc speed is estimated and is assumed to be at the hub height

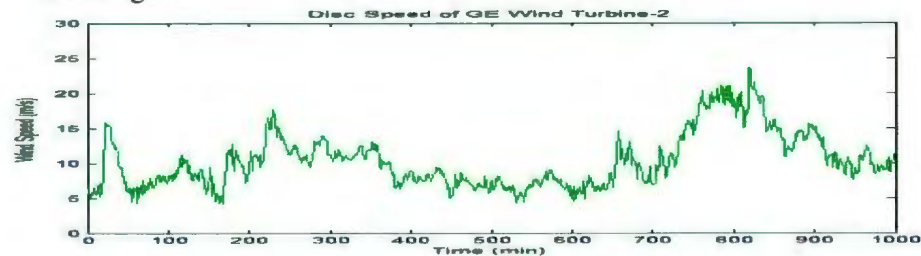


Figure N.4: Estimated disc Speed (adjusted for turbulence and shear) for GE 1.5 MW wind

turbine-2 at hub height. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).



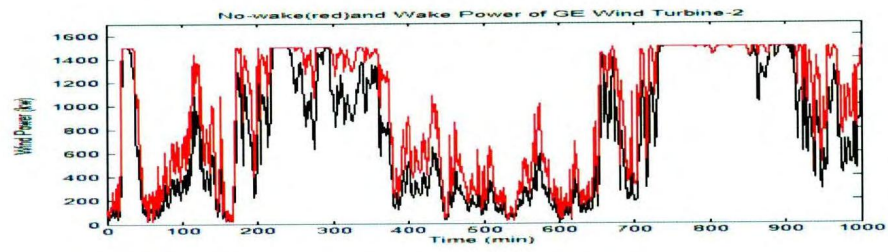


Figure N.5: Comparison of power estimated with wake (black) and without wake (red) effect for GE 1.5 MW wind turbine-2. (Note: Time Scale: X axis: 1 unit =10 minute; 1000 unit = 10000 minutes).



