Developing a Wind speed prediction tool using artificial neural networks and designing Wind Park in Syria using WASP software

By

Aubai AL Khatib

A Thesis Submitted to
Faculty of Engineering at Cairo University
and
Faculty of Engineering at Kassel University
in Partial Fulfillment of the
Requirements for the Degree of
Master of Science
In
Renewable Energy and Energy Efficiency

Faculty of Engineering

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Cairo University — **Kassel University**
Giza, Egypt — **Kassel, Germany**

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Content

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Nomenclature

Abbreviations:

The abbreviations used in the ANN tool are:

Training function:

Train-BR	Is a network training function that updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. The process is called Bayesian regularization.
Train-BFG	Is a network training function that updates weight and bias values according to the BFGS quasi-Newton method.
Train-LM	Is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. trainlm is often the fastest backpropagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.
Train-GDM	Is a network training function that updates weight and bias values according to gradient descent with momentum.
Train-GDA	Is a network training function that updates weight and bias values according to gradient descent with adaptive learning rate.
Train-GD	Is a network training function that updates weight and bias values according to gradient descent.
Train-SCG	Is a network training function that updates weight and bias values according to the scaled conjugate gradient method.
Train-RP	Is a network training function that updates weight and bias values according to the resilient backpropagation algorithm (Rprop).
Train-OSS	is a network training function that updates weight and bias values according to the one-step secant method.
Train-GDX	is a network training function that updates weight and bias values according to gradient descent momentum and an adaptive learning rate.
Train-CGP	is a network training function that updates weight and bias values according to conjugate gradient backpropagation with Polak-Ribiére updates.
Train-CGF	is a network training function that updates weight and bias values according to conjugate gradient backpropagation with Fletcher-Reeves updates.
Train-CGB	is a network training function that updates weight and bias values according to the conjugate gradient backpropagation with Powell-Beale restarts.
Train-BFG	is a network training function that updates weight and bias values according to the BFGS quasi-Newton method.

Learning functions

learncon	Is the conscience bias learning function used to increase the net input to neurons that have the lowest average output until each neuron responds approximately an equal percentage of the time.
learngd	Is the gradient descent weight and bias learning function.
learngdm	Is the gradient descent with momentum weight and bias learning function.
learnh	Is the Hebb weight learning function.
learnhd	Is the Hebb weight learning function.(Hebb with decay weight learning rule)
learnis	Is the instar weight learning function.
learnk	Is the Kohonen weight learning function.
learnlv1	Is the LVQ1 weight learning function.
learnlv2	Is the LVQ2 weight learning function.
learnos	Is the outstar weight learning function.
learnp	Is the perceptron weight/bias learning function.
learnpn	Is a weight and bias learning function. It can result in faster learning than learnp when input vectors have widely varying magnitudes.
learnsom	Is the self-organizing map weight learning function.
learnsomb	Is the batch self-organizing map weight learning function.
learnwh	Is the Widrow-Hoff weight/bias learning function, and is also known as the delta or least mean squared (LMS) rule.

Declaration on Independent Work

"With this, I declare that I have written this thesis on my own, distinguished citations, and used no other than the named sources and aids."

Signature

…………..

Abstract

The purpose of this thesis is to show the different prediction possibilities in wind speed by using the artificial neural network for the time shift wind speed prediction using Matlab program. Additionally using the WASP program for sizing a suggested wind farm and do the prediction possibilities horizontally and vertically. Also the steps for sizing the suggested wind speed prediction tool were included. And the pre-steps to be done for the input data before processed by the proposed ANN tool. An error calculation was also carried out in order to evaluate the performance of the suggested ANN prediction tool and to show the improvement of errors with the different approaches. The best root square error was /0.0505/. Information about wind data were obtained by the help of the Syrian research center. A complete 100 [MW] wind farm module was studied using the WASP program, with the help of "Grid integration of Al Haijana Wind Park" study [[1]]. V90 turbine from Vestas was selected for this wind farm. A detailed study for the awake effect was done using the WASP program.

[1] The study of my colleges is not shown in this work. It can be ordered from Kassel University.

1. Chapter 1: introduction

General introduction

Introduction of wind prediction

1) General Introduction:

In this master thesis I will try to show how neural networks work by using the Matlab program. This ANN will be used for wind speed prediction with time. A complete design of a wind farm using the WASP program of ALHijana location in Syria near Damascus city will be done. With both programs the whole possibility of wind prediction can be covered (Horizontal, Vertical, and future time prediction). Also this thesis will include a manual calculation of the energy yield from one wind turbine, as the reference for the WASP program calculation (to insure the correctness of the results) and if possible the output of the wind prediction tool will be used for Energy calculations. The next figure shows the work that was done.

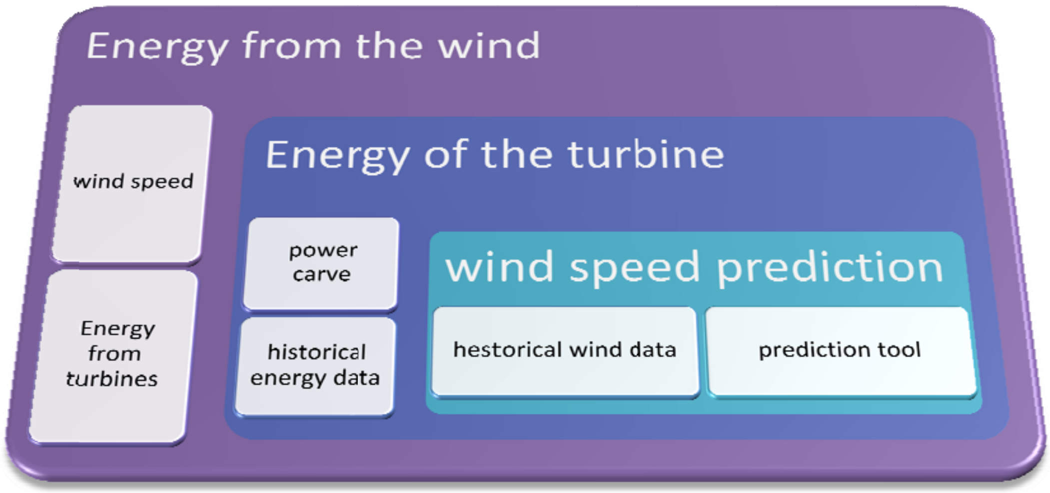


Figure 1-1 needed data for wind energy prediction

1.1. Background:

Syria is a developing country located in Asia on the Mediterranean Sea and considered part of the Middle East counties. Syria is a self-dependent country in the energy point of view, but with the growing demand of the industrial and commercial sector for energy the situation will change. The Syrian government now knows the fact that oil is no longer a reliable source of energy due to the fact that it is depleting, it is now concentrating more of the renewable energy application that can provide a sustainable source of energy within the county itself.

1.2. Syrian wind energy situation:

In 2004-2005 a study of the possible wind farm location was carried out by the energy research center in Damascus. The output of this study is the expected energy yield from the selected locations. The location were selected on the bases of wind speed evaluation and due to that a metrological measurement station was installed in those locations and data of wind speed, pressure, temperature and wind direction was generated till now.

For the present time, the Syrian government is already in the final stages of contracting for a wind farm in Ktena area. With the help of the energy research center in Damascus the development in this sector is growing and being activated.

2) Introduction of wind prediction:

In this part we will give a general view of the technics and possibilities used for wind speed prediction and energy afterword.

State-of-the-Art in Wind Prediction:

It is important to differentiate between wind speed prediction and wind energy prediction. Where the first one is important for the weather forecasting and people how works in meteorology. A lot of numerical weather predictions (NWP) tools are already developed and in used for good wind speed prediction, for different locations, what is more that data output of those modules can be obtained and used by anyone from the internet web sites (Lange, 2009).

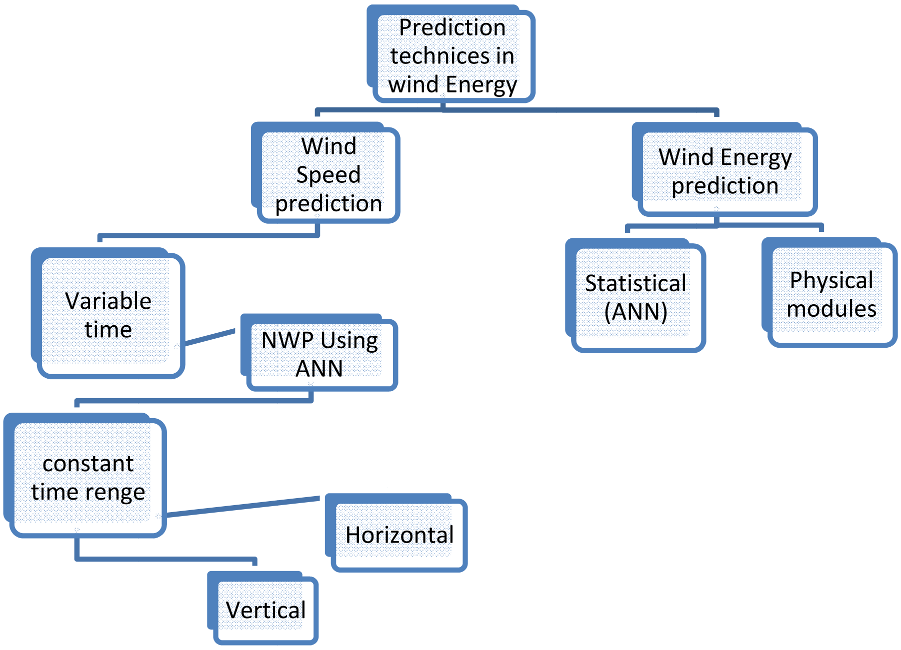


Figure 1-2 different wind energy prediction possibilities

Figure 1-2 shows the different possibility of using prediction in wind energy with the different prediction tools that can be used for every situation. A very important criteria for the assessment of the accuracy in the energy yield from a wind farm is the used prediction tool. There are different methods used for wind Speed and Energy prediction, in this Chapter we will talk about the strength and weakness of the different prediction methods used in this field.

2.1. State-of-the-Art in Wind Speed Prediction:

It is always important to choose the input of the prediction tool, the more detailed input we have the more accurate output from our prediction tool we can get [2], and in this case the important inputs that lead to the formation of the wind speed are the atmospheric Temperature, Pressure, and humidity of course the time as the main input for the prediction tool as the purpose of the tool is to predict something in the future.

Wind speed is a non-linear fluctuating function; it is why forecasting using normal method is very difficult. The technique of solving a nonlinear problem is a method of using the intelligent engineering represented by a neural network, a genetic algorithm, a chaos fractal, etc. These techniques are already adopted as numerical prediction, prediction of the weather, etc. this is shown in Figure 1-2 with the wind speed prediction/ variable time/ NWP and that lead to a generated data about the Expected wind speed at a specific period time in the Future.

[2] the usage of more factors as input for the prediction tool will lead to more variables in the wind speed equation is understood by the developed ANN

The fact that most of the wind farm locations are always not in the same location of the meteorological measurement station (this is called the horizontal interpolation "from the grid points to the co-ordinate of the turbine") and the height of the used wind turbine is not the same height of the meteorological measurement station (this is called Vertical interpolation), prediction is needed. There also comes the role of the prediction tools that can help us with transferring the measured data (or even the predicted data from the NWP) to the location of interest. This is shown in Figure 1-2 with the wind speed prediction………. Constant time range/ Vertical and/or horizontal and that will lead to the fact that now we have the needed predicted data (from a measured/predicted input data) at the location of interest (Rabunal, 2006).

2.2. State-of-the-Art in Wind Power Prediction:

There is two different ways to transfer the output of the NWP to a power generated from the wind turbine (farm):

1- Statistical system
2- Physical system

2.2.1. Statistical system:

The statistical approach is based on training with the available measurement data. The idea is to derive a statistical relation between the given input from the weather prediction and the measured power output of wind turbine (farms). Hence, these systems completely rely on data analysis ignoring the meteorological details. For these systems we can use the artificial neural networks (ANN).

Several different methods to determine the relation between forecast and power output have been developed. One very prominent example is the system WPPT by the Danish Technical University. Another example is the system developed by ISET from Germany which provides forecasts for a number of German TSOs. The system works on artificial neural networks (ANN) which are trained with either historical wind farm data or measurements from transformer stations where a number of wind farms is connected. In addition, the system provides an online estimation of the wind power that is currently fed into the electrical grid based on extrapolating measurements at representative wind farms (Hayashi, 2009).

The advantage of statistical systems is clearly that the predictions are inherently adapted to the location of the wind farm such that systematical errors are automatically reduced. The disadvantage lies in the need for long-term measurement data and an additional effort for the training. Moreover, it is difficult for these systems to correctly predict rare atmospheric conditions if they appear too seldom during the training period. Unfortunately, a correct prediction of these rare situations is rather important and can otherwise lead to large forecast errors.

2.2.2. *Physical system:*

Physical systems use parameterizations based on a detailed physical description of the lower atmosphere. The calculation of the Power yield from a wind turbine can be carried out by using this simple Equation (Burton, 2001):

$$P = \frac{1}{2} c_p \rho v^3 A \qquad \text{Equation 1-1}$$

For this we need to get data about the density of the air in the studied location and the measured wind speed in that location, also it is important to know the swept area of the chosen wind turbine.

As we know that the energy yield per month/year/… is the multiplication of the power with time:

$$E = P \times t \qquad \text{Equation 1-2}$$

And to be able to calculate the power output of a wind turbine within a specific time in the future it is important to know the wind speed at the same exact time in the future. For that we will need to use a prediction tool that can give us the needed data (Like the NWP). Additionally this will help in the energy market management where the generated energy from the producers is given one day ahead to the coordination center that will manage this data and select the price of energy for the upcoming day. So in this tool we are using the normal methods for Energy calculation, but keep in mind that when we talk about a wind farm the weak losses and other parameters should be considered.

2. Chapter 2 ARTIFICIAL NEURAL NETWORKS

What are ANNs?

Why do we use ANN?

History of ANN

Benefits of ANN

Biological Model

WHAT ARE ANNs?

The term artificial neural network (ANN) has been conducted right after the recognition of the way the human brain computes. The human brain computes in an entirely different way from the conventional computer, the brain is a highly complex, nonlinear and parallel information processing system. The brain computing process to perform a certain computation is many times faster than the fastest digital computer in existence today, due to the capability to organize its structural constituents, known as neurons. The brain accomplishes perceptual recognition tasks routinely, e.g. recognizing familiar face embedded in an unfamiliar scene. A neural network is a machine that is designed to model the way in which the brain performs a particular task. The network is implemented by using electronic components or is simulated in software on a digital computer. A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network from its environment through a learning process.

2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective.

WHY DO WE USE NEURAL NETWORKS?

As neural networks can work in nonlinear way, it can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. With their great ability to give meaning for complex data or imprecise data, neural networks need training. A trained neural network can be describe as the learning process of humans in this case it can be thought of as “expert” in the category of information it has been given to analyze (e.g. in school the human will have a teacher for history and another one for physics, so an “expert in this particular information”). This expert (input training data) should be able to provide projections given new situations of interest and answer the “What is” questions. Other advantages include (KUMAR, 2009):

1. Adaptive learning**:** An ability to learn how to do tasks based on the data given for training or initial experience.

2. Self-Organization**:** An ANN can create its own organization or representation of the information it receives during learning time.

3. Real Time Operation**:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

HISTORY OF ANN

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback in several eras. Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert, published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis. Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding. The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to do too much.

BENEFITS OF ANN

1. They are extremely powerful computational devices.

2. Massive parallelism makes them very efficient.

3. They can learn and generalize from training data – so there is no need for enormous feats of programming.

3. They are particularly fault tolerant – this is equivalent to the “graceful degradation” found in biological systems.

4. They are very noise tolerant – so they can cope with situations where normal symbolic systems would have difficulty.

5. In principle, they can do anything a symbolic/logic system can do, and more

BIOLOGICAL MODEL

The human nervous system can be broken down into three stages that may be represented as follows:

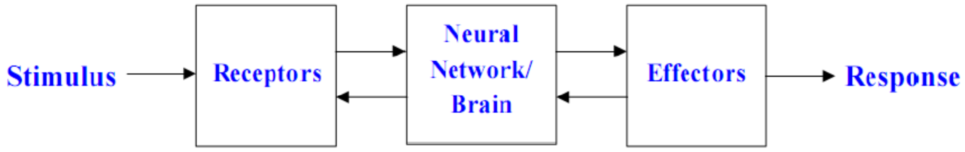


Figure 2-1 Block diagram of a human nervous system (KUMAR, 2009).

The receptors collect information from the environment. The effectors generate interactions with the environment e.g. activate muscles. The flow of information/activation is represented by arrows. There is a hierarchy of interwoven levels of organization:

1. Molecules and Ions

2. Synapses

3. Neuronal microcircuits

4. dendritic trees

5. Neurons

6. Local circuits

7. Inter-regional circuits

8. Central nervous system

There are approximately 10 billion neurons in the human cortex. Each biological neuron is connected to several thousands of other neurons. The typical operating speed of biological neurons is measured in milliseconds.

The majority of neurons encode their activations or outputs as a series of brief electrical pulses. The neuron s cell body processes the incoming activations and converts the into output activations. The neurons nucleus contains the genetic material in the form of DNA. This exists in most types of cells. Dendrites are fibers which emanate from the cell body and provide the receptive zones that receive activation from other neurons. Axons are fibers acting as transmission lines that send activation to other neurons. The junctions that allow signal transmission between axons and dendrites are called synapses. The process of transmission is by diffusion of chemicals called neurotransmitters across the synaptic cleft.

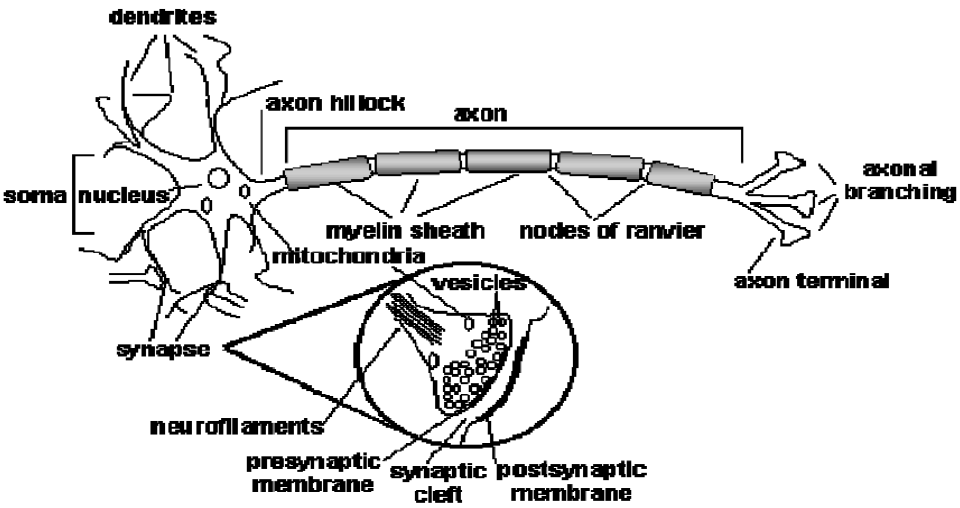


Figure 2-2 Schematic diagram of a biological neuron (KUMAR, 2009)

3. Chapter 3 STRUCTURE OF ANN

Mathematical Model of a Neuron

Network Architecture

Learning Process

MATHEMATICAL MODEL OF A NEURON

A neuron is an information processing unit that is fundamental to the operation of a neural network. The three basic elements of the neuron model are:

1. A set of weights, each of which is characterized by a strength of its own. A signal “xj” connected to neuron “k” is multiplied by the weight “wkj”. The weight of an artificial neuron may lie in a range that includes negative as well as positive values.

2. An adder for summing the input signals, weighted by the respective weights of the neuron.

3. An activation function for limiting the amplitude of the output of a neuron. It is also referred to as squashing function which squashes the amplitude range of the output signal to some finite value.

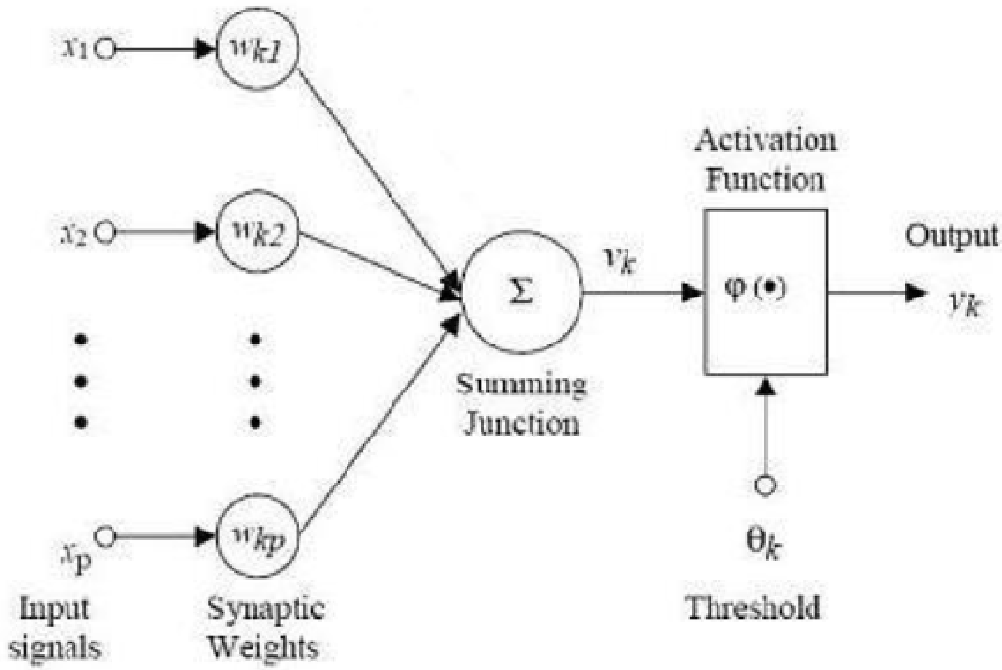


Figure 3-1 Model of ANN (KUMAR, 2009)

$$v_k = \sum_{j=1}^{p} w_{kj} \times x_j \quad \text{Equation 3-1}$$

And

$$y_k = \varphi(v_k + \theta_k) \quad \text{Equation 3-2}$$

NETWORK ARCHITECTURES

In the previous chapter we focused on the definition of a neural network, but in this one we will focus on classes of ANN. There are three fundamental different classes of network architectures (Freeman, 2001):

1) Single-layer Feed forward Networks:

In a layered neural network the neurons are organized in the form of layers. In the simplest form of a layered network, we have an input layer of source nodes that projects onto an output layer of neurons, but not vice versa. This network is strictly a Feed forward type. In single-layer network, there is only one input and one output layer. Input layer is not counted as a layer since no mathematical calculations take place at this layer. On other words a feed forward network is that data can flow only in one direction from the input layer through the hidden layers and finally to the output layer. There are no feedbacks connections presented in this type (in which connections are extended from the output layer into the input layer).

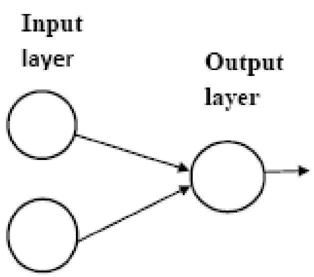


Figure 3-2 Single-layer feed forward Network (KUMAR, 2009)

2) Multilayer Feed forward Networks

The second type of a feed forward neural network is known by the presence of one or more hidden layers, whose computational nodes are correspondingly called hidden neurons. The prepuce of the hidden neuron is to add up more computation between the input layer and the output one of cores in some useful manner (e.g. improves the accuracy of the used network, enable the network to do more difficult operations and so on…). By having more hidden layers added, the network is enabled to comprehend more input data and extract higher order statistics. . The input signal is applied to the neurons in the second layer. The output signal of second layer is used as inputs to the third layer, and so on for the rest of the network.

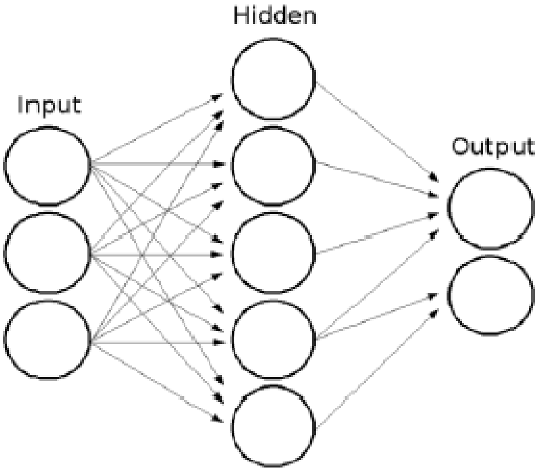


Figure 3-3 Multi-layer feed forward network (KUMAR, 2009)

3) Recurrent networks

A recurrent neural network has at least one feedback loop. A recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons. Self-feedback refers to a situation where the output of a neuron is fed back into its own input. The presence of feedback loops has a profound impact on the learning capability of the network and on its performance. On other words it can be said that the activation values of the units undergo a relaxation process such that the network will evolve to a stable state in which these activations do not change anymore.

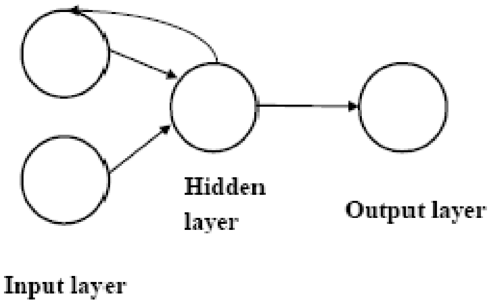
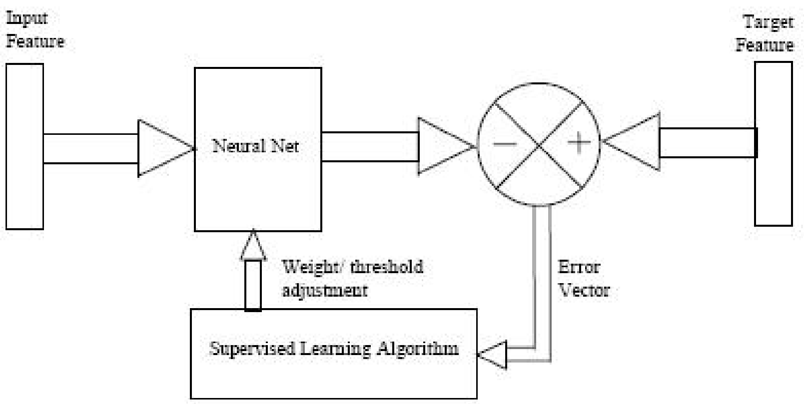


Figure 3-4 Recurrent network (KUMAR, 2009)

LEARNING PROCESSES

A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs (e.g. the pressure as input to produce the desired output "wind speed"). Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a *priori* knowledge. Another way is to "train" the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. By learning rule we mean a procedure for modifying the weights and biases of a network. The purpose of learning rule is to train the network to perform some task (e.g. wind speed prediction). They fall into three broad categories:



1. Supervised learning:

It is also called Associative learning the learning rule is provided with a set of training data of proper network behavior. As the inputs are applied to the network, the network outputs are compared to the targets. The inputs are applied either by an external teacher (the trainer) or by the system which contains the network (self-supervised). The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

2. Reinforcement learning:

It is similar to supervised learning, except that, instead of being provided with the correct output for each network input, the algorithm is only given a grade. The grade is a measure of the network performance over some sequence of inputs. Whenever the results (output) is getting a good grade (e.g. 10 means the output is the same as the measured value, 0 means the predicted output has nothing to do with the expected one) then the prediction is improves.

3. Unsupervised learning:

Also called self-organization in which the weights and biases are modified in response to network inputs only. There are no target outputs available. Most of these algorithms perform some kind of clustering operation. They learn to categorize the input patterns into a finite number of classes. In this type the network is trained in a way to respond to clusters of pattern within the input. In this case the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning type, there is no a *priori* set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli.

4. Chapter 4 BACK PROPAGATION ALGORITHM

Introduction

Learning Process

Flowchart

INTRODUCTION

Multiple layer perceptrons have been applied successfully to solve some difficult diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm. This algorithm is based on the error-correction learning rule. It may be viewed as a generalization of an equally popular adaptive filtering algorithm- the least mean square (LMS) algorithm. Error back-propagation learning consists of two passes through the different layers of the network: a forward pass and a backward pass (Turetsky, 2000). In the forward pass, an input vector is applied to the nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the weights of the networks are all fixed. During the backward pass, the weights are all adjusted in accordance with an error correction rule. The actual response of the network is subtracted from a desired response to produce an error signal. This error signal is then propagated backward through the network, against the direction of synaptic connections. The weights are adjusted to make the actual response of the network move closer to the desired response. A multilayer perceptron has three distinctive characteristics:

1. The model of each neuron in the network includes a nonlinear activation function. The sigmoid function is commonly used which is defined by the logistic function:

$$y = \frac{1}{1+e^{-x}} \qquad \text{Equation 4-1}$$

   Another commonly used function is hyperbolic tangent.

$$y = \frac{1-e^{-x}}{1+e^{-x}} \qquad \text{Equation 4-2}$$

   The presence of nonlinearities is important because otherwise the input- output relation of the network could be reduced to that of single layer perceptron.

2. The network contains one or more layers of hidden neurons that are not part of the input or output of the network. These hidden neurons enable the network to learn complex tasks.
3. The network exhibits a high degree of connectivity. A change in the connectivity of the network requires a change in the population of their weights.

LEARNING PROCESS

To illustrate the process a three layer neural network with two inputs and one output, which is shown in the picture below, is used.

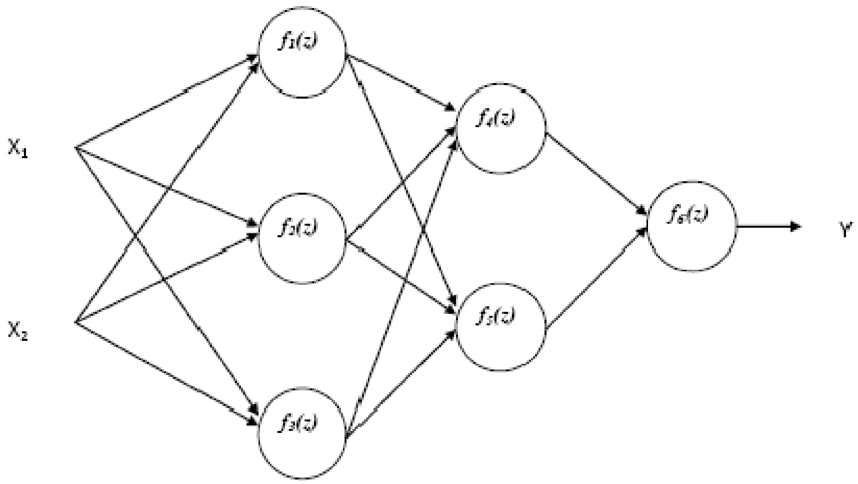


Figure 4-1 Three layer neural network with two inputs and single output (KUMAR, 2009)

Signal "z" is adder output signal, and "*y = f(z)*" is output signal of nonlinear element. Signal "*y*" is also output signal of neuron. The training data set consists of input signals (*x1* and *x2*) assigned with corresponding target (desired output) *y'*. The network training is an iterative process. In each iteration weights coefficients of nodes are modified using new data from training data set. Symbols "*wmn*" represent weights of connections between output of neuron "*m*" and input of neuron "*n*" in the next layer. Symbols "*yn*" represents output signal of neuron n.

$$y_1 = f_1(w_{11}x_1 + w_{21}x_2)$$ Equation 4-3

$$y_2 = f_2(w_{12}x_1 + w_{22}x_2)$$ Equation 4-4

$$y_3 = f_3(w_{13}x_1 + w_{23}x_2)$$ Equation 4-5

$$y_4 = f_4(w_{14}y_1 + w_{24}y_2 + w_{34}y_3)$$ Equation 4-6

$$y_5 = f_5(w_{15}y_1 + w_{25}y_2 + w_{35}y_3)$$ Equation 4-7

$$y_6 = f_6(w_{46}y_4 + w_{56}y_5)$$ Equation 4-8

The desired output value (the target), which is found in training data set. The difference is called error signal δ of output layer neuron.

$$\delta = y' - y$$ Equation 4-9

$$\delta_4 = w_{46}\delta$$ Equation 4-10

$$\delta_5 = w_{56}\delta$$ Equation 4-11

$$\delta_3 = w_{34}\delta_4 + w_{35}\delta_5$$ Equation 4-12

$$\delta_2 = w_{24}\delta_4 + w_{25}\delta_5$$ Equation 4-13

$$\delta_1 = w_{14}\delta_4 + w_{15}\delta_5 \qquad \text{Equation 4-14}$$

When the error signal for each neuron is computed, the weights coefficients of each neuron input node may be modified. In formulas below *df(z)/dz* represents derivative of neuron activation function. The correction *wij(n)* applied to the weight connecting neuron *j* to neuron *i* is defined by the delta rule: Weight correction = learning rate parameter*local gradient*i/p signal of neuron *i*

$$\Delta w_{ij}(n) = \eta.\delta_i(n).y_j(n) \qquad \text{Equation 4-15}$$

The local gradient *δi(n)* depends on whether neuron i is an output node or a hidden node:

1- If neuron *i* is an output node, *δi(n)* equals the product of the derivative *dfi(z)/dz* and the error signal *ei(n)*, both of which are associated with neuron i.

2- If neuron *j* is a hidden node, *δi(n)* equals the product of the associated derivative *dfi(z)/dz* and the weighted sum of the *δs* computed for the neurons in the next hidden or output layer that are connected to neuron *j*.

FLOW CHART

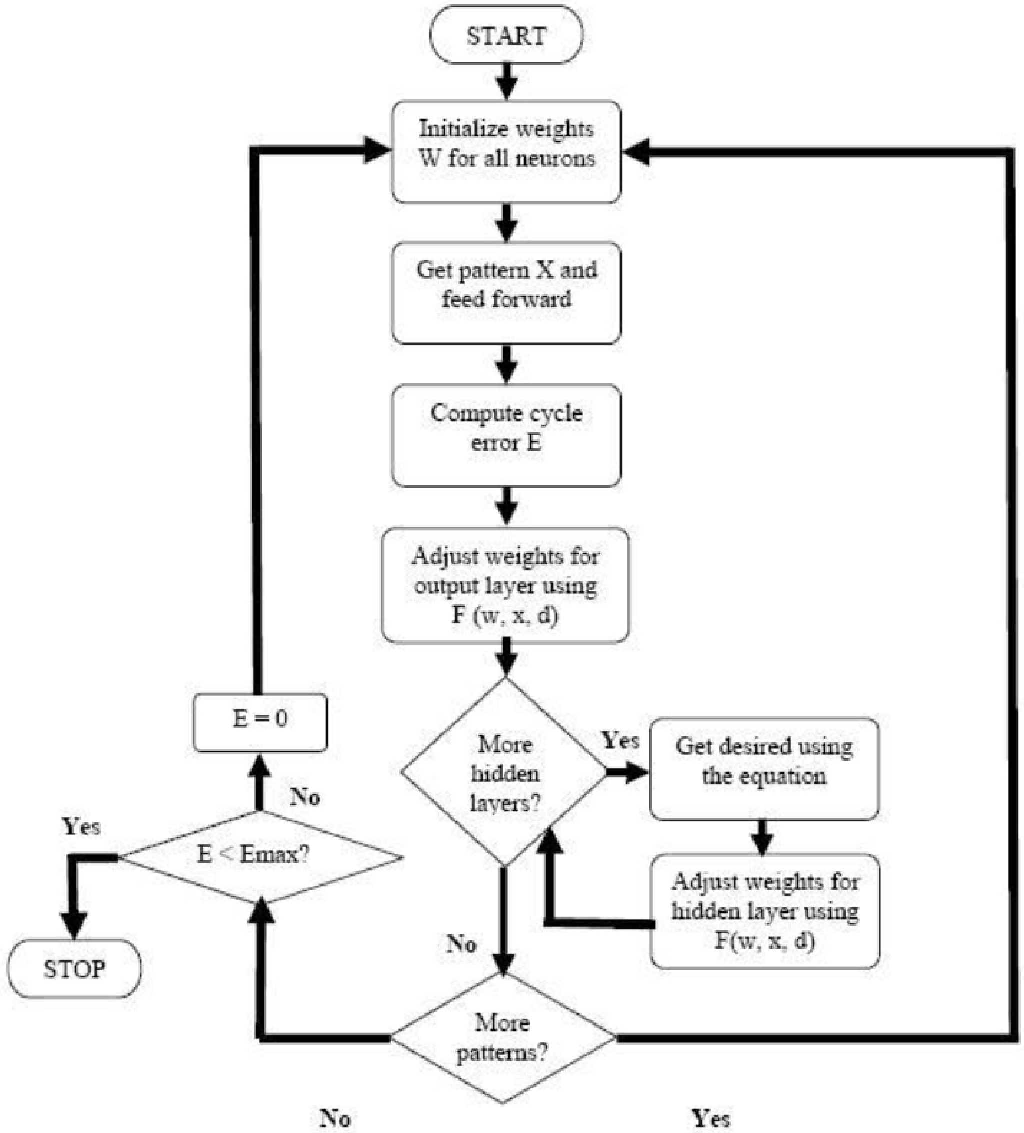


Figure 4-2 Flowchart showing working of BPA **(KUMAR, 2009)**

5. Chapter 5 building the artificial neural network:

Introduction

Practical work step

5.1. Introduction:

In this part we will discuss the work and Pre- work that has been done to build the proposed prediction tool for wind speed using the ANN, and that can be classified as:

1- Data acquisition & pre-processing.
2- Data Conversion & Normalization.
3- Statistical Analysis.
4- Design of Neural Network.
5- Training.
6- Testing.
7- Energy calculation.

The next figure can show the work parts that are to be done in this chapter:

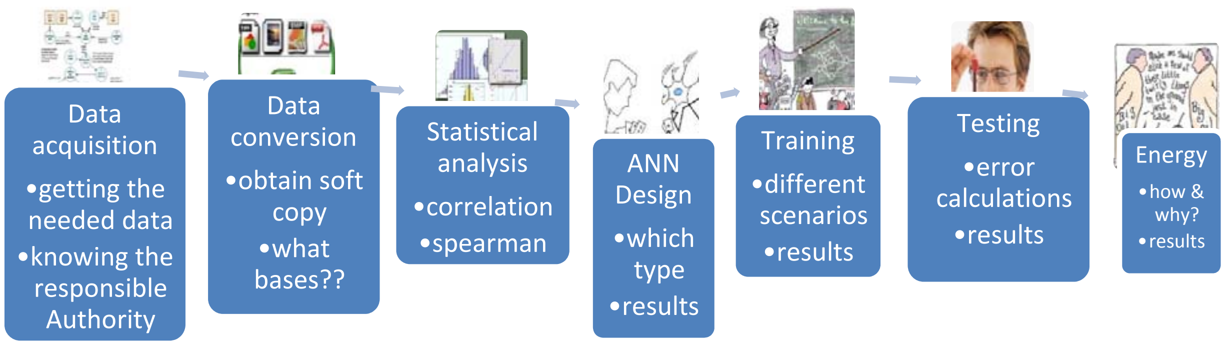


Figure 5.1-1 the steps used for wind energy prediction

5.2. Practical work steps:

5.2.1. Data acquisition & pre-processing:

In this stage data collection has been done to the location of interest. The available data about the selected location is the pressure, temperature, wind speed and wind direction for two different heights. Unfortunately the available data was not complete for all years for Example the data of year 2008 was only available for one month and almost ten days. This fact will lead to more work in the data normalization and also the data were not available for all heights.

Table 5.2—1 available data about the selected location

station	day	hour	speed 40 s wvt	direct 40 d1 wvt	direct 40 sd1 wvt	speed 40 max	speed 40 std	speed 10 avg	speed 10 max	speed 10 std	temp	pressure
14	1	0	1.656	199.8	8.55	2.01	0.183	1.184	1.57	0.142	3.344	947.24
14	1	10	1.549	185.6	9.74	1.91	0.164	1.136	1.47	0.097	3.581	947.1
…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…
14	366	2230	2.803	278.1	8.74	4.71	0.643	2.579	3.73	0.48	3.624	945.58
14	366	2240	3.069	282.2	7.22	4.29	0.385	2.593	3.55	0.379	3.392	945.68

5.2.2. Data Conversion & Normalization:

A software copy of the measured data has been created in this stage and normalized as it is divided by the max value of every parameter. Also the data was reduced due to the fact that the Excel sheet will not be able to take the complete number of wind reading, the Matlab memory usage will be at its max and the reading of year 2008 are not completely available. The expected total number of reading for one year (as every ten minute a reading is registered) is the number of 10 min in one hour multiplied by the number of hours in one day and finally by the number of days in the year and that gives 52560/reading/. As the year 2008 was not completely available all the years (from 2004—till—2007) were reduced to match the number of reading of year 2008 (that was 5980). In this step the data is now ready to be used in the statistical analysis & as input of the ANN prediction tool.

5.2.3. Statistical Analysis:

Before starting with characteristics of the proposed wind speed prediction tool it was important to analysis the available data (Input, Target data of the ANN tool), as the input, Target data is a measured data of wind speed, pressure, Temperature and direction with reading every 10 minute there it is a huge amount of input data that need to be calcified as importance (in this step the data can be used as in the row data or after conversion).

The usage of the row data (without normalization) will give better results but will not overcome the problems of incorrect measurement or unexpected wind changes in direction or speed. Still the row data was used in this step because those effects are not visible when dealing with data between different years (it will be more visible when using the data of the same year with different heights for example).

This can be done by statistical analysis to this input data in order to find the strength of the relationship between the different input data specially to be related to the wind speed (the parameter of interest for prediction).

Correlation analysis is a statistical tool which studies the relationship between two variables (K.Sreelakshmi, 2008).

5.2.3.1. Correlation analysis:

5.2.3.2. Introduction:

Correlation analysis involves methods and techniques used for studying and measuring the extent of the relationship between two variables. In other words, correlation analysis is statistical procedure by which we can determine the degree of association or relationship between two or more variables. The amount of correlation in a sample (of data) is measured by the sample coefficient of correlation, which is, generally, denoted by ‘r’ or by ‘ρ’. (S.Chand, 2009)

5.2.3.3. Coefficient of correlation:

Correlation may be defined as a tendency towards interrelation variation and the coefficient of correlation is a measure of such a tendency, i.e., the degree to which the two variables are interrelated is measured by a coefficient which is called the coefficient of correlation. It gives the degree of correlation.

5.2.3.4. Properties of coefficient of correlation:

1- It is a measure of the closeness of a fit in a relative sense.
2- Correlation coefficient lies between ‘-1’ and ‘+1’, i.e., $-1 \leq r \leq +1$.
3- The correlation is prefect and positive if ‘r=1’ and is perfect and negative if ‘r=-1’.
4- If ‘r=0’, then there is no correlation between the two variables and thus the variables are said to be independent.
5- The correlation coefficient is a pure number and is not affected by a change if origin and scale in magnitude.

5.2.3.5. Types of correlations:

1- Positive correlation (if the values of the two variables deviate in the same direction).
2- Negative or inverse correlation (if the values of the two variables deviate in opposite direction).
3- Linear correlation (if the plotted points are approximately on or near about a straight line).
4- Perfectly linear correlation (when all the plotted points lie exactly on a straight line).
5- Perfect correlation (if the deviation in one variable is followed by a corresponding and proportional deviation in the other).
6- Direct of perfect positive correlation (if the correlation is perfectly linear and the line runs from the lower left hand corner to the upper right hand corner).
7- Inverse or perfect negative correlation (if the correlation is perfectly linear and the line runs from the upper left hand corner to the lower right hand corner).
8- High degree positive correlation
9- High degree negative correlation

10- No correlation
11- Curvilinear correlation

5.2.3.6. *Methods to study correlation:*

1- Scatter diagram method or Dot diagram method.
2- Karl Perason's coefficient of correlation method.
3- Spearman's rank correlation method.
4- Concurrent deviation.
5- Two-way frequency table method.

5.2.4. Spearman's rank correlation coefficient:

The coefficient of rank correlation is based on the various values of the variates and is denoted by 'R'. It is applied to the problems in which data cannot be measured quantitatively but qualitative assessment is possible. In this case the vest individual is given rank number 1, next rank 2 and so on; this coefficient of rank correlation is given by the formula:

$$R = 1 - \frac{6 \times \Sigma D^2}{n(n^2-1)} \qquad \text{Equation 5.2-1}$$

Where D^2 is the square of the difference of corresponding ranks, and 'n' is the number if pairs of observations.

5.2.4.1. Our case:

In our case we don't have the ranking given with the data of interest (pressure, temperature, direction and wind speed) and duplication is available in the data that is why using Spearman's when equal ranks are given to more than two attributes will be needed.

If two or more individuals are placed together in any classification with respect to an attribute, i.e., if in case of variable data, that are more than one item with the same rank in either or both the series (i.e. **Tie Rank**) then the Spearman's Rank correlation coefficient formula given above (Equation number one) does not give the correlation coefficient for tie rank. The problem is solved by assigning average rank to each of these individuals who are put in tie. In order to find the rank correlation coefficient of repeated ranks or tie ranks, an adjustment or correction factor is added to the Spearman's rank correlation formula. This factor is given as:

$$correction\ factor = \frac{m(m^2-1)}{12} \qquad \text{Equation 5.2-2}$$

Where 'm' is the number of times an item is repeated. This correction factor is to be added for each repeated value in both the series.

$$R = 1 - \frac{6\left[\Sigma D^2 + \frac{m_1(m_1^2-1)}{12} + \frac{m_2(m_2^2-1)}{12} + \frac{m_3(m_3^2-1)}{12} + \cdots\right]}{n(n^2-1)} \qquad \text{Equation 5.2-3}$$

When applying the last equation (3) on our data it is important to keep in your mind the following notes:

1- You need to keep the same order of the data as it is given (whatever you do with the data you have to make sure that the same value of first variable ‘X’ is still corresponding to the same first value of the second variable ‘Y’ and so on).
2- Higher wind speed values are the one of interest for us that is why we are using Spearman’s ranking method of correlation.
3- Make sure that repeated data will take the same rank value and will be averaged afterword.
4- Make sure that the value directly coming after the repeated one is taking the next value of ranking without repeating taken into consideration.

5.2.5. Design of Neural Network:

This part will be done in two distinguished steps:

1- No prediction with time is done: the wind speed of one year is predicted from the Pressure, Temperature and wind direction of the same year [3].
2- Prediction with time is done: the wind data of one year is used as input to predict the wind speed of the next year.
3- The final approach of the suggested wind speed prediction tool.

5.2.5.1. No prediction with time is done:

At the beginning the approach was to get familiar with the neural network tool used in Matlab program by trying to build a very basic and simple ANN tool for wind speed prediction from a well-known input data like the available pressure, temperature, and wind direction for sure to predict the wind speed.

The purpose of this basic apportion is to use the different available options in the Matlab tool (Like different training function, activation function, and validation function possibilities). And for that reason the first ANN tool was built to get the wind speed curve as an output from a pressure, temperature, and wind direction input.

With this type of system no prediction of wind speed for the future is made only prediction of wind speed of the same year input data is done. As already motioned in the theoretical part that the ANN can be made as more than one hidden layer and in every hidden layer any number of neurons can be achieved, also the training function can be easily changed. But how to know what is the best for our ANN tool??

---

[3] Another approach was also to predict the wind speed of one year from the wind speed data of the same year. This approach is used in order to get the difference between the different variable in the prediction tool. Like the training functions, activation functions and so on. The results of this approach are not shown in this work. Yet it is done.

It is important to have some general notes about the selection of a good training data, sizing of the network, and so on……

5.2.5.2. General notes:

1- Training data: Unfortunately there is no single definition that applies to all cases. As with many aspects of neural-network systems, experience is often the best teacher. As you gain facility with using networks, you will also gain an appreciation for how to select and prepare training sets. Thus we shall give only a few guidelines here.
   In general, you can use as many data as you have available to train the network, although you may not need to use them all. From the available training data, a small subset is often all that you need to train a network successfully. The remaining data can be used to test the network to verify that the network can perform the desired mapping on input vectors it has never encountered during training.
2- If you are training a network to perform in a noisy environment, such as the pixel-image-to ASCII example, then including some noisy input vectors in the data set. Sometimes the addition of noise to the input vectors during training helps the network to converge even if no noise is expected on the inputs.
3- Make sure that the training data cover the entire expected input space. During the training process, training vector pairs is randomly selected from the set of inputs that is why in any event don't train the network completely with input vectors of one class, and then switch to another class because the network will forget the original training.
4- If the output function is Sigmoidal, then you will have to scale the output values. Because of the form of the Sigmoid function, the network outputs can never reach 0 or 1. Therefore, use values such as 0.1 and 0.9 to represent the smallest and largest output values.
5- You can shift the Sigmoid so that, for example, the limiting values become (+-) 0.4. Moreover, you can change the slope of the linear portion of the Sigmoid curve by including a multiplicative constant in the exponential. There are many such possibilities that depend largely on the problem being solved Sigmoid are often called "squashing" functions, because they compress an infinite input range into a finite output range. Sigmoid functions are characterized by the fact that their slopes must approach zero as the input gets large. This causes a problem when you use steepest descent to train a multilayer network with sigmoid functions, because the gradient can have a very small magnitude and, therefore, cause small changes in the weights and biases, even though the weights and biases are far from their optimal values. The purpose of the resilient backpropagation (Rprop) training algorithm is to eliminate these harmful effects of the magnitudes of the partial derivatives.

1- Network sizing: Just how many nodes are needed to solve a particular problem? Are three layers always sufficient? As with the questions concerning proper training data, there are not strict answers to questions such as these. Generally, three layers are sufficient. Sometimes, however, a problem seems to be "easier" to solve with more than one hidden layer. In this case, "easier" means that the network learns faster.

   The size of the input layer is usually dictated by the nature of the application. You can often determine the number of output nodes by deciding whether you want analog values or binary values on the output unites.

   Determining the number of the units to use in the hidden layer is not usually as straightforward as it is for the input and output layers. The main idea is to use as few hidden-layer units as possible, because each unit adds to the load in the CPU during simulations. Finally we can say that the size of the hidden layer needs to be only a relatively small fraction of the input layer. If the network fails to converge to a solution then maybe that more hidden nodes are required. If it does converge, you might try fewer hidden nodes and settle on a size on the basis of overall system performance.

   It is also possible to remove hidden units that are superfluous. If you examine the weight values on the hidden nodes periodically as the network trains, you will see that weights on certain nodes change very little from their starting values. These nodes may not be participating in the learning process, and fewer hidden units may suffice. There is also an automatic method, developed by Rumelhart, for pruning unneeded nodes from the network (Focken, 1988).

2- Weights and learning parameters: Weights should be initialized to small, random values / say between (+-)0.5/ as for the bias it is common to treat it as another weight. Selection of the value for the learning rate parameter,η, has a significant effect on the network performance. Usually – η- must be a small number /on the order of 0.05 to 0.25/ to ensure that the network will settle to a solution. A small value of η means that the network will have to make a large number of iterations, but that is the price to be paid. It is often possible to increase the size of η as learning proceeds. Increasing η as the network error decreases will often help to speed convergence by increasing the step size as the error reaches a minimum, but the network may bounce around too far from the actual minimum value if η gets too large. To avoid this problem we usually use the momentum technique to increase the speed of convergence and to stay on the right curse of the errors. Another way speeding the convergence is the local minimum Figure 5.2-1 illustrate the idea where u can see that if the weighting changes to the minimum at a local point is different that global minimum (z_{min}) this will lead to unacceptable high error. Fortunately, this problem does not appear to cause much difficulty in practice. If a network stops learning before reaching an acceptable solution, a change in the number of hidden nodes or in the learning parameters will often fix the problem; of we can simply start over with a different set of initial weights. When a network reaches an acceptable solution there is no guarantee that it has reached the global minimum rather than a local one. If the solution is acceptable from an error standpoint, it does not matter whether the minimum is global or local, or even whether the training was halted at some point before a true minimum was reached.

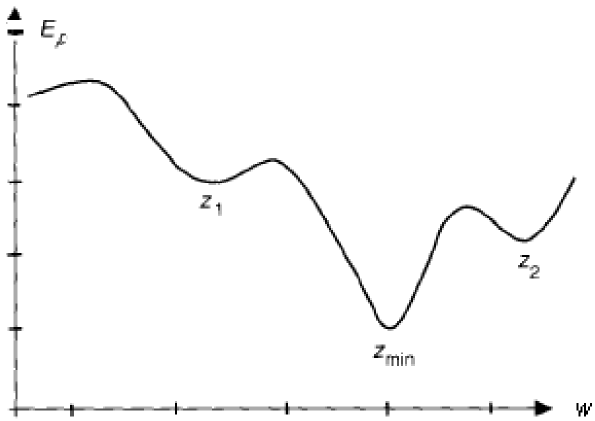


Figure 5.2-1 Local and global minimum

5.2.5.3. With time prediction tool:

This time the neural network is trained on the data of the year 2007 to produce the wind speed of 2008 and so on. So in this case the effect of different characteristic of wind speed will be obvious and also hard to overcome. For that it is important to get an idea how the neural network in Matlab works.

5.2.6. Regression Analysis:

We know that the correlation studies the relationship between two variables X and Y. in this part, we shall consider the related problem of prediction or estimation of the value of one variable from a known value of other variable to which it is related. When there are two variables X and Y and if Y is influenced by X (in our case how the wind speed (Y) is affected by the (X) pressure, Temperature, Wind direction /or previous wind speed data/), i.e., if Y depends on X, then we get a simple linear regression or simple regression equation of 'Y on X'. Here Y is known as dependent variable or regression or explained variable and X is known as independent variable or predictor or explanatory (S.Chand, 2009).

Regression shows a relationship between the average values of two variables. Thus regression is very helpful in estimating and predicting the average value of one variable for a given value of the other variable. The estimate or prediction may be made with the help of a regression line which shows the average value of one variable 'x' for a given value of the other variable 'y'. The best average value of one variable associated with the given value of the other variable may also be estimated or predicted by means of an equation and the equation is known as regression equation.

5.2.6.1. *Types of regression:*

1- Simple regression: the regression analysis confined to the study of only two variables at a time.
2- Multiple regressions: the regression analysis for studying more than two variables at a time.
3- Linear regression: if the regression curve is a straight line, then there is a linear regression between the two variables under study. In other words, in linear regression the relationship between the two variables X and Y is linear.

In order to estimate the best average values of the two variables, two regression equations are required and they are used separately. One equation is used for estimating the value of X variable for a given value of Y variable and the second equation is used for estimating the value of Y variable for a given value of X variable. In both cases, the assumption is that one is an independent variable and the other is a dependent variable and vice versa.

5.2.6.2. *Utility of regression analysis:*

1- The cause and effect relations are indicated for the study of regression analysis.
2- It establishes the rate of change in one variable in terms of the changes in another variable.
3- It is useful in economic analysis as regression equation can determine an increase in the cost of living index for a particular increase in general price level.
4- It helps in prediction and thus it can estimate the values of unknown quantities.
5- It helps in determining the coefficient of correlation as: $r = \sqrt{b_{yx} \times b_{xy}}$.
6- It enables us to study the nature of relation between the variables.
7- It can be useful to all natural, social and physical sciences, where the data are in functional relationship.

5.2.6.3. *Lines of regressions:*

A line of regression is the line which gives the best estimate of one variable X for any given value of the other variable Y. so it can be said that the line of regression of X on Y is the line which gives the best estimate for the values of X for a specified value of Y (the exact opposite can be said on the line of regression of Y on X).

5.2.6.4. *Regression coefficients:*

There are two regression coefficients (Y on X) $b_{yx} = r \times \frac{\sigma_y}{\sigma_x}$ and (X on Y) $b_{xy} = r \times \frac{\sigma_x}{\sigma_y}$

5.2.6.5. *Properties of regression coefficients:*

1- The correlation coefficient is the geometric mean of the regression coefficients i.e., $r = \sqrt{b_{yx} \times b_{xy}}$.
2- If one of the regression coefficients is greater than unity, then the other is less than unity.
3- Arithmetic mean of the regression coefficient is greater that the correlation coefficient.

4- Regression coefficients are independent of change of origin but not of scale.
5- Both regression coefficients will have the same sign, i.e., either both are positive or both are negative.
6- The sign of correlation coefficient is same as that of regression coefficients, i.e., r>0 if b_{xy}>0 and b_{yx}>0; and r<0 if regression coefficients are negative.

With that information we can have an idea about the charts that appear in Matlab ANN tool under the bottom regression [4].

5.2.7. Training:

In this step there is no direct low or formula to get the exact number of neurons or what is the right training function to be used. A try and error method can be used in this case. The different possibility can be carried out and the best will be chosen. The testing part can show in details the best results of this part. For example the fastest training function is generally trainlm, and it is the default training function for feedforwardnet. The quasi-Newton method, trainbfg, is also quite fast. Both of these methods tend to be less efficient for large networks (with thousands of weights), since they require more memory and more computation time for these cases. Also, trainlm performs better on function fitting (nonlinear regression) problems than on pattern recognition problems (Matlab, 2010).

5.2.8. Testing:

In this part we will try to determine the accuracy of the proposed ANN tool for wind prediction.

5.2.8.1. Detailed results analysis:

After giving a good idea about the expected results of the used ANN tool for wind speed prediction (refer to spearman's rank correlation & Regression analysis), a method for accuracy is needed. By accuracy we mean the ability to calculate the error of the prediction and be able to compare results of the different proposed prediction tools. The most used way of error calculation is the Root mean square deviation.

5.2.8.2. Root mean square deviation:

The root mean square deviation (RMSD) or root mean square error (RMSE) is a frequently-used measure of the differences between values predicted by a model or an estimator and the values actually observed from the thing being modeled or estimated. RMSD is a good measure of precision. These individual differences are also called residuals, and the RMSD serves to aggregate them into a single measure of predictive power. (Wikipedia®, http://en.wikipedia.org/wiki/Root_mean_square_deviation, 2010)

[4] Not shown in this work yet included in the CD

$$RMSD = \sqrt{MSE(x')} = \sqrt{\frac{\sum_{i=1}^{n}(x_i' - x_i)^2}{n}}$$ Equation 5.2-4

Where:

- "n" is the total number of reading (in our case is the total number of measurement available used as target data of the ANN tool for prediction).

- "x_i'" is the "I" value of the predicted parameter.

- "x_i" is the "I" value of the measured parameter.

With this step done we can now have more accurate understanding of the output results not only a general over view like before. The result of this analysis will help in differentiating between the different results and is a very important parameter for the next step of energy prediction (where the error of this step should be as small as possible so that it will not have that negative effect on the next step of energy prediction tool).

5.2.9. Energy calculations:

After the work that has been done on the wind speed prediction and with the results that we got we can now move to the energy perspective. As mentioned earlier the output of this wind speed prediction tool can be an input to an Energy prediction tool (to predict the amount of energy generated by a wind farm). The question will be now why do we need this type of tool when we have a good predicted wind speed as input and good programs (which means mathematical equations) to calculate the energy??
In this part of the thesis we will try to answer this question.

5.2.9.1. Energy prediction for wind farm:

The energy produced from a specific wind farm can be affected by different factors [5]:

1- The changes in the wind speed & direction (emergency stops due to high winds)
2- Recovery times for routine maintenance
3- Stops due to authorities
4- Stops due to grid outage, lightning strike or ice accumulation
5- Other reasons.

And those factors are not always the same for all wind farms and not always measured. That is why the energy prediction is necessary where with methods those factors can be taken into consideration in the training stage of the proposed prediction tool. As a result it can be said that the energy predicted from an energy prediction tool not only take the mathematical relation between the wind speed and the power generated from the wind farm but also takes all other factors that can be seen or not and lead to a specific energy prediction tool to a specific location.

[5] More detailed factors are mentioned in chapter 7 in Energy yield calculation paragraph

Unfortunately for our location of interest there is no previous wind energy measurement (no old wind farms in the area of AL Hijana) that is why no Energy prediction tool can be built in our case.

5.2.9.2. Our case:

After this introduction what can be done is a "normal" (mathematical) calculation to the energy coming from one turbine, then includes the wind farm time factors into the calculation and the awake effect between turbines to get the energy yield from this wind farm.

The generated data coming as an output of the wind speed prediction tool can be used as input to an energy calculator module build in Matlab or directly used in any wind energy program like the WASP program or WindPro program [6].

The possibility of using the WASP program, the Matlab module and the manual calculation is done in this work. Only the Matlab module will be shown now the other cases are to be shown later.

5.2.9.3. Matlab one wind turbine energy module:

The most important information needed to build this module is:

1- The data of wind speed for the location of interest.
2- The power curve of the proposed wind turbine.
3- Other parameters about the selected location.

5.2.9.3.1. Wind speed data:

The data of the wind speed can be taken from the built prediction tool for the different available years. All the assumptions about the wind data are acceptable for the energy module.

This data should be entered to the module as an input signal and for that a signal builder was used. In each signal builder two signal where generated for the same year.

1- The predicted wind speed (comes from the prediction tool).
2- The measured wind speed (comes from the measurement).

In this case the time signal is taken to be the same time of simulation.

5.2.9.3.2. Power curve data:

The data of the power curve can be taken from any available data sheet of any wind turbine [7]. For our case the data was provided by the WASP exemplary wind turbine files.

---

[6] Only the Matlab results are included in this work.
[7] The criteria of selecting the wind turbine is discussed fully in chapter 7

Table 5.2.9—1 the power curve of the selected wind turbine

Speed [m/s]	Power [MW]	Thrust coefficient
4	0.091	0.8598
5	0.2	0.8356
6	0.362	0.8356
7	0.588	0.8351
8	0.889	0.8189
9	1.256	0.7631
10	1.637	0.6813
11	1.904	0.5515
12	1.988	0.4096
13	1.999	0.3091
14	2	0.2421
15	2	0.1947
16	2	0.1597
17	2	0.1331
18	2	0.1125
19	2	0.0961
20	2	0.0829
21	2	0.0722
22	2	0.0633
23	2	0.056
24	2	0.0501
25	2	0.0453

Table 5.2.9—1 shows the information of the selected wind turbine. And when drawing those data we can get the power curve of the 2 MW selected wind turbine.
That information can be entered to the module by using a look-up table. The first two columns of Table 5.2.9—1 are the important information to be entered. Of course the values of wind speed below /4[m/s]/ will generate zero power output and also wind speed values higher than /25[m/s]/ will Couse no generation.

5.2.9.3.3. Other parameters:

It is important to understand that the power carve of the used wind turbine is given at one value of air density and fixed hub height. So it is important to be able to assume that the air density of our location is almost constant and it’s the same as the one of the selected wind turbine. And for the hub height it is important to draw the roughness curve of the location of interest to be able to say that the changes in wind speed with higher heights are neglected.
For our location the surface was not covered with any type of planes and only small hells with short heights are available that is why the roughness of the area can be take of about 0.25 (Mathew D. S., 2007).

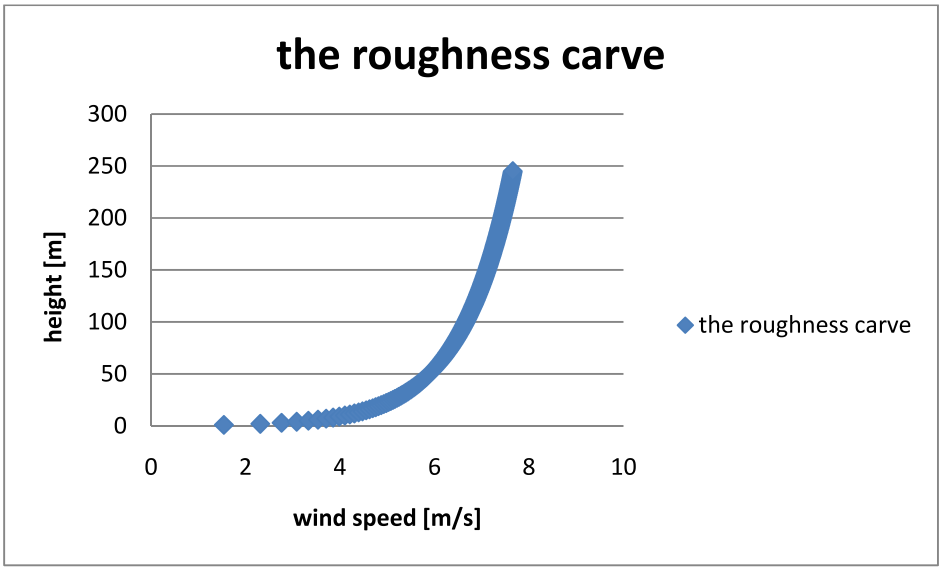


Figure 5.2.9-1 Roughness curve of AL_Hijana location

This figure shows the difference of the wind speed with high for the location. And it can be seen that the changes in the wind between the measured one (40 [m] height) and the hub of the selected wind turbine (105 [m]) is not neglected (a factor of = 2.6[m/s]).

Finally to be able to calculate the energy for a wind farm not only wind turbine the factor of losses should be included (like, awake losses, maintenance factor and others), unfortunately not done in this work of this section.

6. Chapter 6 Technical study

The steps of sizing a wind farm

Implementing the proposed wind farm by using WASP program

6.1.Introduction:

In this part we will concentrate of the sizing of the desired wind farm from the technical point of view with sizing of the different component (Wind turbines, transformers, Cables…… [8])

6.2.The available area of the Wind farm:

From the site information we were able to get the available area that can be used for this study and that was an open area that is completely a desert and owned by the government. This makes it easier in the study to select the most suitable location we want (which means the location with more information available and less obstacles). (Electricity, 2009)

6.3.The calculation of the wind speed:

We were able to get access to the wind data for the metrological station in the location of interest (ALHigana, Syria in this case). The measurement mast was erected on September 14th 2005 and is equipped with the following sensors

- Anemometer at 40m height
- Anemometer at 10m height
- Wind vane at 40m height
- Temperature sensor
- Pressure sensor

Data are recorded in 10 min intervals as mean values (for all parameters) as well as maximum instantaneous values and standard deviation (for the wind speed) within the recording interval.

The available data series ranges from September 14th 2005 to September 28th 2006. For the further calculations a 12-month data cycle from September16th 2005 to September 15th 2006 was used (Decon, 2005).

This data need to be evaluated and pre-prepared before it can be used as an input to the proposed wind turbine in the wind farm, for that we need to get the frequency distribution for the different intervals selected for the wind speed. Table 6—1 shows the selected intervals with frequency of occurrences for the wind speed in that interval.

[8] Some parts are done by my other colleges in this program with different work that is provided as a reference.

Intervals		Frequency
0	0.5	148
0.5	1.5	1032
1.5	2.5	1333
2.5	3.5	922
3.5	4.5	525
4.5	5.5	403
5.5	6.5	324
6.5	7.5	270
7.5	8.5	292
8.5	9.5	261
9.5	10.5	166
10.5	11.5	121
11.5	12.5	76
12.5	13.5	42
13.5	14.5	22
14.5	15.5	20
15.5	16.5	18
16.5	17.5	5
17.5	18.5	0
18.5	19.5	0
19.5	20.5	0
20.5	21.5	0

Table 6—1- frequency distribution

After getting that information we can get the cumulative hour's curve which is important for choosing the wind turbine (The cumulative frequency indicates as a percentage the period within a year in which the wind speed falls below the value of a certain point on the curve (Wikipedia®, 1, 2010).) By using the cumulative frequency, the "mean annual wind speed" can be accurately defined and represented geometrically).Figure 6-1 and Figure 6-2 - shows both the frequency distribution carve and the cumulative hours.

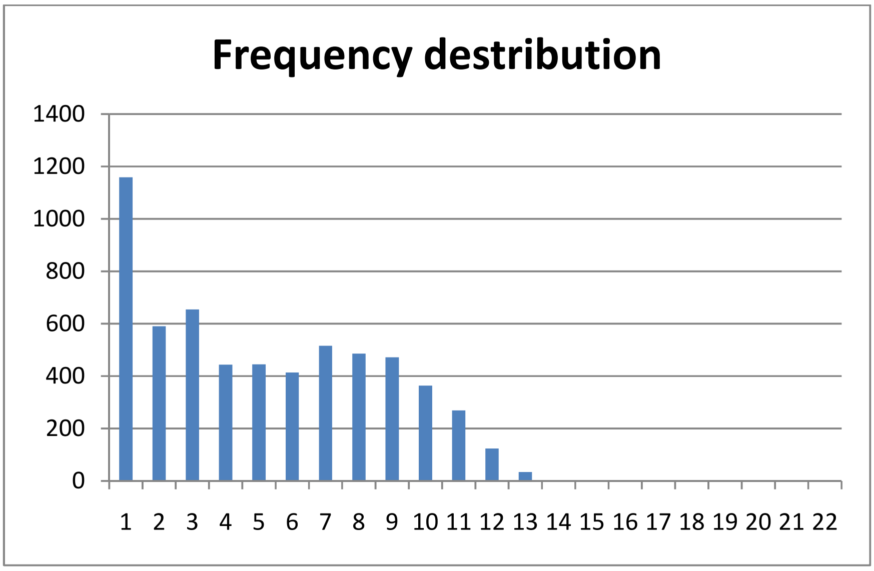


Figure 6-1 frequency distribution

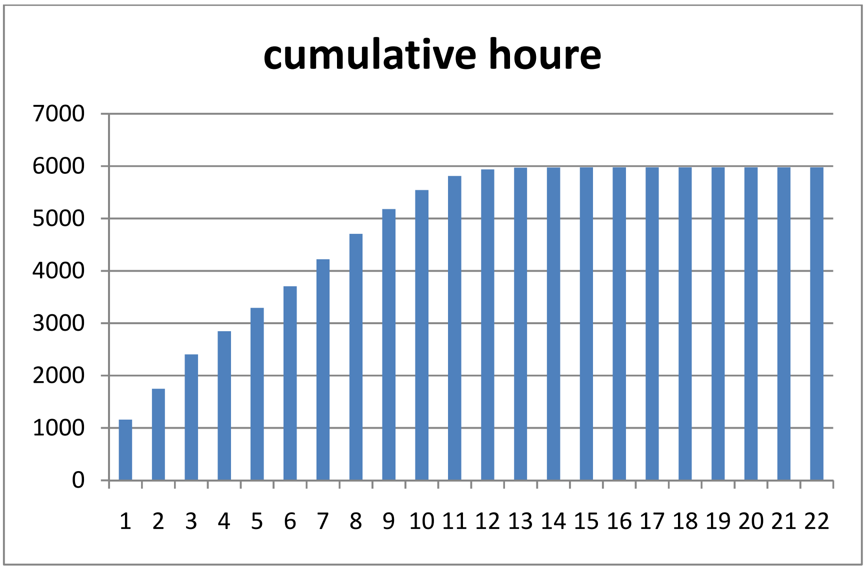


Figure 6-2 cumulative hours

6.4.Site analysis:

After getting the above information we can now try to analysis the site wind situation by getting the Weibull/Rayeigh distribution which can help in getting the probability distribution of the wind speed (this distribution gives the answer for the question what is the probability of a specific wind speed of happening??) that can lead directly to the choosing of our wind turbine, because with this distribution we can know the prevailing wind speed in a location (the most wind speed that occur in a specific site/ It is defined as the wind speed with a cumulative frequency of 50% and, as a rule, it is 0.3 to 0.5 m/s lower than the mean wind speed/). For more detailed information about the calculation of those distribution Please refer to appendix A

The results for both Weibull and Rayleigh distribution are shown in Figure 6-3-Figure 6-4

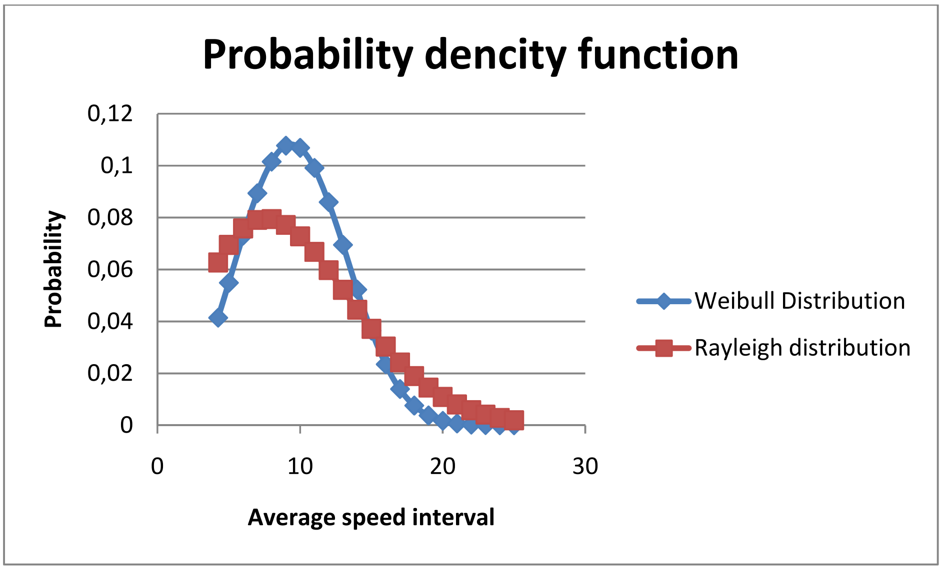


Figure 6-3 the probability density function of both distributions

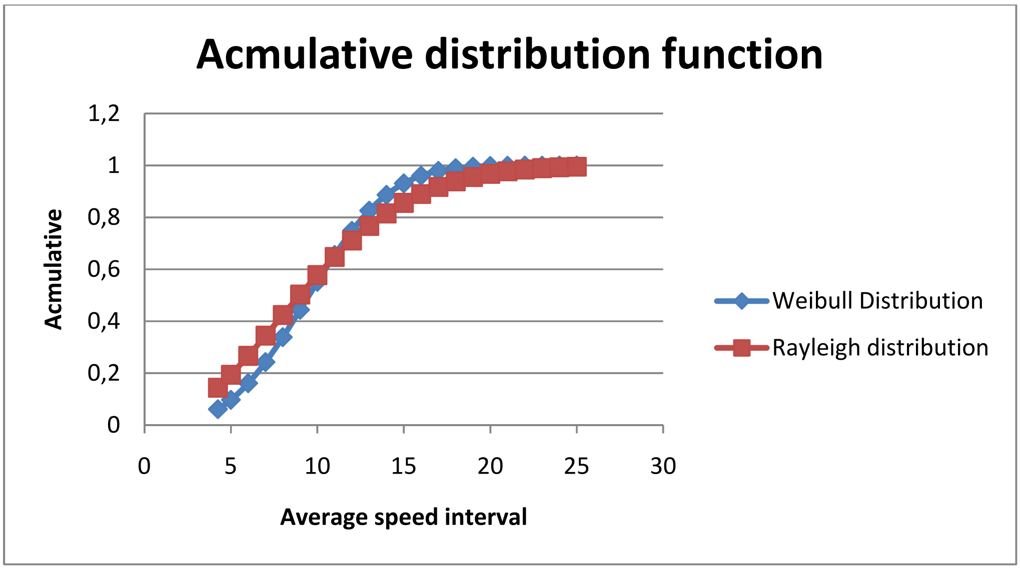


Figure 6-4 the accumulative distribution function of both distributions

From the Figure 7.1-3 we can see that the prevailing wind speed for the site of interest can be taken as 6.1[m/s] with probability of happening 7.5% (Mathew S. , 2007). This information is very important for the next step (selecting the wind turbine).

After getting those information we still have to get the wind turbulence in the location of interest which will also help us on deciding which wind turbine to select, wind turbulence means the deviation of the instantaneous real wind (measured or predicted) from the mean wind speed in the location of interest. Figure 6-5 shows the maximum value of the turbulence in the location of interest which is 9.664 [m/s].

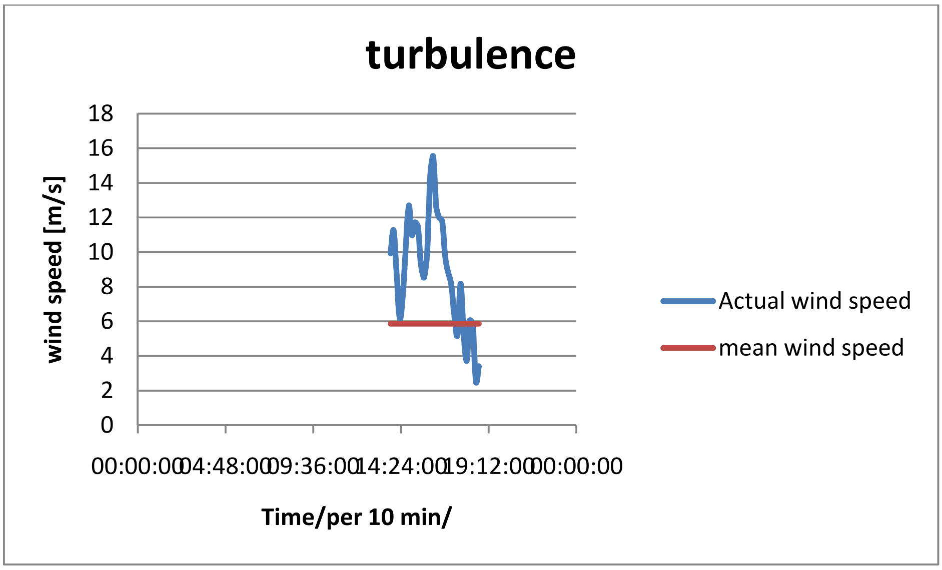


Figure 6-5 turbulence values in the location of interest

After getting the turbulence value we can calculate the turbulence intensity value which is defined as the ratio of the standard division of the wind to the mean wind speed

$$\sigma_0 = \frac{\sigma_v}{V_m} \qquad \text{Equation 6-1}$$

The turbulence intensity changes with the mean wind speed, with the surface roughness, with the atmospheric stability and with the topographic features. The lowest values are measured over the open sea (5% and less) whereas the highest values (20% and more) occur over densely settled areas or forest areas. For our location the turbulence intensity was calculated as 0.502. (Burton, 2001)

6.5. Wind turbine selection criteria:

As mentioned before the most important criteria for choosing the wind turbine is to be able to work most of the time at its rated power which means that we need to consider a turbine with power carve that respond to the prevailing wind speed in the site of interest (in our case that means we need a wind turbine that generate its nominal power with wind speed of between 5---to---9 [m/s], this range is due to the fact that you can't find a wind turbine with the exact characteristic of your site of interest/6.1[m/s]/ and with the control technics the wind turbine will be able to work not only at one wind speed but at a range of that.)

There are still other important criteria affecting the choosing of the wind turbine like:

1- The allowable maximum height in the area of interest (no problem in our case).
2- The capacity of the transportation roads to come to the area of interest [9].
3- The capacity of the connection point to the national grid.
4- Legislations.
5- Turbulence intensity.
6- The goals of your project.
7- Price & availability of the turbines (many turbines have long waiting lists).
8- The reliability of the machine and availability of spare parts.
9- The largest available crane in the area.

With the consideration of all the different limitation of the wind turbine selection we can now see the available wind turbine companies in the market and try to choose the most fitting wind turbine to our situation.

6.6.Energy yield calculation:

After the selection of the wind turbine is done and the power curve is obtained we can now calculate the energy yield from this selected turbine (not from the wind farm yet) with both knowing the frequency distribution and the power carve of the wind turbine we can get the energy output when using equation (2) and that steps are shown in Figure 6-6, Figure 6-7 and Figure 6-8 [10]

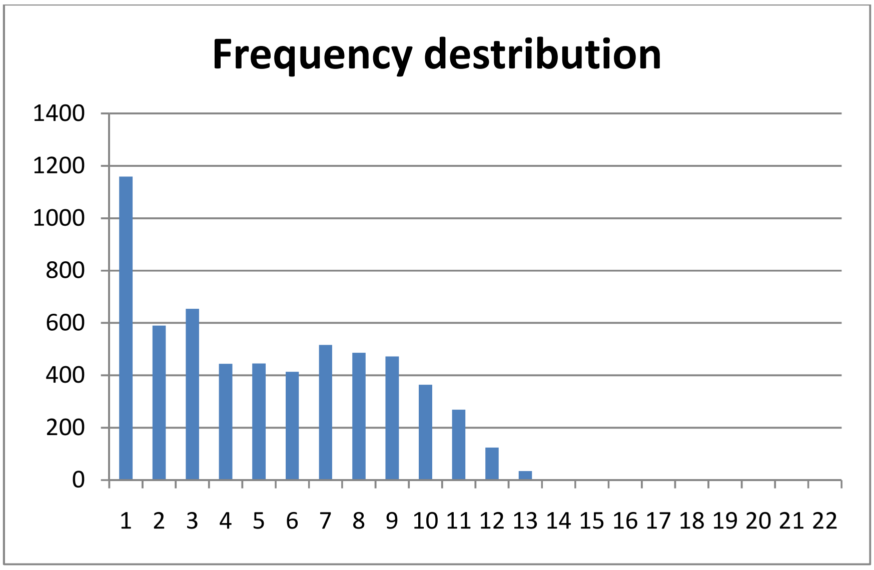


Figure 6-6 frequency distribution of the wind speed in the site of interest

[9] During our site visit there was no actual road that lead to the proposed location.
[10] The results are not the same of the Matlab module or even the WASP program due to the simplicity of the used method here and the data was treated for one year only.

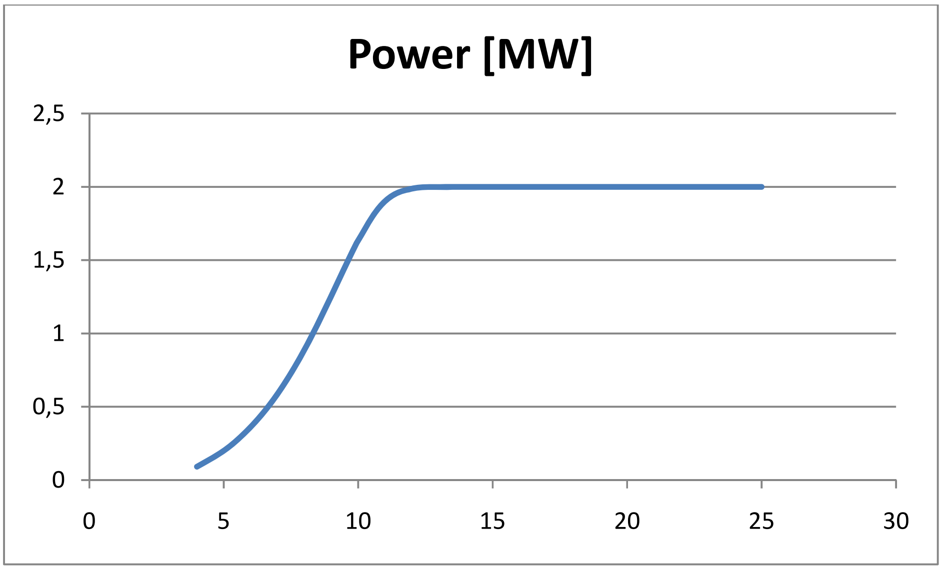


Figure 6-7 power carve of the selected wind turbine

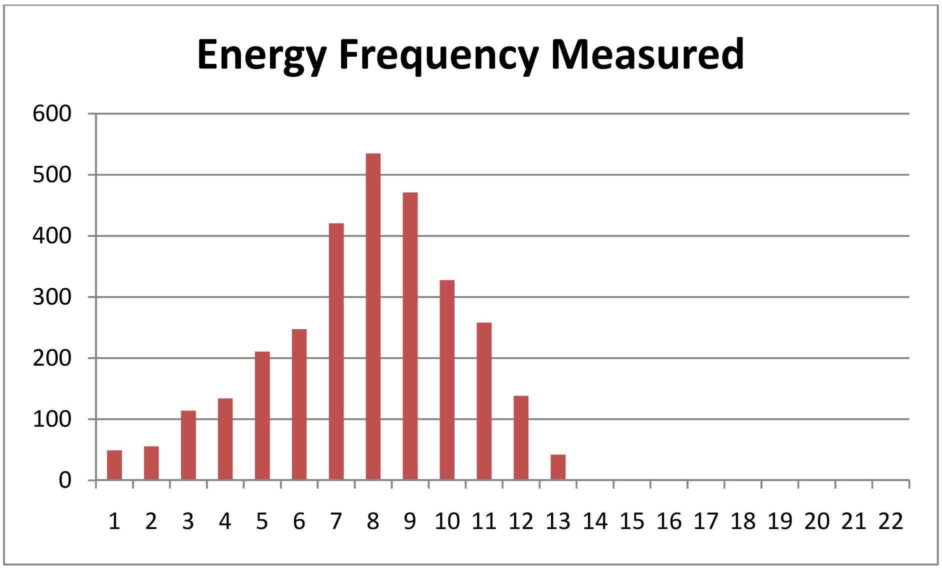


Figure 6-8 energy yield from the selected turbine installed in the site of interest

In practice this energy yield can't be achieved in all cases due to the fact that the turbine will not be available to work at all times (Maintenance, unforeseen repairing times) that is why we should consider the technical availability which include:

1- The availability with time
2- The availability of the power
3- The availability of the energy

The most important term is availability in time, as it can be defined and measured with the highest precision. It is directly linked to the system's technical reliability and low maintenance characteristics and can be define as the ratio of the available time (working time +stand by time) to the normal time (is the overall contiguous observation period without any interruption (calendar time). In general, this is one year, corresponding to 8760 hours. But it is important to note here that not only the turbine availability (
– Recovery times for routine maintenance
– Standstill times due to intervention by the operator or third parties (authorities)
– Standstill times due to external causes (grid outage, lightning strike, ice accumulation)
–"trivial" standstill times for whatever reasons, e.g. of less than 5 hours per year)
, but also the wind turbine the wind availability itself plays an important role in the available time.
What is more we can also get the capacity factor for this wind turbine by using the following equation:

$$c = \frac{P}{P_R} \qquad \text{Equation 6-2}$$

Or

$$c = \frac{annual\ energy\ yield(KWH)}{rated\ power \times 8760(KWH)} \qquad \text{Equation 6-3}$$

And the usage time or the full load hours are calculated as follows:

$$c = \frac{annual\ energy\ yield(KWH)}{rated\ power} \qquad \text{Equation 6-4}$$

6.7.Size of the wind farm criteria:

The overall size of a wind project is a function of many variables including:

1- The amount of land available
2- The number of investors and the size of each investor's contribution
3- The financing available to the project.
4- The ability of the transmission or distribution grid to handle the additional energy from the project without substantial system upgrades
5- The number of turbines available to the project

After getting the above information we can now move to use the WASP program in order to get the calculation of the wind farm for the location of interest.

6.8.The Wind Atlas Analysis and Application Program-WASP:

6.8.i. introduction:

In 1987 the Wind Energy and Atmospheric Physics Department at Risø National Laboratory introduced WASP – a powerful tool for wind data analysis, wind atlas generation, wind climate estimation, wind farm power production calculations and siting of wind turbines. Over the years, the program has become the industry standard for wind resource assessment and siting of wind turbines and wind farms and it has been employed in more than 100 countries around the world.

6.8.ii. What is WASP:

WAsP is a PC-program for the vertical and horizontal extrapolation of wind climate statistics. It contains several models to describe the wind flow over different terrains and close to sheltering obstacles. Conceptually, WAsP consists of five main calculation blocks:

Analysis of raw data:

This option enables an analysis of any time-series of wind measurements to provide a statistical summary of the observed, site-specific wind climate. This part is implemented in separate software tools: the Observed Wind Climate (OWC) Wizard and the WAsP Climate Analyst.

Generation of wind atlas data:

Analyzed wind data can be converted into a regional wind climate or wind atlas data set. In a wind atlas data set the wind observations have been 'cleaned' with respect to site-specific conditions. The wind atlas data sets are site-independent and the wind distributions have been reduced to some standard conditions.

Wind climate estimation:

Using a wind atlas data set calculated by WAsP or one obtained from another source – e.g. the European Wind Atlas – the program can estimate the wind climate at any specific point by performing the inverse calculation as is used to generate a wind atlas. By introducing descriptions of the terrain around the predicted site, the models can predict the actual, expected wind climate at this site.

Estimation of wind power potential:

The total energy content of the mean wind is calculated by WAsP. Furthermore, an estimate of the actual, annual mean energy production of a wind turbine can be obtained by providing WAsP with the power curve of the wind turbine in question.

Calculation of wind farm production:

Given the thrust coefficient curve of the wind turbine and the wind farm layout, WAsP can finally estimate the wake losses for each turbine in a farm and thereby the net annual energy production of each wind turbine and of the entire farm, i.e. the gross production minus the wake losses.

All the above information was taken from the WASP help pdf. (Wasp, 2010)

7. Chapter 7: Results & discussions:

The results obtained from the wind speed prediction tool

The results obtained from the wind farm using WASP program

7.1. Introduction:

In this chapter the different results obtained from this study will be shown and discussed, starting with the results of the first part of building the ANN tool and ending with the results of testing that tool.

7.2. Spearman's Rank:

After applying Spearman's Rank correlation to the available data (from 2005 till 2010) we can see that the results of this correlation in the following tables (Table 7.1—1 Table 7.1—2 Table 7.1—3 Table 7.1—4 Table 7.1—5 Table 7.1—6).

2005				
Correlation	**Wind Speed**	**Direction**	**Temperature**	**pressure**
Wind Speed	**1**			
Direction	**0.1809837**	**1**		
Temperature	**0.116399565**	**0.2220646**	**1**	
pressure	**-0.43455286**	**-0.38459405**	**-0.46953767**	**1**

Table 7.1—1- show the correlation results for year 2005

2006				
Correlation	**Wind Speed**	**Direction**	**Temperature**	**pressure**
Wind Speed	**1**			
Direction	**0.188449223**	**1**		
Temperature	**0.263956326**	**0.173749479**	**1**	
pressure	**-0.52840981**	**-0.25514078**	**-0.6619082**	**1**

Table 7.1—2- show the correlation results for year 2006

2007				
Correlation	**Wind Speed**	**Direction**	**Temperature**	**pressure**
Wind Speed	**1**			
Direction	**0.174979619**	**1**		
Temperature	**0.21958178**	**0.106950166**	**1**	
pressure	**-0.52320475**	**-0.21197464**	**-0.65131926**	**1**

Table 7.1—3- show the correlation results for year 2007

2008				
Correlation	**Wind Speed**	**Direction**	**Temperature**	**pressure**
Wind Speed	**1**			
Direction	**0.232188687**	**1**		
Temperature	**0.257124942**	**0.214808385**	**1**	
pressure	**-0.49489753**	**-0.29900903**	**-0.70568132**	**1**

Table 7.1—4- show the correlation results for year 2008

2009				
Correlation	**Wind Speed**	**Direction**	**Temperature**	**pressure**

Wind Speed	1			
Direction	0.210513565	1		
Temperature	0.102809652	0.055866131	1	
Pressure	-0.47915355	-0.22657499	-0.44663685	1

Table 7.1—5- show the correlation results for year 2009

2010				
Correlation	Wind Speed	Direction	Temperature	pressure
Wind Speed	1			
Direction	0.252717557	1		
Temperature	0.125183999	0.10367574	1	
pressure	-0.38966982	-0.27658302	-0.36094419	1

Table 7.1—6- show the correlation results for year 2010

From the previous tables it can be concluded:

1- The correlation is not the same for the different years which will lead to the difficulty in getting good results out of the used prediction tool (Due to the fact that the ANN tool will be trained on the data of one of those years).
2- For all the years in general it can be seen that the pressure has strong negative relation with the wind speed and the same with the temperature and that is as expected from the will know relations of the pressure, Temperature and wind speed (as we already know that the places with higher temperature is also a place with lower pressure /negative relation/ and the gradient of the pressure will lead to the wind movement and with higher gradient we have higher wind speed , the place with the lower pressure will have a high wind speed /negative relation/).
3- For the wind direction it can be seen that it has no big effect (Relation) to all other studied parameters that will mean it will not have that much effect on the built wind speed prediction tool, yet it is better to be used as input so this small effect is not neglected.
4- For the temperature it can be seen that it has no big effect (relation) to the wind speed (our output of interest) yet it is strongly related to the pressure, and as the pressure is strongly related to the wind speed it is important to involve this parameter in the prediction tool as an input (Experimental work will be done in the next step to show the importance of this work).
5- The relation between the different parameter can be drawn and described as one of the correlation types (not done here).

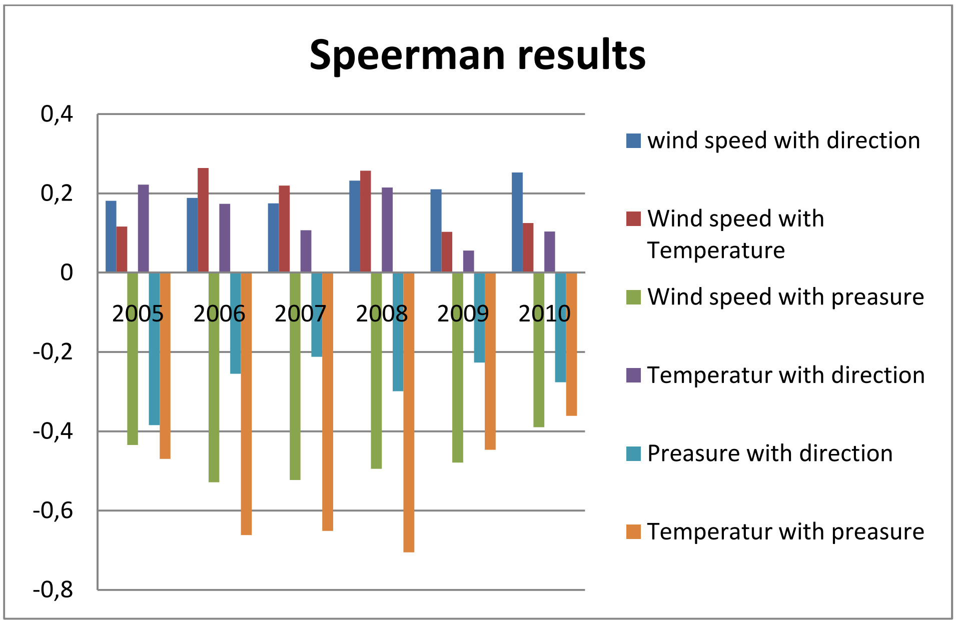


Figure 7.1-1 the results of spearman's analysis

This figure shows the different possible correlation between the available input data and the target data the next following points will show how to read this figure:

1- It can be seen from this figure that the year /2008/ and /2006/ for example have almost the same relation strength between wind speed and temperature, yet the other available years have another correlation.
2- The temperature and pressure for all year are highly related. Unfortunately not with the same strength for all the years.

Now we are ready to start with building the ANN tool for wind speed prediction.

7.3.Prediction tool at constant time:

After getting that information it is good to start by doing our experimental work. It is proposed to use the input data of three parameter (pressure, temperature, and wind direction) in order to get a good wind speed output the next coming Table 7.1—7 shows the different output figures that shows the results of choosing every parameter alone and then together as one input. It is important to keep in mind that the Matlab program accepts the input data as a matrix and also gives the output results in the same form. The input data is to be managed as a horizontal input matrix (vertical input matrix take too much area in the memory of the used computer and that lead to the need of a super computer with a very fast processor). Also it can be seen from the Table 7.1—7 that a new parameter (Δe) is introduced in order to evaluate the accuracy & acceptance of the generated results, and it represent the difference between the measured wind speed data and predicted wind speed of the same year [11]. Yet it is still important to mention the fact that the error of the same point of time is easy to overcome but the error of deviation between the predicted wind speed and the measured one is the one of importance here due to the fact that the output of this tool will soon be used to predict the generated power of the designed wind farm and then be used in the energy market.

Used input data	Training data	Δe	Output figures	Used parameter data
Only pressure	Trained on 2008 data	7	Appendix A-1-to-5	TRAINLM LEARNGDM MSE TANSIG
Only temperature	Trained on 2008 data	13	Appendix A-6-to-10	TRAINLM LEARNGDM MSE TANSIG
Only direction	Trained on 2008 data	9	Appendix A-11-to-15	TRAINLM LEARNGDM MSE TANSIG
All together	Trained on 2008 data	5	Figures 7.2.3.4.5.6	TRAINLM LEARNGDM MSE TANSIG

Table 7.1—7- the results of wind speed prediction tool with different input data. The last Colum of the table shows the training method, Adoption function, performance function and the activation function.

[11] In the testing part a more accurate error calculation is done.

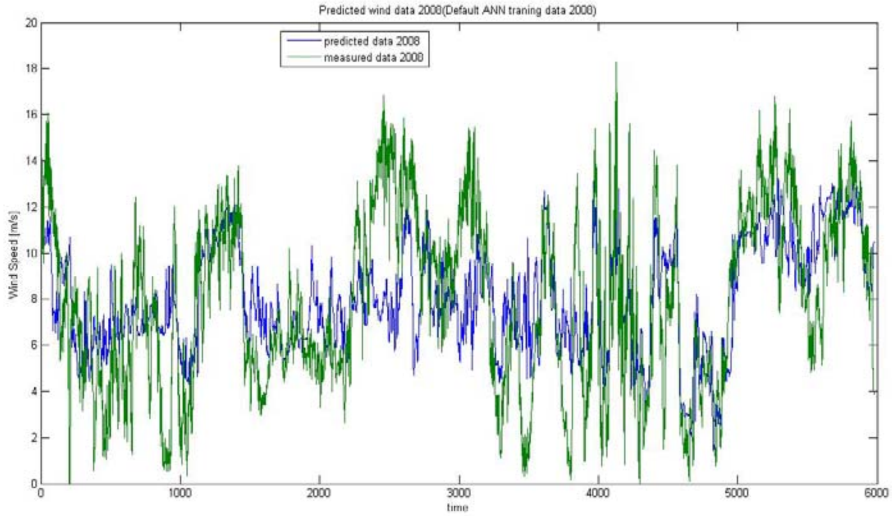


Figure 7.1-2 Deviation of predicted wind speed and measured one for 2008

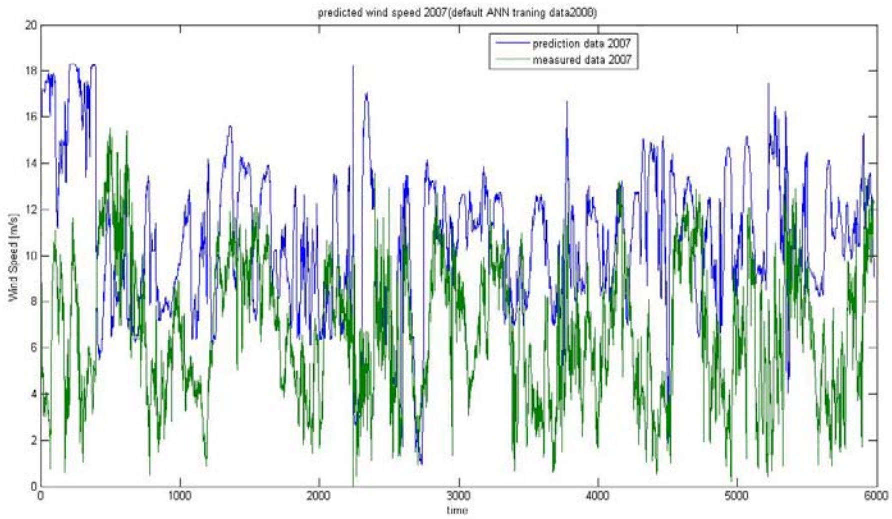


Figure 7.1-3 Deviation of predicted wind speed and measured one for 2007

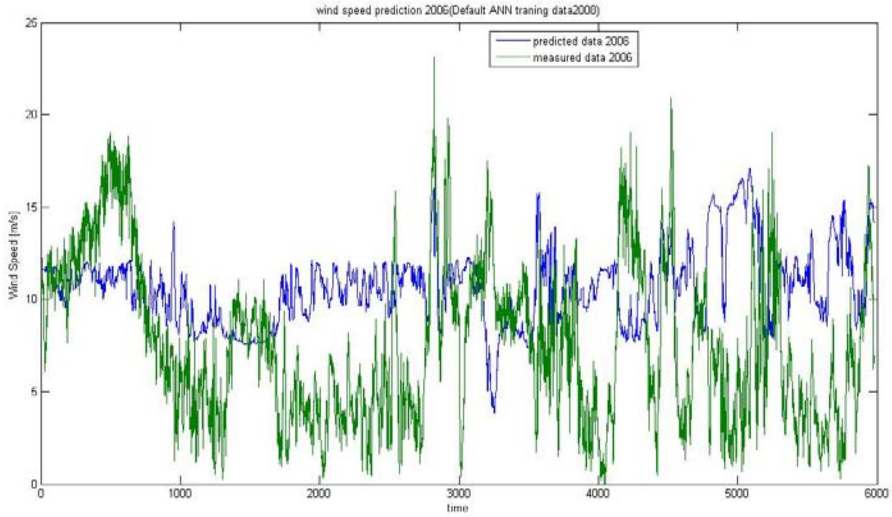


Figure 7.1-4 predicted wind speed and measured one for 2006

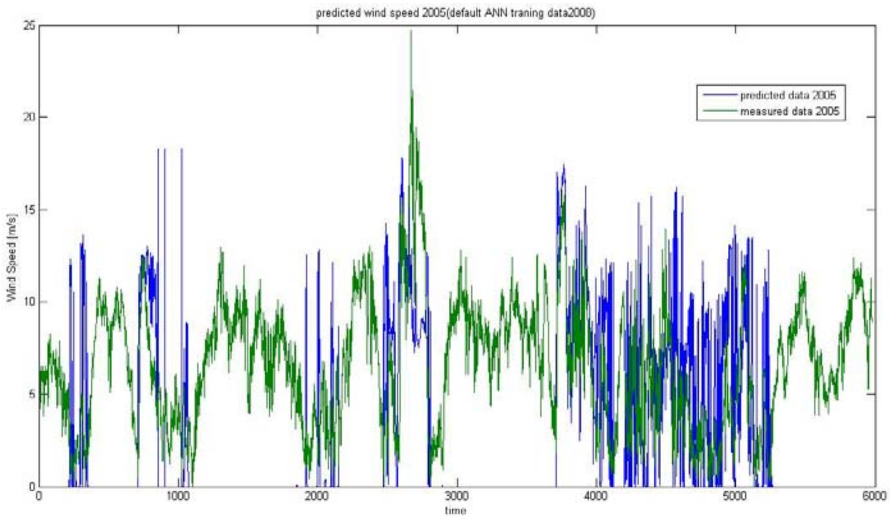


Figure 7.1-5 predicted wind speed and measured one for 2005

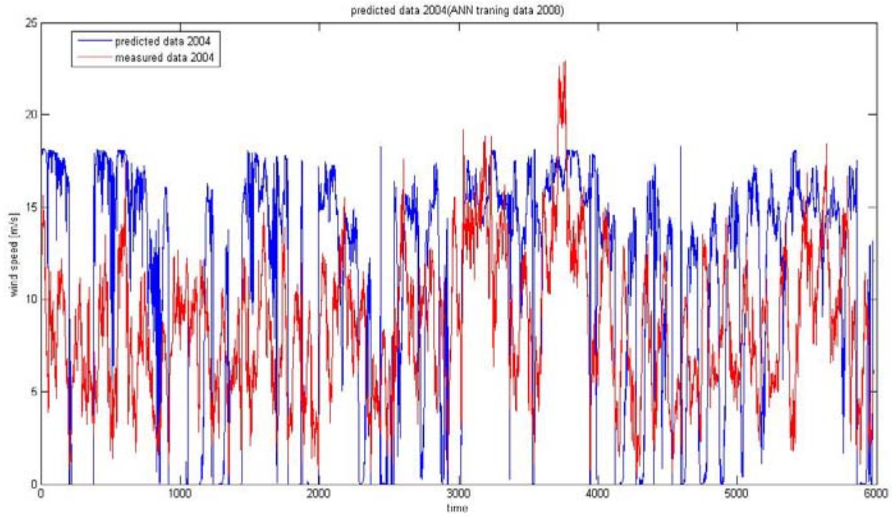


Figure 7.1-6 predicted wind speed and measured one for 2004

From all the information and results of before it can be seen that the usage of all (pressure, temperature, wind direction) data as input is much more useful for the prediction process than the usage of ever input alone [12]

The next step now will be to get the best size of the proposed network, by that we mean the number of hidden layers, the best training function, the best activation function, and the best number of neurons.

For this situation I have conducted some experiences on the proposed ANN with different training functions and the results were as the following:

Used input data	Training data	Training function	Output figures	Used parameter data
All together	Trained on 2008 data	TRAINBFG	Appendix A-16-to-20	LEARNGDM MSE TANSIG
All together	Trained on 2008 data	TRAINBR	Appendix A-21-to-25	LEARNGDM MSE TANSIG
All together	Trained on 2008 data	TRAINCGB	Appendix A-26-to-30	LEARNGDM MSE TANSIG
All together	Trained on 2008 data	TRAINCGF	Appendix A-31-to-35	LEARNGDM MSE

[12] The upcoming "Results" shows the reason for that.

				TANSIG
All together	Trained on 2008 data	TRAINCGP	Appendix A-36-to-40	LEARNGDM MSE TANSIG
All together	Trained on 2008 data	TRAINGD	Appendix A-41-to-45	LEARNGDM MSE TANSIG
All together	Trained on 2008 data	TRAINGDM	Appendix A-46-to-50	LEARNGDM MSE TANSIG
All together	Trained on 2008 data	TRAINR	Appendix A-51-to-55	LEARNGDM MSE TANSIG
All together	Trained on 2008 data	TRAINRP	Appendix A-56-to-60	LEARNGDM MSE TANSIG
All together	Trained on 2008 data	TRAINSCG	Appendix A-61-to-65	LEARNGDM MSE TANSIG
All together	Trained on 2007 data	TRAINLM	Appendix A-66-to-70	LEARNGDM MSE TANSIG

Table 7.1—8- the results of wind speed prediction tool with different training functions. The last Colum of the table shows the Adoption function, performance function and the activation function.

Regarding the above information the best training function to train our proposed ANN can be seen. And the next step will be to continue with the sizing of the network by doing test on:

1- Different training data (Which year data can corresponded more likely to all the other years).
2- Number of the hidden layers and the number of neurons inside that hidden layer.
3- The best activation function to be used.

From the previous tables it can be concluded:

1- The best training data is the data of the year 2008 due to the fact that the characteristic of this year is “somehow” acceptable to all the other years.
2- The training was done on the available data at the time of work (Which is only from 2004 till 2008).
3- In all the possibilities it can be seen that the older the predicted year are the more error is produced due to the fact that this tool is not using the online learning method[13] but using the supervised learning method[14].

[13] for more information please refer to reference 1
[14] for more information please refer to chapter 3

4- In all the possibilities it can be seen that the year 2007, 2006 and 2005 are not good predicted by the proposed wind speed prediction tool [15] due to the fact that in those particular years the correlation coefficient between the pressure and temperature is not that well correlated, and there is a good changes in that correlation coefficient between the pressure and wind speed.
5- It can be seen that the best situation is the one illustrated with figures-31 to 35- as the prediction of the older years is still can be considered better than other situations (for that reason the quality of the predicted wind speed of the same year of training /2008/ is reduced).
6- Figures from 16—to –30 gives a very good predicted wind speed for the same year of the training data /2008/, yet not that good prediction to the older years[16].
7- The other figures can be considered as a bad choice of one or two parameters (no good training function, activation function, or/and number of neurons).

7.4. Prediction tool with time:

The following table shows the output of this stage.

Used input data	Training data	Number of hidden layers	Output figures	Used parameter data
One year of 2007 altogether.	Trained on 2008 target data	2	Appendix A-71-to-75	TRAINLM LEARNGDM MSE TANSIG
One year of 2007 wind speed	Trained on 2008 target data	2	Appendix A-76-to- 80	TRAINLM LEARNGDM MSE TANSIG
Two year of 2006-2007 wind speed	Trained on getting 2008 data	2	Appendix A- 81-to- 85	TRAINLM LEARNGDM MSE TANSIG
Two year of 2007-2008 wind speed	Trained on getting 2008 data	2	Results are not included	TRAINLM LEARNGDM MSE TANSIG
One year of 2005 altogether.	Trained on 2006 target data	2	Results are not included	TRAINLM LEARNGDM MSE TANSIG

15 please refer to chapter 5—spearman's rank --- our case
16 Please keep in mind conclusion number 3

One year of 2006 altogether	Trained on 2007 target data	2	Results are not included	TRAINLM LEARNGDM MSE TANSIG
One year of 2007 altogether	Trained on 2008 target data	2	Results are not included	Different training functions LEARNGDM MSE TANSIG

Table 7.1—9- shows the results of using different possibilities of input data, prediction with time and with two year input.

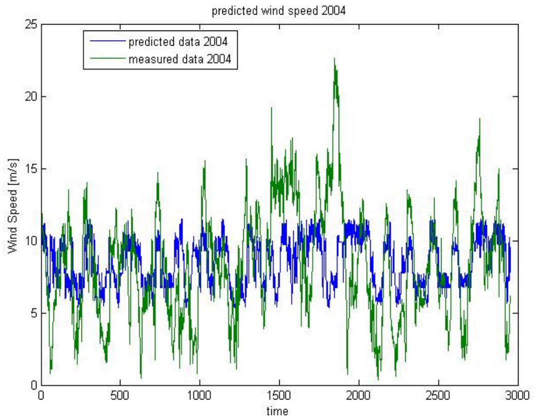
It can be seen clearly from this table that:

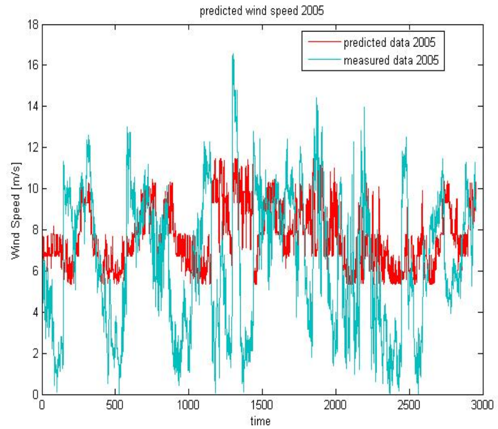
1- With more data variation between the input and the target data, more sophisticated wind speed prediction tool is needed. Due to the fact that more non-similarity is found in both the target and the input data that make it harder to the training function to find a better relation between the previous two.
2- Some results are not shown because they don't add any improvement to the suggested wind speed prediction tool. Still these steps are necessary to confirm the correction of previous conclusions and give an idea for the next steps [17].
3- The approach of using two years as input was suggested in order to overcome the problem mentioned earlier [18].
4- Unfortunately the results of this approach were unsatisfying and not acceptable. That is why the new approach is used.

7.5. The new approach:

After trying to lengthen the input data for the prediction tool had a negative effect on the results. A new approach is used to get better results. In this new approach the number of the input data is reduced to the half which means that the data of one year is taken only as six months. The results of this approach were as the following:

[17] For example the usage of different training data as input can be seen from the spearman analysis point of view. Or the usage of different training functions makes sure that: changing the training function will not be able to overcome the problem of un-similarity between the input and target data.
[18] In conclusion number 1





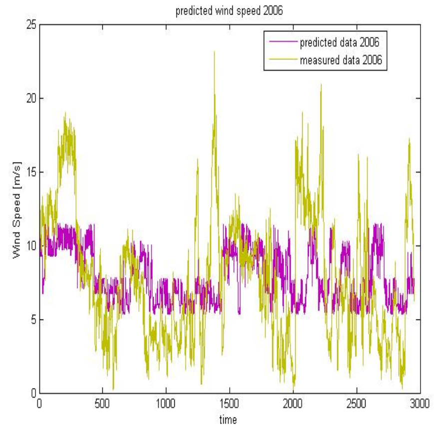
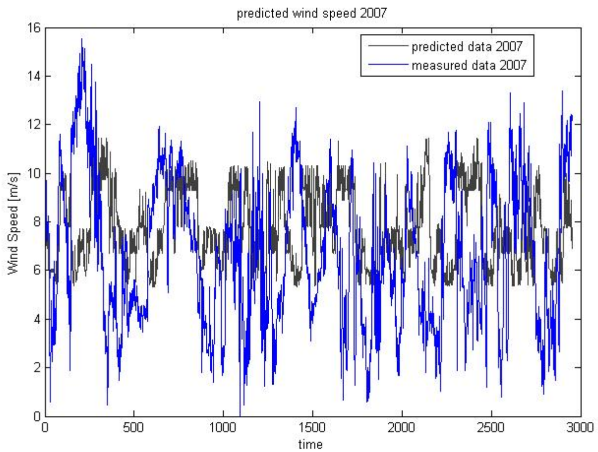


Figure 7.1-7 Predicted wind speed 2004 (half year)

Figure 7.1-8 Predicted wind speed 2005 (half year)

Figure 7.1-9 Predicted wind speed 2006 (half year)



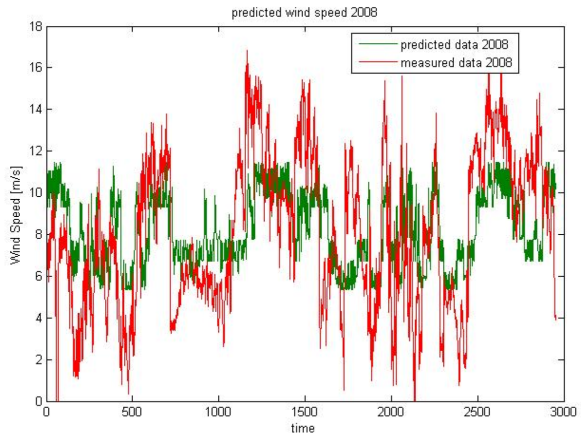


Figure 7.1-10 Predicted wind speed 2007 (half year)

Figure 7.1-11 Predicted wind speed 2008 (half year)

The previous figures show the predicted wind speed for the different half years with wind speed as inputs for this tool.

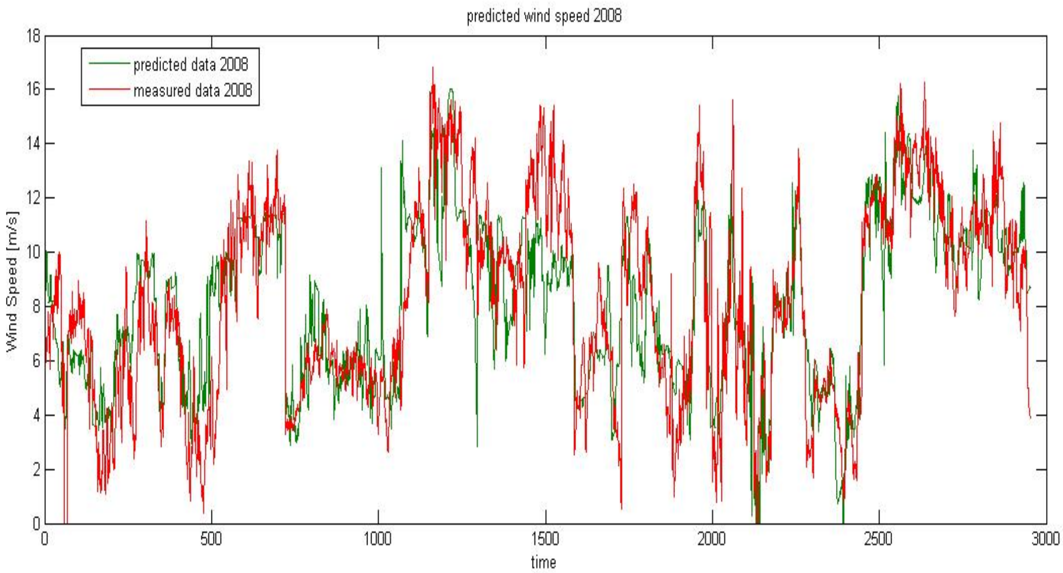


Figure 7.1-12 Predicted wind speed 2008 (half year altogether as input)

This figure shows the predicted 2008 half year when using the pressure, temperature and wind direction as input for this prediction. More understanding of those figures can be found in error calculations.

Used input data	Training data	Number of hidden layers	Output figures	Used parameter data
First half of 2008 year (wind speed)	Trained on 2008 target data(second half)	2	Figures 6.7.8.9.10	TRAINLM LEARNGDM MSE TANSIG
First half of 2008 year (altogether)	Trained on 2008 target data	2	Results are not shown [19]	TRAINLM LEARNGDM MSE TANSIG
First half of 2008 year (altogether)	Trained on 2008 target data	2	Results are not shown [19]	Different training functions LEARNGDM MSE

[19] The results of this part is discussed and shown in the error calculations. All the figures of this stage are available and can be seen in the CD included with this work.

				TANSIG
First half of 2008 year (altogether)	Trained on 2008 target data	2	Results are not shown [19]	TRAINCGP LEARNGDM MSE Different activation functions
First half of 2008 year (Wind speed)	Trained on 2008 target data	2	Results are not shown [19]	TRAINCGP LEARNGDM MSE Different activation functions

Table 7.1—10- The results of different possibilities in the new approach

It can be concluded from the previous table that:

1- The new approach gives better results for the prediction.
2- The detailed discussion of the results of this step will be done later, and will be clearer than now.

7.6. Error calculation of the previous suggested wind speed prediction tools:

The results of this step will show the maximum, minimum, average and the root mean square errors for the different scenarios done in the ANN tool. The results of this step will be shown in steps from the most primitive proposed ANN tool till the last suggested ANN tool.

7.5.1. Prediction at constant time:

First ANN tool:

Starting with the basic ANN tool with pressure, Temperature, and wind Direction as input for predicting the wind speed (altogether or every one alone):

default type of ANN with different training data (2008)																				
Description	max					min					avarage					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
preasure	15.145	7.899	14.93	7.735	9.977	-8.69	-11.5	-10.9	-9.68	-9.26	0.53247	-1.75	-0.82	-1.716	-0.0126	0.0776	0.069	0.0795	0.066	0.06728
temperature	15.804	10.63	15.31	7.997	0	-17.4	-17.4	-15.9	-17.2	0	2.23931	-0.59	-2	-3.976	0	0.1133	0.094	0.1003	0.108	#DIV/0!
direction	18.596	12.03	10.68	9.173	11.01	-16.9	-14.9	-16.5	-16.8	-8.7	-3.2604	0.086	-4.92	-4.466	0.022	0.1311	0.092	0.126	0.123	0.05472

Table 7.1—11- The RMSD of the different years wind prediction tool with different input data (max, min, and average error is also included)

In Table 7.1—11 it can be seen that RMSD (Root Mean Square deviation) for the same year of the training data is the best (2008) and whenever we go back with time the prediction accuracy is reduced and the error is enlarged.

1- The maximum error of years 2004 & 2006 are the worth and the maximum error of 2007 is the best (keep in mind that the maximum will depend on the maximum reading of that year which the ANN tool is trying to predict).
2- The same discussion can be conducted for the minimum & average error. the minas sign means that the predicted value in more than the real (measured) value, and as the average is mines means that the values where the prediction tool make the wind speed value more than the measured one is more.
3- The RMSD for 2008 and wind direction as input is better than the one of pressure as input, but for previous years the opposite is correct. This means that pressure as input for the prediction tool is the best suitable one.

Second ANN tool:

Now we can try altogether the different input parameters (Pressure, Temperature and wind direction) and in the same step we can include different training data as input of the ANN tool.

default type of ANN with different training data (2008-2007)																				
Description	max					min					avarage					RMSD				
Years	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
2008 training data	15.531	13.96	12.47	8.525	9.59	-16.2	-17.8	-15.8	-18.2	-10.7	-1.8815	4.103	-3.01	-4.001	-0.03	0.128	0.12	0.105	0.107	0.05
2007 training data	22.752	15.67	17.51	8.371	12.15	-15.2	-15.5	-7.44	-8.59	-9.84	4.3987	-4.08	1.353	-0.039	0.091	0.166	0.13	0.09	0.049	0.08

Table 7.1—12- The RMSD of the different years wind prediction tool with different training data (max, min, and average error is also included)

In Table 7.1—11 Table 7.1—12 it can be seen that RMSD for the input altogether is better that ever input parameter alone. Also the error is increasing with moving backward with time (previous years) due to the fact that the prediction tool is not online learning tool.

1- Now it is obvious that the training data of 2008 is better that the previous years (in our case 2007) and the error, in its different types, is the minimum in the case of 2008.
2- The spearman's ranking analysis is obvious in these figures as it can be seen the some years has random changes with for example higher maximum error values. And that is a very hard obstacle to overcome keeping in mind note number-1-.
3- The results of errors for the parameter all together is better that that of the parameter alone and this means in the upcoming work the usage of all parameter together is more preferable.

Third ANN tool:

In this step we move to the network sizing (number of neurons in the hidden layers, number of hidden layers and so on….) with still trying different training data.

one year input with three hidden layers and different training data																				
Description	max					min					avarage					RMSD				
Year		2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
year 2008 training	21.036	21.04	20.37	13.31	9.594	-18.1	-18.1	-17.6	-18	-12.8	3.94646	3.946	-4.51	-0.947	0.057	0.137	0.137	0.1406	0.115	0.049
year 2007 training	13.467	13.47	16.78	9.242	16.71	-15.5	-15.5	-8.71	-7.96	-10.2	-5.5216	-5.52	1.734	0.003	5.963	0.143	0.143	0.0959	0.043	0.135

Table 7.1—13- The RMSD of the different years wind prediction tool with different training data & three hidden layers (max, min, and average error is also included)

Table 7.1—13- The RMSD of the different years wind prediction tool with different training data & three hidden layers (max, min, and average error is also included)shows the results of an ANN tool with three hidden layers and 10-20 neurons in the first and second hidden layers.

1- The results are improved a little. But this improvement is not good enough to use the available resources on bigger ANN size [20].
2- Still no change with the fact that year 2008 as a training year is better than the other years.
3- This approach can be recommended in case this tool will be used afterword in the energy prediction tool.
4- It can be concluded that the changes in the number of hidden layers and neurons in side that has no big effect in our case [21].

Forth ANN tool:

After getting the idea of the layers now we can try a different training functions for our ANN tool in order to be able to choose the best training function possible for our case (for more information about the training function please refer to the help in Matlab program).

different training functions																				
Description	max					min					avarage					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
Bayesian Regulation	12.227	16.53	18.46	10.86	10.02	-18	-18.3	-17	-18.3	-10.9	-8.3043	-9.62	-1.79	-5.375	-0.05	0.178	0.2	0.1247	0.167	0.051
Fletcher-Reev	18.005	17.24	17.46	8.371	10.33	-16.1	-16.1	-11.4	-11.6	-11.4	-1.2824	-0.05	-1.59	-1.03	-0.04	0.115	0.126	0.1026	0.075	0.056
Marquardt	22.781	20.42	16.42	13.31	10.02	-17.5	-18.2	-18	-17.8	-11.2	3.2116	1.594	-5.38	-2.049	0.021	0.173	0.155	0.1513	0.139	0.051
Quasi-netwton	20.7	13.82	8.536	11.16	9.595	-17.7	-18.2	-13.5	-18.3	-10.3	-5.948	-6.63	-4.22	-3.299	-0.05	0.155	0.152	0.112	0.107	0.053

Table 7.1—14 The RMSD of the different years wind prediction tool with different training functions (max, min, and average error is also included)

Table 7.1—14 shows the results of using different training functions and the best situation will be with the lowest values of errors.

1- Almost all the shown training functions gives a good results of the same year training data (in our case year 2008)

[20] For more information please refers to the general note in the Design of Neural network

[21] The effect of time has not been shown in this study, yet has be calculated

2- In this case as the error is almost the same for year 2008 with different training function we can concentrate on the previous years and in this case is the second row of our table of results can give good prediction accuracy for the older years.
3- This step help to choose the best training function for the ANN prediction tool. In our case that was “Conjugate Gradient with Beale-Powell Restarts” (Matlab).

Fifth ANN tool:

In this step different activation & performance function were to be chosen.

different activation functions																				
Description	max					min					avarage					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
purelin Act.	14.462	16.4	14.89	7.597	9.977	-7.77	-8.09	-7.95	-17.6	-8.07	0.1817	-1.29	-0.48	-1.413	-0.0657	0.069	0.067	0.0791	0.061	0.069
logsig Act.	21.036	10.64	10.48	7.997	9.518	-18.1	-17.4	-15.9	-17.2	-11.1	3.94646	0.982	-3.31	-5.603	-0.0345	0.137	0.104	0.1052	0.124	0.056
MSE Perf.	5.7026	13.55	11.93	9.173	11.01	-17.2	-15.4	-16.5	-16.8	-10.4	-7.1904	1.473	-2.81	-2.825	0.0113	0.15	0.096	0.098	0.094	0.056
sum Perf.	13.228	13.23	9.79	9.069	10.76	-13.2	-13.2	-13.1	-17.4	-11.7	-1.1099	-1.11	-3.01	-2.493	-0.0036	0.071	0.071	0.1007	0.08	0.062

Table 7.1—15 The RMSD of the different years wind prediction tool with different Activation & performance functions (max, min, and average error is also included)

Table 7.1—15 shows the results when using different Activation function (the default case is not included in this table), and different performance functions.

1- It can be seen that the RMSD of the different years is improved.
2- The problem of the different characteristic wind properties is reduced in this case.
3- The problem lies with the maximum error which is not reduced; on the contrary it was increased. And that will lead to less reliability of the used tool, due to the fact that the power will be affected to the power three of those values. This will lead to a problem in the energy market problems.

7.5.2. Future wind prediction tool:

With the previous information it is good to move forward to building a prediction tool that has as input the year before the one of interest for prediction (e.g. If I want to get 2008 wind speed data I enter 2007 wind speed data as input to the ANN tool).

What is the better input (wind speed or the pressure, temperature and wind direction) can be known in this step (all the previous steps are to be done again of this case). Also the statistical analysis will help in this case (the impact of this analysis is already well explained in previous paragraph in this Chapter).

First ANN Tool:

In this step a comparison has been done between using the wind speed as an-input of the prediction tool or to use the pressure, temperature and wind direction as input of the prediction tool. The results were as the following table:

different inputs with time																				
Description	max					min					avarage					RMSD				
Years	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
Wind data input	0	17.33	17.48	7.866	11.82	0	-7.81	-9.74	-10.2	-7.73	0	-0.08	1.141	-0.016	1.4833	0	0.062	0.0824	0.051	0.07493
all as input	0	11.57	15.19	5.447	11.49	0	-16.8	-16.3	-13.7	-9.81	0	-5.6	-2.21	-3.79	-0.0325	0	0.139	0.1214	0.092	0.05967

Table 7.1—16 The RMSD of the different years wind prediction tool with different input data (max, min, and average error is also included)

It can be noted from this table that:

1- The year 2004 has no error due to the fact that it can only be used as input to the next year 2005.
2- The year 2009 has no measured data (when this analysis was taken) that is why the error calculation can't be done. (Only prediction that was available).
3- The Spearman's correlation analysis in clear in this case. The RMSD is very high due to the fact that the characteristic of the wind speed is different from one year to another.
4- Using the pressure, temperature, wind direction input in better for RMSD for the case of predicting the same year of the training data (so better results could be achieve for the year of interest, in our case 2009).
5- Using the wind speed as input gives better RMSD results for the prediction of previous years but higher values of RMSD for the same year of training data.
6- The difference in using those two different input data can be related to:
   - using more input data means more complicated prediction tool should be used (with more complicated data analysis, training function….)
   - using less input data (only wind speed) means less complication in the prediction tool is needed which can lead to an easier understanding for the relation between the input and output (not too much variables are included as input to determine the output).
   - When using the output of this prediction tool for energy prediction also then more accuracy is need and more input can be used (keeping in mind that the most preferable ANN to be used for this case is the online learning tool).

Second ANN tool:

In this step an attempt has been carried out with using two years as input data instead of only one year. The attempt was done in order to try to include more variation for the neural network as an try to obtain better prediction results. The following table shows the results of this attempt with the usage of different years input data.

two year input for prediction with time tool																				
Description	max					min					avarage					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
two year 2007-2008	NP	15.68	15.21	8.52	9.099	NP	-17.5	-13.9	-7.88	-10.4	NP	-0.36	-1.6	0.098	0.065	NP	0.098	0.057	0.038	0.057
two year 2006-2007	NP	17.61	15.89	8.731	15.56	NP	-22.7	-8.23	-8.03	-10.6	NP	-0.42	-0	0.257	5.677	NP	0.159	0.0441	0.068	0.127

Table 7.1—17 The RMSD of the different years wind prediction tool with different input data (max, min, and average error is also included)

From the previous table it can be concluded:

1- The usage of 2007-2008 as input data is better than the usage of years 2006-2007 as input as RMSD is better in the first case than the other one.
2- The improvement between this case and the case before is not that much.
3- As stated from Spearman's analysis the characteristic of the wind speed is changing from one year to another that is why the new approach will be to reduce the range of the input data to less than one year.
4- More input data means the need of more neurons and hidden layers, and more sophisticated training function.

Third ANN Tool:

Although it was planned that an energy prediction tool to be built in this Master thesis, only a tool for wind speed prediction was build. Building an Energy prediction tool means a data about the generated power of a previous wind farm should be available. Unfortunately there are no previous wind farms in the area of interest (Syria) that is why the approach of wind speed tool with one year input data and more detailed input is used with different training functions and the results were as in the next table

different training functions																				
Description	max					min					avarage					RMSD				
Years	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
Bayesian Regulation	0	16.86	14.09	12.35	10.1	0	-10.1	-11.1	-13	-10.7	0	-0.66	-0.45	-0.712	-9E-05	0	0.075	0.0791	0.075	0.06691
Fletcher-Reev	0	17.2	13.02	8.371	11.14	0	-8.95	-10.4	-10.2	-8.42	0	-0	-0.39	-0.703	0.0462	0	0.074	0.0786	0.071	0.066973
Marquardt	0	20.42	12.62	11.05	9.874	0	-18.2	-9.73	-10.1	-8.66	0	1.594	-0.5	-0.913	-0.063	0	0.155	0.0787	0.068	0.066888
Quasi-netwton	0	16.92	13.24	11.34	10.49	0	-9.04	-9.38	-9.98	-8.51	0	-1.24	-0.49	-0.864	-0.055	0	0.074	0.0786	0.069	0.066996

Table 7.1—18 The RMSD of the different years wind prediction tool with different training functions (max, min, and average error is also included)

The results show:

1- For the year of training the RMSD is almost the same in all cases.
2- With the RMSD for all the years there is not that much difference.
3- The problem is with the maximum and minimum errors, where in some cases we have about 20.42 [m/s] which is too much for the usage of this tool in energy calculation afterward.

As this step finish it can be seen that a new approach need to be adapted where we can have more accurate prediction and less complications.

7.5.3. The new approach of ANN prediction tool:

As the old approach was about increasing the number of input data in order to get the most possible cases included in the input sample, it was proven wrong due to the different characteristic of wind speed between one year and another. In this new approach less data will be used as input to the wind prediction tool that will lead to the more understanding of the characteristic of the wind speed for the year of input.

In this case the data of one year will be divided to days. Some days are for training and others are for validation (in other word testing) so the year was divided into two parts (six month each). To make sure that all the characteristic of the wind in the year of interest is covered (not talking only data for two seasons and neglect the other seasons of the year) the data od wind was taken as first day for training and the next day for testing and so on. Figure 7.1-13 shows this idea.

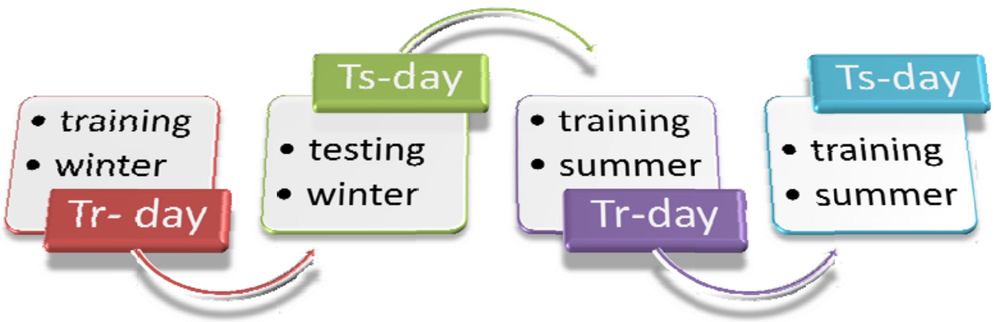


Figure 7.1-13 the new approach of wind prediction tool (Tr =training; Ts=testing).

First ANN Tool:

In this step a testing for the better input to be selected as already done in previous analysis. This step will answer the question which is better to use as input for the prediction tool only the wind speed or its components like pressure, temperature, and so on??

Table 7.1—19 can show the error results for this step:

new approach different input data																				
Description	max					min					avarage					RMSD				
Year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
wind speed	15.0991	7.403	17.66	9.0182	8.721	-10.488	-10.6	-9.983	-10.676	-11.16	-0.1083	-1.2029	0.0295	-1.042	-0.036	0.09768	0.09411	0.1106	0.0956	0.0831
all togather	19.7683	16.29	7.508	14.384	8.864	-16.383	-16.7	-15.5	-16.158	-9.136	-5.2869	-4.1659	-6.921	-1.718	0.038	0.23051	0.22188	0.21244	0.18023	0.0559

Table 7.1—19 The RMSD of the different years wind prediction tool with different input data (max, min, and average error is also included)

In can be concluded in this step that:

1- The usage of pressure, temperature, and wind direction as input for the neural network is better in the case of the training data year.
2- The entire previous conclusion done in previous steps can be seen in this case also, which means that the usage of more detailed input will lead to better energy prediction.
3- What is really important to know that the accuracy of this approach is better than the previous ones epically in the maximum, minimum and average errors (this can be seen with comparing figures).

Second ANN Tool:

In this step different training function as been tested on the proposed ANN tool for wind speed prediction and the results were as follows:

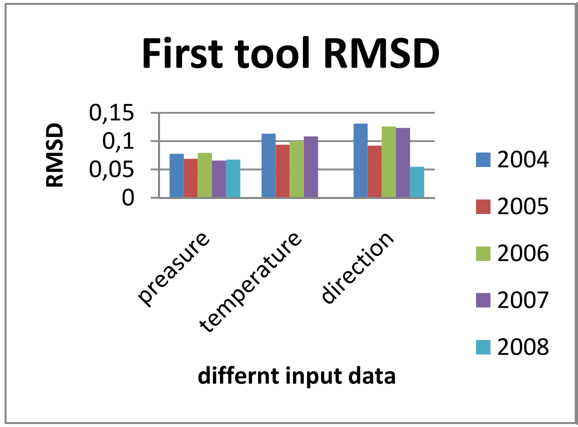
new approach different training functions																				
Description	max					min					avarage					RMSD				
year	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008	2004	2005	2006	2007	2008
Bayesian Regulation	22.656	14.337	20.742	8.1926	15.125	-15.6	-16.528	-16.406	-9.329	-10.928	5.55079	1.12457	-6.757	-0.0584	1.1008	0.2354	0.2124	0.238	0.052	0.1864
Fletcher-Reev	20.8179	15.67	16.484	12.057	9.1973	-13.57	-15.942	-11.036	-14.78	-8.1627	4.81845	-3.8739	-0.982	-1.954	0.0118	0.1912	0.1939	0.1325	0.137	0.0753
Marquardt	NP	20.416	10.394	13.31	10.017	NP	-18.207	-16.543	-17.83	-11.179	NP	2.76337	-4.991	-0.9776	0.1883	NP	0.1548	0.1513	0.139	0.0505
Quasi-netwton	20.5755	12.553	20.906	12.82	7.7981	-16.05	-16.828	-12.626	-16.08	-8.969	-2.3128	-3.7653	-0.977	-3.5376	0.0218	0.1985	0.1528	0.1384	0.137	0.0449

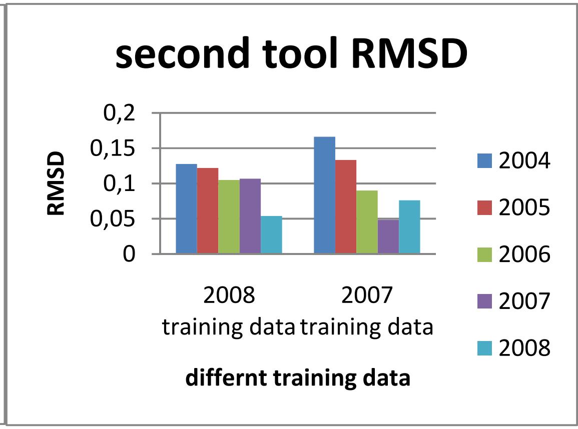
Table 7.1—20-The RMSD of the different years wind prediction tool with different training functions (max, min, and average error is also included)

The results can be described:

1- The RMSD of using the Quasi-netwton gives the best results but always keep in mind the other values of the errors.
2- There is no direct low to use when choosing the training function. That is why trying is the best approach to be done.
3- As no feed-back is given to the prediction tool errors will not be minimized by only changing the input or the training data.

After this detailed error study figures with the development of the RMSE can be drown and the differences between the different approaches can be seen. Also an important result can be noted form the following coming figures (specially Figure 7.1-24) that the new approach (with less wind data as input for the prediction tool) is better for a short term wind speed prediction with training every one cycle, yet the old approach is better for long term wind speed prediction and re-training will be needed every 3 cycle.





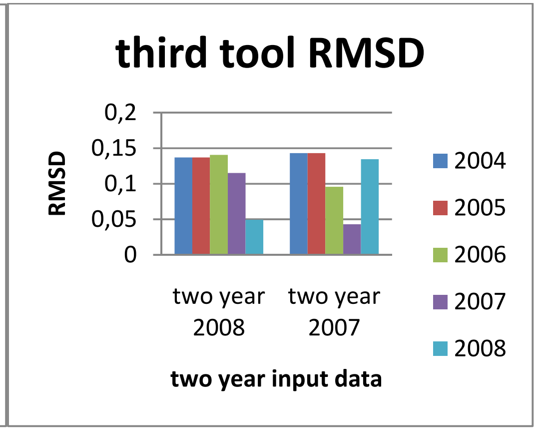
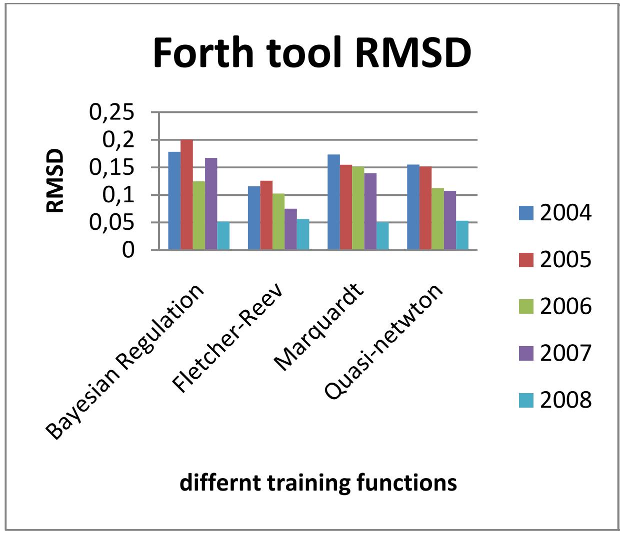


Figure 7.1--7.1-14 The RMS error of the first tool

Figure 7.1--7.1-15 The RMS error of the second tool

Figure 7.1--7.1-16 The RMS error of the third tool



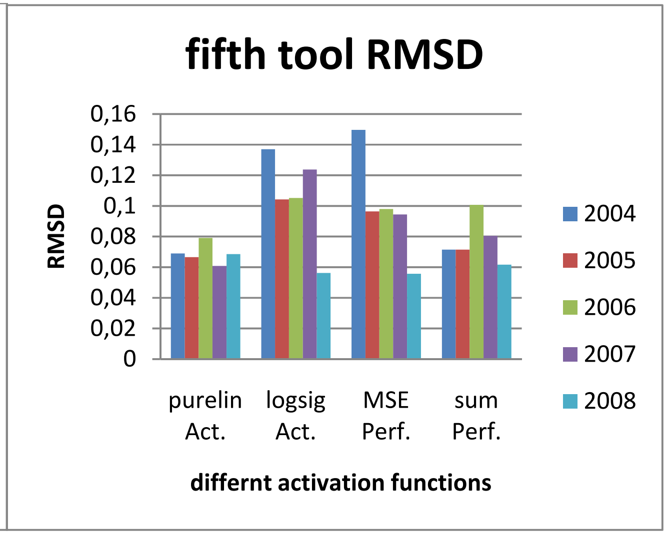


Figure 7.1-17 The RMS error of the forth tool (no time Shift)

Figure 7.1-18 The RMS error of the fifth tool (no time Shift)

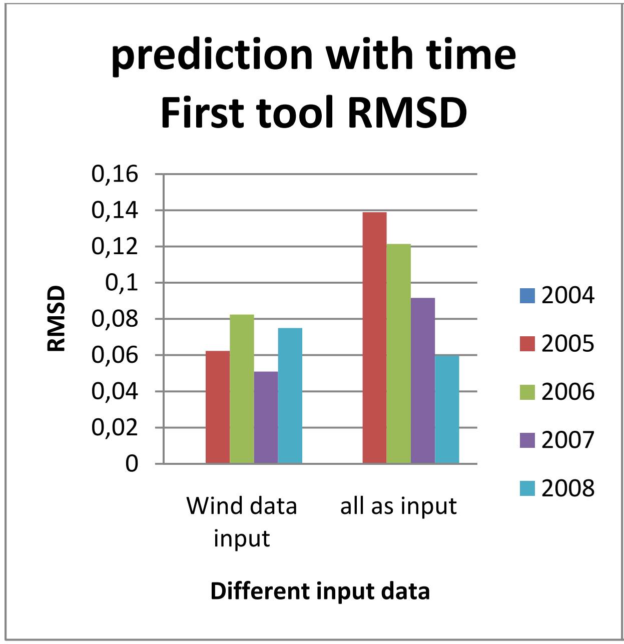


Figure 7.1-19 The RMS error of the first tool

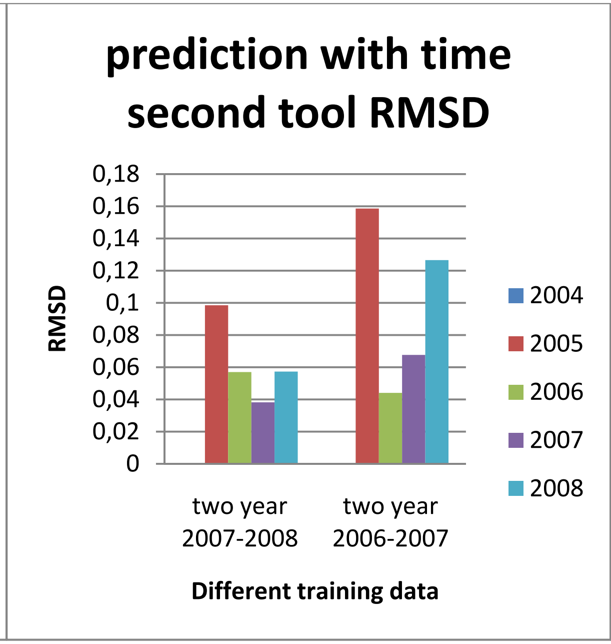


Figure 7.1-20 The RMS error of the second tool

(with time old approach)

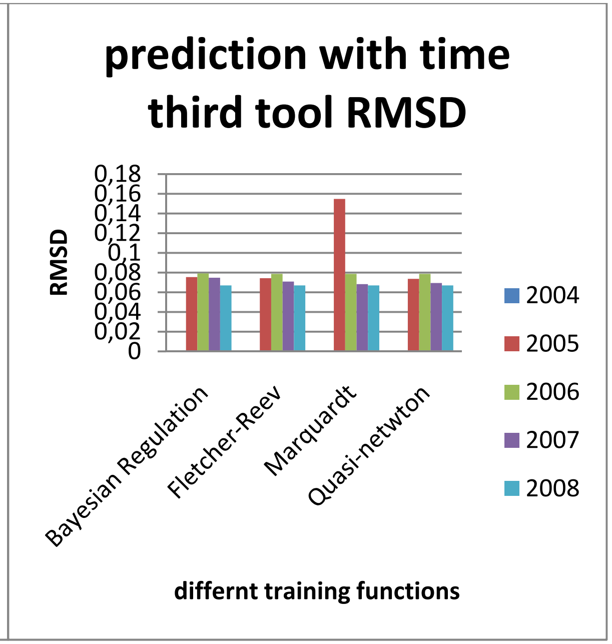
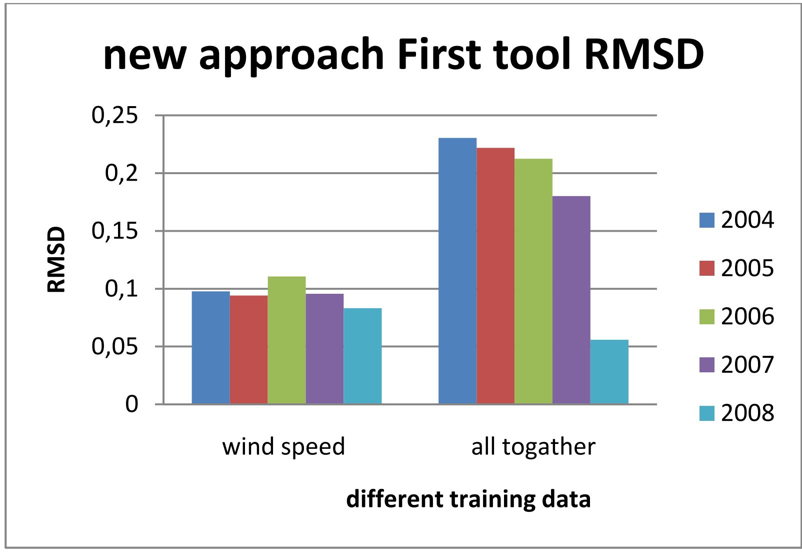


Figure 7.1-21 The RMS error of the third tool



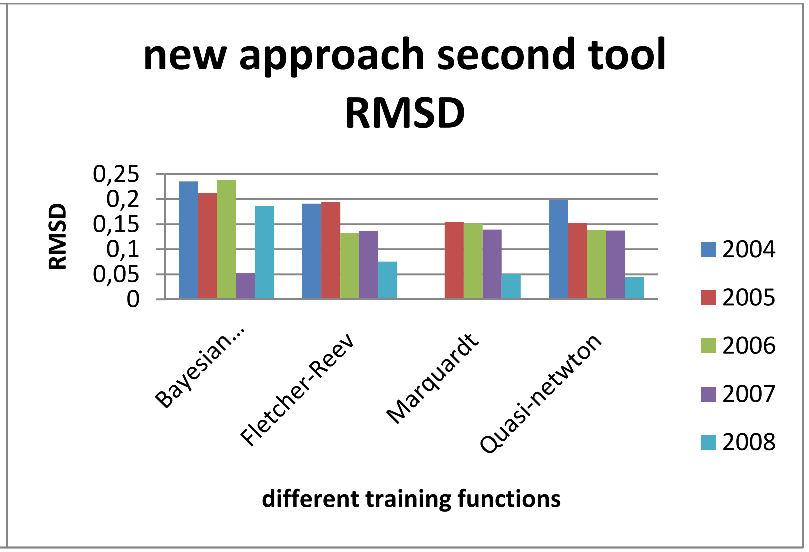


Figure 7.1-22 The RMS error of the first tool (with time new approach)

Figure 7.1-23 The RMS error of the second tool (with time new approach)

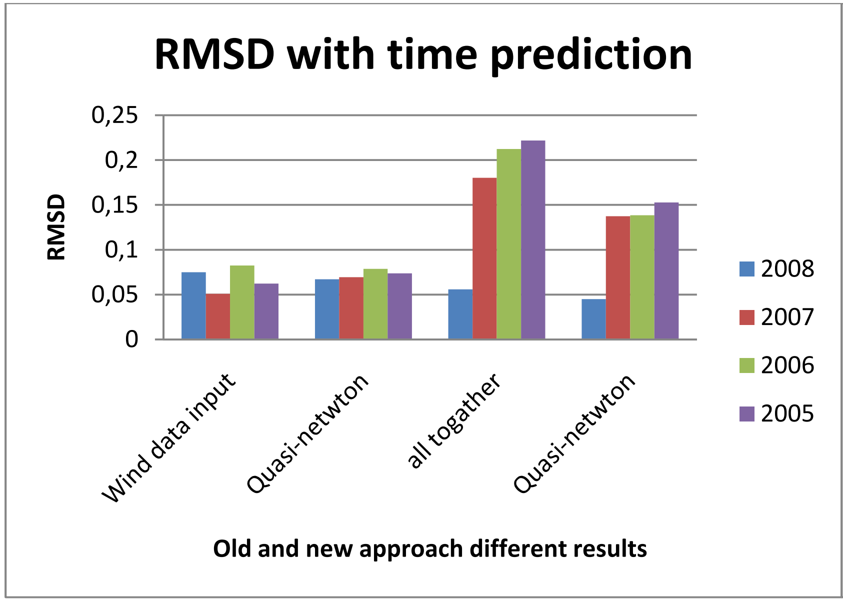


Figure 7.1-24 The RMS error reduction for 2008 with the usage of the new approach

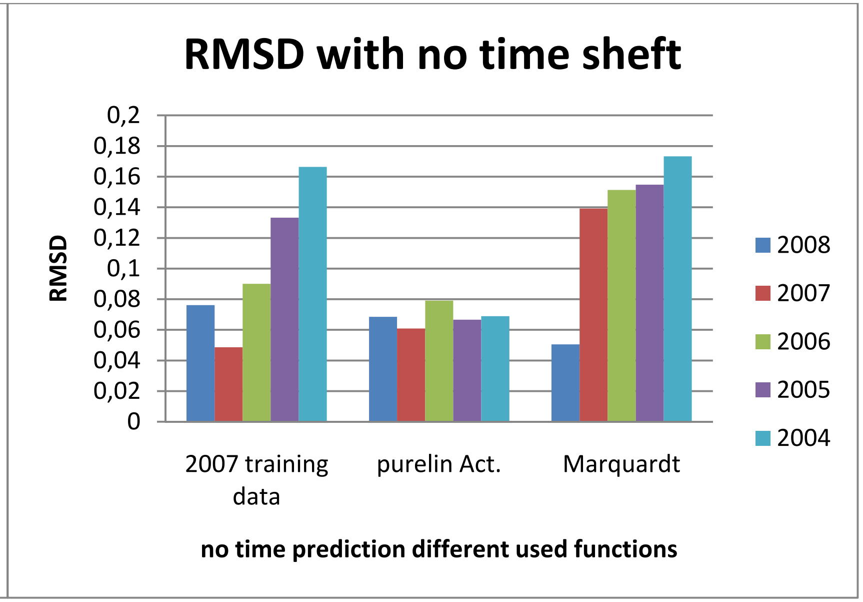


Figure 7.1-25 the reduction of the RMS error with the different proposed tools (no time Shift)

7.5.4. Wind energy module:

When all the previous information is available, the Matlab module can be built. Unlike the case of wind speed prediction, there is no tool used in this module only the modeling library & blocks are being used.

The next figure shows the blocks used in this module and how they are connected.

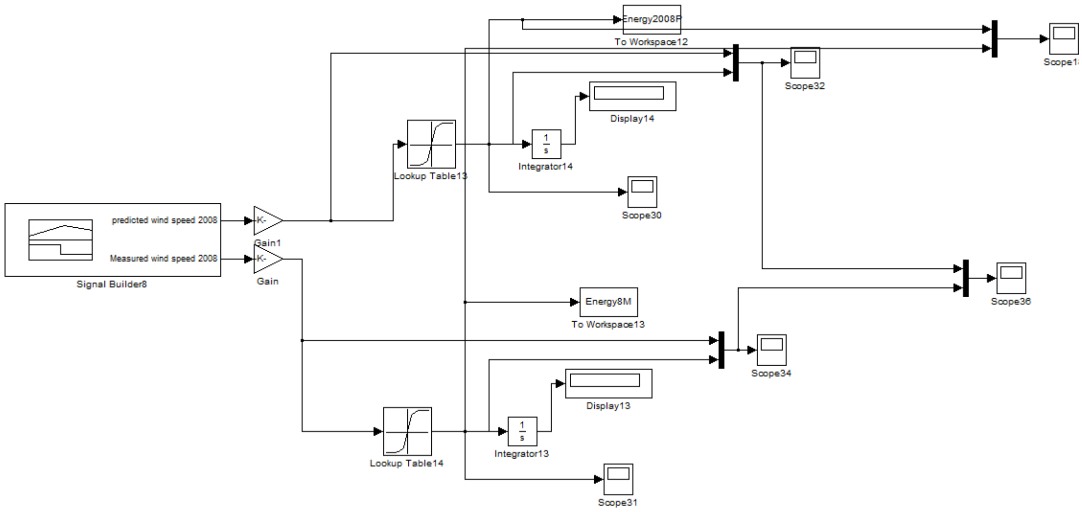


Figure 7.1-26 the block diagram of the energy module

The roughness figure is used to translate the wind speed from the height of the measurement device to the hub height of the selected wind turbine. Also an integration Element is used in this module in order to calculate the area under the expected generated power and the calculated generated power and compare between the results. The result output of this module is the power curve with time of half month produced from the selected turbine.

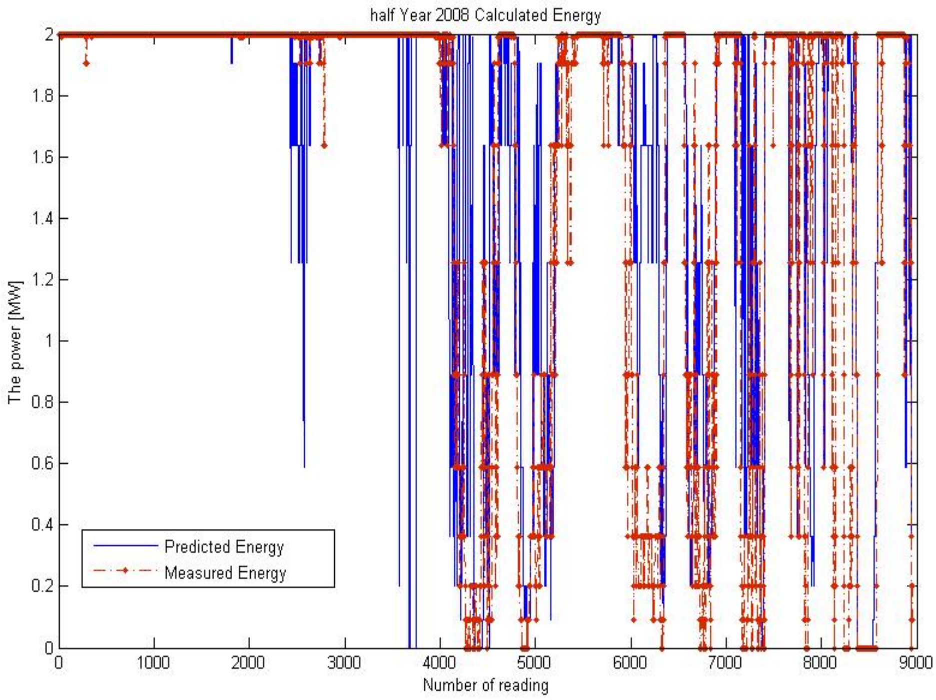


Figure 7.1-27 the block diagram of the energy module

The above figure shows the calculated wind energy from both measurements and predictions (the green points are the measured). It can be seen:

1- The energy calculated in both scenarios is almost the same which lead to a good prediction of wind energy.
2- The energy shown in this figure is the same of the training data for the wind speed prediction tool.
3- There are some of changes between the two lines that come directly from the deviation of the predicted wind speed.
4- Other figures of energy calculated for previous years are shown in the Appendix B and shows that there is a big deviations between the measured values and the predicted one that comes directly from the errors of the predicted wind speed[22].

7.6. The practical work:

When working with the WASP environment the first step will be to generate the wind atlas from the data available on the location of interest (in our case ALhijana).

7.6.2. Data acquisition:

After going for one month to the country of interest, Syria, where the proposed wind farm is going to be established we were able to get the wind speed and direction for the location of interest “ALhijana” (also the pressure and temperature) from the National Energy research Center in Damascus Syria for the years 2005 till 2010 with different heights (10-40 m) from the nearest measurement station to the location of

[22] The errors are well discussed before.

interest. This data is prepared to be as an input to the WASP-OWC wizard tool which in its turn can give us the different values that describe the characteristic of the wind condition in the regime of interest (all the results of this study will be shown in the form of report generated by WASP program). After this step it is important to get an electronic map of the location of interest.

7.6.3. Maps:

In this step we went into a field trip to the chosen location “ALhijana” in Syria and where able to get some photos for the location with a GPS coordinate. It was surprising to know that in the location so called “ALhijana” is divided into two parts as shown in the upcoming Figure 7.1-28

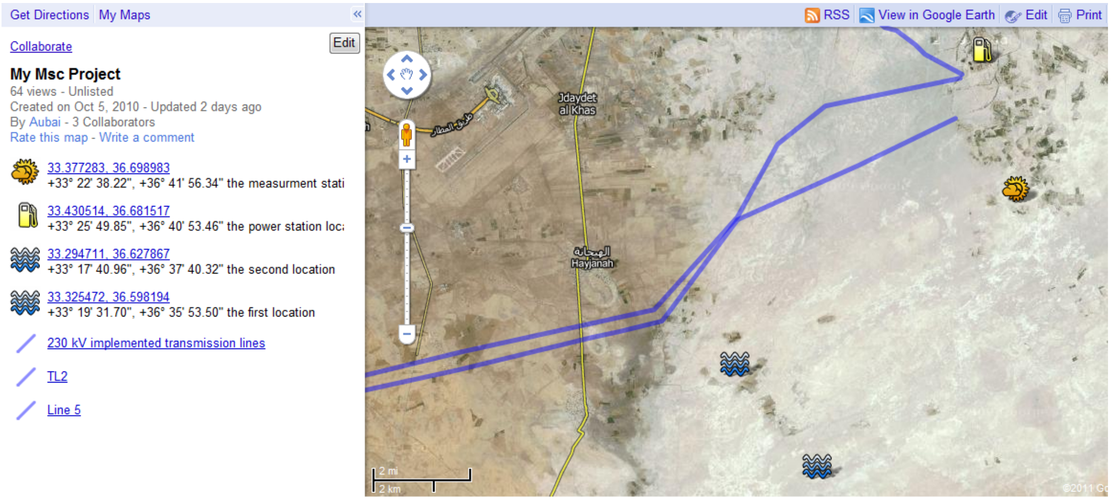


Figure 7.1-28 map of location that shows the important locations of the different important component of the wind farm.

Fortunately for us the location of interest has already been chosen by the Energy Research center in Syria and we were able to get a softcopy of the map of the location of interest from the Center and directly use it in the WASP program (the changes between the real coordinate and the electronic map was also provided by the Center) [23].

7.6.4. Turbine selection:

This is the part where we have to decide on the type of the proposed used turbine [24]. The interest of the Syrian Energy Research Center was on turbines of 2 MW capacities [25]. As the WASP program already contain a sample wind turbine data sheet for different companies with the power carve, hub height …, one of those chooses was taken.

[23] For more information about the location please refer to the theoretical chapters

[24] The criteria of wind turbine selection was discussed in chapter 7

[25] note that a pre-feasibility study was done for the location and other type of turbine was chosen

7.6.5. Turbine positioning:

This stage is where we distribute the selected wind turbines into rows. The distance between the different turbines is taken as the Danish wind energy association says:

"As a rule of thumb, turbines in wind parks are usually spaced somewhere between 5 and 9 rotor diameters apart in the prevailing wind direction, and between 3 and 5 diameters apart in the direction perpendicular to the prevailing winds."

This distance depend mostly on the available area (which will lead directly to the cost) and the awake effect (which also indirectly will lead to the revenues as this loses affect the output energy of the wind farm). In our case the land was for free (due to the fact that the land is already owned by the owner of the project) and the area was big enough to choose the distance that we want.

7.6.6. Resource grid:

The final step in WASP will be to generate the resource grid which is a result to all the other steps and helps to give you the energy and mostly any other characteristic of the selected area on the electronic map entered earlier to the WASP program. Also results will be shown in the report.

7.6.7. Results:

This part shows the results obtained from the WASP program. We will start with the wind atlas for the location generated with WASP program and end up with the energy generated with the same program.

7.6.7.1. Wind Atlas ALHijana output' Observed Wind Climate

Produced on 10/26/2010 at 2:36:40 PM by licenced user: Eng.Aubai using WAsP version: 10.00.0214.

Site description: 'ALhijana WASP wind data 2005'; Position: 36.00°N 33.00°E; Anemometer height: 40.00 m a.g.l.

Table 7.6.7.1—1 meterological data of the site

Parameter	Measured	Emergent	Discrepancy
Mean wind speed [m/s]	unknown	6.41	unknown
Mean power density [W/m²]	unknown	365 W/m²	unknown

Table 7.6.7.1—2 meterological data of the site

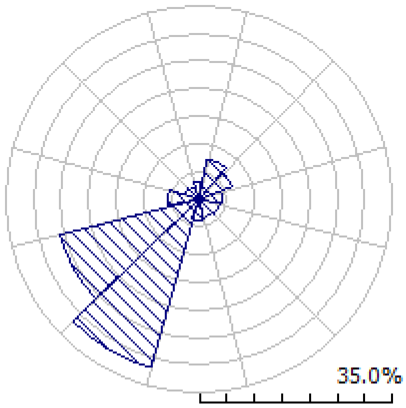


Figure 7.6.7.1-1 Wind rose of the selected location

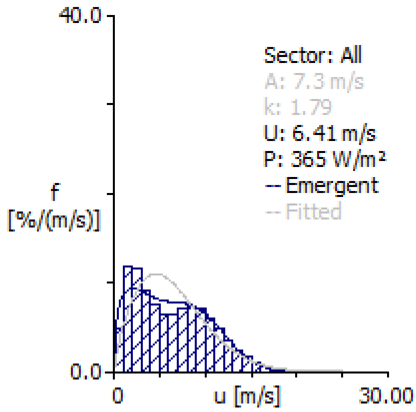


Figure 7.6.7.1-2 Frequency distribution of the selected location

	0	30	60	90	120	150	180	210	240	270	300	330
A	3.2	5.0	4.3	3.3	2.9	2.5	2.9	10.2	9.0	5.1	3.0	2.5
k	1.42	1.95	1.74	1.49	1.48	1.45	1.28	3.47	2.26	1.29	1.08	1.42
U	2.91	4.45	3.84	2.97	2.60	2.27	2.68	9.14	7.98	4.75	2.92	2.27
P	45	106	77	44	30	21	42	610	531	229	77	21
f	3.2	7.3	6.3	4.3	3.8	3.3	3.9	31.6	25.9	5.5	2.6	2.2

Table 7.6.7.1—3 different metorological data with different angles

	Weibull-A	Weibull-k	Mean speed	Power density
Source data	-	-	(not available from the file)	
Fitted	7.3 m/s	1.79	6.51 m/s	365 W/m²
Emergent	-	-	6.41 m/s	365 W/m²
Combined	7.2 m/s	1.72	6.41 m/s	365 W/m²

Table 7.6.7.1—4 Weibull information about the selected site[26]

[26] For detailed information please refer to the appendix B

A and U are given in m/s, P in W/m² and the frequencies of occurrence in per mille and per cent (f).

7.6.7.2. The results of the suggested wind farm:

This part now shows the results of the suggested wind farm with the different energy output, awake losses and the distination between the different wind turbines.

7.6.7.2.1.The wind farm short report generated by WASP program is:

This is the summary results of the selected wind farm as generated by WASP program:

Parameter	Total	Average	Minimum	Maximum
Net AEP [GWh]	364.140	7.283	7.038	7.649
Gross AEP [GWh]	386.251	7.725	7.641	7.927
Wake loss [%]	5.72	-	-	-

Table 7.6.7.2—1 the total energy generated by the Wind farm

7.6.2.2. The wind farm map:

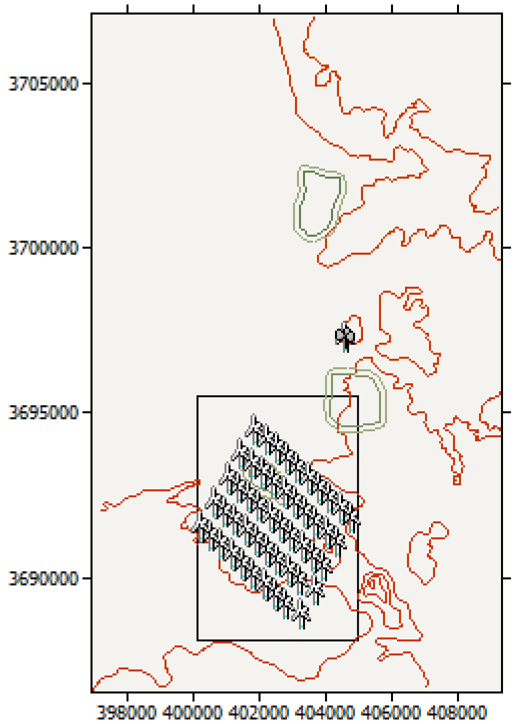


Figure 7.6.7.2-1 the wind farm location

All of the parameters in the project are default values.

Results analysis:

1- A detailed report about the awake effect and energy of different point in the resource grid can be seen in this following link and in Appendix B :
2- The A,K constants of Weibull distribution are calculated both manually and by the WASP program (Also by Frank the study was conducted using Windpro.

Program) and all had the same values also that were true for the average wind speed of the location.

	K	A	Average wind speed
Manually	1.69	6.95	6.1
WASP	1.7	7.2	6.41

3- From the site visit it was understood that the area of the wind farm is an open one so the location of the turbine is not controlled by the limited area. In this case the location was taken near the measurement station with different distance between the wind turbines just in order to show the importance of the awake effect calculation.
4- Another location will be shown to the wind turbine in the visited area in Syria.
5- The energy yield of the wind farm can be affected badly due to the awake losses (referring to the first scenario, with high awake losses and the second one with lower awake losses). The energy yield also can be affected by the type of the used turbine and the wind characteristic of the area of interest).

8. Chapter 8 conclusion & future works:

The conclusion:

All the results before can show:

1- The prediction concept can differ a lot when the ANN for long term data prediction or only for short term prediction. Long term prediction needs a more complicated ANN tool for the wind speed prediction, for example a helping function can be used to help the suggested wind speed prediction tool (specially the training function that will be used). The short term prediction gives better results [27], yet can work on only small range.
2- There is no direct method for the sizing of the ANN tool [28]. It depends on the purpose of the used neural network, and the builder experience.
3- A correlation analysis to the input data can help with:
   A- Understanding the relationship between the different used data
   B- Can help with building the helping function for long term prediction.
   C- Gives a good base for expecting the results that comes out from the ANN tool.
4- Although some results were completely unacceptable, they helped in reducing the possibilities and making the best use of the available data.
5- A previous treating of the available data can help improve the accuracy of the prediction tool afterword. Especially when this data is used for long term

[27] Better results means that the error is reduced to an acceptable levels.
[28] For example which training function to use or the number of the neurons inside the hidden layers

prediction (keep in mind that the ANN should have all the available cases in the training data in order to be able to predict all the possible coming situations).

6- If the energy data were available [29], the same approach of the wind speed prediction tool will be used.
7- Any error in the predicted wind speed will affect directly on the expected energy. What's more the errors of the deviation with time are the most important error to overcome, because this time of error can have a direct effect on the energy market.
8- The usage of the new approach (half year data input) has two important effects:
   A- A better results were obtained for the same year of training
   B- The error in the other years (previous once) is increased which is not good for the energy calculation afterword.
9- For the wind farm design it is important to get the exact map of the selected location with all information about:
   A- The geographical information about the land.
   B- The residential map of the location.
   C- The electrical grid that are in this location.
10- The more data used (when available) the better the results of the WASP program will be.
11- The awake affect is very important when calculating the energy output of the wind farm, and when the area is available then it is better to reduce this error as much as possible. The awake affect can be reduced by extending the distance between the turbines in the same row and two rows.
12- The distance between two turbines in one row is between 3 to 5 of the rotor diameter of the selected turbine, and the distance between two turbines of the different rows is between 5 to 9 of the rotor diameter of the selected turbine [30].
13- With the usage of WASP program and the proposed ANN tool in Matlab we achieve all types of wind speed prediction possible.

Recommendations for future work:

This study does not take into consideration the usage of online neural network for wind speed prediction. Which means the results of the used ANN tool is not improved with time, which in its turn will lead to the fact that the suggested prediction tool can work for only two years and then will not give acceptable results after that. What is more a helping function can be improved in order to improve the results of long time prediction. A better data about the energy generated can be collected (as new wind farm are to be installed in Syria in the next coming years) and then used to build an artificial neural network for energy

[29] There is no wind farm in Syria to use the data of that in our energy prediction tool.
[30] This is stated in the WASP program and taken from the Danish wind energy association.

prediction and integrate the results of the wind prediction tool in the new one. Also a better wind farm programs for wind farm design can be used for example WindPro. Or OpenWind (Keep in mind that the WASP program is the best for horizontal and vertical wind prediction and WindPro with difficult locations use the WASP program for climate calculation). More parameters about the wind can be obtained and used as input for the prediction tool such as humidity.

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Contents

List of figures

Appendix A

In this part I will show the different results (output) obtained from the used ANN tool for wind prediction with the different proposed training functions, Input data, performance functions and different aproachs.

Pressure as input of the proposed ANN

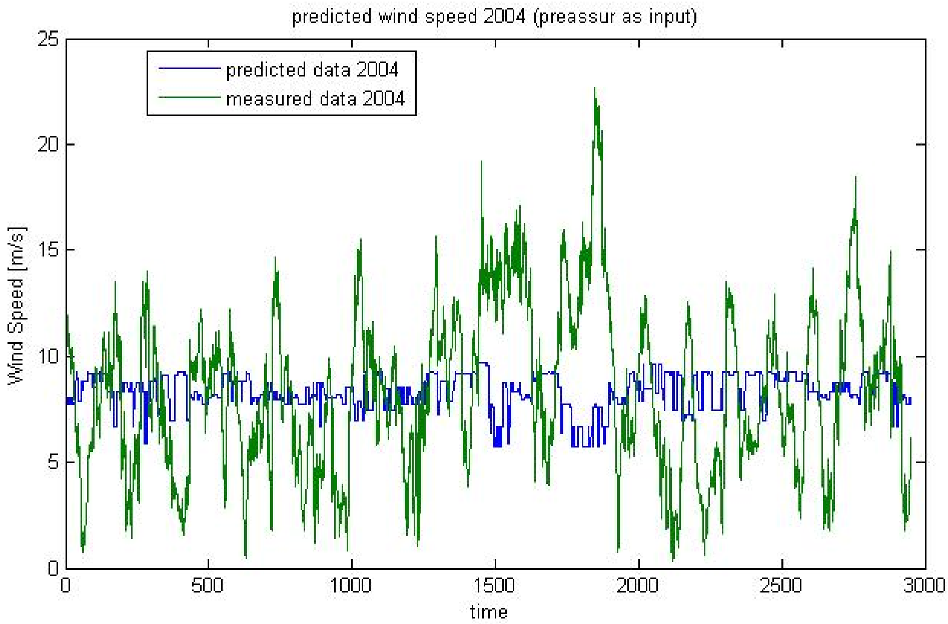


Figure 2-- predicted wind speed for 2004

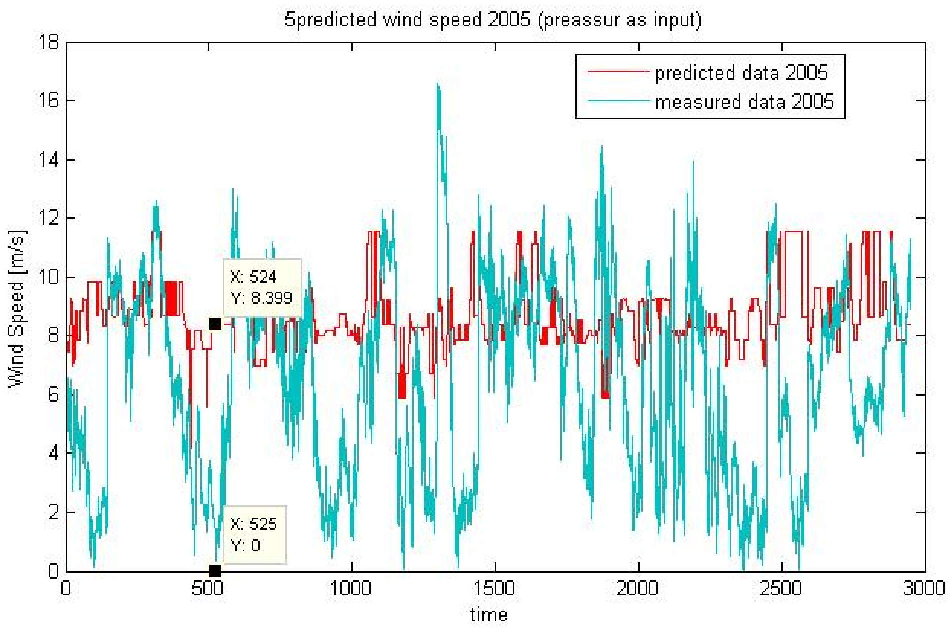


Figure 3-predicted wind speed for 2005

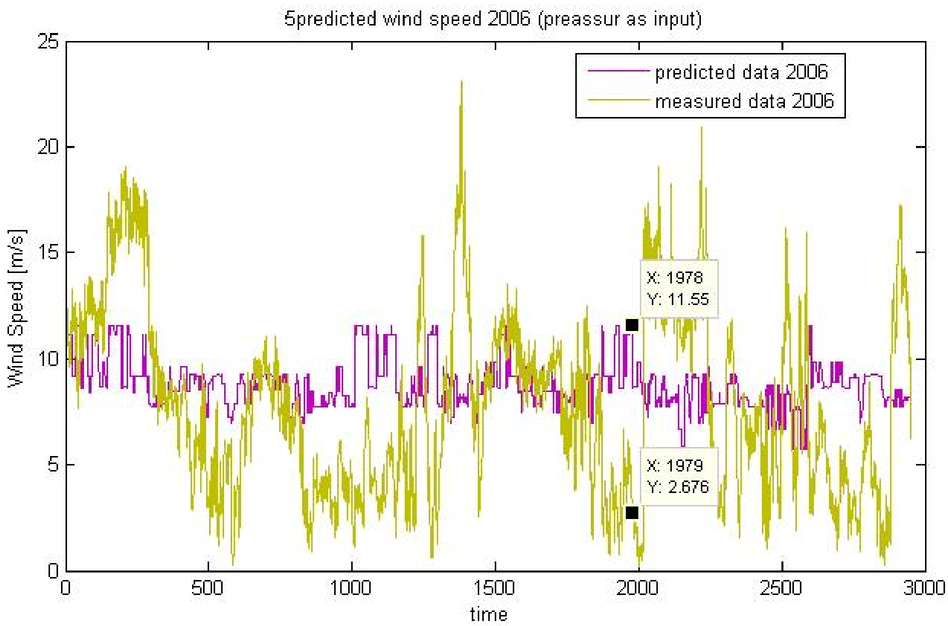


Figure 4-predicted wind speed for 2006

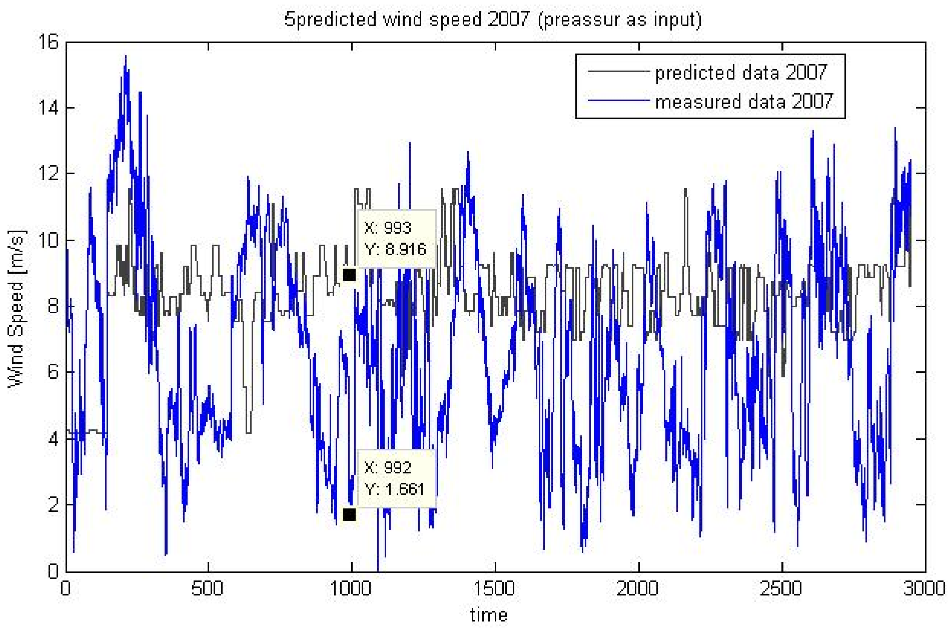


Figure 5- predicted wind speed for 2007

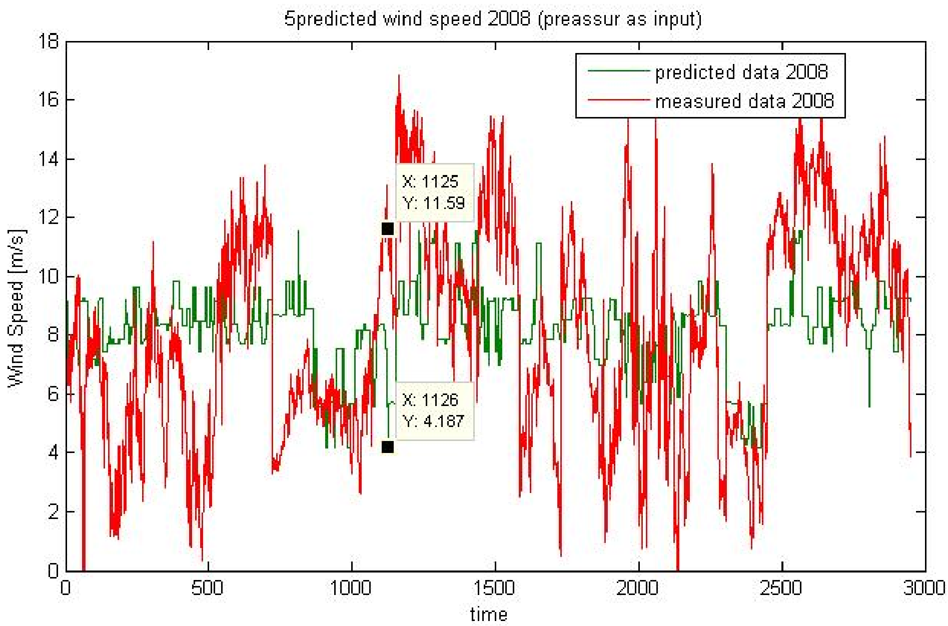


Figure 6- predicted wind speed for 2008

Temperature as input of the proposed ANN

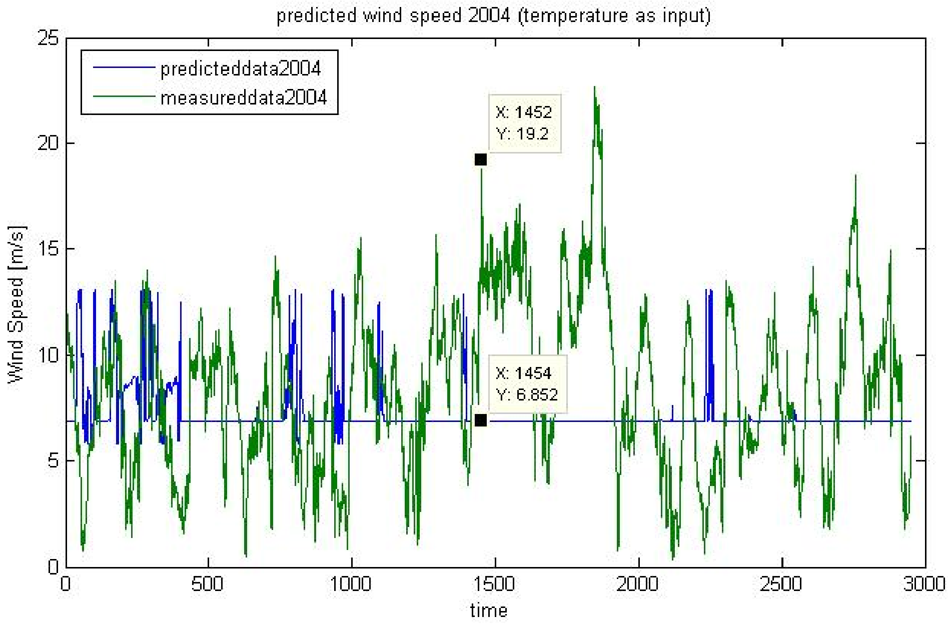


Figure 7- predicted wind speed for 2004

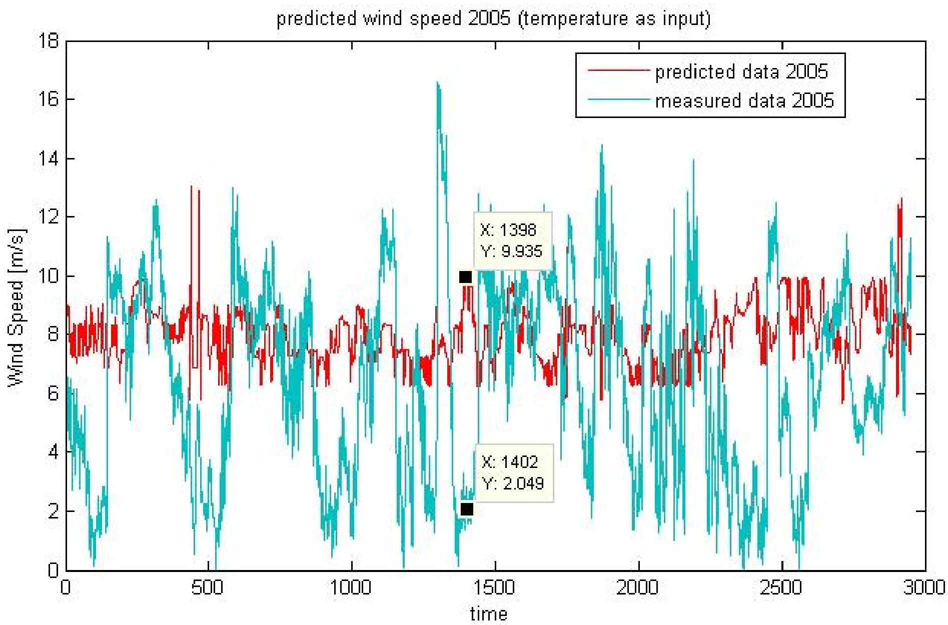


Figure 8- predicted wind speed for 2005

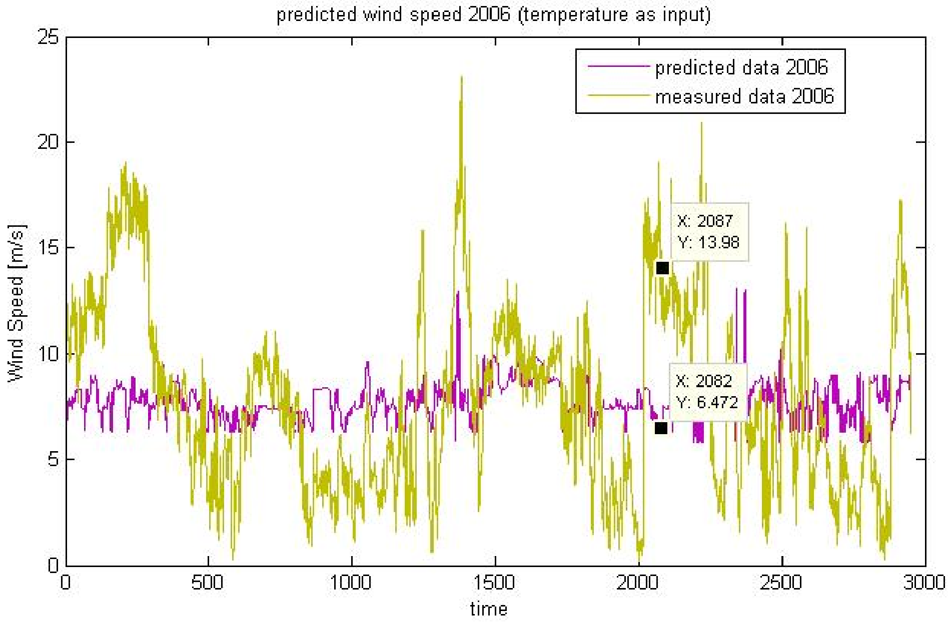


Figure 9- predicted wind speed for 2006

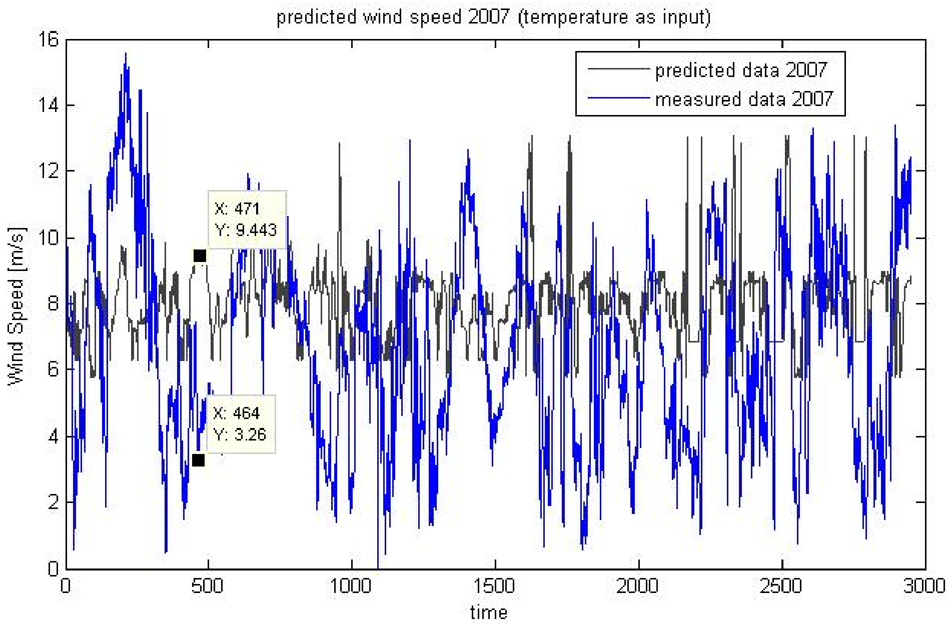


Figure 10- predicted wind speed for 2007

Figure 11- predicted wind speed for 2008 unavailable

Direction of the wind speed as input of the proposed ANN

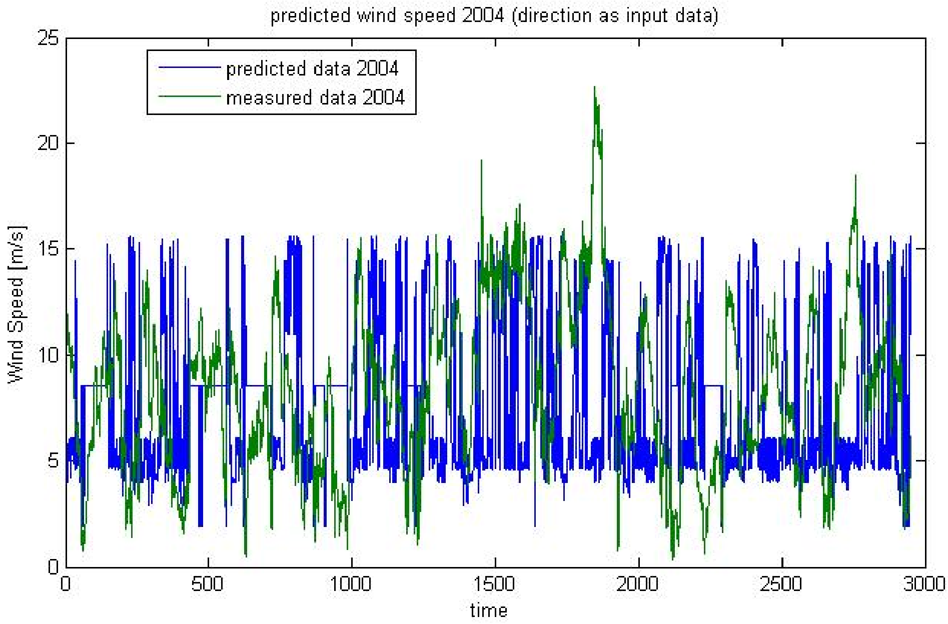


Figure 12- predicted wind speed for 2004

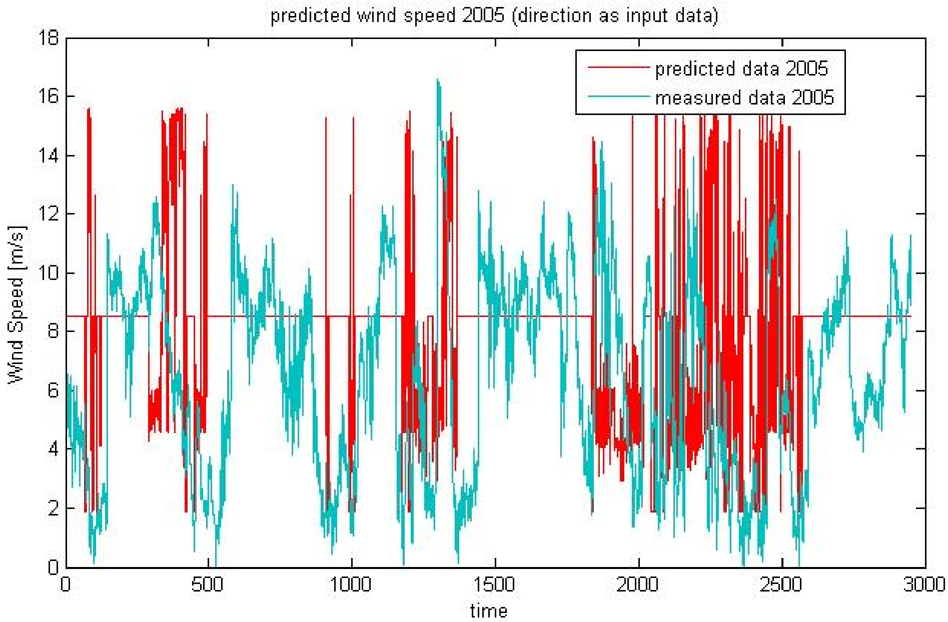


Figure 13 predicted wind speed for 2004

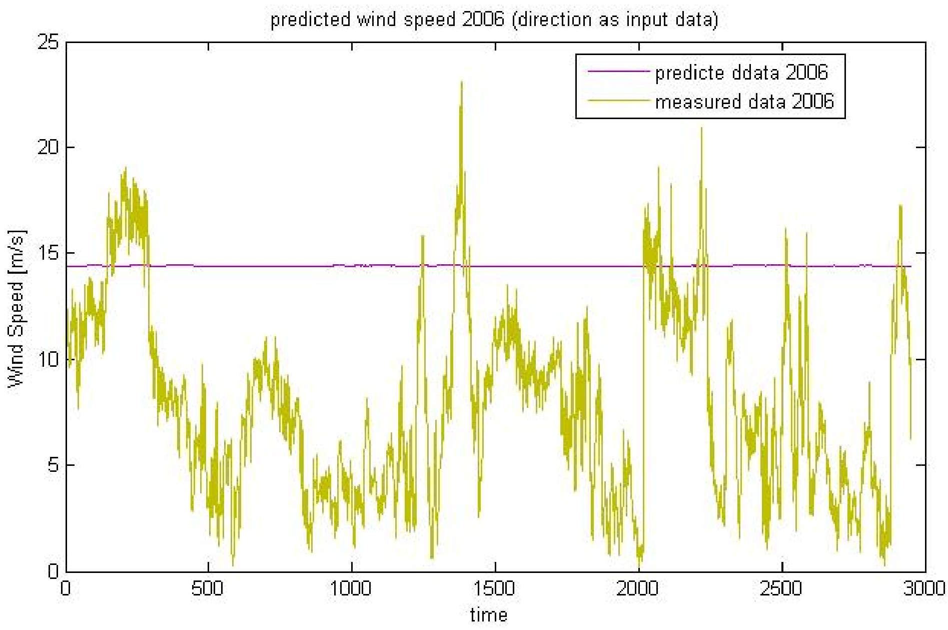


Figure 14- predicted wind speed for 2006

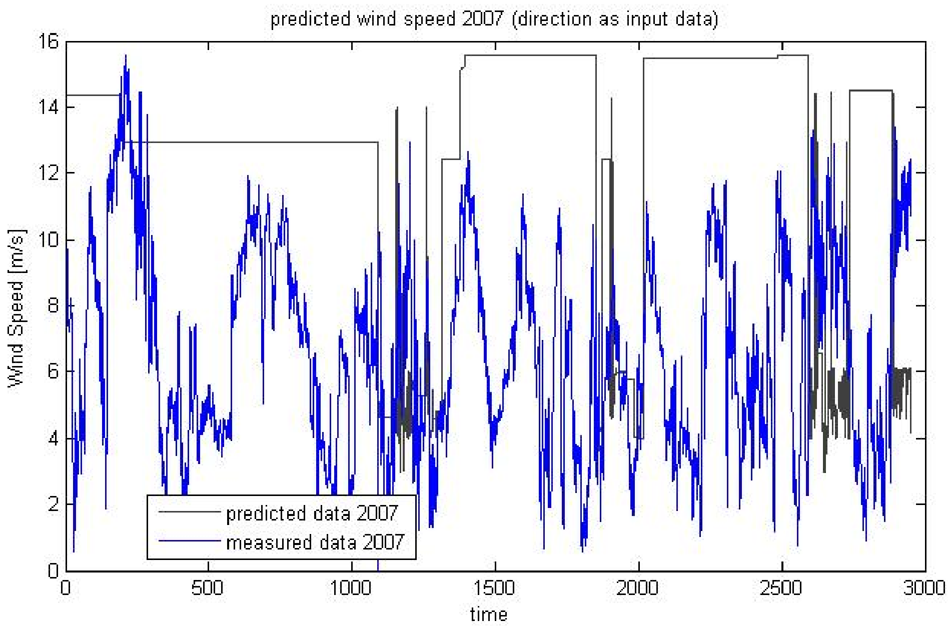


Figure 15- predicted wind speed for 2007

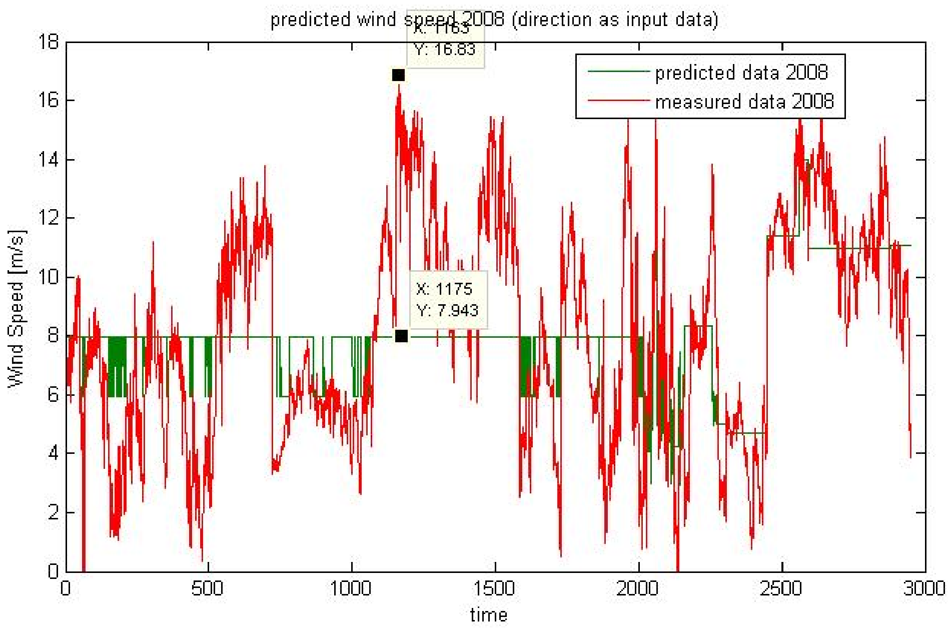


Figure 16- predicted wind speed for 2008

Different training functions:

BFGS Quasi-netwton

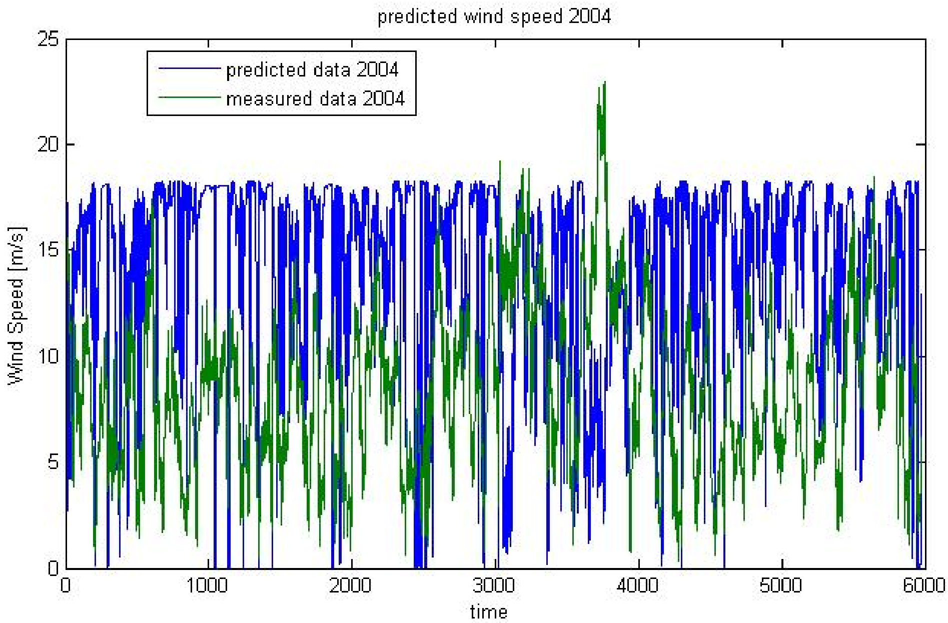


Figure 17- predicted wind speed for 2004

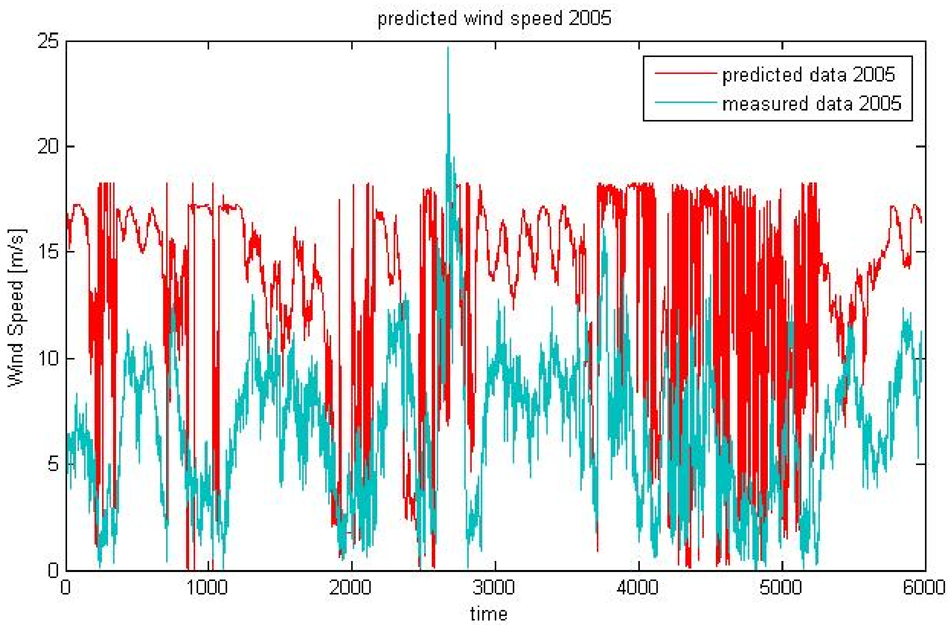


Figure 18- predicted wind speed for 2005

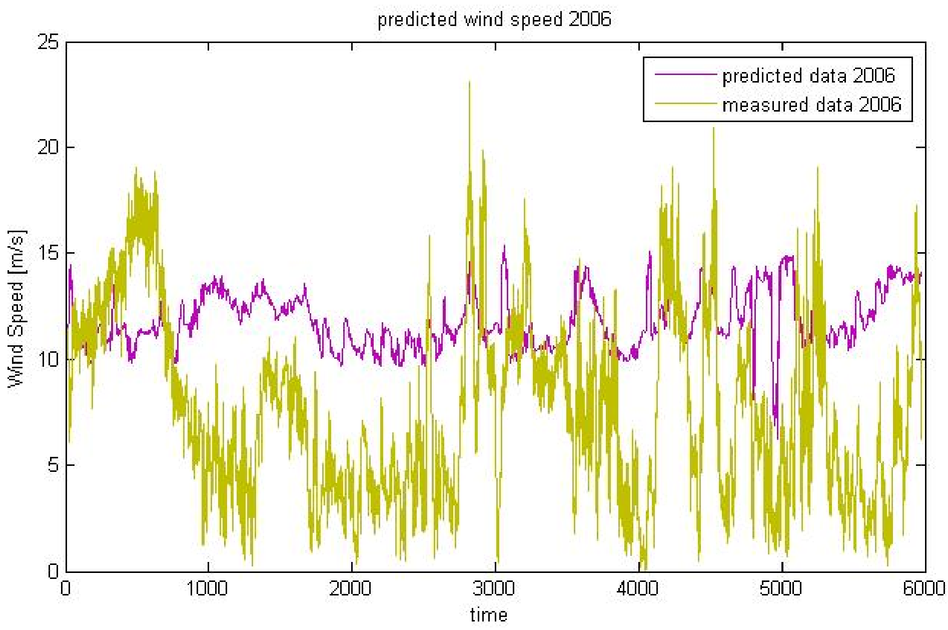


Figure 19- predicted wind speed for 2006

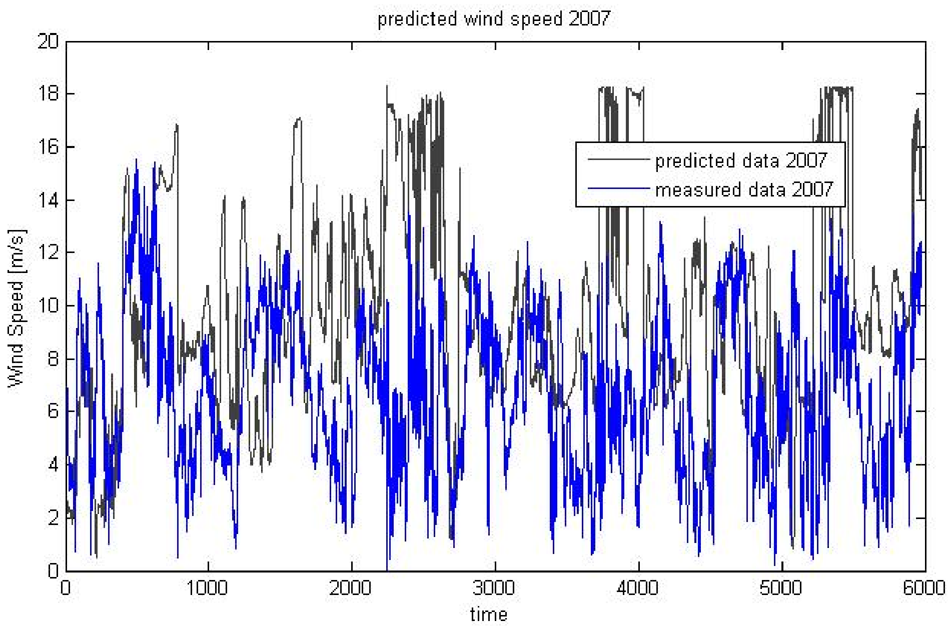


Figure 20- predicted wind speed for 2007

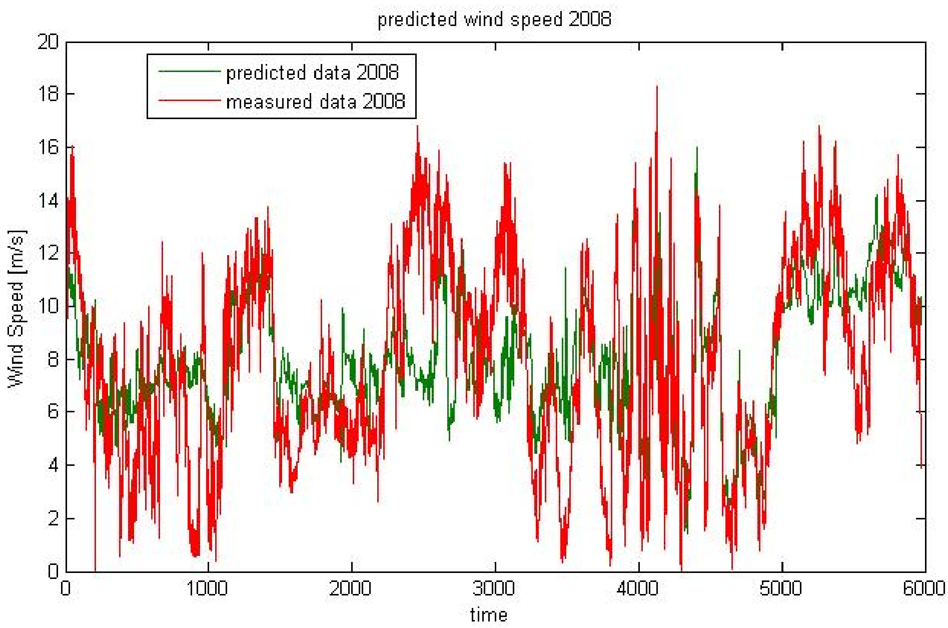
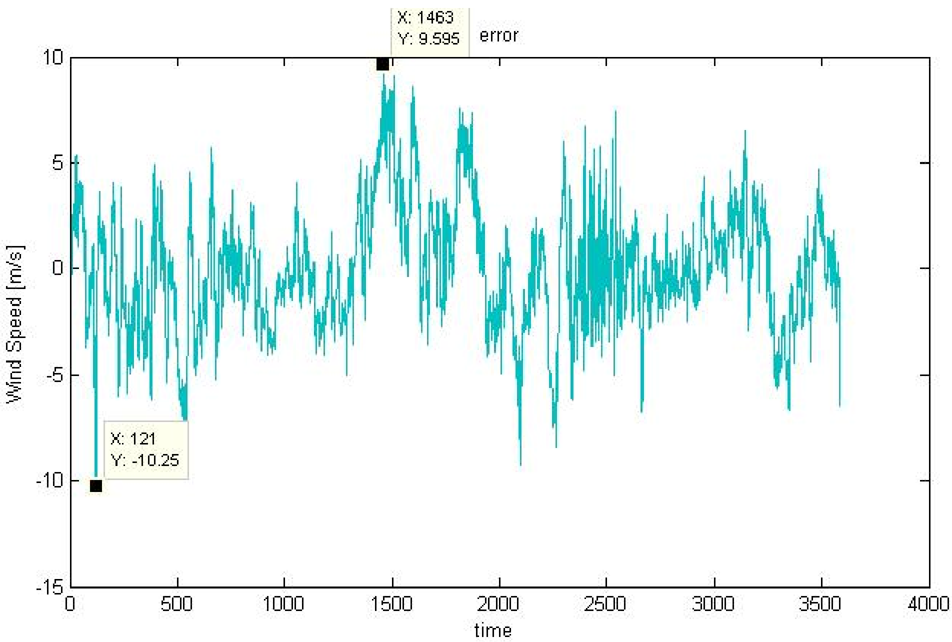


Figure 21- predicted wind speed for 2008



The Error resulting from the training presses.

Bayesian Regulation

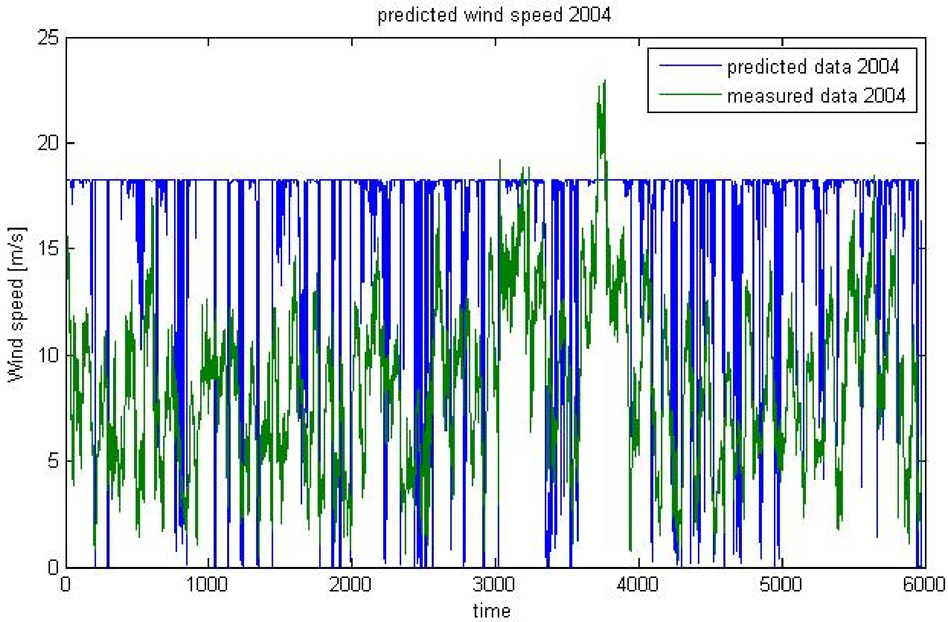


Figure 22- predicted wind speed for 2004

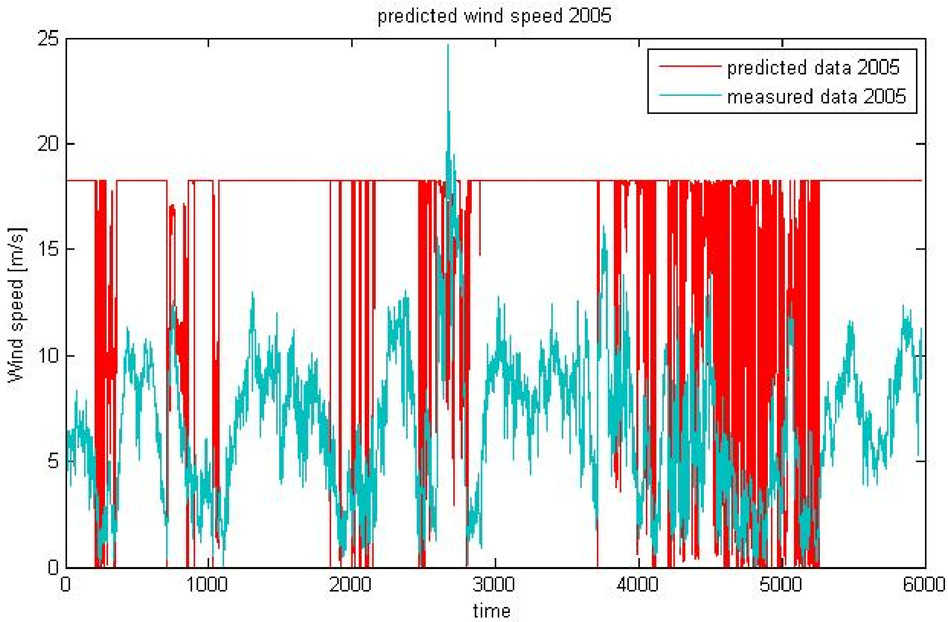


Figure 23- predicted wind speed for 2005

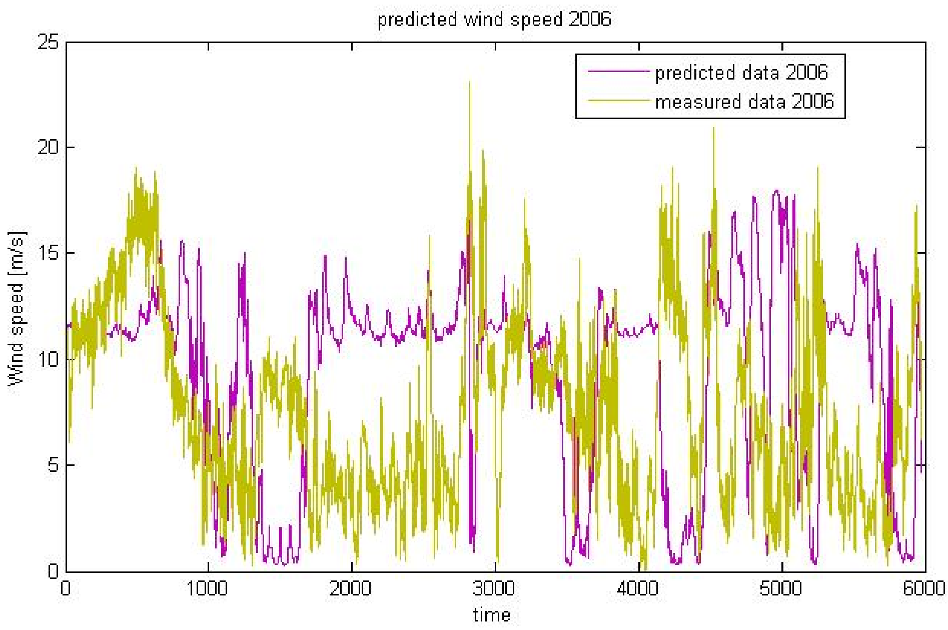


Figure 24- predicted wind speed for 2006

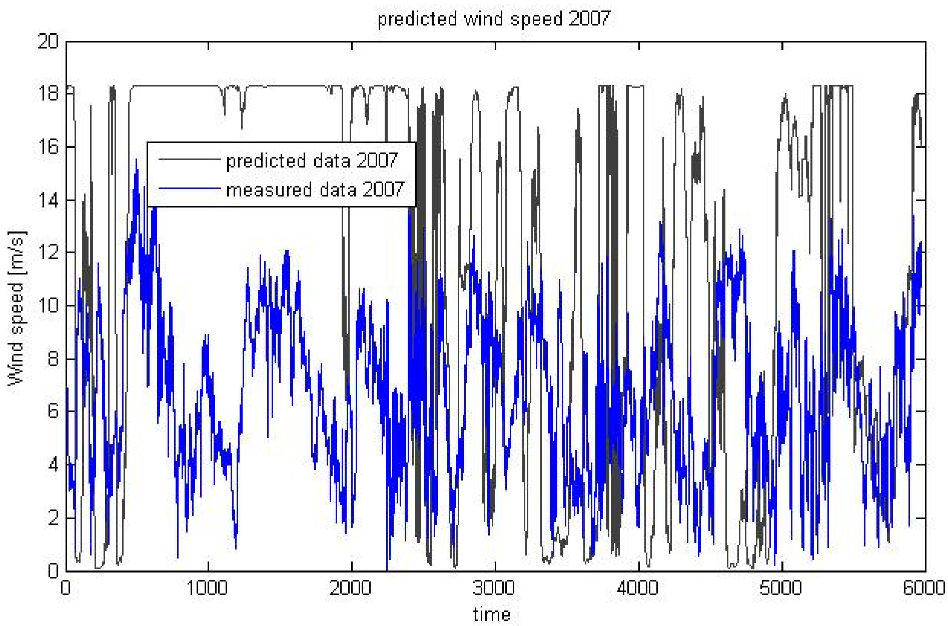


Figure 25- predicted wind speed for 2007

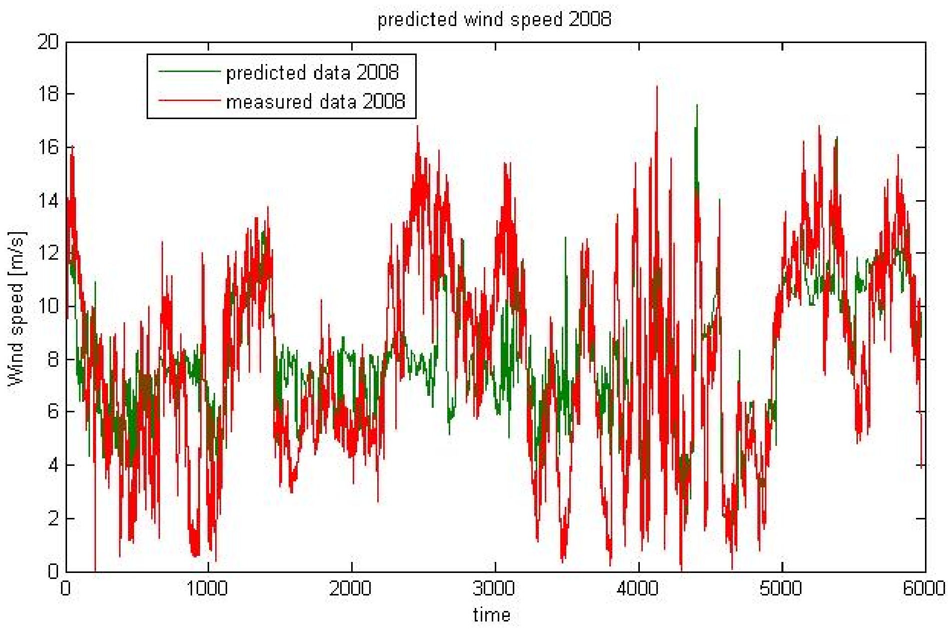
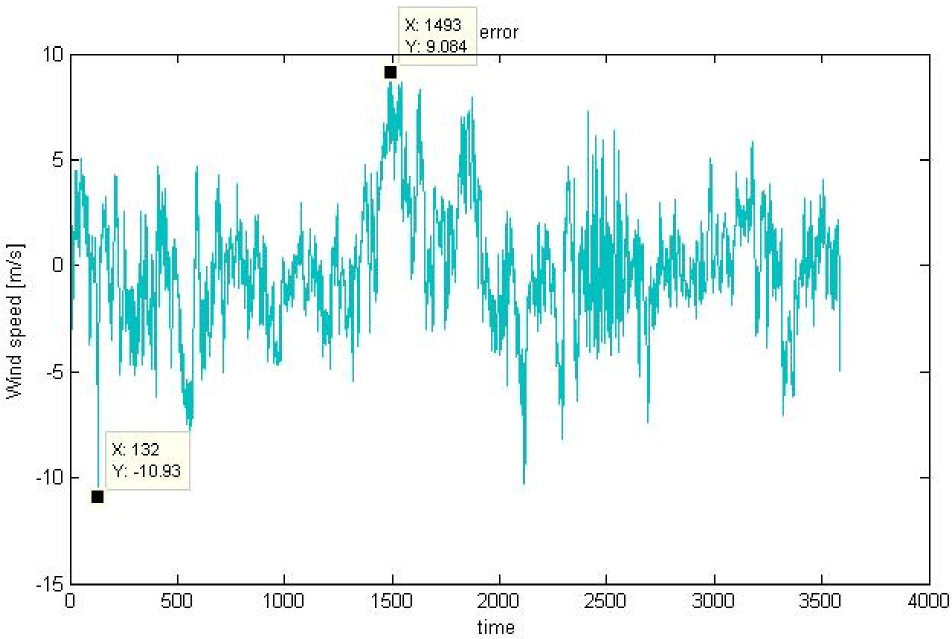


Figure 26- predicted wind speed for 2008



The Error resulting from the training presses.

Conjugate gradient backpropagation with Fletcher-R.

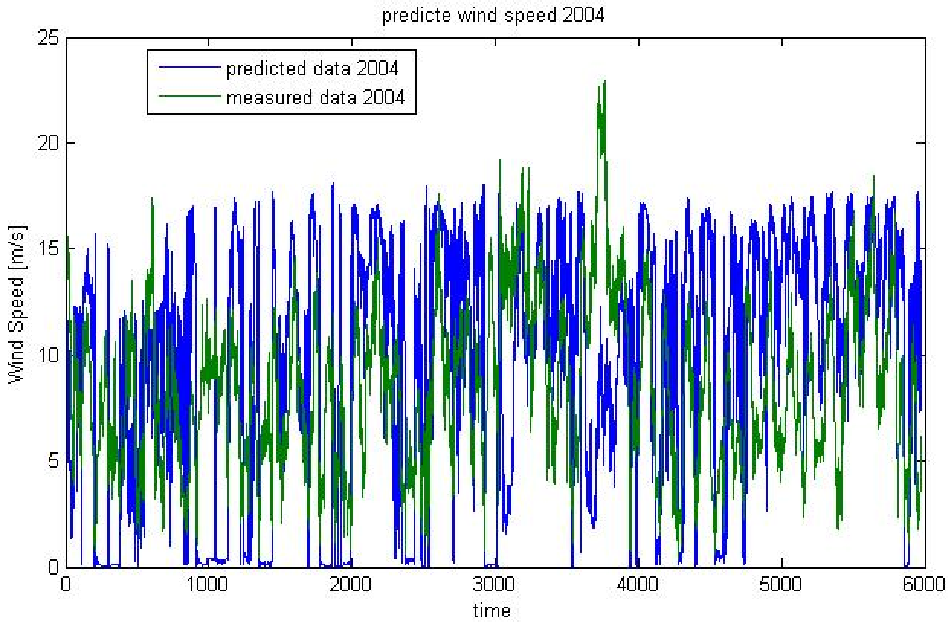


Figure 27- predicted wind speed for 2004

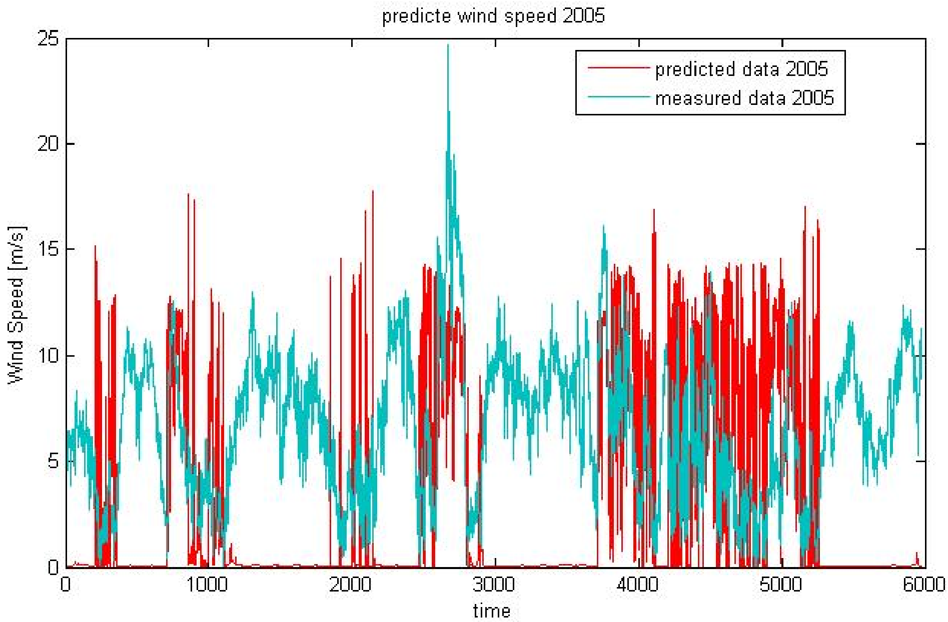


Figure 28- predicted wind speed for 2005

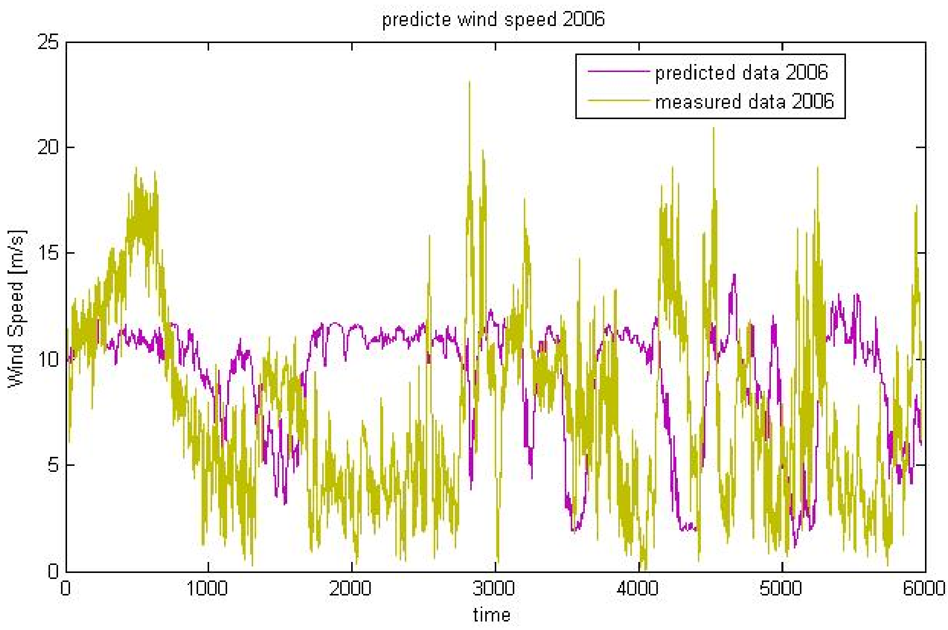


Figure 29- predicted wind speed for 2006

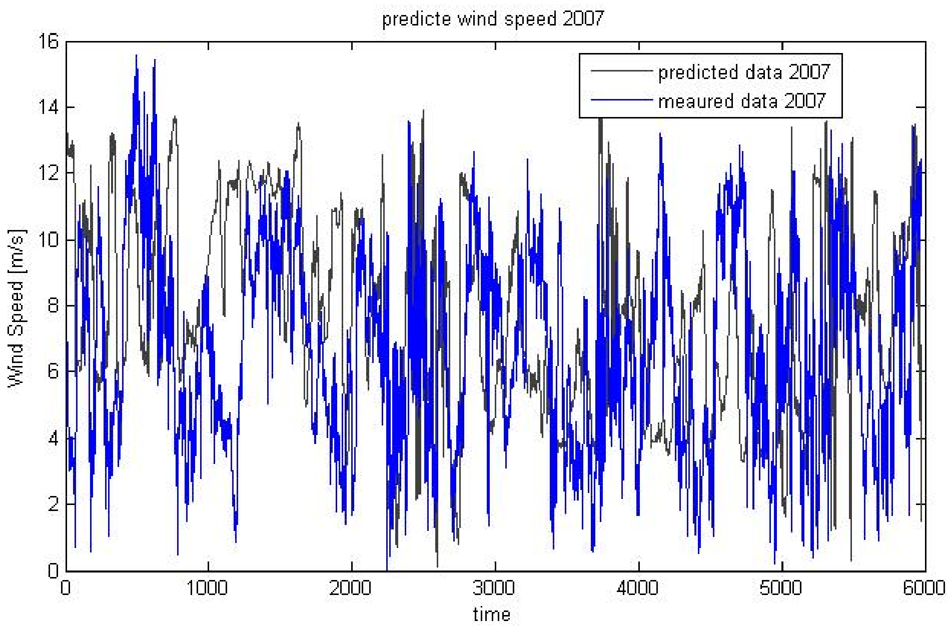


Figure 30- predicted wind speed for 2007

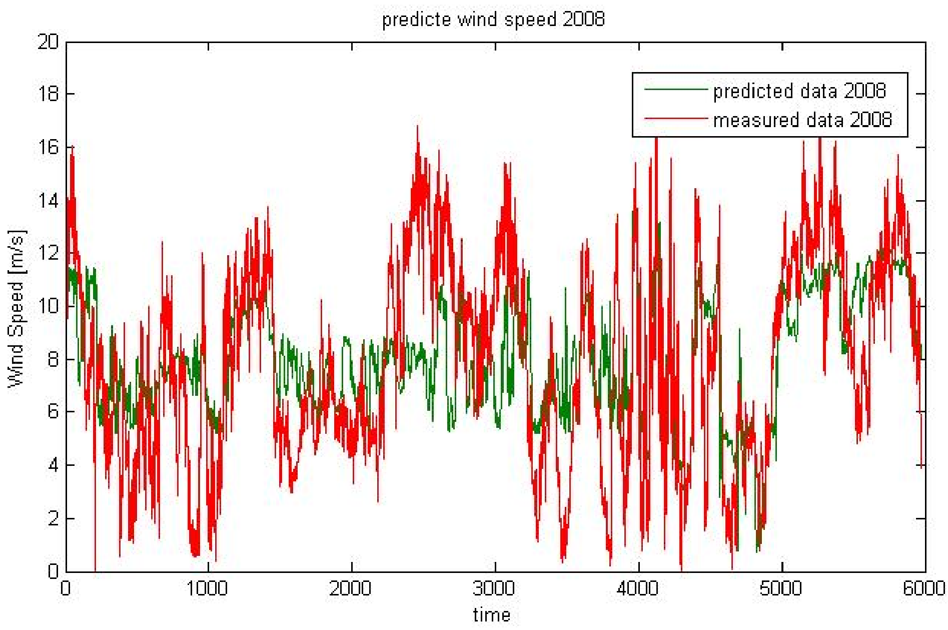


Figure 31- predicted wind speed for 2008

Conjugate Gradient with Beale-Powell Restarts

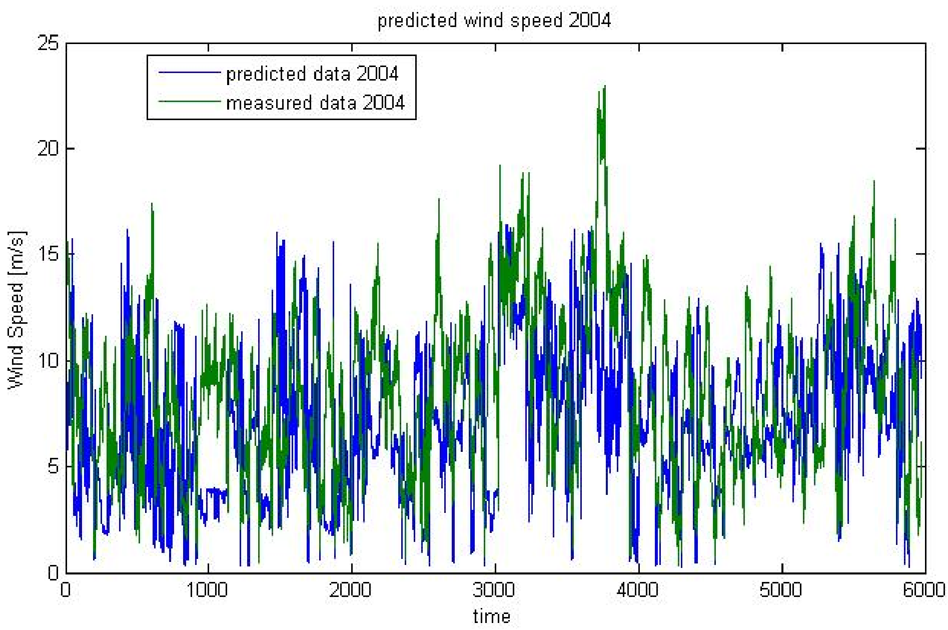


Figure 32- predicted wind speed for 2004

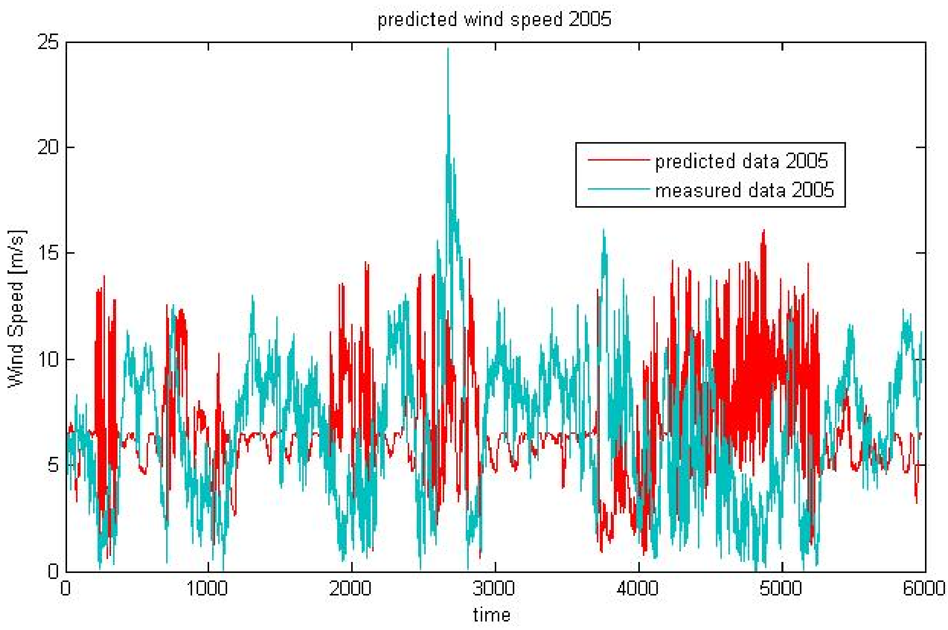


Figure 33- predicted wind speed for 2005

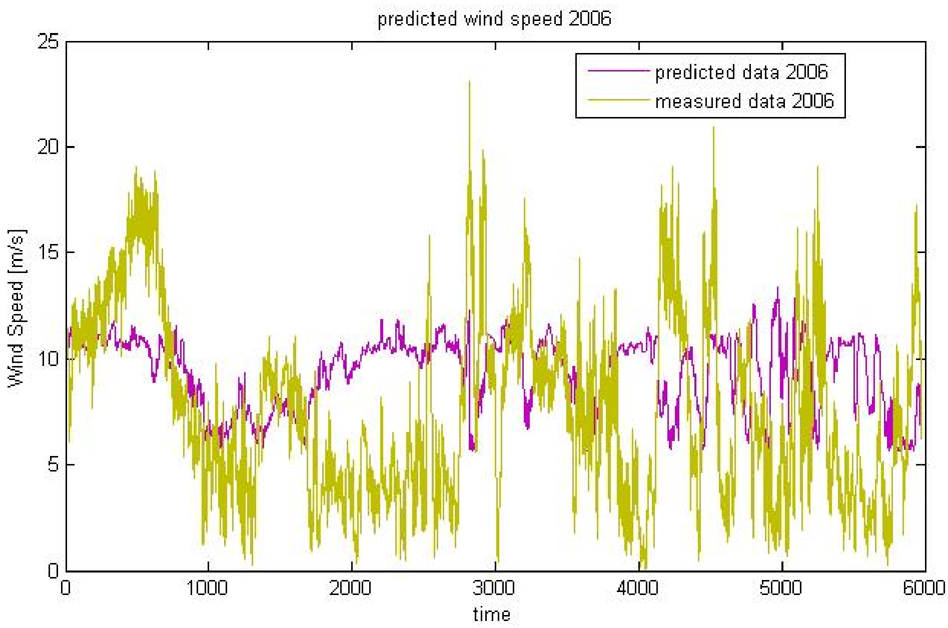


Figure 34- predicted wind speed for 2006

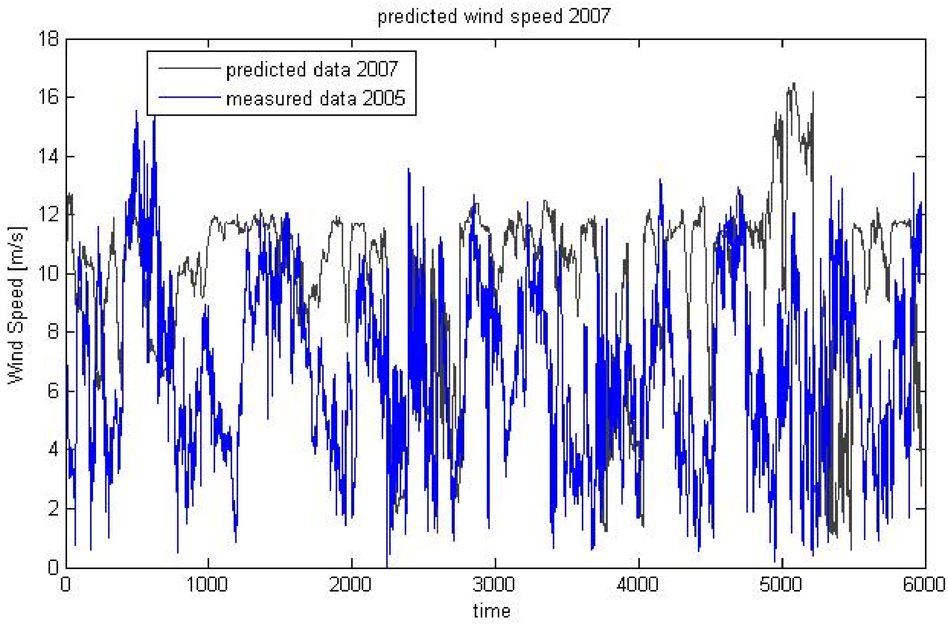


Figure 35- predicted wind speed for 2007

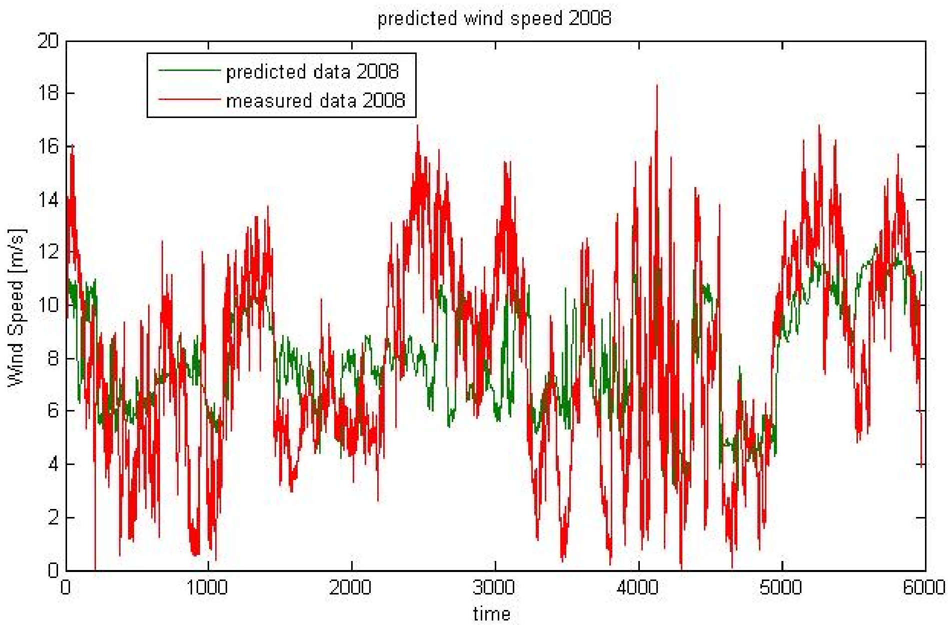
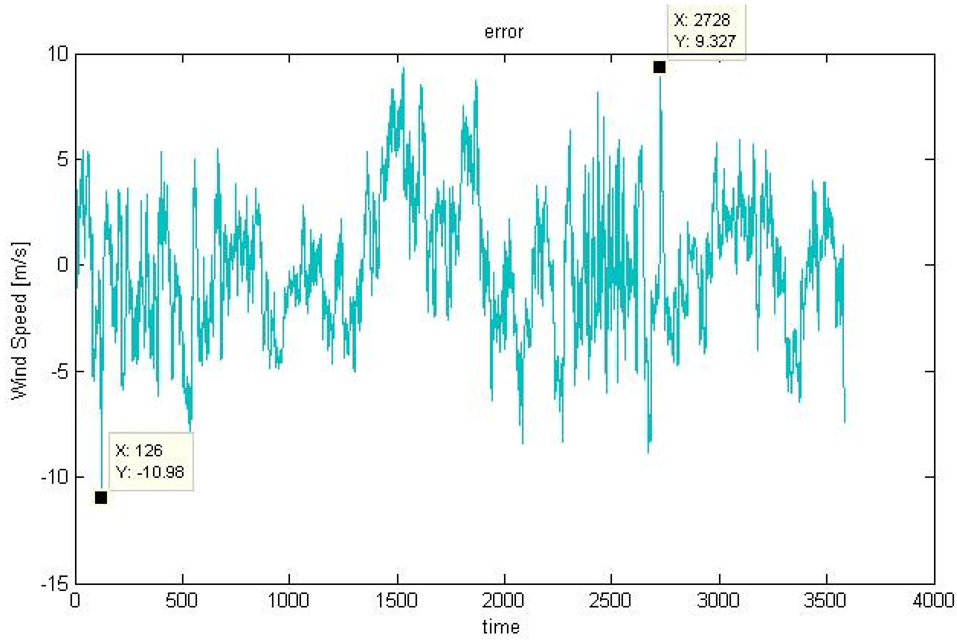


Figure 36- predicted wind speed for 2008



The Error resulting from the training presses.

Conjugate Gradiend with Polak-Ribiere Restarts

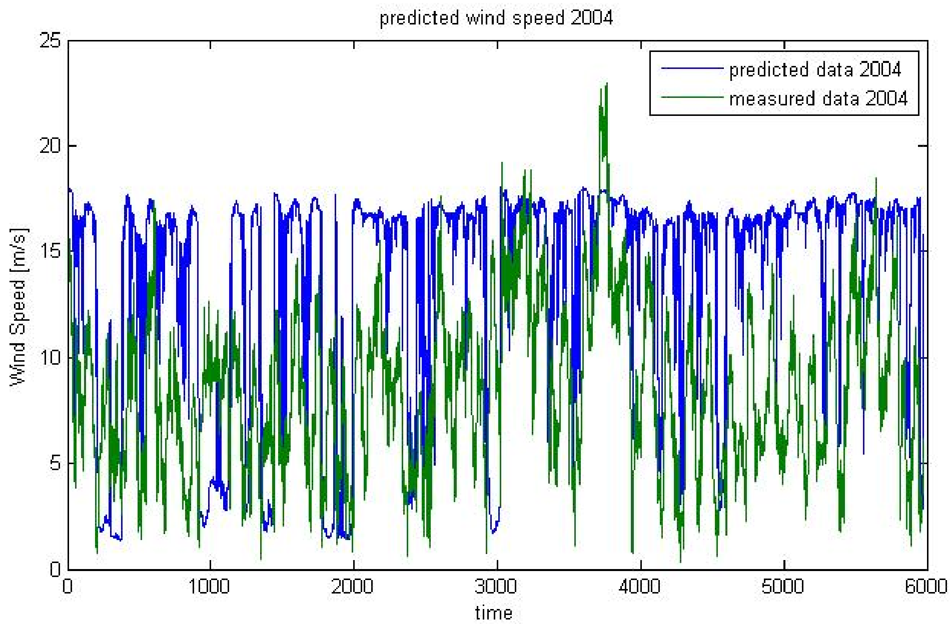


Figure 37- predicted wind speed for 2004

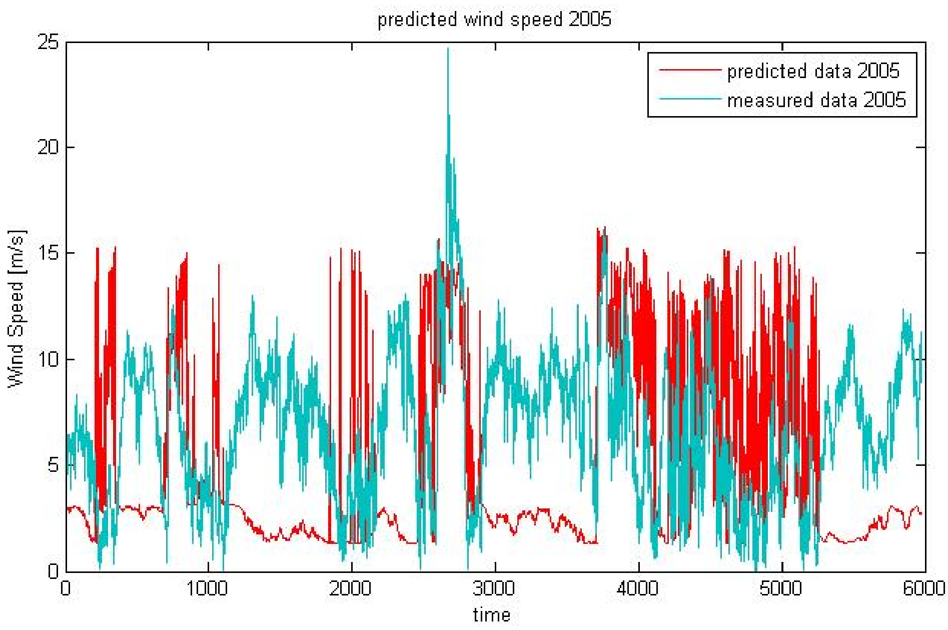


Figure 38- predicted wind speed for 2005

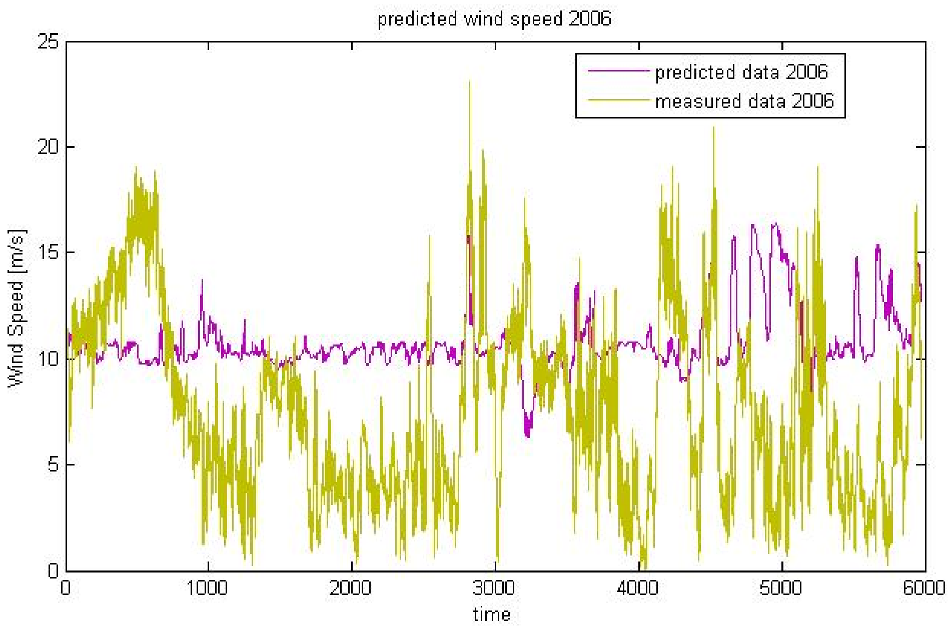


Figure 39- predicted wind speed for 2006

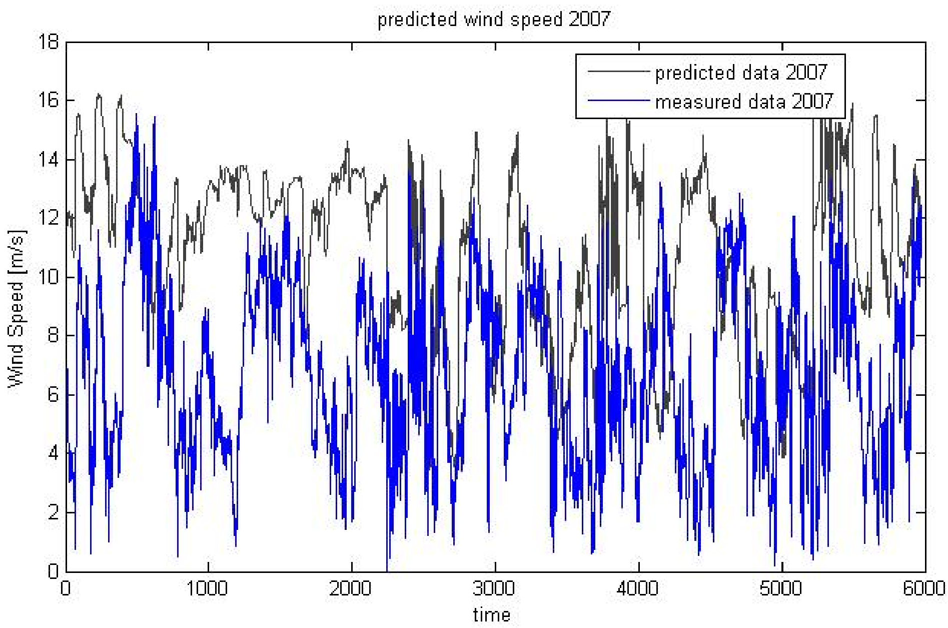


Figure 40- predicted wind speed for 2007

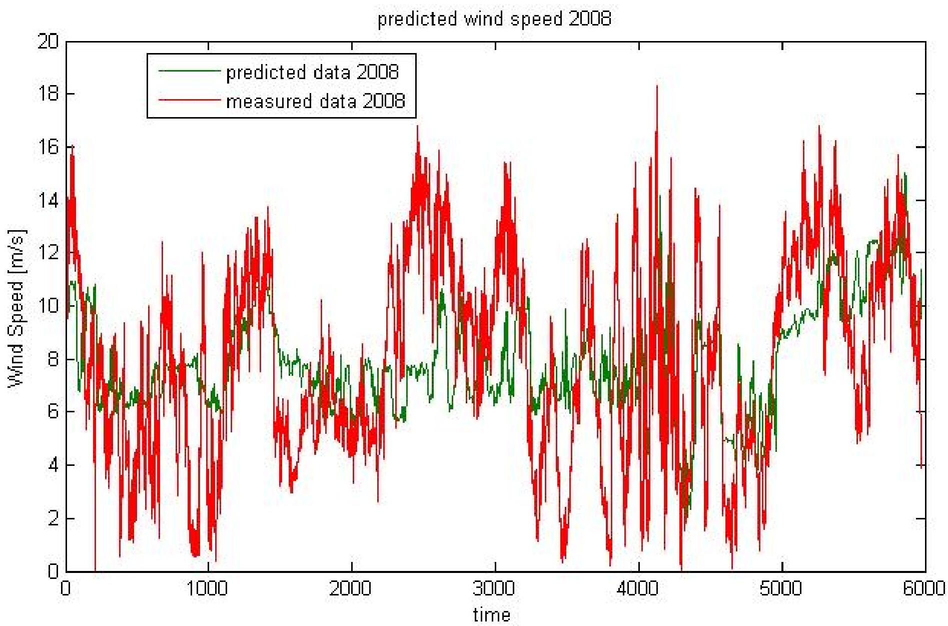


Figure 41- predicted wind speed for 2008

Gradient Descent Backprogration

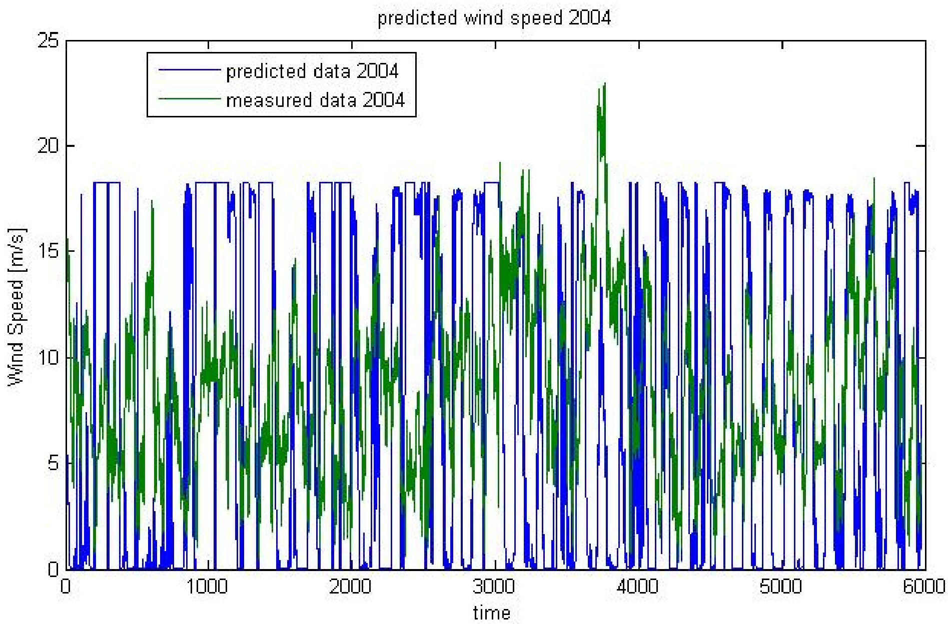


Figure 42- predicted wind speed for 2004

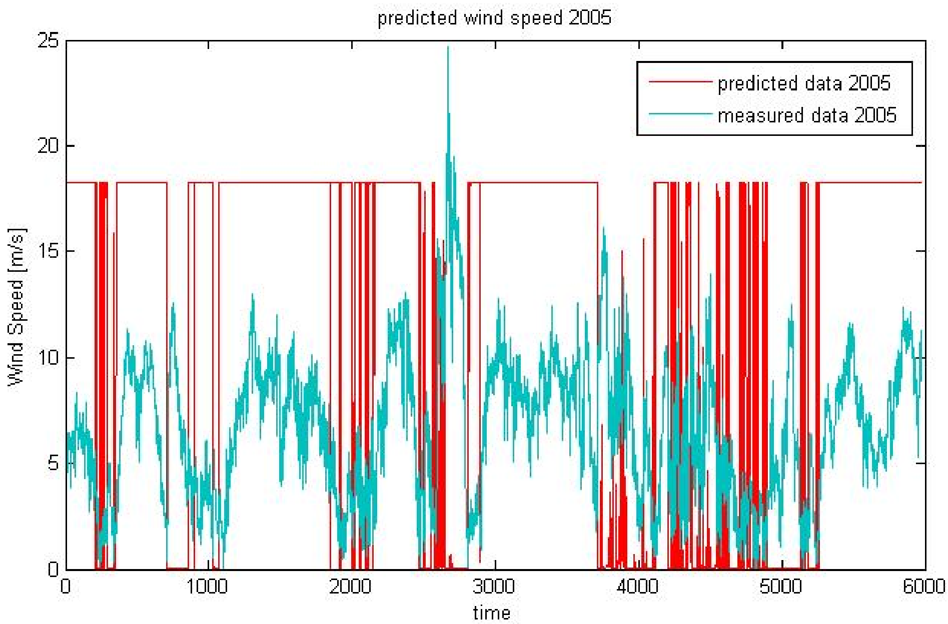


Figure 43- predicted wind speed for 2005

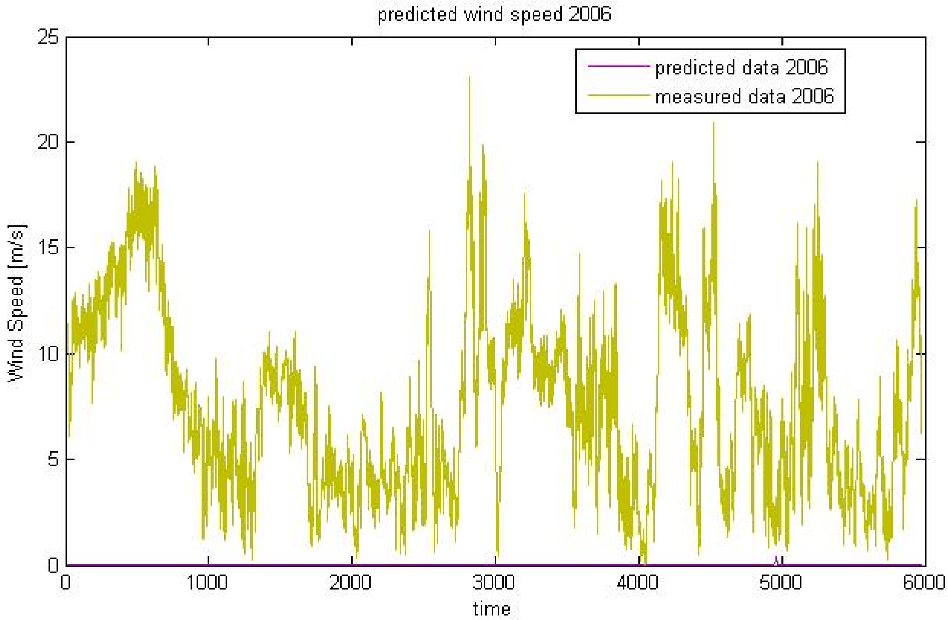


Figure 44- predicted wind speed for 2006

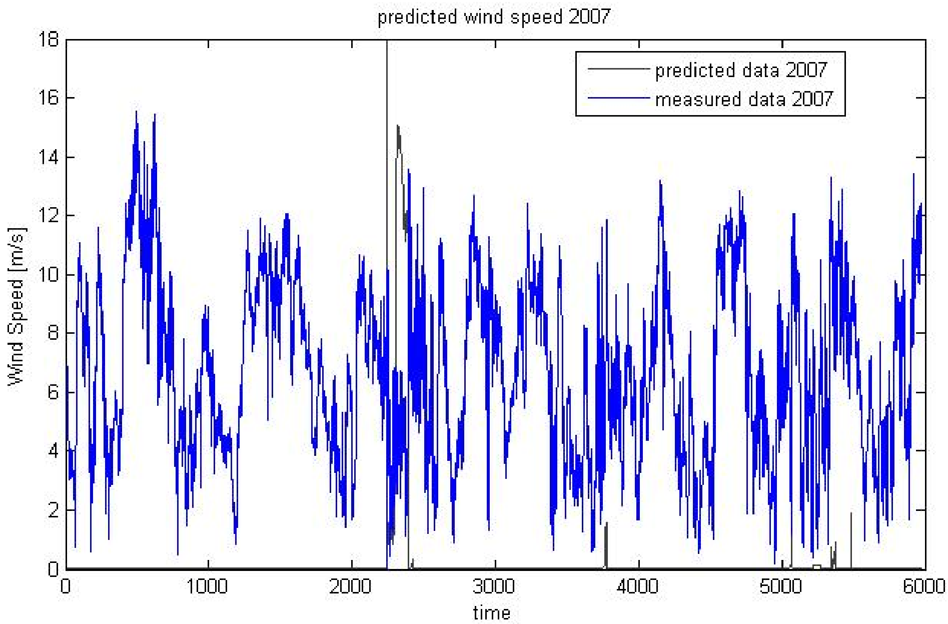


Figure 45- predicted wind speed for 2007

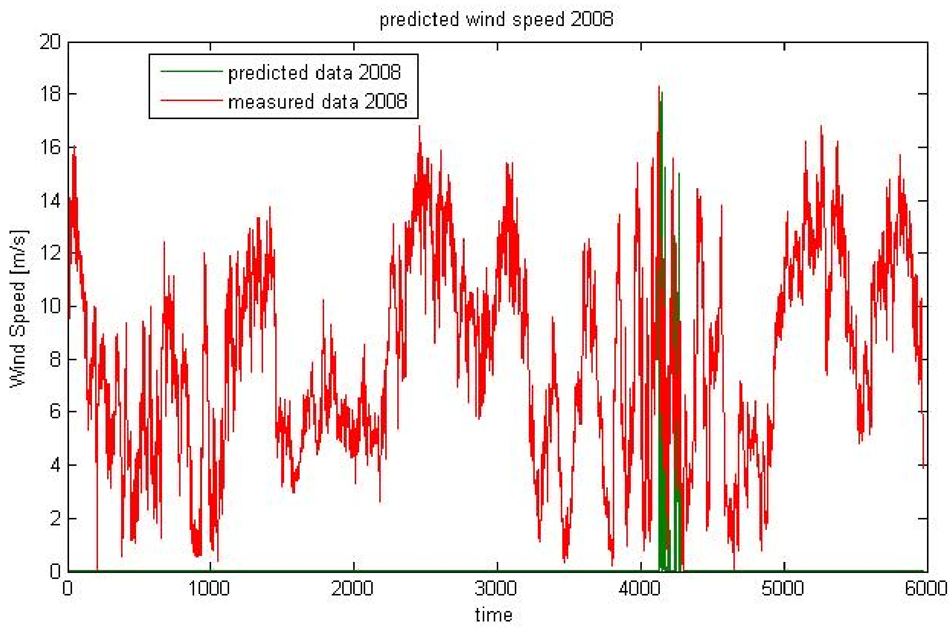
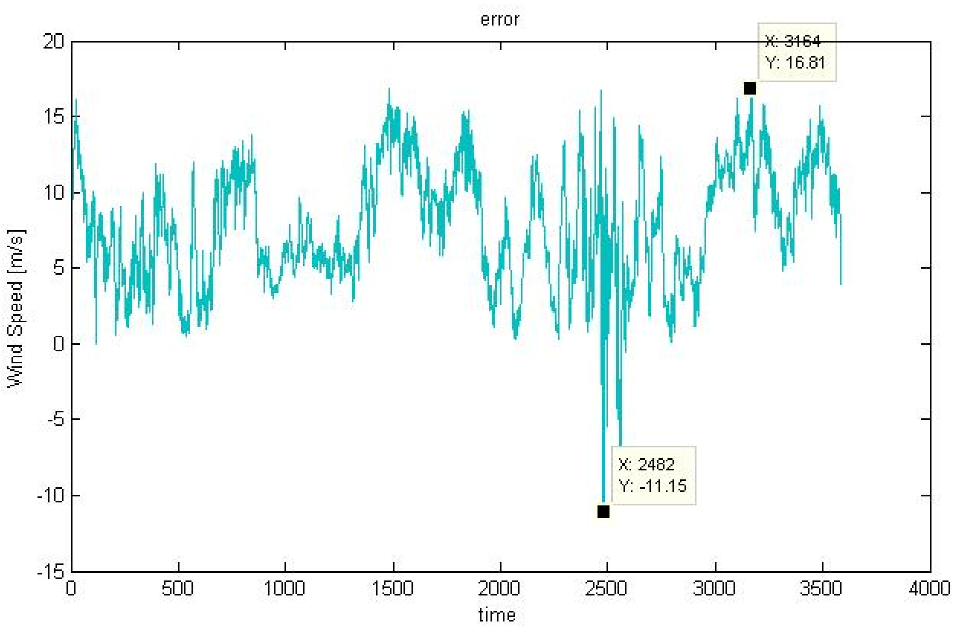


Figure 46- predicted wind speed for 2008



The Error resulting from the training presses.

Gradiant Descent Backpropagation with Adaptive learning

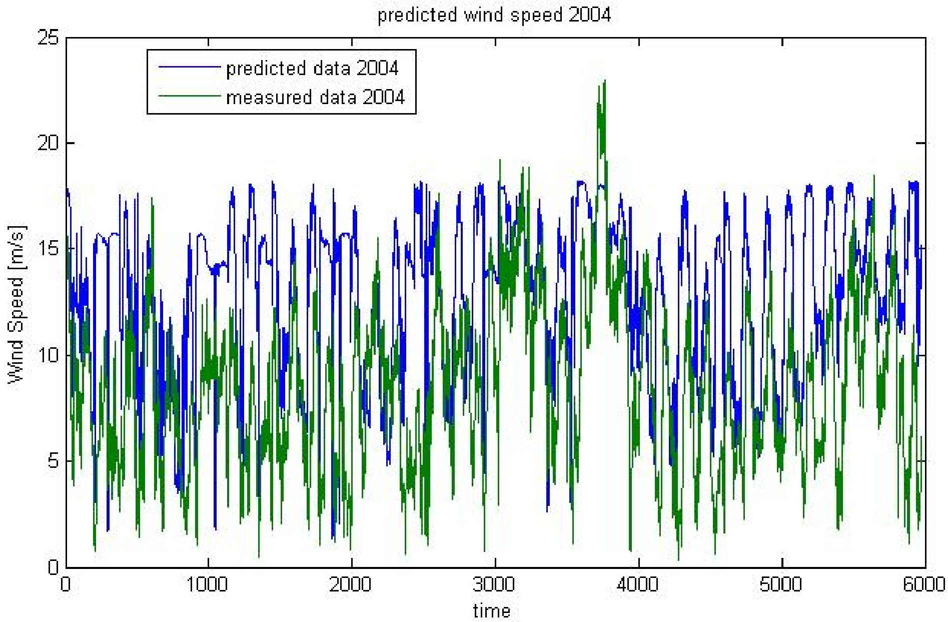


Figure 47- predicted wind speed for 2004

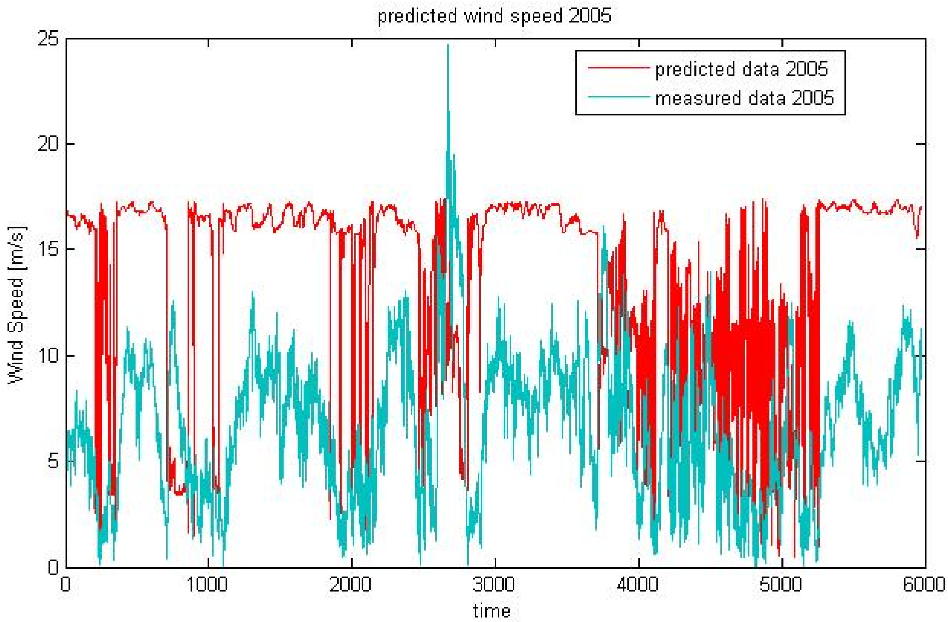


Figure 48- predicted wind speed for 2005

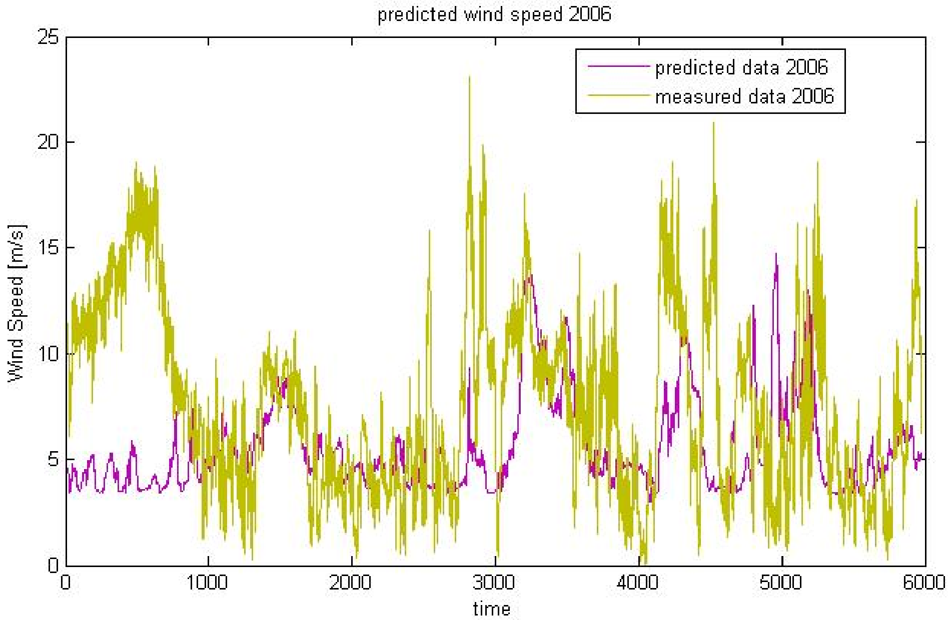


Figure 49- predicted wind speed for 2006

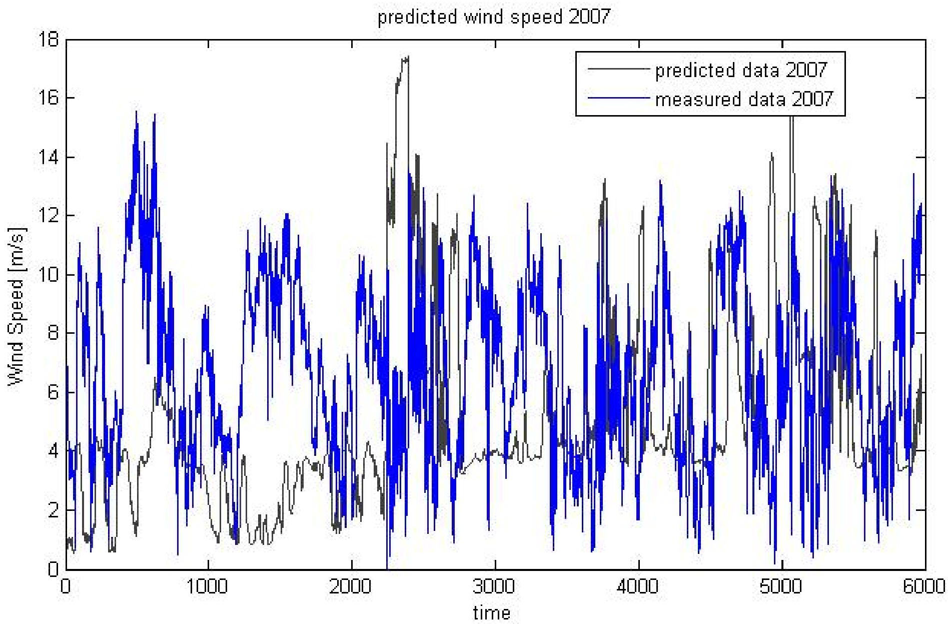


Figure 50- predicted wind speed for 2007

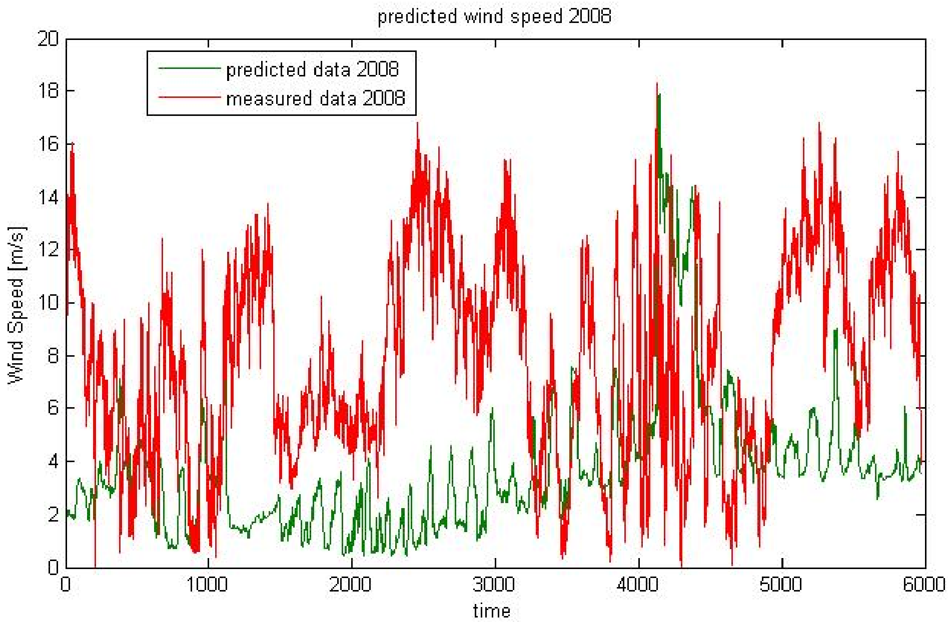
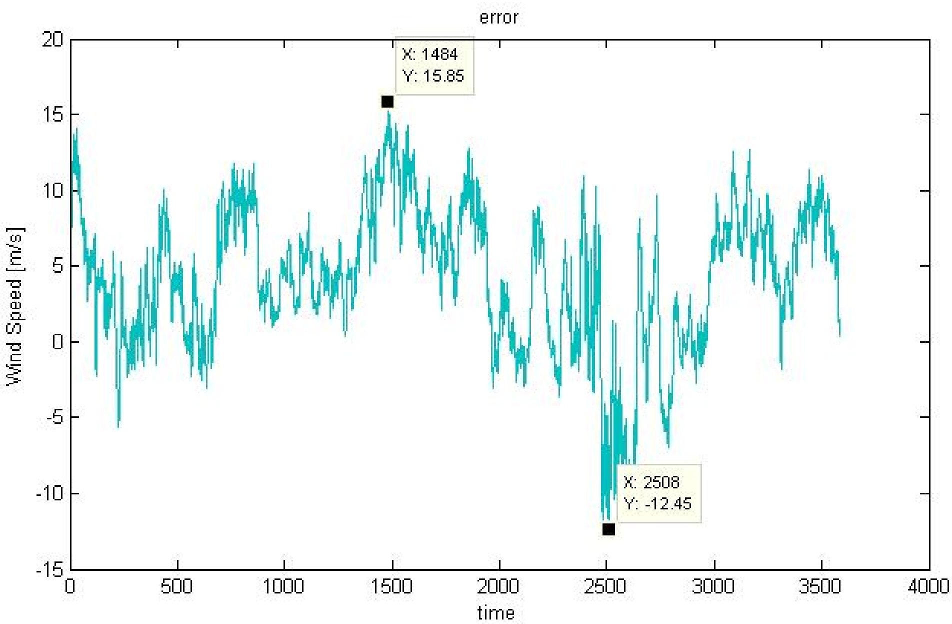


Figure 51- predicted wind speed for 2008



The Error resulting from the training presses.

Random Order Weight-Bias Learning Rules

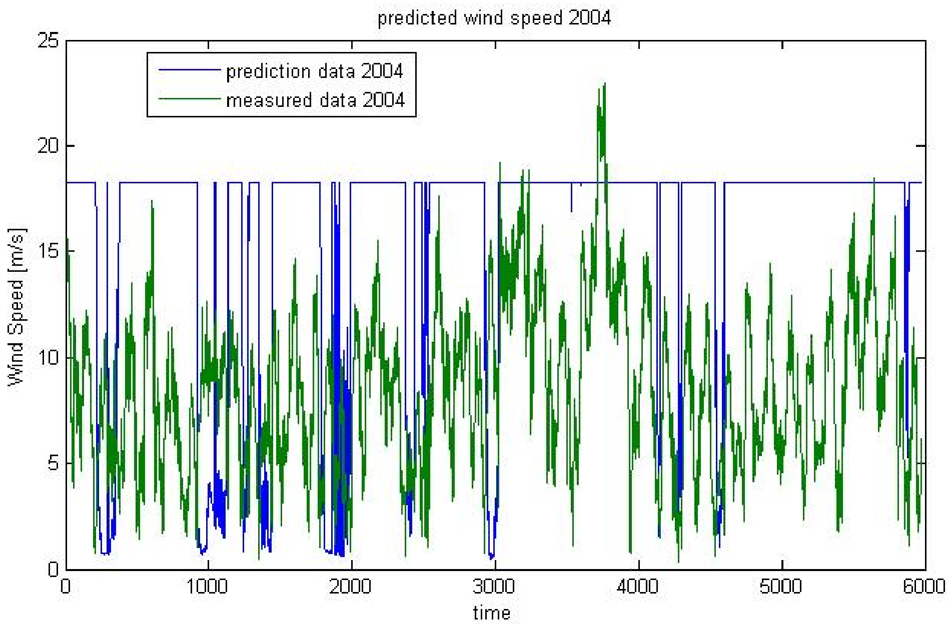


Figure 52- predicted wind speed for 2004

Figure 53-predicted wind speed for 2005

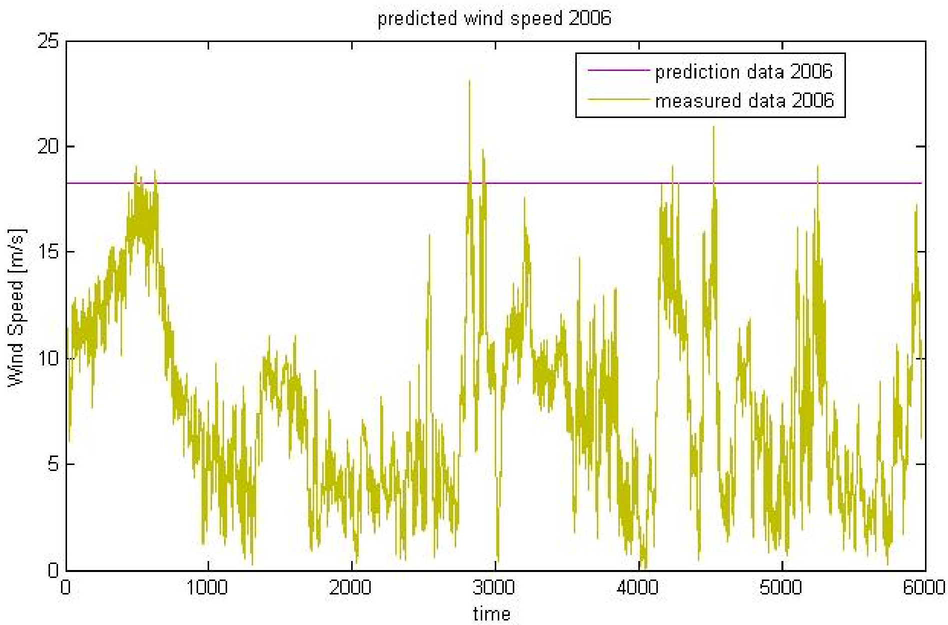


Figure 54- predicted wind speed for 2006

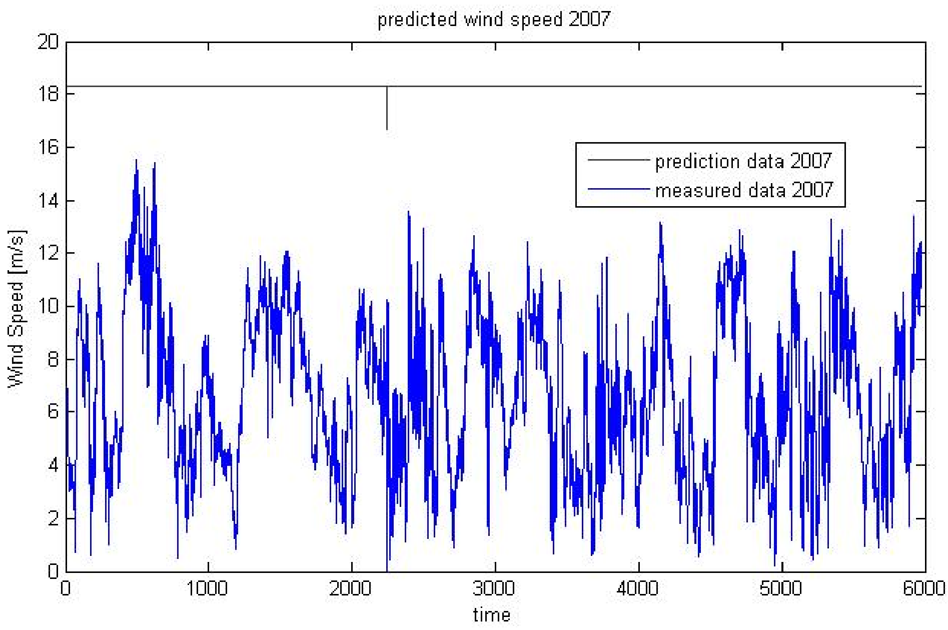


Figure 55- predicted wind speed for 2007

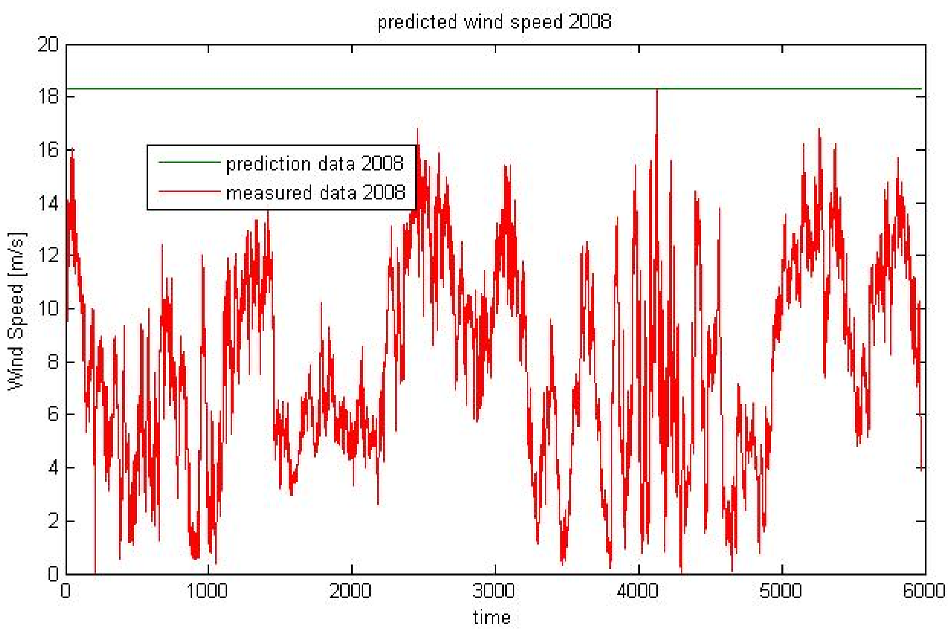


Figure 56- predicted wind speed for 2008

RProp

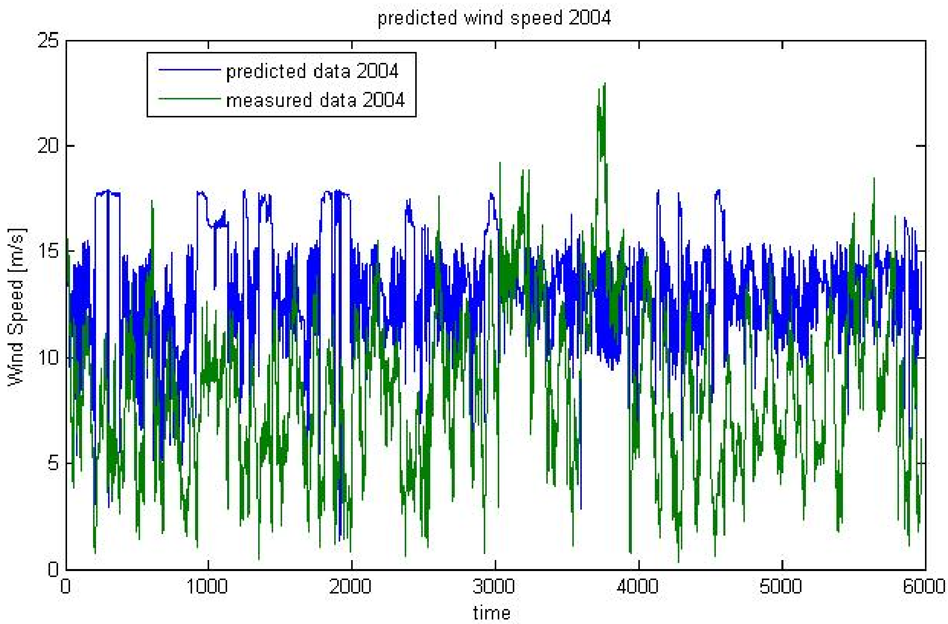


Figure 57- predicted wind speed for 2004

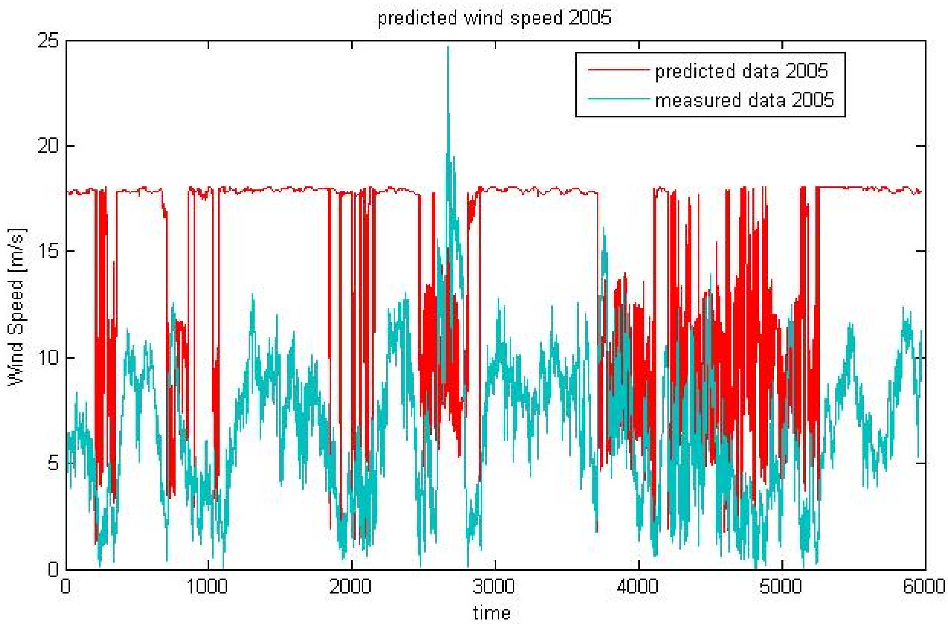


Figure 58- predicted wind speed for 2005

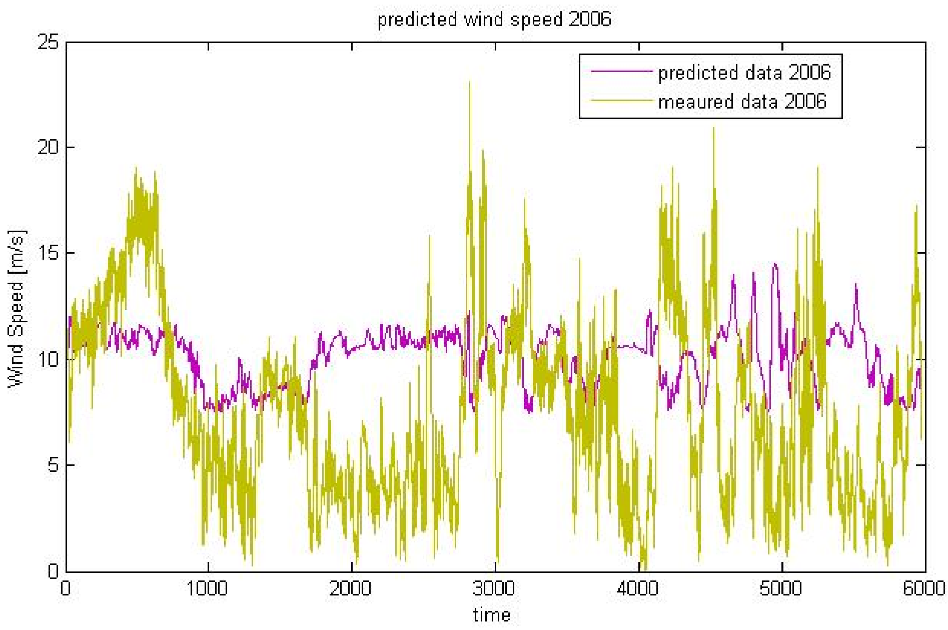


Figure 59- predicted wind speed for 2006

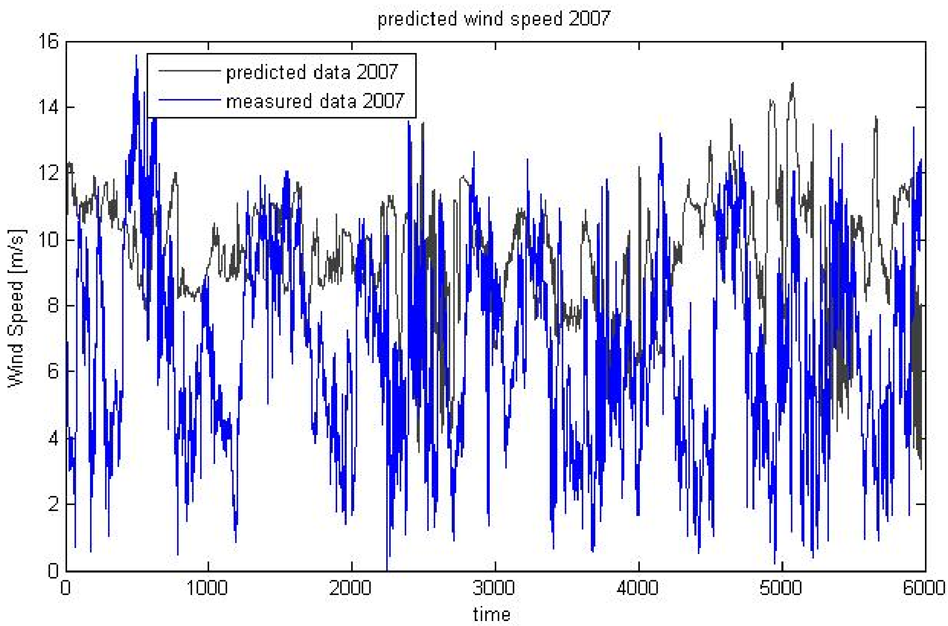


Figure 60- predicted wind speed for 2007

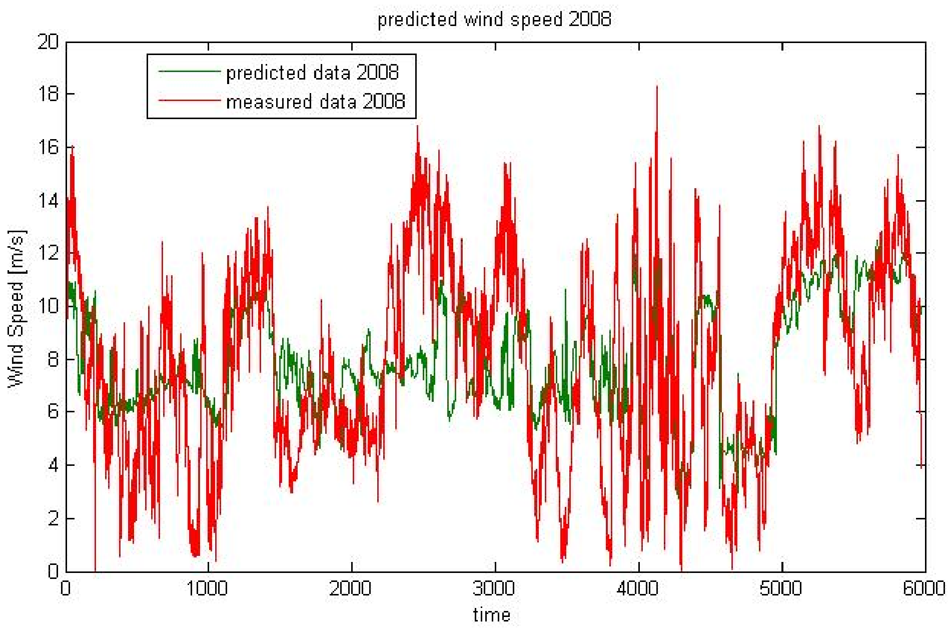
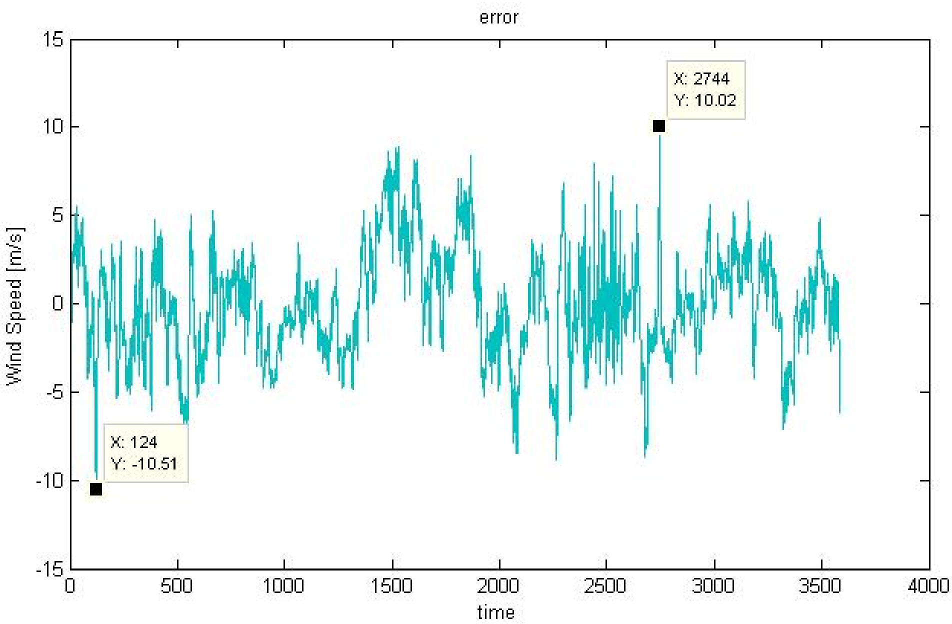


Figure 61- predicted wind speed for 2008



The Error resulting from the training presses.

Scaled Conjugate Gradient

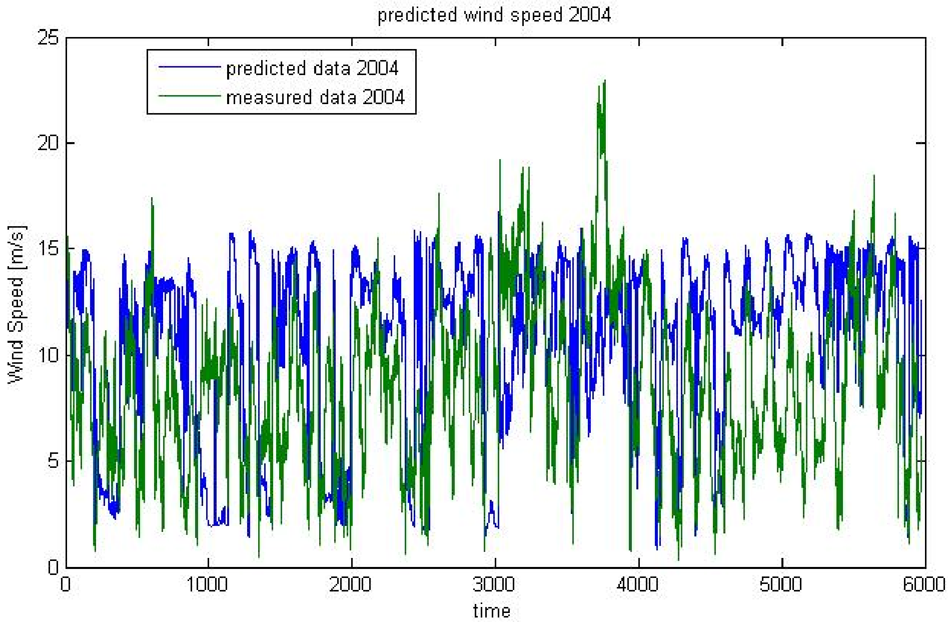


Figure 62- predicted wind speed for 2004

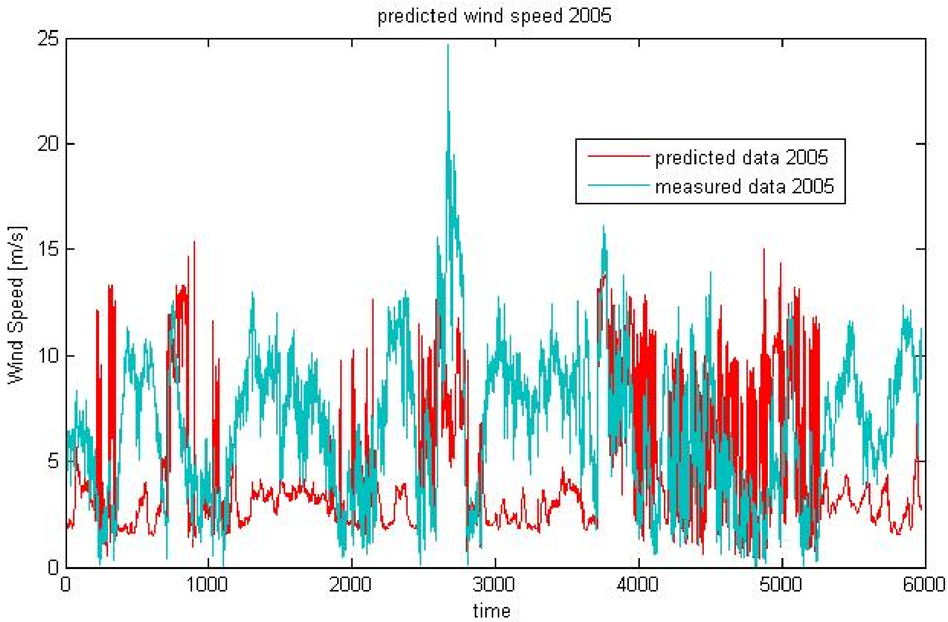


Figure 63- predicted wind speed for 2005

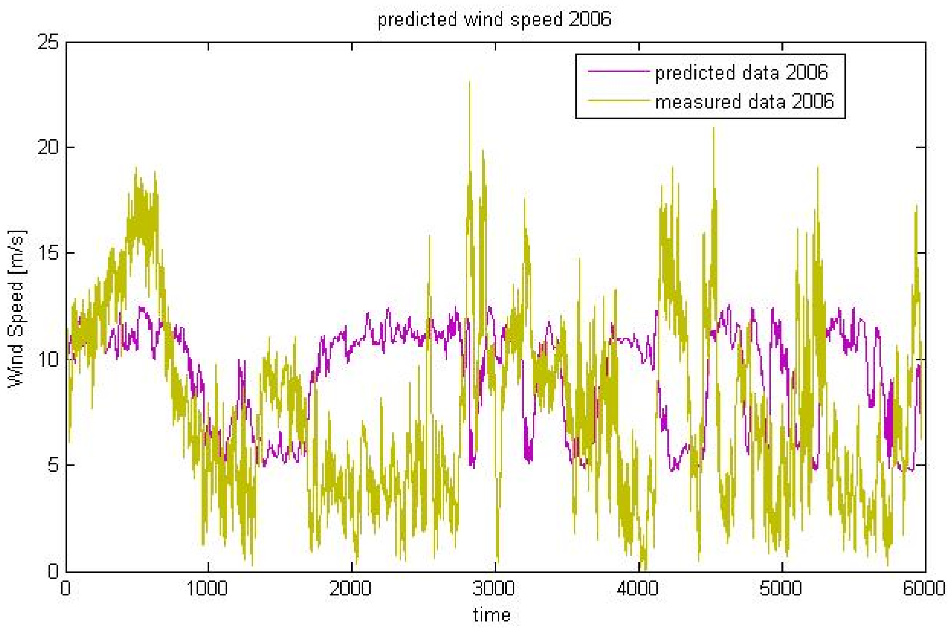


Figure 64- predicted wind speed for 2006

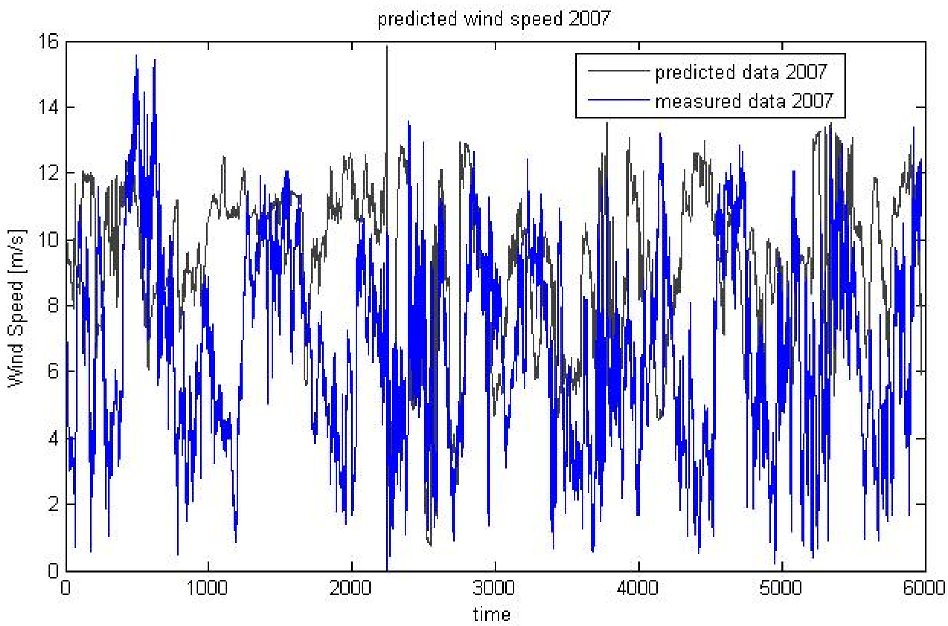


Figure 65- predicted wind speed for 2007

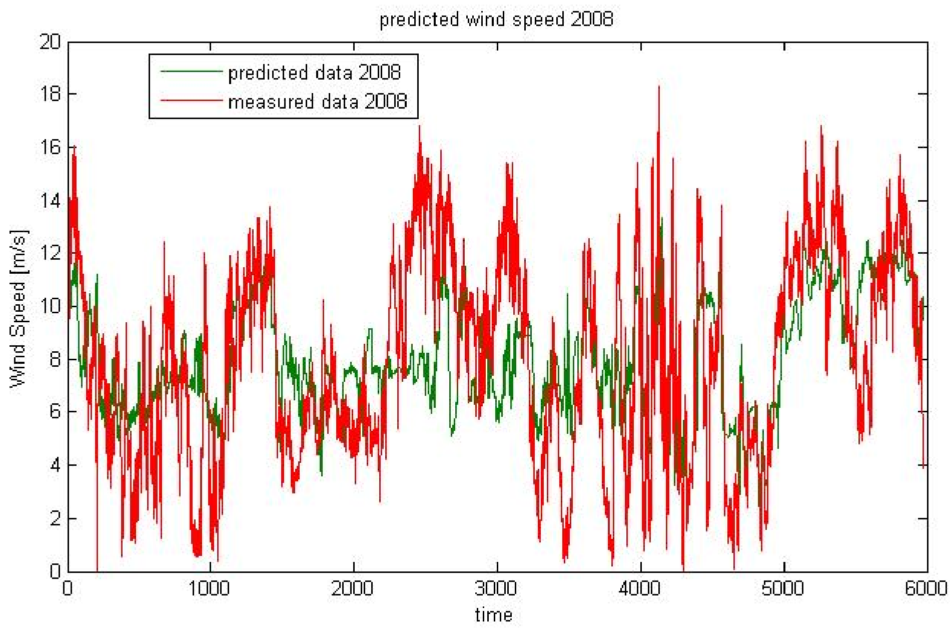


Figure 66- predicted wind speed for 2008

Year 2007 as training data:

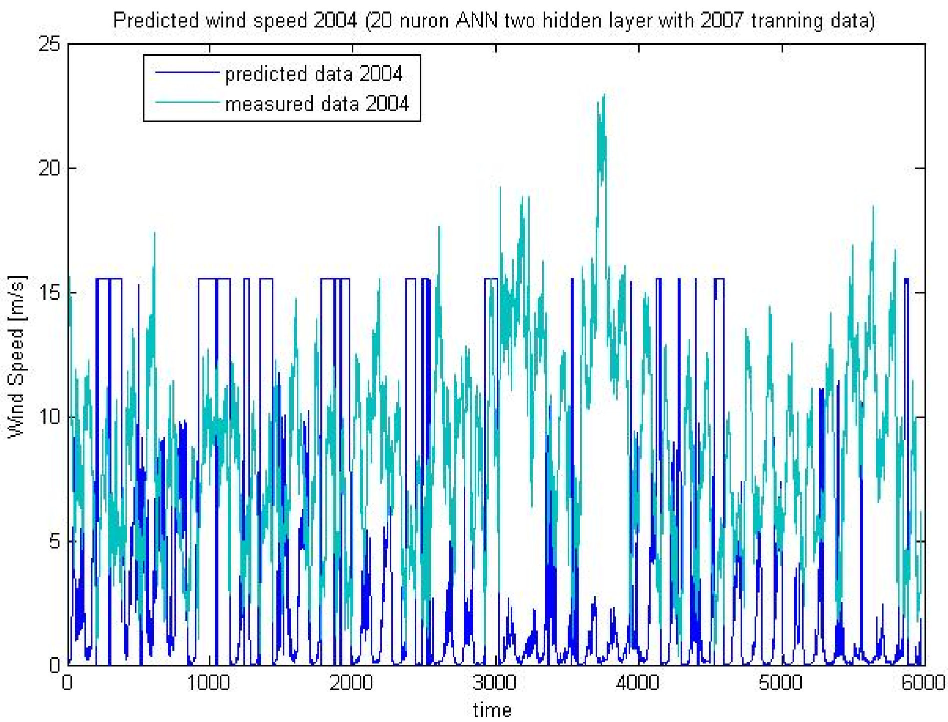


Figure 67- predicted wind speed for 2004 / from 2007 training data/

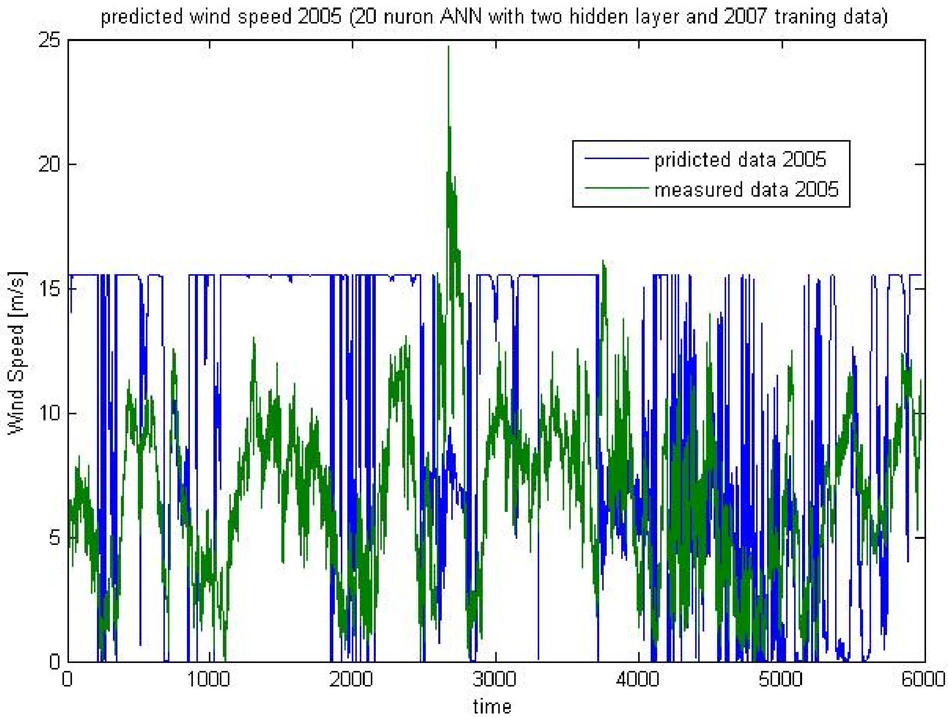


Figure 68- predicted wind speed for 2005 / from 2007 training data/

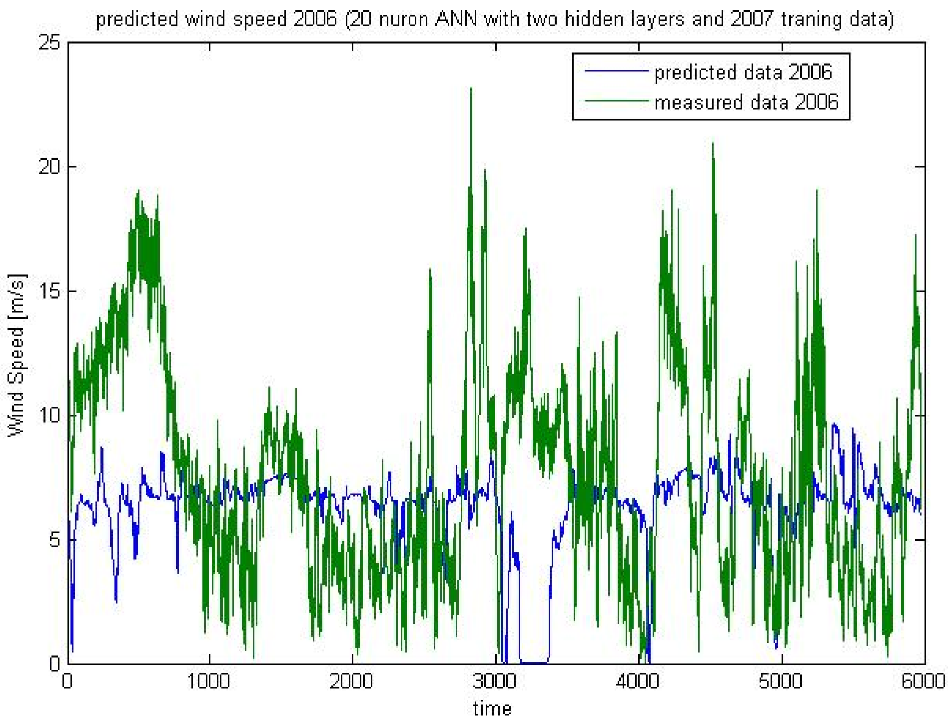


Figure 69- predicted wind speed for 2006 / from 2007 training data/

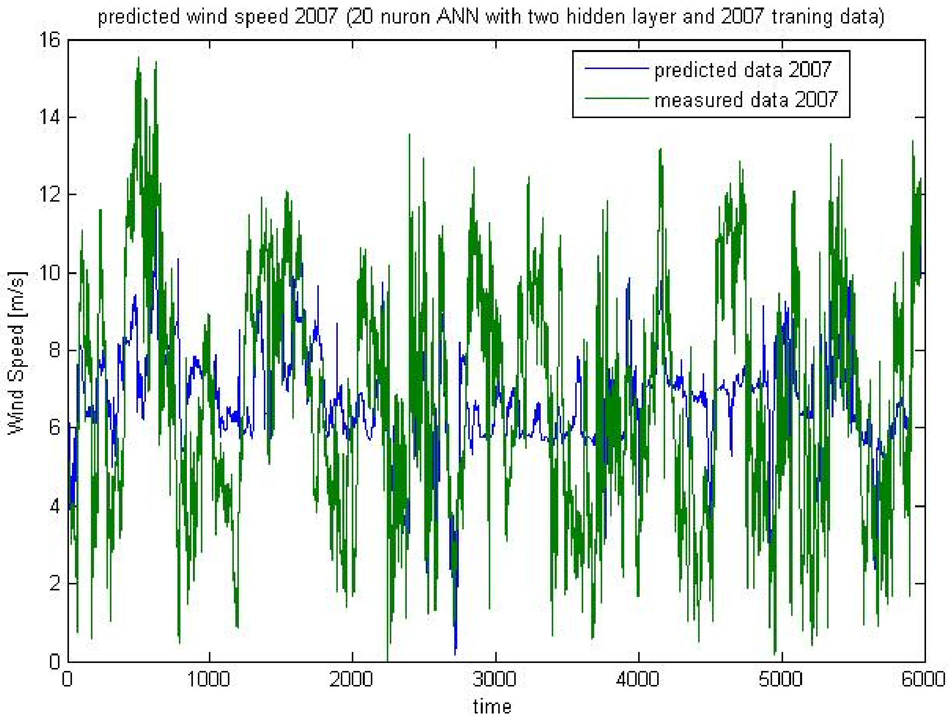


Figure 70- predicted wind speed for 2007 / from 2007 training data/

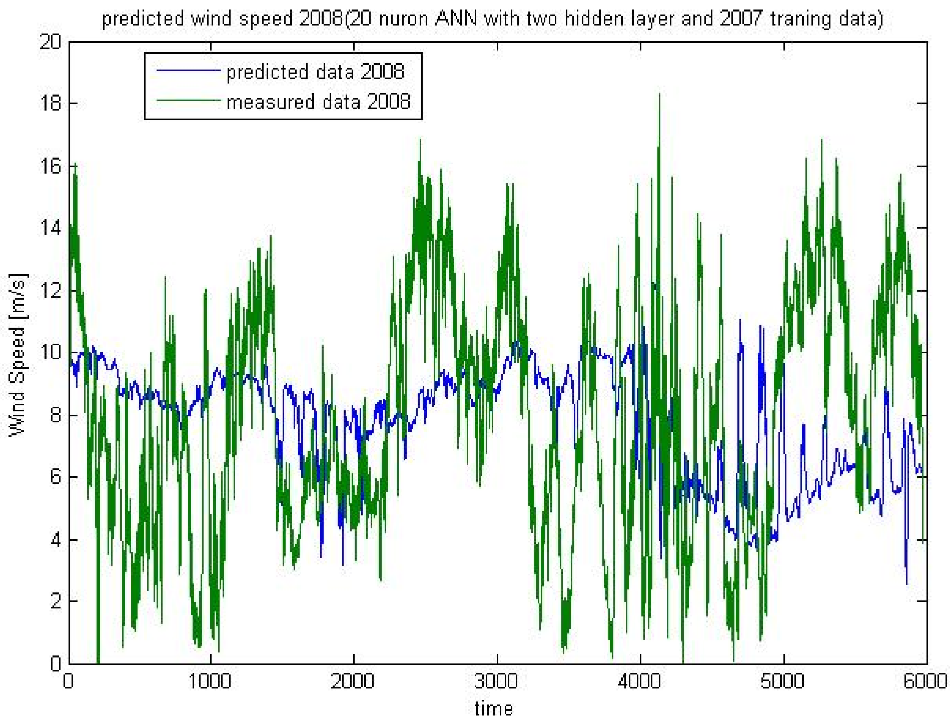


Figure 71- predicted wind speed for 2008 / from 2007 training data/

Wind speed prediction tool using previous wind speed data as input:

Presser, Temperature and wind direction as input of the year of interest:

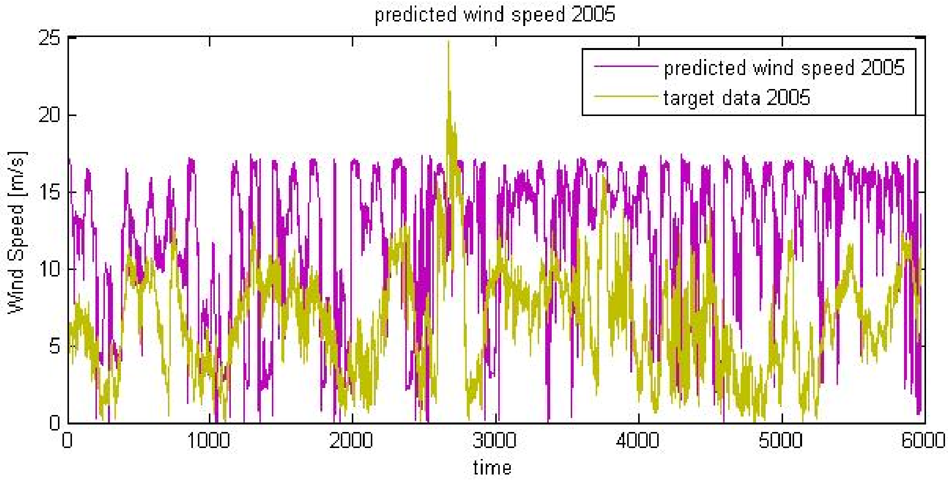


Figure 72- predicted wind speed 2005 /2004 as input/

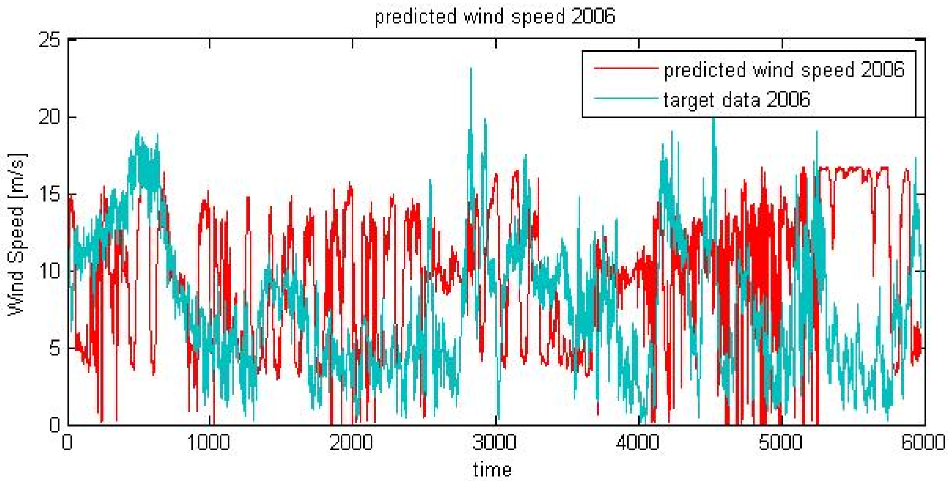


Figure 73- predicted wind speed 2006 /2005 as input/

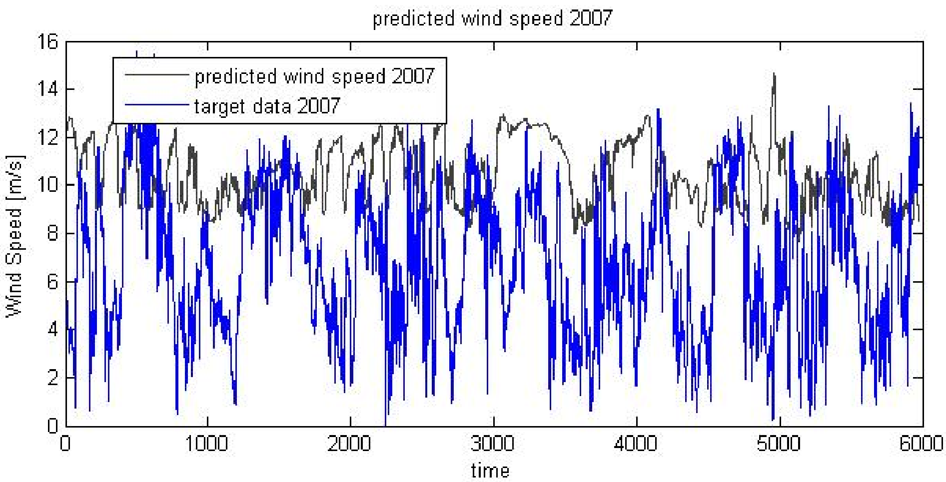


Figure 74- predicted wind speed 2007 /2006 as input/

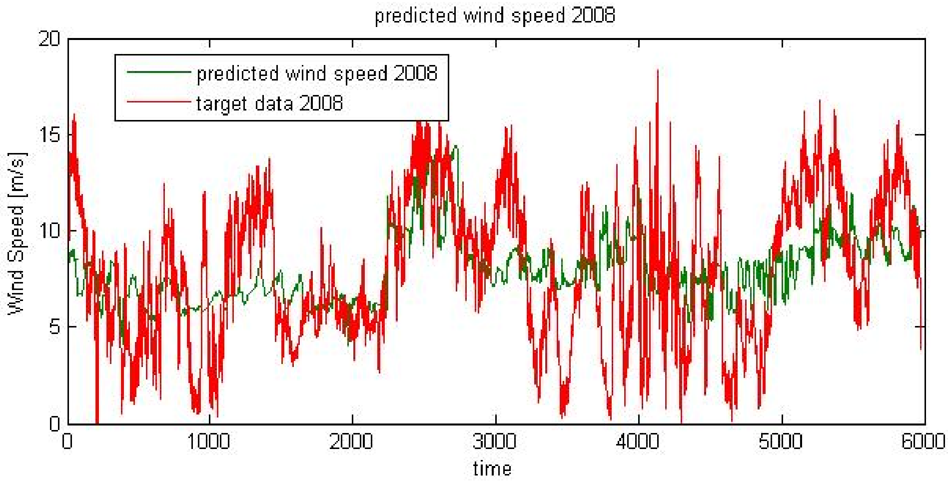


Figure 75- predicted wind speed 2008 /2007 as input/

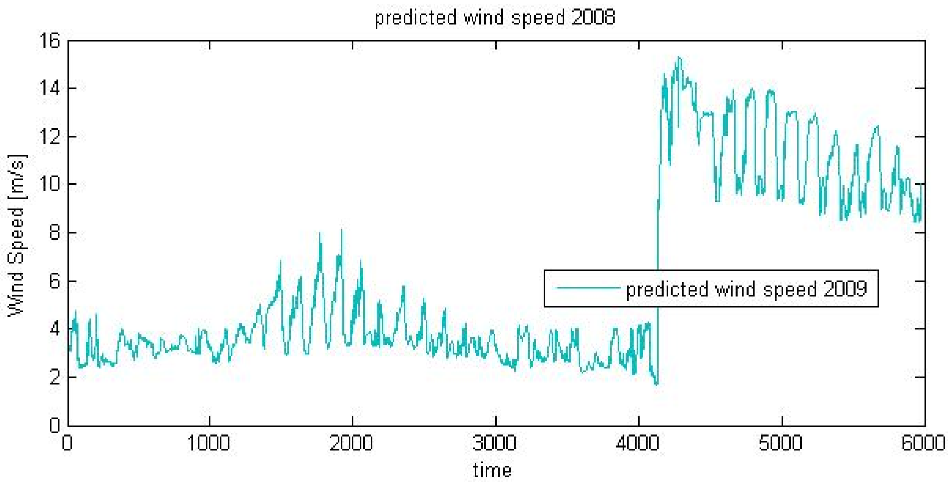


Figure 76- predicted wind speed 2009 /2008 as input/

Wind speed as input of the year of interest:

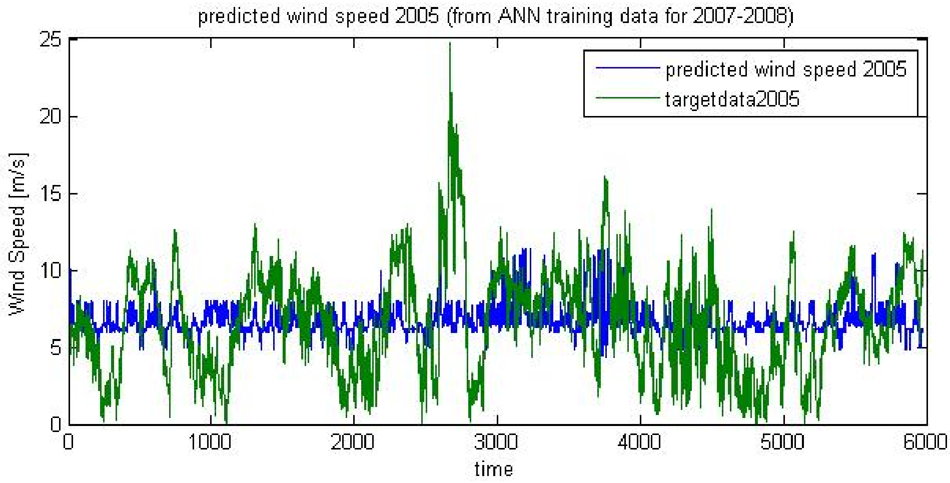


Figure 77- predicted wind speed 2005 /2004 as input/

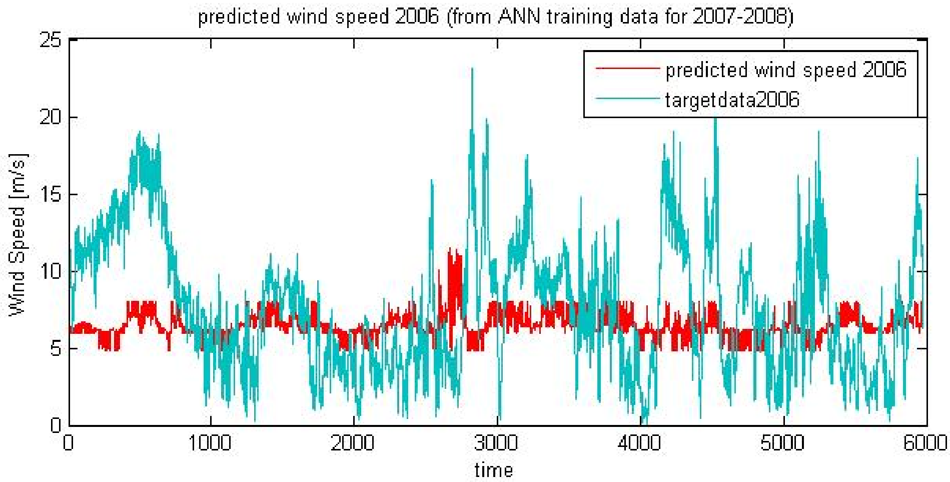


Figure 78- predicted wind speed 2006 /2005 as input/

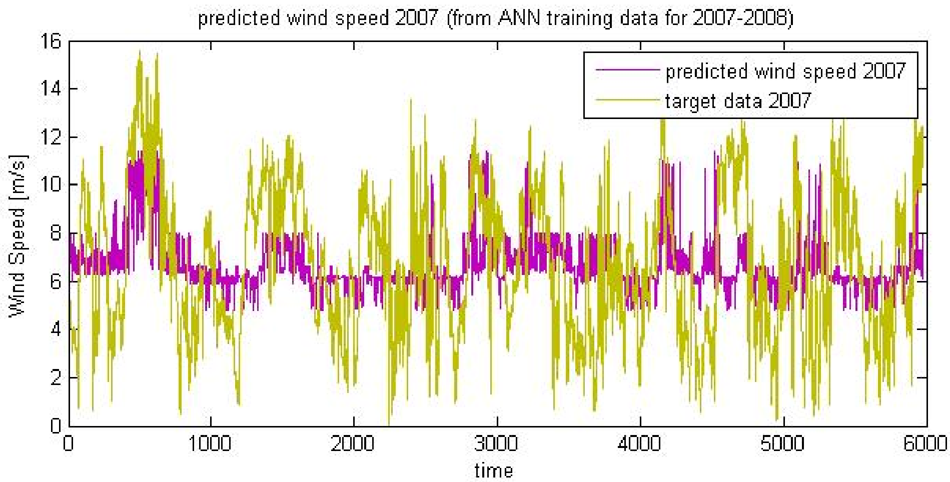


Figure 79- predicted wind speed 2007 /2006 as input/

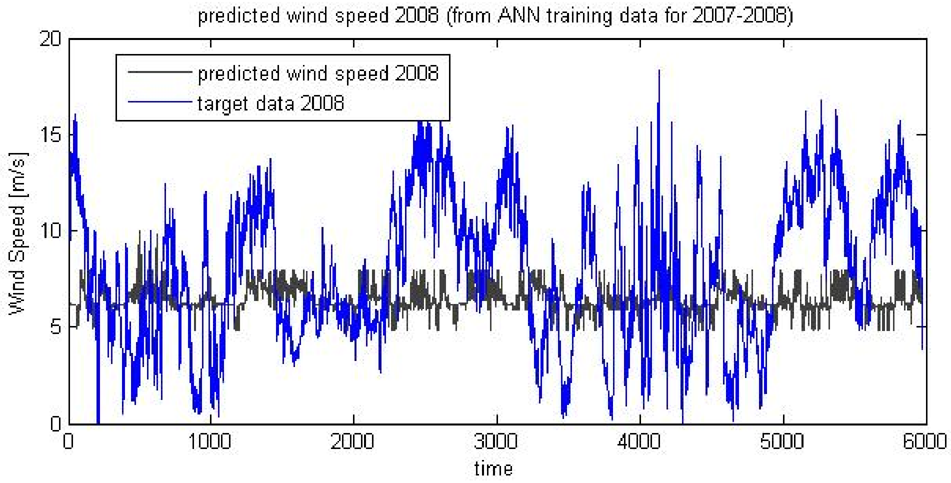


Figure 80- predicted wind speed 2008 /2007 as input/

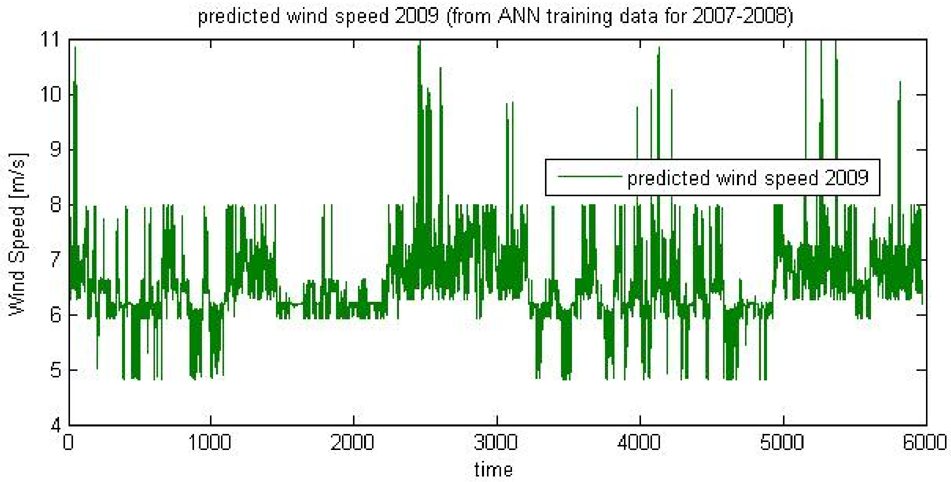


Figure 81- predicted wind speed 2009 /2008 as input/

Two year wind speed as input of the year of interest:

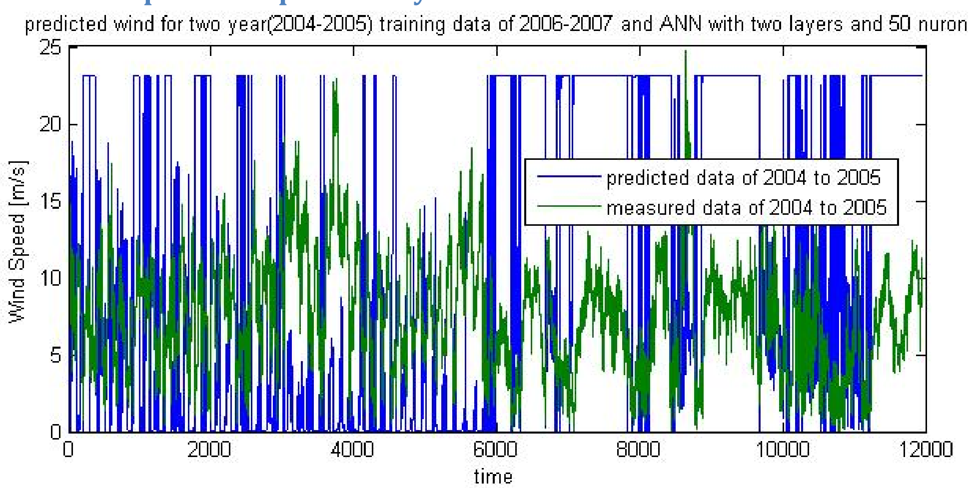


Figure 82- predicted wind speed 2004-2005

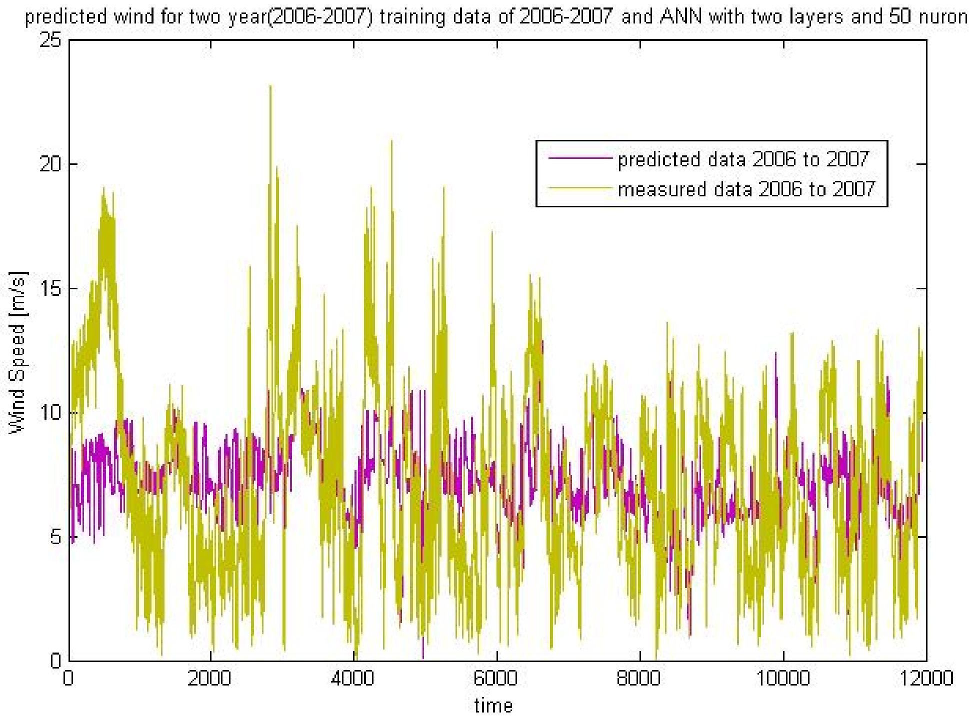


Figure 83- predicted wind speed 2006-2007

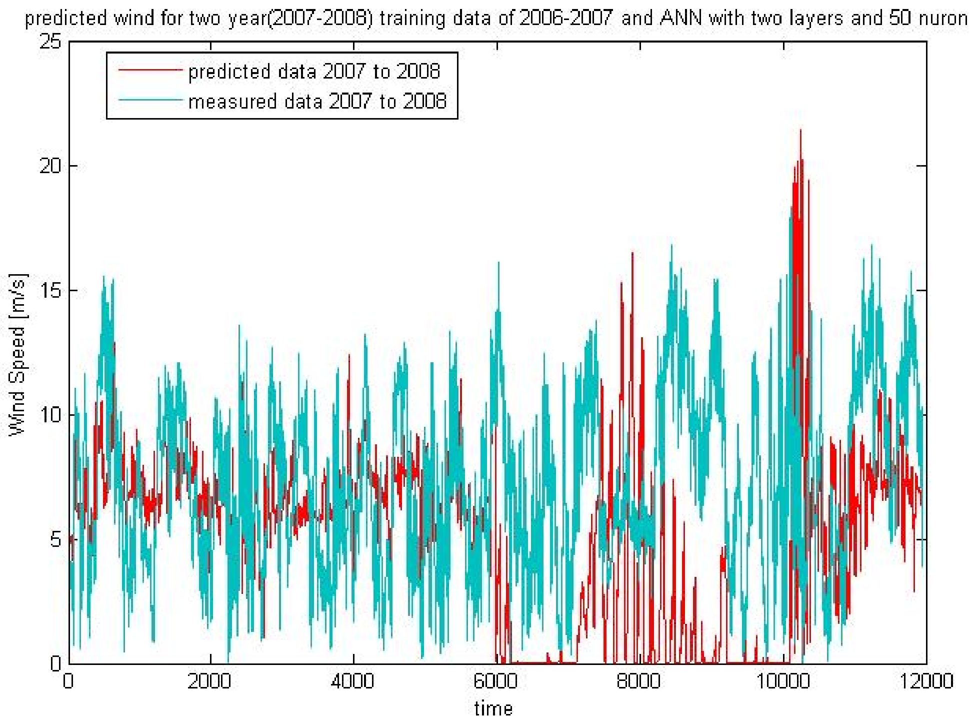


Figure 84- predicted wind speed 2007-2008

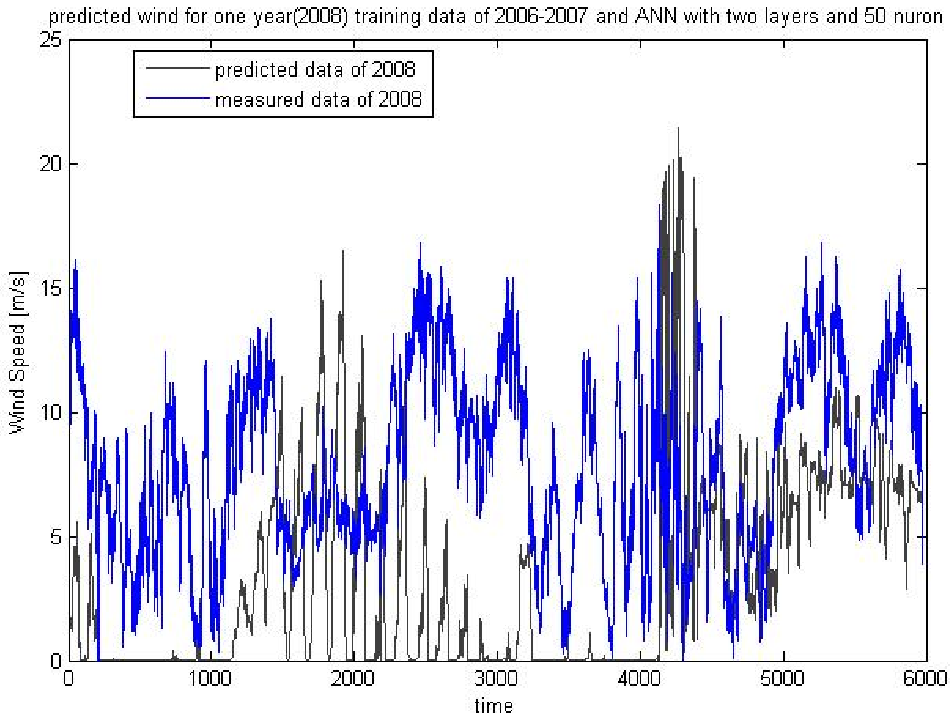


Figure 85- predicted wind speed 2008

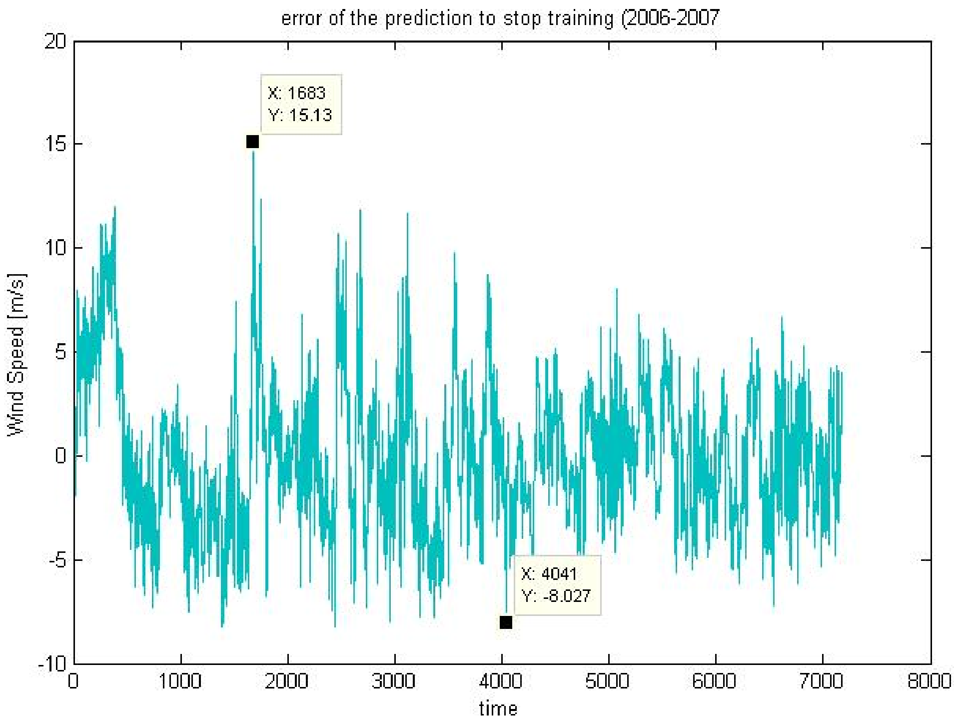


Figure 86-error of prediction tool

Energy results of the different years:

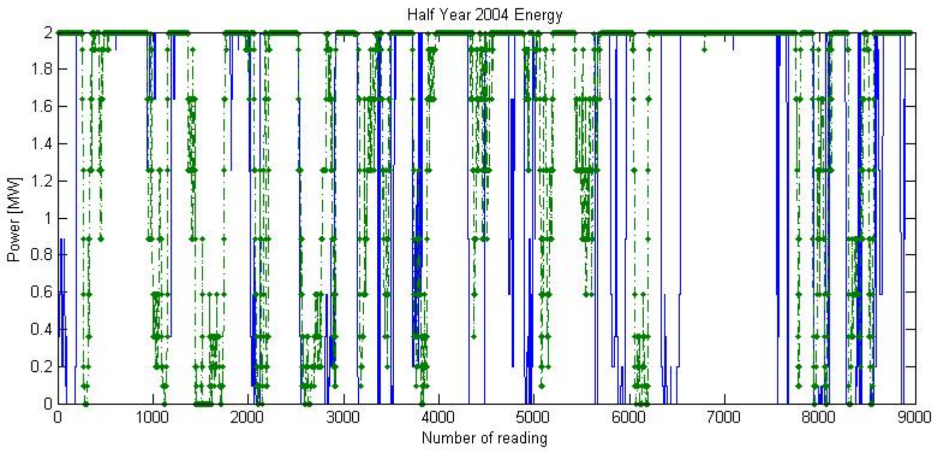


Figure 87 the energy output of Half year 2004

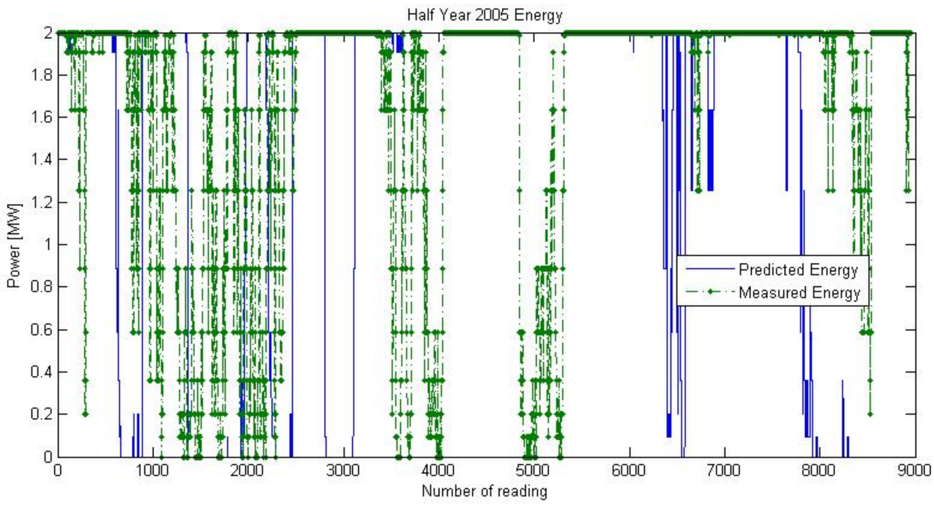


Figure 88 the energy of Half year 2005

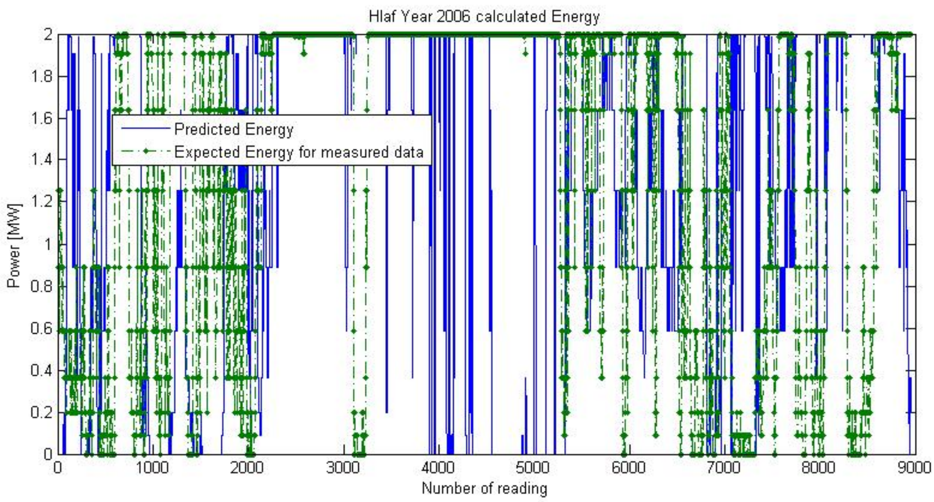


Figure 89 the energy of Half year 2006

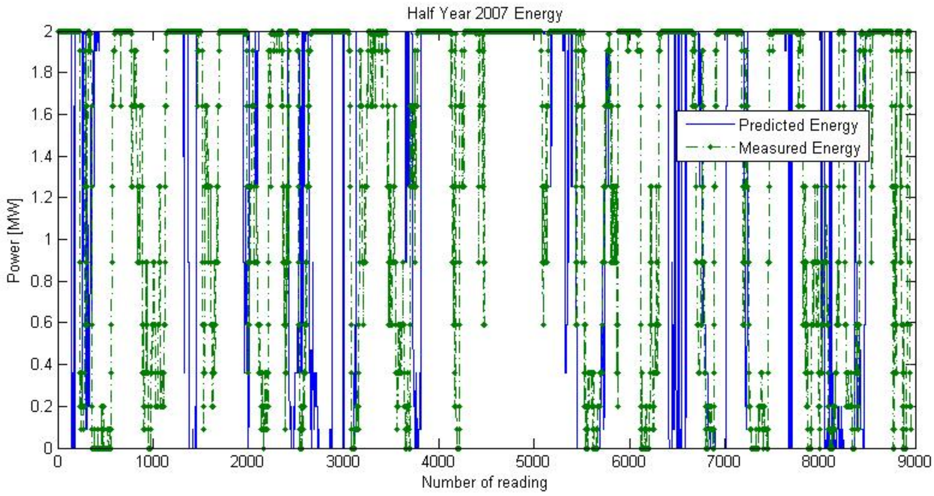


Figure 90 the energy of Half year 2007

Appendix B

This part will contain the results obtained from the wind farm study using the WASP program. The results of the different suggested wind farm [31] is shown.

The 100 [MW] suggested farm results:

'Turbine cluster 2' wind farm

Produced on 1/29/2011 at 5:58:40 PM by licenced user: Eng.Aubai using WAsP version: 10.00.0214.

Summary results

Parameter	Total	Average	Minimum	Maximum
Net AEP [GWh]	394.855	7.897	7.706	8.234
Gross AEP [GWh]	415.597	8.312	8.242	8.479
Wake loss [%]	4.99	-	-	-

Site results

Site	Location [m]	Turbine	Elevation [m a.s.l.]	Height [m a.g.l.]	Net AEP [GWh]	Wake loss [%]
Turbine site 001	(404000, 3690000)	Vestas V90 (2 MW)	603.345	105	7.874	5.59
Turbine site 002	(403678.4,3 690297.0)	Vestas V90 (2 MW)	606.5621	105	7.811	6.4
Turbine site 003	(403356.8,3 690595.0)	Vestas V90 (2 MW)	606.5834	105	7.779	6.77
Turbine site 004	(403035.1,3 690892.0)	Vestas V90 (2 MW)	604.6382	105	7.769	6.88
Turbine site 005	(402713.5,3 691189.0)	Vestas V90 (2 MW)	602.8908	105	7.758	6.92
Turbine site	(402391.8,3	Vestas V90	601.8009	105	7.744	6.94

[31] Comes from the study of the Syrian grid done by Rifat my other college in this project.

006	691487.0)	(2 MW)				
Turbine site 007	(402070.2,3 691784.0)	Vestas V90 (2 MW)	601.1765	105	7.742	6.88
Turbine site 008	(401748.6,3 692081.0)	Vestas V90 (2 MW)	600.8882	105	7.760	6.59
Turbine site 009	(401427.0,3 692379.0)	Vestas V90 (2 MW)	600.9099	105	7.798	6.1
Turbine site 0010	(401105.3,3 692676.0)	Vestas V90 (2 MW)	600.6731	105	7.988	3.81
Turbine site 0011	(404416.7,3 690729.0)	Vestas V90 (2 MW)	609.6718	105	7.987	5.8
Turbine site 0012	(404095.1,3 691026.0)	Vestas V90 (2 MW)	613.9481	105	7.909	6.54
Turbine site 0013	(403773.5,3 691324.0)	Vestas V90 (2 MW)	609.7452	105	7.854	6.86
Turbine site 0014	(403451.8,3 691621.0)	Vestas V90 (2 MW)	604.3538	105	7.789	6.97
Turbine site 0015	(403130.2,3 691918.0)	Vestas V90 (2 MW)	602.3264	105	7.749	7.07
Turbine site 0016	(402808.6,3 692216.0)	Vestas V90 (2 MW)	601.5246	105	7.738	7.03
Turbine site 0017	(402486.9,3 692513.0)	Vestas V90 (2 MW)	601.1592	105	7.727	6.97
Turbine site 0018	(402165.3,3 692810.0)	Vestas V90 (2 MW)	601.071	105	7.743	6.59
Turbine site 0019	(401843.7,3 693107.0)	Vestas V90 (2 MW)	600.9026	105	7.783	6.08
Turbine site 0020	(401522.1,3 693405.0)	Vestas V90 (2 MW)	601.0204	105	7.992	3.73
Turbine site 0021	(403750.5,3 689271.0)	Vestas V90 (2 MW)	600	105	7.967	3.92
Turbine site 0022	(403261.7,3 689569.0)	Vestas V90 (2 MW)	599.9999	105	7.872	4.99

Turbine site 0023	(402940.0,3 689866.0)	Vestas V90 (2 MW)	600.0001	105	7.846	5.19
Turbine site 0024	(402618.4,3 690163.0)	Vestas V90 (2 MW)	600.9354	105	7.844	5.27
Turbine site 0025	(402296.8,3 690461.0)	Vestas V90 (2 MW)	601.4407	105	7.859	5.32
Turbine site 0026	(401975.1,3 690758.0)	Vestas V90 (2 MW)	601.1777	105	7.864	5.31
Turbine site 0027	(401653.5,3 691055.0)	Vestas V90 (2 MW)	600.9335	105	7.871	5.27
Turbine site 0028	(401331.9,3 691353.0)	Vestas V90 (2 MW)	600.6346	105	7.875	5.18
Turbine site 0029	(401010.2,3 691650.0)	Vestas V90 (2 MW)	600.5585	105	7.891	4.97
Turbine site 0030	(400688.6,3 691947.0)	Vestas V90 (2 MW)	600.3589	105	8.037	3.22
Turbine site 0031	(403333.8,3 688543.0)	Vestas V90 (2 MW)	599.9999	105	8.234	0.8
Turbine site 0032	(402844.9,3 688840.0)	Vestas V90 (2 MW)	599.9999	105	8.193	1.29
Turbine site 0033	(402523.3,3 689137.0)	Vestas V90 (2 MW)	599.9999	105	8.172	1.51
Turbine site 0034	(402201.7,3 689435.0)	Vestas V90 (2 MW)	600.0001	105	8.164	1.59
Turbine site 0035	(401880.0,3 689732.0)	Vestas V90 (2 MW)	600.1694	105	8.151	1.65
Turbine site 0036	(401558.4,3 690029.0)	Vestas V90 (2 MW)	600.2662	105	8.155	1.66
Turbine site 0037	(401236.8,3 690326.0)	Vestas V90 (2 MW)	600.2634	105	8.158	1.65
Turbine site 0038	(400915.2,3 690624.0)	Vestas V90 (2 MW)	600.1056	105	8.162	1.65
Turbine site 0039	(400593.5,3 690921.0)	Vestas V90 (2 MW)	600.0001	105	8.167	1.59

Turbine site 0040	(400271.9,3 691218.0)	Vestas V90 (2 MW)	600.0737	105	8.191	1.32
Turbine site 0041	(404833.4,3 691458.0)	Vestas V90 (2 MW)	599.7106	105	7.751	5.96
Turbine site 0042	(404511.8,3 691755.0)	Vestas V90 (2 MW)	600.6378	105	7.706	6.59
Turbine site 0043	(404190.2,3 692052.0)	Vestas V90 (2 MW)	601.4543	105	7.752	6.55
Turbine site 0044	(403868.6,3 692350.0)	Vestas V90 (2 MW)	601.183	105	7.767	6.55
Turbine site 0045	(403546.9,3 692647.0)	Vestas V90 (2 MW)	600.8831	105	7.769	6.52
Turbine site 0046	(403225.3,3 692944.0)	Vestas V90 (2 MW)	600.8527	105	7.757	6.49
Turbine site 0047	(402903.7,3 693242.0)	Vestas V90 (2 MW)	601.1168	105	7.749	6.38
Turbine site 0048	(402582.0,3 693539.0)	Vestas V90 (2 MW)	601.1906	105	7.773	6.0
Turbine site 0049	(402260.4,3 693836.0)	Vestas V90 (2 MW)	601.1225	105	7.831	5.4
Turbine site 0050	(401938.8,3 694134.0)	Vestas V90 (2 MW)	601.1901	105	8.038	3.09

Site wind climates

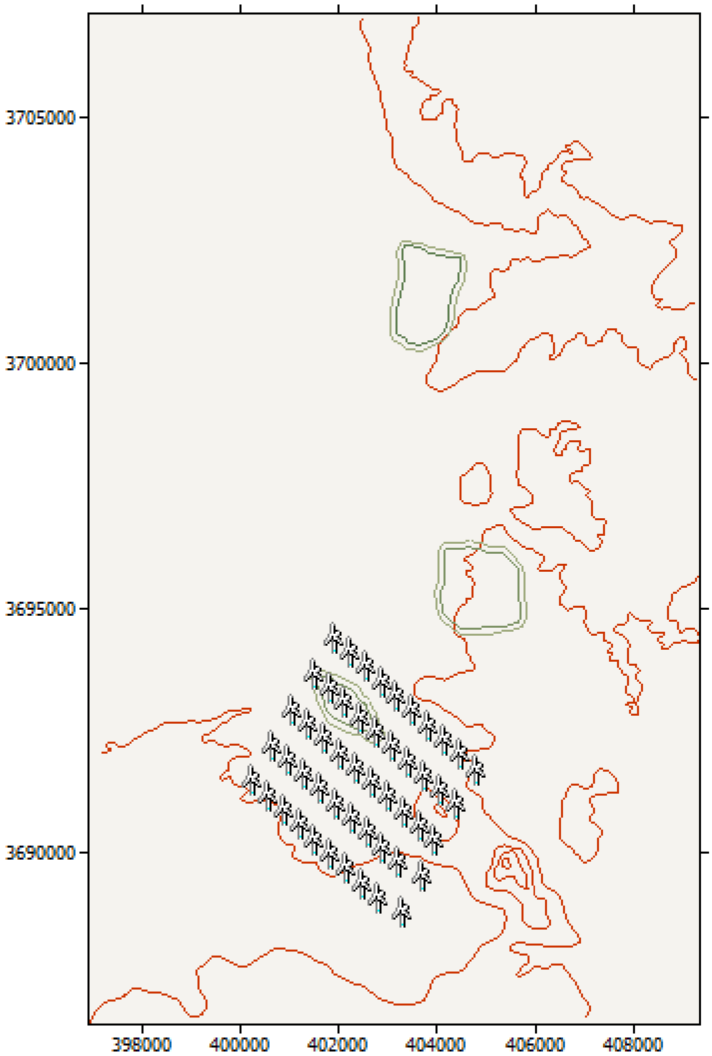
Site	Location [m]	Height [m a.g.l.]	A [m/s]	k	U [m/s]	E [W/m²]	RIX [%]	dRIX [%]
Turbine site 001	(404000, 3690000)	105	9.0	1.84	8.00	653	0.0	0.0
Turbine site 002	(403678.4,3 690297.0)	105	9.0	1.85	8.00	652	0.0	0.0
Turbine site 003	(403356.8,3 690595.0)	105	9.0	1.84	8.00	654	0.0	0.0

Turbine site 004	(403035.1,3 690892.0)	105	9.0	1.84	8.00	654	0.0	0.0
Turbine site 005	(402713.5,3 691189.0)	105	9.0	1.84	8.00	653	0.0	0.0
Turbine site 006	(402391.8,3 691487.0)	105	9.0	1.84	7.98	650	0.0	0.0
Turbine site 007	(402070.2,3 691784.0)	105	9.0	1.84	7.98	648	0.0	0.0
Turbine site 008	(401748.6,3 692081.0)	105	9.0	1.84	7.97	647	0.0	0.0
Turbine site 009	(401427.0,3 692379.0)	105	9.0	1.84	7.97	646	0.0	0.0
Turbine site 0010	(401105.3,3 692676.0)	105	9.0	1.84	7.97	646	0.0	0.0
Turbine site 0011	(404416.7,3 690729.0)	105	9.1	1.84	8.12	686	0.0	0.0
Turbine site 0012	(404095.1,3 691026.0)	105	9.1	1.85	8.10	678	0.0	0.0
Turbine site 0013	(403773.5,3 691324.0)	105	9.1	1.84	8.08	675	0.0	0.0
Turbine site 0014	(403451.8,3 691621.0)	105	9.0	1.84	8.03	662	0.0	0.0
Turbine site 0015	(403130.2,3 691918.0)	105	9.0	1.84	8.00	653	0.0	0.0
Turbine site 0016	(402808.6,3 692216.0)	105	9.0	1.84	7.98	650	0.0	0.0
Turbine site 0017	(402486.9,3 692513.0)	105	9.0	1.84	7.97	646	0.0	0.0
Turbine site 0018	(402165.3,3 692810.0)	105	9.0	1.84	7.96	643	0.0	0.0
Turbine site 0019	(401843.7,3 693107.0)	105	9.0	1.84	7.95	642	0.0	0.0
Turbine site 0020	(401522.1,3 693405.0)	105	9.0	1.84	7.97	645	0.0	0.0

Turbine site 0021	(403750.5,3 689271.0)	105	9.0	1.85	7.96	641	0.0	0.0
Turbine site 0022	(403261.7,3 689569.0)	105	8.9	1.85	7.95	640	0.0	0.0
Turbine site 0023	(402940.0,3 689866.0)	105	8.9	1.85	7.94	638	0.0	0.0
Turbine site 0024	(402618.4,3 690163.0)	105	8.9	1.85	7.95	639	0.0	0.0
Turbine site 0025	(402296.8,3 690461.0)	105	9.0	1.84	7.96	644	0.0	0.0
Turbine site 0026	(401975.1,3 690758.0)	105	9.0	1.84	7.97	646	0.0	0.0
Turbine site 0027	(401653.5,3 691055.0)	105	9.0	1.84	7.97	647	0.0	0.0
Turbine site 0028	(401331.9,3 691353.0)	105	9.0	1.84	7.97	646	0.0	0.0
Turbine site 0029	(401010.2,3 691650.0)	105	9.0	1.84	7.97	646	0.0	0.0
Turbine site 0030	(400688.6,3 691947.0)	105	9.0	1.84	7.97	646	0.0	0.0
Turbine site 0031	(403333.8,3 688543.0)	105	9.0	1.85	7.96	643	0.0	0.0
Turbine site 0032	(402844.9,3 688840.0)	105	9.0	1.85	7.96	643	0.0	0.0
Turbine site 0033	(402523.3,3 689137.0)	105	9.0	1.85	7.96	642	0.0	0.0
Turbine site 0034	(402201.7,3 689435.0)	105	9.0	1.85	7.96	642	0.0	0.0
Turbine site 0035	(401880.0,3 689732.0)	105	9.0	1.85	7.95	640	0.0	0.0
Turbine site 0036	(401558.4,3 690029.0)	105	9.0	1.84	7.96	643	0.0	0.0
Turbine site 0037	(401236.8,3 690326.0)	105	9.0	1.84	7.96	643	0.0	0.0

Turbine site 0038	(400915.2,3690624.0)	105	9.0	1.84	7.96	644	0.0	0.0
Turbine site 0039	(400593.5,3690921.0)	105	9.0	1.84	7.96	644	0.0	0.0
Turbine site 0040	(400271.9,3691218.0)	105	9.0	1.84	7.96	644	0.0	0.0
Turbine site 0041	(404833.4,3691458.0)	105	8.9	1.85	7.91	631	0.0	0.0
Turbine site 0042	(404511.8,3691755.0)	105	8.9	1.85	7.92	631	0.0	0.0
Turbine site 0043	(404190.2,3692052.0)	105	9.0	1.85	7.96	642	0.0	0.0
Turbine site 0044	(403868.6,3692350.0)	105	9.0	1.84	7.97	647	0.0	0.0
Turbine site 0045	(403546.9,3692647.0)	105	9.0	1.84	7.97	647	0.0	0.0
Turbine site 0046	(403225.3,3692944.0)	105	9.0	1.84	7.96	644	0.0	0.0
Turbine site 0047	(402903.7,3693242.0)	105	8.9	1.85	7.95	639	0.0	0.0
Turbine site 0048	(402582.0,3693539.0)	105	8.9	1.85	7.94	637	0.0	0.0
Turbine site 0049	(402260.4,3693836.0)	105	8.9	1.85	7.95	639	0.0	0.0
Turbine site 0050	(401938.8,3694134.0)	105	9.0	1.85	7.96	642	0.0	0.0

The wind farm lies in a map called 'Alhidjana7 28-9-2010'.



The wind farm is in a project called 'Project 1'

A wind atlas called 'Wind atlas 1' was used to calculate the predicted wind climates

Calculation of annual output for 'Turbine cluster 2'

Decay constants: 0.075 0.075 0.075 0.075 0.075 0.075 0.075 0.075 0.075 0.075 0.075 0.075

Sector 1 (0°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	4.2	1.63	3.22	3.79	54.371	45.019	82.8

Turbine site 002	4.3	1.63	3.27	3.86	58.020	48.472	83.55
Turbine site 003	4.3	1.63	3.31	3.89	60.248	50.563	83.92
Turbine site 004	4.3	1.63	3.28	3.85	57.965	48.404	83.51
Turbine site 005	4.3	1.63	3.26	3.83	56.591	47.101	83.23
Turbine site 006	4.3	1.63	3.26	3.82	56.005	46.608	83.22
Turbine site 007	4.3	1.63	3.26	3.81	55.852	46.814	83.82
Turbine site 008	4.3	1.63	3.25	3.81	55.727	46.952	84.25
Turbine site 009	4.3	1.63	3.24	3.81	55.708	50.475	90.61
Turbine site 0010	4.3	1.63	3.23	3.82	55.655	55.655	100.0
Turbine site 0011	4.3	1.63	3.24	3.84	57.056	49.177	86.19
Turbine site 0012	4.3	1.63	3.21	3.84	56.128	48.358	86.16
Turbine site 0013	4.3	1.63	3.20	3.81	54.986	47.239	85.91
Turbine site 0014	4.2	1.63	3.21	3.80	54.675	46.914	85.81
Turbine site 0015	4.3	1.63	3.22	3.81	55.124	47.331	85.86
Turbine site 0016	4.3	1.63	3.23	3.81	55.393	47.567	85.87
Turbine site 0017	4.3	1.63	3.25	3.81	55.489	47.628	85.83
Turbine site 0018	4.3	1.63	3.25	3.81	55.582	47.715	85.85

Turbine site 0019	4.3	1.63	3.25	3.81	55.620	50.743	91.23
Turbine site 0020	4.3	1.63	3.24	3.81	55.683	55.683	100.0
Turbine site 0021	4.3	1.63	3.24	3.81	55.414	45.152	81.48
Turbine site 0022	4.3	1.63	3.25	3.82	56.019	45.869	81.88
Turbine site 0023	4.3	1.63	3.27	3.83	56.967	46.789	82.13
Turbine site 0024	4.3	1.63	3.30	3.86	58.587	48.353	82.53
Turbine site 0025	4.3	1.63	3.29	3.85	57.897	47.813	82.58
Turbine site 0026	4.3	1.63	3.27	3.83	56.787	46.932	82.65
Turbine site 0027	4.3	1.63	3.25	3.82	56.134	46.770	83.32
Turbine site 0028	4.3	1.63	3.24	3.82	55.959	47.019	84.02
Turbine site 0029	4.3	1.63	3.24	3.82	55.859	50.624	90.63
Turbine site 0030	4.3	1.63	3.23	3.82	55.777	55.777	100.0
Turbine site 0031	4.3	1.63	3.25	3.81	55.768	46.008	82.5
Turbine site 0032	4.3	1.63	3.25	3.82	55.819	45.385	81.31
Turbine site 0033	4.3	1.63	3.25	3.82	55.900	45.509	81.41
Turbine site 0034	4.3	1.63	3.25	3.82	56.065	45.741	81.59
Turbine site 0035	4.3	1.63	3.27	3.83	56.920	46.695	82.04

Turbine site 0036	4.3	1.63	3.26	3.83	56.779	46.761	82.36
Turbine site 0037	4.3	1.63	3.26	3.83	56.582	47.085	83.22
Turbine site 0038	4.3	1.63	3.25	3.83	56.377	47.373	84.03
Turbine site 0039	4.3	1.63	3.24	3.82	56.069	50.825	90.65
Turbine site 0040	4.3	1.63	3.24	3.82	56.093	56.093	100.0
Turbine site 0041	4.3	1.63	3.27	3.82	56.272	56.272	100.0
Turbine site 0042	4.3	1.63	3.26	3.81	55.911	55.911	100.0
Turbine site 0043	4.2	1.63	3.22	3.79	54.329	54.329	100.0
Turbine site 0044	4.2	1.63	3.23	3.80	54.744	54.744	100.0
Turbine site 0045	4.2	1.63	3.23	3.80	54.906	54.906	100.0
Turbine site 0046	4.2	1.63	3.23	3.80	54.974	54.974	100.0
Turbine site 0047	4.3	1.63	3.23	3.81	55.102	55.102	100.0
Turbine site 0048	4.3	1.63	3.23	3.81	55.375	55.375	100.0
Turbine site 0049	4.3	1.63	3.23	3.81	55.346	55.346	100.0
Turbine site 0050	4.3	1.63	3.23	3.81	55.530	55.530	100.0
Sector 1 total	-	-	-	-	2802.136	2485.480	88.7

Sector 2 (30°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	6.5	2.15	7.33	5.75	317.620	276.078	86.92
Turbine site 002	6.5	2.15	7.37	5.76	321.658	274.422	85.31
Turbine site 003	6.5	2.15	7.39	5.77	322.695	275.335	85.32
Turbine site 004	6.5	2.15	7.42	5.76	323.184	275.715	85.31
Turbine site 005	6.5	2.15	7.40	5.75	320.553	273.251	85.24
Turbine site 006	6.5	2.15	7.38	5.73	317.287	270.199	85.16
Turbine site 007	6.4	2.15	7.37	5.71	314.157	267.205	85.05
Turbine site 008	6.4	2.15	7.36	5.70	313.016	266.097	85.01
Turbine site 009	6.4	2.15	7.36	5.70	313.391	266.446	85.02
Turbine site 0010	6.5	2.15	7.36	5.72	315.395	273.061	86.58
Turbine site 0011	6.6	2.14	7.45	5.86	338.442	305.932	90.39
Turbine site 0012	6.6	2.15	7.29	5.81	324.074	292.260	90.18
Turbine site 0013	6.5	2.14	7.34	5.79	323.521	291.521	90.11
Turbine site 0014	6.5	2.15	7.35	5.75	318.604	286.591	89.95
Turbine site 0015	6.5	2.15	7.36	5.72	315.858	283.876	89.87
Turbine site 0016	6.5	2.15	7.35	5.71	314.376	282.405	89.83

Turbine site 0017	6.4	2.15	7.35	5.70	312.659	280.699	89.78
Turbine site 0018	6.4	2.15	7.35	5.71	313.629	281.620	89.79
Turbine site 0019	6.5	2.15	7.35	5.71	314.375	282.338	89.81
Turbine site 0020	6.5	2.15	7.36	5.72	315.660	283.599	89.84
Turbine site 0021	6.5	2.15	7.35	5.73	316.428	279.915	88.46
Turbine site 0022	6.5	2.15	7.34	5.72	314.159	263.158	83.77
Turbine site 0023	6.4	2.15	7.33	5.71	312.788	262.275	83.85
Turbine site 0024	6.4	2.15	7.34	5.71	313.392	262.823	83.86
Turbine site 0025	6.5	2.15	7.36	5.73	316.208	265.481	83.96
Turbine site 0026	6.5	2.15	7.37	5.72	316.059	265.342	83.95
Turbine site 0027	6.5	2.15	7.37	5.71	314.967	264.291	83.91
Turbine site 0028	6.4	2.15	7.37	5.70	313.261	262.656	83.85
Turbine site 0029	6.4	2.15	7.37	5.71	314.046	263.438	83.89
Turbine site 0030	6.5	2.15	7.36	5.72	315.558	270.675	85.78
Turbine site 0031	6.5	2.15	7.35	5.74	317.297	274.828	86.62
Turbine site 0032	6.5	2.15	7.35	5.73	316.543	263.618	83.28
Turbine site 0033	6.5	2.15	7.35	5.73	315.732	262.445	83.12

Turbine site 0034	6.5	2.15	7.35	5.72	315.397	262.170	83.12
Turbine site 0035	6.5	2.15	7.34	5.72	314.124	260.960	83.08
Turbine site 0036	6.5	2.15	7.35	5.71	314.302	261.097	83.07
Turbine site 0037	6.4	2.15	7.36	5.71	313.909	260.708	83.05
Turbine site 0038	6.4	2.15	7.36	5.70	312.709	259.541	83.0
Turbine site 0039	6.4	2.15	7.36	5.71	313.474	260.830	83.21
Turbine site 0040	6.5	2.15	7.36	5.72	315.112	268.571	85.23
Turbine site 0041	6.4	2.15	7.27	5.64	301.396	301.396	100.0
Turbine site 0042	6.4	2.15	7.25	5.69	305.880	305.880	100.0
Turbine site 0043	6.4	2.15	7.29	5.70	310.361	310.361	100.0
Turbine site 0044	6.4	2.15	7.32	5.71	311.862	311.862	100.0
Turbine site 0045	6.4	2.15	7.34	5.69	311.173	311.173	100.0
Turbine site 0046	6.4	2.15	7.34	5.69	310.944	310.944	100.0
Turbine site 0047	6.4	2.15	7.35	5.71	313.144	313.144	100.0
Turbine site 0048	6.5	2.15	7.35	5.73	315.887	315.887	100.0
Turbine site 0049	6.5	2.15	7.35	5.74	317.659	317.659	100.0
Turbine site 0050	6.5	2.15	7.34	5.74	316.494	316.494	100.0

Sector 2 total	-	-	-	-	15780.420	13998.270	88.71

Sector 3 (60°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	5.6	1.93	6.36	4.97	200.258	200.258	100.0
Turbine site 002	5.6	1.93	6.25	4.93	192.804	168.474	87.38
Turbine site 003	5.5	1.93	6.22	4.91	189.545	162.466	85.71
Turbine site 004	5.5	1.93	6.24	4.91	190.360	160.273	84.19
Turbine site 005	5.5	1.93	6.27	4.91	191.604	161.430	84.25
Turbine site 006	5.5	1.93	6.28	4.91	191.275	161.106	84.23
Turbine site 007	5.6	1.93	6.29	4.93	193.840	163.553	84.38
Turbine site 008	5.5	1.93	6.28	4.91	191.600	161.431	84.25
Turbine site 009	5.5	1.93	6.27	4.89	189.245	159.203	84.13
Turbine site 0010	5.5	1.93	6.27	4.88	188.623	158.638	84.1
Turbine site 0011	5.6	1.92	6.35	5.01	204.743	204.743	100.0
Turbine site 0012	5.7	1.94	6.36	5.04	207.989	186.929	89.87
Turbine site 0013	5.7	1.93	6.40	5.01	206.345	185.142	89.72
Turbine	5.6	1.93	6.37	4.96	199.909	178.838	89.46

site 0014							
Turbine site 0015	5.6	1.93	6.32	4.93	194.709	173.842	89.28
Turbine site 0016	5.6	1.93	6.31	4.95	196.325	175.452	89.37
Turbine site 0017	5.5	1.93	6.30	4.92	193.260	172.509	89.26
Turbine site 0018	5.5	1.93	6.28	4.90	190.722	170.071	89.17
Turbine site 0019	5.5	1.93	6.27	4.89	188.883	168.326	89.12
Turbine site 0020	5.5	1.93	6.27	4.89	188.880	168.332	89.12
Turbine site 0021	5.5	1.93	6.28	4.92	192.682	192.682	100.0
Turbine site 0022	5.5	1.93	6.26	4.91	190.919	166.614	87.27
Turbine site 0023	5.5	1.93	6.24	4.89	188.812	160.670	85.1
Turbine site 0024	5.5	1.93	6.23	4.88	187.308	155.883	83.22
Turbine site 0025	5.5	1.93	6.24	4.89	188.872	156.386	82.8
Turbine site 0026	5.5	1.93	6.26	4.90	189.577	156.999	82.82
Turbine site 0027	5.6	1.93	6.27	4.92	193.011	160.278	83.04
Turbine site 0028	5.5	1.93	6.28	4.92	192.502	159.740	82.98
Turbine site 0029	5.5	1.93	6.27	4.90	190.816	158.155	82.88
Turbine site 0030	5.5	1.93	6.27	4.89	189.086	156.543	82.79

Turbine site 0031	5.5	1.93	6.28	4.92	192.629	192.629	100.0
Turbine site 0032	5.5	1.93	6.27	4.92	192.000	172.418	89.8
Turbine site 0033	5.5	1.93	6.27	4.91	191.394	163.072	85.2
Turbine site 0034	5.5	1.93	6.27	4.91	190.852	158.276	82.93
Turbine site 0035	5.5	1.93	6.25	4.90	189.391	156.161	82.45
Turbine site 0036	5.5	1.93	6.25	4.89	189.311	155.385	82.08
Turbine site 0037	5.5	1.93	6.26	4.89	188.924	154.695	81.88
Turbine site 0038	5.5	1.93	6.27	4.92	192.220	157.930	82.16
Turbine site 0039	5.5	1.93	6.27	4.91	191.511	157.251	82.11
Turbine site 0040	5.5	1.93	6.27	4.90	190.236	156.061	82.04
Turbine site 0041	5.5	1.93	6.23	4.86	185.406	185.406	100.0
Turbine site 0042	5.5	1.93	6.25	4.91	190.723	190.723	100.0
Turbine site 0043	5.6	1.93	6.31	4.95	196.527	196.527	100.0
Turbine site 0044	5.6	1.93	6.32	4.95	197.306	197.306	100.0
Turbine site 0045	5.6	1.93	6.32	4.95	197.102	197.102	100.0
Turbine site 0046	5.6	1.93	6.32	4.94	195.878	195.878	100.0
Turbine site 0047	5.6	1.93	6.31	4.92	193.993	193.993	100.0

Turbine site 0048	5.5	1.93	6.29	4.90	191.393	191.393	100.0
Turbine site 0049	5.5	1.93	6.28	4.89	189.704	189.704	100.0
Turbine site 0050	5.5	1.93	6.27	4.90	189.887	189.887	100.0
Sector 3 total	-	-	-	-	9630.890	8616.762	89.47

Sector 4 (90°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	4.3	1.73	4.29	3.87	72.326	72.326	100.0
Turbine site 002	4.3	1.73	4.24	3.85	70.302	70.302	100.0
Turbine site 003	4.3	1.73	4.20	3.83	68.335	62.358	91.25
Turbine site 004	4.3	1.73	4.21	3.82	68.018	57.692	84.82
Turbine site 005	4.3	1.73	4.23	3.82	68.730	57.351	83.44
Turbine site 006	4.3	1.73	4.25	3.82	69.110	57.629	83.39
Turbine site 007	4.3	1.73	4.26	3.85	70.440	58.761	83.42
Turbine site 008	4.3	1.73	4.26	3.85	70.864	58.990	83.24
Turbine site 009	4.3	1.73	4.26	3.85	70.436	58.506	83.06
Turbine site 0010	4.3	1.73	4.26	3.83	69.900	57.988	82.96
Turbine	4.3	1.73	4.23	3.87	71.112	71.112	100.0

site 0011							
Turbine site 0012	4.4	1.73	4.32	3.95	77.333	77.333	100.0
Turbine site 0013	4.4	1.73	4.30	3.90	74.118	67.938	91.66
Turbine site 0014	4.3	1.73	4.29	3.87	72.353	62.671	86.62
Turbine site 0015	4.3	1.73	4.27	3.86	71.540	61.381	85.8
Turbine site 0016	4.3	1.73	4.27	3.86	71.317	61.183	85.79
Turbine site 0017	4.3	1.73	4.27	3.85	70.546	60.454	85.69
Turbine site 0018	4.3	1.73	4.26	3.84	70.263	60.186	85.66
Turbine site 0019	4.3	1.73	4.26	3.83	69.872	59.814	85.6
Turbine site 0020	4.3	1.73	4.26	3.83	69.849	59.813	85.63
Turbine site 0021	4.3	1.73	4.27	3.85	70.946	70.946	100.0
Turbine site 0022	4.3	1.73	4.27	3.85	70.740	70.740	100.0
Turbine site 0023	4.3	1.73	4.26	3.84	70.091	64.020	91.34
Turbine site 0024	4.3	1.73	4.24	3.83	68.881	59.319	86.12
Turbine site 0025	4.3	1.73	4.23	3.82	68.657	57.814	84.21
Turbine site 0026	4.3	1.73	4.24	3.82	68.996	57.368	83.15
Turbine site 0027	4.3	1.73	4.25	3.85	70.311	58.157	82.71

Turbine site 0028	4.3	1.73	4.25	3.84	70.135	57.624	82.16
Turbine site 0029	4.3	1.73	4.25	3.83	69.570	56.881	81.76
Turbine site 0030	4.3	1.73	4.26	3.85	70.665	57.887	81.92
Turbine site 0031	4.3	1.73	4.26	3.85	70.744	70.744	100.0
Turbine site 0032	4.3	1.73	4.26	3.85	70.448	70.448	100.0
Turbine site 0033	4.3	1.73	4.26	3.84	70.240	65.423	93.14
Turbine site 0034	4.3	1.73	4.26	3.84	70.075	61.327	87.52
Turbine site 0035	4.3	1.73	4.25	3.84	69.754	59.036	84.63
Turbine site 0036	4.3	1.73	4.25	3.83	69.461	58.109	83.66
Turbine site 0037	4.3	1.73	4.25	3.82	68.958	56.940	82.57
Turbine site 0038	4.3	1.73	4.25	3.85	70.239	57.688	82.13
Turbine site 0039	4.3	1.73	4.25	3.84	69.918	57.064	81.62
Turbine site 0040	4.3	1.73	4.25	3.83	69.443	56.432	81.26
Turbine site 0041	4.4	1.73	4.31	3.88	73.167	73.167	100.0
Turbine site 0042	4.4	1.73	4.33	3.90	74.398	74.398	100.0
Turbine site 0043	4.4	1.73	4.32	3.89	74.000	74.000	100.0
Turbine site 0044	4.3	1.73	4.29	3.87	72.450	72.450	100.0

Turbine site 0045	4.3	1.73	4.28	3.86	71.812	71.812	100.0
Turbine site 0046	4.3	1.73	4.28	3.86	71.781	71.781	100.0
Turbine site 0047	4.3	1.73	4.28	3.86	71.782	71.782	100.0
Turbine site 0048	4.3	1.73	4.27	3.83	69.838	69.838	100.0
Turbine site 0049	4.3	1.73	4.27	3.86	71.259	71.259	100.0
Turbine site 0050	4.3	1.73	4.26	3.85	70.750	70.750	100.0
Sector 4 total	-	-	-	-	3536.275	3198.994	90.46

Sector 5 (120°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	3.7	1.63	3.73	3.27	39.128	39.128	100.0
Turbine site 002	3.7	1.63	3.74	3.28	39.898	31.681	79.41
Turbine site 003	3.7	1.63	3.73	3.28	39.483	30.500	77.25
Turbine site 004	3.6	1.63	3.71	3.26	38.667	29.364	75.94
Turbine site 005	3.6	1.63	3.72	3.26	38.618	28.500	73.8
Turbine site 006	3.6	1.63	3.73	3.26	38.927	26.625	68.4
Turbine site 007	3.7	1.63	3.73	3.27	39.128	28.222	72.13
Turbine	3.7	1.63	3.74	3.27	39.242	26.688	68.01

site 008							
Turbine site 009	3.6	1.63	3.74	3.26	39.038	26.871	68.83
Turbine site 0010	3.6	1.63	3.74	3.25	38.735	26.701	68.93
Turbine site 0011	3.6	1.63	3.66	3.25	37.781	37.781	100.0
Turbine site 0012	3.7	1.63	3.75	3.32	41.684	33.706	80.86
Turbine site 0013	3.7	1.63	3.71	3.28	39.223	29.188	74.41
Turbine site 0014	3.6	1.63	3.71	3.26	38.651	30.021	77.67
Turbine site 0015	3.6	1.63	3.73	3.26	38.871	27.845	71.63
Turbine site 0016	3.7	1.63	3.73	3.27	39.126	27.773	70.99
Turbine site 0017	3.6	1.63	3.74	3.26	38.866	27.381	70.45
Turbine site 0018	3.6	1.63	3.74	3.25	38.548	26.901	69.79
Turbine site 0019	3.6	1.63	3.74	3.24	38.289	25.628	66.93
Turbine site 0020	3.6	1.63	3.74	3.24	38.030	27.002	71.0
Turbine site 0021	3.7	1.63	3.75	3.27	39.462	39.462	100.0
Turbine site 0022	3.7	1.63	3.76	3.28	39.743	30.888	77.72
Turbine site 0023	3.7	1.63	3.76	3.28	39.881	29.678	74.42
Turbine site 0024	3.7	1.63	3.76	3.28	39.866	31.326	78.58

Turbine site 0025	3.6	1.63	3.74	3.26	38.884	27.725	71.3
Turbine site 0026	3.6	1.63	3.74	3.25	38.590	27.302	70.75
Turbine site 0027	3.7	1.63	3.74	3.27	39.152	27.680	70.7
Turbine site 0028	3.6	1.63	3.74	3.26	39.007	27.404	70.26
Turbine site 0029	3.6	1.63	3.74	3.25	38.620	25.819	66.85
Turbine site 0030	3.7	1.63	3.74	3.27	39.302	27.976	71.18
Turbine site 0031	3.7	1.63	3.75	3.27	39.496	39.496	100.0
Turbine site 0032	3.6	1.63	3.75	3.27	39.244	30.387	77.43
Turbine site 0033	3.6	1.63	3.75	3.26	39.163	29.097	74.3
Turbine site 0034	3.6	1.63	3.75	3.26	39.137	30.656	78.33
Turbine site 0035	3.6	1.63	3.75	3.26	39.255	28.185	71.8
Turbine site 0036	3.6	1.63	3.75	3.26	38.960	27.817	71.4
Turbine site 0037	3.6	1.63	3.74	3.25	38.640	27.129	70.21
Turbine site 0038	3.7	1.63	3.74	3.27	39.303	27.723	70.54
Turbine site 0039	3.6	1.63	3.74	3.26	39.054	26.117	66.87
Turbine site 0040	3.6	1.63	3.74	3.25	38.701	27.459	70.95
Turbine site 0041	3.7	1.63	3.79	3.29	40.795	40.795	100.0

Turbine site 0042	3.7	1.63	3.80	3.30	41.224	32.844	79.67
Turbine site 0043	3.7	1.63	3.77	3.29	40.254	31.090	77.23
Turbine site 0044	3.7	1.63	3.75	3.27	39.573	30.103	76.07
Turbine site 0045	3.7	1.63	3.74	3.27	39.353	29.930	76.06
Turbine site 0046	3.7	1.63	3.75	3.27	39.396	28.731	72.93
Turbine site 0047	3.7	1.63	3.75	3.27	39.467	30.551	77.41
Turbine site 0048	3.6	1.63	3.74	3.25	38.493	28.013	72.77
Turbine site 0049	3.7	1.63	3.74	3.27	39.419	29.477	74.78
Turbine site 0050	3.7	1.63	3.74	3.27	39.234	29.438	75.03
Sector 5 total	-	-	-	-	1960.604	1487.804	75.88

Sector 6 (150°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	3.2	1.60	3.26	2.91	23.426	23.426	100.0
Turbine site 002	3.3	1.60	3.31	2.95	24.944	21.688	86.95
Turbine site 003	3.3	1.60	3.33	2.96	25.352	20.407	80.49
Turbine site 004	3.3	1.60	3.31	2.94	24.718	20.396	82.51
Turbine	3.3	1.60	3.29	2.93	24.198	18.584	76.8

site 005							
Turbine site 006	3.3	1.60	3.29	2.92	24.061	19.047	79.16
Turbine site 007	3.3	1.60	3.29	2.92	24.052	18.127	75.37
Turbine site 008	3.3	1.60	3.29	2.92	24.093	18.810	78.08
Turbine site 009	3.3	1.60	3.29	2.92	24.108	17.970	74.54
Turbine site 0010	3.3	1.60	3.30	2.93	24.161	18.696	77.38
Turbine site 0011	3.3	1.60	3.24	2.92	23.577	23.577	100.0
Turbine site 0012	3.3	1.60	3.26	2.96	24.851	21.689	87.27
Turbine site 0013	3.3	1.60	3.23	2.91	23.350	19.403	83.1
Turbine site 0014	3.2	1.60	3.25	2.91	23.213	18.984	81.78
Turbine site 0015	3.3	1.60	3.27	2.91	23.599	18.268	77.41
Turbine site 0016	3.3	1.60	3.28	2.92	23.846	18.813	78.89
Turbine site 0017	3.3	1.60	3.29	2.92	23.894	17.929	75.03
Turbine site 0018	3.3	1.60	3.29	2.92	23.887	18.448	77.23
Turbine site 0019	3.3	1.60	3.29	2.92	23.880	17.634	73.84
Turbine site 0020	3.3	1.60	3.30	2.92	23.866	18.291	76.64
Turbine site 0021	3.3	1.60	3.30	2.93	24.208	24.208	100.0

Turbine site 0022	3.3	1.60	3.31	2.93	24.421	24.421	100.0
Turbine site 0023	3.3	1.60	3.32	2.94	24.635	20.496	83.2
Turbine site 0024	3.3	1.60	3.33	2.94	24.953	19.951	79.95
Turbine site 0025	3.3	1.60	3.32	2.94	24.690	19.821	80.28
Turbine site 0026	3.3	1.60	3.31	2.93	24.440	18.766	76.79
Turbine site 0027	3.3	1.60	3.30	2.93	24.294	19.209	79.07
Turbine site 0028	3.3	1.60	3.30	2.93	24.228	18.366	75.8
Turbine site 0029	3.3	1.60	3.30	2.93	24.214	19.023	78.56
Turbine site 0030	3.3	1.60	3.30	2.93	24.203	18.249	75.4
Turbine site 0031	3.3	1.60	3.30	2.93	24.269	24.269	100.0
Turbine site 0032	3.3	1.60	3.30	2.93	24.283	24.283	100.0
Turbine site 0033	3.3	1.60	3.30	2.93	24.307	20.900	85.98
Turbine site 0034	3.3	1.60	3.30	2.93	24.345	20.285	83.32
Turbine site 0035	3.3	1.60	3.31	2.93	24.573	21.124	85.96
Turbine site 0036	3.3	1.60	3.31	2.93	24.496	20.279	82.79
Turbine site 0037	3.3	1.60	3.31	2.93	24.416	20.930	85.72
Turbine site 0038	3.3	1.60	3.30	2.93	24.343	20.111	82.62

Turbine site 0039	3.3	1.60	3.30	2.93	24.281	20.796	85.65
Turbine site 0040	3.3	1.60	3.30	2.92	24.077	19.872	82.54
Turbine site 0041	3.3	1.60	3.33	2.94	25.038	25.038	100.0
Turbine site 0042	3.3	1.60	3.33	2.95	25.294	21.947	86.77
Turbine site 0043	3.3	1.60	3.29	2.93	24.394	20.326	83.33
Turbine site 0044	3.3	1.60	3.28	2.92	23.903	19.614	82.06
Turbine site 0045	3.3	1.60	3.28	2.92	23.820	18.479	77.58
Turbine site 0046	3.3	1.60	3.29	2.92	23.887	18.893	79.09
Turbine site 0047	3.3	1.60	3.29	2.92	23.977	18.075	75.38
Turbine site 0048	3.3	1.60	3.29	2.92	24.066	18.718	77.78
Turbine site 0049	3.3	1.60	3.29	2.92	24.043	17.905	74.47
Turbine site 0050	3.3	1.60	3.29	2.92	24.041	18.526	77.06
Sector 6 total	-	-	-	-	1211.216	1003.064	82.81

Sector 7 (180°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	4.0	1.48	3.90	3.59	62.304	60.157	96.55
Turbine	4.2	1.37	4.05	3.84	83.156	74.947	90.13

site 002							
Turbine site 003	4.4	1.31	4.19	4.07	102.168	92.733	90.76
Turbine site 004	4.1	1.42	4.02	3.73	74.526	62.530	83.9
Turbine site 005	4.0	1.48	3.96	3.62	64.690	52.864	81.72
Turbine site 006	4.0	1.48	3.94	3.61	64.070	52.122	81.35
Turbine site 007	4.0	1.48	3.94	3.61	63.829	51.978	81.43
Turbine site 008	4.0	1.48	3.94	3.61	63.757	52.050	81.64
Turbine site 009	4.0	1.48	3.94	3.61	63.757	52.108	81.73
Turbine site 0010	4.0	1.48	3.94	3.61	63.756	52.123	81.75
Turbine site 0011	4.0	1.48	3.94	3.64	65.256	65.256	100.0
Turbine site 0012	4.0	1.48	3.88	3.64	64.156	57.500	89.63
Turbine site 0013	4.0	1.48	3.89	3.61	62.891	52.026	82.72
Turbine site 0014	4.0	1.48	3.90	3.60	62.592	50.658	80.93
Turbine site 0015	4.0	1.48	3.92	3.60	63.112	50.950	80.73
Turbine site 0016	4.0	1.48	3.93	3.61	63.342	51.427	81.19
Turbine site 0017	4.0	1.48	3.95	3.62	64.458	52.386	81.27
Turbine site 0018	4.0	1.48	3.98	3.66	66.830	54.145	81.02

Turbine site 0019	4.1	1.48	4.00	3.68	68.347	55.573	81.31
Turbine site 0020	4.0	1.48	3.94	3.62	64.142	51.688	80.58
Turbine site 0021	4.0	1.47	3.94	3.62	64.849	64.849	100.0
Turbine site 0022	4.1	1.40	4.00	3.74	75.927	70.052	92.26
Turbine site 0023	4.2	1.34	4.08	3.90	88.617	80.436	90.77
Turbine site 0024	4.4	1.31	4.18	4.07	102.050	91.577	89.74
Turbine site 0025	4.2	1.35	4.09	3.90	88.378	78.031	88.29
Turbine site 0026	4.1	1.41	4.00	3.73	74.237	64.107	86.36
Turbine site 0027	4.0	1.47	3.95	3.63	65.334	55.449	84.87
Turbine site 0028	4.0	1.48	3.95	3.61	64.037	54.240	84.7
Turbine site 0029	4.0	1.48	3.94	3.61	63.974	54.213	84.74
Turbine site 0030	4.0	1.48	3.94	3.61	63.925	54.202	84.79
Turbine site 0031	4.0	1.46	3.95	3.64	66.609	66.609	100.0
Turbine site 0032	4.0	1.46	3.96	3.65	67.249	67.249	100.0
Turbine site 0033	4.0	1.44	3.97	3.66	68.792	68.792	100.0
Turbine site 0034	4.1	1.42	3.98	3.69	71.523	71.523	100.0
Turbine site 0035	4.2	1.36	4.05	3.84	83.838	83.838	100.0

Turbine site 0036	4.1	1.38	4.03	3.79	80.021	80.021	100.0
Turbine site 0037	4.1	1.40	4.01	3.75	76.331	76.331	100.0
Turbine site 0038	4.1	1.42	3.99	3.70	72.415	72.415	100.0
Turbine site 0039	4.0	1.44	3.97	3.67	69.025	69.025	100.0
Turbine site 0040	4.0	1.45	3.97	3.66	68.604	68.604	100.0
Turbine site 0041	4.3	1.32	4.09	3.95	92.588	92.588	100.0
Turbine site 0042	4.3	1.32	4.07	3.95	91.902	84.963	92.45
Turbine site 0043	4.0	1.48	3.90	3.59	62.140	51.180	82.36
Turbine site 0044	4.0	1.48	3.91	3.60	62.659	51.096	81.55
Turbine site 0045	4.0	1.48	3.92	3.60	62.936	50.981	81.0
Turbine site 0046	4.0	1.48	3.92	3.60	63.037	50.857	80.68
Turbine site 0047	4.0	1.48	3.94	3.62	64.209	51.603	80.37
Turbine site 0048	4.1	1.48	4.02	3.70	69.649	56.477	81.09
Turbine site 0049	4.1	1.48	4.07	3.75	73.356	59.839	81.57
Turbine site 0050	4.1	1.48	4.07	3.75	73.341	59.746	81.46
Sector 7 total	-	-	-	-	3542.691	3146.112	88.81

Sector 8 (210°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	12.5	3.74	31.68	11.28	4374.694	4191.361	95.81
Turbine site 002	12.5	3.75	31.96	11.32	4429.339	4223.249	95.35
Turbine site 003	12.6	3.74	32.05	11.34	4443.467	4217.793	94.92
Turbine site 004	12.6	3.74	32.18	11.35	4464.027	4237.647	94.93
Turbine site 005	12.5	3.74	32.09	11.33	4447.585	4221.243	94.91
Turbine site 006	12.5	3.75	32.00	11.30	4427.576	4200.971	94.88
Turbine site 007	12.5	3.75	31.95	11.29	4417.530	4190.690	94.86
Turbine site 008	12.5	3.75	31.93	11.28	4412.168	4185.081	94.85
Turbine site 009	12.5	3.75	31.94	11.28	4411.972	4184.733	94.85
Turbine site 0010	12.5	3.76	31.93	11.27	4410.169	4207.481	95.4
Turbine site 0011	12.7	3.72	32.13	11.51	4502.887	4294.752	95.38
Turbine site 0012	12.6	3.74	31.52	11.41	4393.454	4164.436	94.79
Turbine site 0013	12.6	3.73	31.64	11.39	4402.305	4161.744	94.54
Turbine site 0014	12.6	3.74	31.75	11.33	4399.920	4155.964	94.46
Turbine site 0015	12.5	3.74	31.85	11.30	4406.447	4160.406	94.42
Turbine site 0016	12.5	3.75	31.87	11.29	4404.374	4157.357	94.39

Turbine site 0017	12.5	3.75	31.88	11.27	4403.073	4155.195	94.37
Turbine site 0018	12.5	3.75	31.89	11.25	4398.123	4149.361	94.34
Turbine site 0019	12.5	3.75	31.89	11.25	4396.954	4147.888	94.34
Turbine site 0020	12.5	3.76	31.92	11.27	4406.898	4188.983	95.06
Turbine site 0021	12.5	3.76	31.89	11.25	4396.005	4245.884	96.59
Turbine site 0022	12.4	3.76	31.84	11.24	4385.625	4235.523	96.58
Turbine site 0023	12.4	3.76	31.81	11.23	4379.900	4229.710	96.57
Turbine site 0024	12.5	3.75	31.84	11.24	4387.308	4237.424	96.58
Turbine site 0025	12.5	3.75	31.95	11.27	4411.063	4261.287	96.6
Turbine site 0026	12.5	3.75	31.98	11.28	4418.568	4268.819	96.61
Turbine site 0027	12.5	3.75	32.00	11.28	4421.996	4272.353	96.62
Turbine site 0028	12.5	3.75	31.98	11.28	4418.141	4268.437	96.61
Turbine site 0029	12.5	3.76	31.97	11.28	4417.380	4267.594	96.61
Turbine site 0030	12.5	3.76	31.96	11.27	4415.093	4265.304	96.61
Turbine site 0031	12.5	3.76	31.91	11.26	4403.341	4403.341	100.0
Turbine site 0032	12.5	3.76	31.91	11.26	4404.153	4404.153	100.0
Turbine site 0033	12.5	3.76	31.91	11.26	4402.934	4402.934	100.0

Turbine site 0034	12.5	3.76	31.90	11.26	4401.627	4401.627	100.0
Turbine site 0035	12.5	3.75	31.87	11.25	4392.482	4392.482	100.0
Turbine site 0036	12.5	3.75	31.91	11.26	4401.129	4401.129	100.0
Turbine site 0037	12.5	3.75	31.94	11.26	4407.597	4407.597	100.0
Turbine site 0038	12.5	3.75	31.95	11.27	4409.601	4409.601	100.0
Turbine site 0039	12.5	3.76	31.95	11.26	4410.479	4410.479	100.0
Turbine site 0040	12.5	3.76	31.96	11.27	4413.137	4413.137	100.0
Turbine site 0041	12.4	3.76	31.56	11.17	4325.773	4095.583	94.68
Turbine site 0042	12.4	3.76	31.45	11.16	4307.466	4042.280	93.84
Turbine site 0043	12.4	3.75	31.61	11.22	4348.467	4087.792	94.01
Turbine site 0044	12.5	3.75	31.73	11.25	4374.884	4112.566	94.0
Turbine site 0045	12.5	3.75	31.79	11.26	4387.211	4124.628	94.01
Turbine site 0046	12.5	3.75	31.82	11.26	4388.677	4125.373	94.0
Turbine site 0047	12.4	3.75	31.84	11.23	4381.500	4116.653	93.96
Turbine site 0048	12.4	3.75	31.85	11.21	4376.426	4110.573	93.93
Turbine site 0049	12.4	3.75	31.84	11.21	4377.546	4115.455	94.01
Turbine site 0050	12.4	3.75	31.85	11.24	4388.011	4160.529	94.82

Sector 8 total	-	-	-	-	220106.506	211486.589	96.08

Sector 9 (240°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	11.1	2.50	25.94	9.84	2849.182	2662.683	93.45
Turbine site 002	11.0	2.49	25.51	9.77	2778.773	2594.380	93.36
Turbine site 003	11.0	2.49	25.33	9.74	2749.448	2566.000	93.33
Turbine site 004	11.0	2.49	25.41	9.75	2761.414	2577.709	93.35
Turbine site 005	11.0	2.49	25.54	9.77	2780.607	2596.266	93.37
Turbine site 006	11.0	2.49	25.62	9.77	2789.588	2604.479	93.36
Turbine site 007	11.0	2.49	25.64	9.76	2790.873	2605.556	93.36
Turbine site 008	11.0	2.49	25.66	9.76	2791.969	2623.971	93.98
Turbine site 009	11.0	2.49	25.66	9.76	2792.187	2647.189	94.81
Turbine site 0010	11.0	2.49	25.67	9.75	2791.668	2791.668	100.0
Turbine site 0011	11.2	2.48	25.65	9.93	2837.796	2638.966	92.99
Turbine site 0012	11.3	2.51	26.00	9.99	2904.119	2702.527	93.06
Turbine site 0013	11.2	2.50	26.05	9.95	2897.361	2694.986	93.02
Turbine	11.1	2.50	25.94	9.87	2857.870	2654.766	92.89

site 0014							
Turbine site 0015	11.1	2.50	25.80	9.81	2825.368	2622.126	92.81
Turbine site 0016	11.0	2.50	25.74	9.79	2810.501	2608.905	92.83
Turbine site 0017	11.0	2.50	25.70	9.77	2801.074	2603.620	92.95
Turbine site 0018	11.0	2.49	25.66	9.75	2789.168	2616.083	93.79
Turbine site 0019	11.0	2.49	25.64	9.75	2786.177	2641.129	94.79
Turbine site 0020	11.0	2.49	25.67	9.76	2792.559	2792.559	100.0
Turbine site 0021	11.0	2.49	25.63	9.74	2782.383	2687.165	96.58
Turbine site 0022	11.0	2.49	25.58	9.73	2772.817	2649.137	95.54
Turbine site 0023	10.9	2.49	25.51	9.71	2758.866	2635.272	95.52
Turbine site 0024	10.9	2.49	25.44	9.70	2748.705	2625.361	95.51
Turbine site 0025	11.0	2.49	25.49	9.72	2761.963	2638.618	95.53
Turbine site 0026	11.0	2.49	25.55	9.74	2773.583	2650.104	95.55
Turbine site 0027	11.0	2.49	25.58	9.74	2779.166	2655.648	95.56
Turbine site 0028	11.0	2.49	25.61	9.75	2783.423	2659.811	95.56
Turbine site 0029	11.0	2.49	25.63	9.75	2784.724	2661.038	95.56
Turbine site 0030	11.0	2.49	25.63	9.75	2785.407	2785.407	100.0

Turbine site 0031	11.0	2.49	25.62	9.74	2782.142	2782.142	100.0
Turbine site 0032	11.0	2.49	25.62	9.74	2781.744	2781.744	100.0
Turbine site 0033	11.0	2.49	25.61	9.74	2780.399	2780.399	100.0
Turbine site 0034	11.0	2.49	25.60	9.73	2777.695	2777.695	100.0
Turbine site 0035	11.0	2.49	25.54	9.72	2766.223	2766.223	100.0
Turbine site 0036	11.0	2.49	25.56	9.73	2770.924	2770.924	100.0
Turbine site 0037	11.0	2.49	25.58	9.73	2774.684	2774.684	100.0
Turbine site 0038	11.0	2.49	25.59	9.73	2776.718	2776.718	100.0
Turbine site 0039	11.0	2.49	25.61	9.74	2779.732	2779.732	100.0
Turbine site 0040	11.0	2.49	25.61	9.74	2779.685	2779.685	100.0
Turbine site 0041	10.9	2.50	25.51	9.71	2762.442	2548.149	92.24
Turbine site 0042	11.0	2.50	25.53	9.72	2768.432	2554.213	92.26
Turbine site 0043	11.0	2.51	25.76	9.79	2815.978	2600.912	92.36
Turbine site 0044	11.0	2.50	25.82	9.79	2822.411	2607.250	92.38
Turbine site 0045	11.0	2.50	25.81	9.79	2819.058	2605.853	92.44
Turbine site 0046	11.0	2.50	25.76	9.76	2803.296	2593.332	92.51
Turbine site 0047	11.0	2.50	25.70	9.73	2789.430	2586.276	92.72

Turbine site 0048	11.0	2.50	25.64	9.73	2781.045	2604.762	93.66
Turbine site 0049	11.0	2.50	25.63	9.74	2784.421	2639.212	94.78
Turbine site 0050	11.0	2.50	25.63	9.75	2788.627	2788.627	100.0
Sector 9 total	-	-	-	-	139613.815	133391.663	95.54

Sector 10 (270°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	6.6	1.43	5.54	5.98	276.495	250.467	90.59
Turbine site 002	6.6	1.43	5.49	5.96	272.841	246.951	90.51
Turbine site 003	6.5	1.43	5.45	5.93	268.449	242.941	90.5
Turbine site 004	6.5	1.43	5.46	5.93	268.836	243.701	90.65
Turbine site 005	6.5	1.43	5.48	5.94	270.703	246.366	91.01
Turbine site 006	6.5	1.43	5.50	5.95	272.306	248.819	91.37
Turbine site 007	6.5	1.43	5.51	5.95	273.075	252.552	92.48
Turbine site 008	6.6	1.43	5.52	5.95	273.546	260.592	95.26
Turbine site 009	6.6	1.43	5.52	5.95	273.666	273.666	100.0
Turbine site 0010	6.6	1.43	5.52	5.95	273.944	273.944	100.0
Turbine	6.6	1.43	5.44	5.97	270.827	243.512	89.91

site 0011							
Turbine site 0012	6.8	1.44	5.64	6.15	294.268	266.303	90.5
Turbine site 0013	6.6	1.43	5.52	6.02	278.761	251.824	90.34
Turbine site 0014	6.6	1.43	5.52	5.98	275.411	249.293	90.52
Turbine site 0015	6.6	1.43	5.52	5.96	274.256	249.557	90.99
Turbine site 0016	6.6	1.43	5.52	5.96	274.164	250.671	91.43
Turbine site 0017	6.5	1.43	5.51	5.94	272.871	252.326	92.47
Turbine site 0018	6.5	1.43	5.51	5.94	272.276	259.328	95.24
Turbine site 0019	6.5	1.43	5.52	5.95	273.006	273.006	100.0
Turbine site 0020	6.6	1.43	5.52	5.95	274.151	274.151	100.0
Turbine site 0021	6.6	1.44	5.56	5.98	277.926	260.673	93.79
Turbine site 0022	6.6	1.44	5.59	6.01	281.516	259.669	92.24
Turbine site 0023	6.6	1.44	5.59	6.01	281.618	259.770	92.24
Turbine site 0024	6.6	1.44	5.53	5.97	275.367	253.800	92.17
Turbine site 0025	6.5	1.43	5.49	5.93	270.626	249.266	92.11
Turbine site 0026	6.5	1.43	5.50	5.94	271.851	250.439	92.12
Turbine site 0027	6.5	1.43	5.51	5.94	272.398	252.079	92.54

Turbine site 0028	6.5	1.43	5.51	5.95	272.962	260.017	95.26
Turbine site 0029	6.5	1.43	5.52	5.95	273.180	273.180	100.0
Turbine site 0030	6.5	1.43	5.52	5.95	273.411	273.411	100.0
Turbine site 0031	6.6	1.43	5.54	5.97	276.049	276.049	100.0
Turbine site 0032	6.6	1.43	5.54	5.97	275.889	275.889	100.0
Turbine site 0033	6.6	1.43	5.54	5.97	276.263	276.263	100.0
Turbine site 0034	6.6	1.43	5.55	5.97	276.452	276.452	100.0
Turbine site 0035	6.6	1.44	5.56	5.98	277.602	277.602	100.0
Turbine site 0036	6.6	1.43	5.53	5.96	274.674	274.674	100.0
Turbine site 0037	6.5	1.43	5.51	5.94	272.462	272.462	100.0
Turbine site 0038	6.5	1.43	5.51	5.94	272.518	272.518	100.0
Turbine site 0039	6.5	1.43	5.51	5.94	272.901	272.901	100.0
Turbine site 0040	6.5	1.43	5.51	5.94	272.809	272.809	100.0
Turbine site 0041	6.8	1.46	5.80	6.16	304.206	274.195	90.13
Turbine site 0042	6.9	1.47	5.88	6.23	313.448	283.491	90.44
Turbine site 0043	6.7	1.45	5.73	6.12	297.018	268.718	90.47
Turbine site 0044	6.6	1.44	5.58	6.00	279.860	253.343	90.52

Turbine site 0045	6.5	1.43	5.52	5.94	272.833	248.047	90.92
Turbine site 0046	6.5	1.43	5.52	5.93	272.571	249.003	91.35
Turbine site 0047	6.5	1.43	5.53	5.94	273.602	252.990	92.47
Turbine site 0048	6.6	1.43	5.54	5.96	275.000	261.993	95.27
Turbine site 0049	6.6	1.43	5.53	5.95	274.023	274.023	100.0
Turbine site 0050	6.6	1.43	5.54	5.98	276.616	276.616	100.0
Sector 10 total	-	-	-	-	13821.500	13092.307	94.72

Sector 11 (300°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	4.0	1.24	2.54	3.77	54.042	40.624	75.17
Turbine site 002	4.1	1.23	2.56	3.80	55.644	42.815	76.94
Turbine site 003	4.1	1.23	2.56	3.81	55.893	43.009	76.95
Turbine site 004	4.0	1.24	2.53	3.77	53.912	42.264	78.39
Turbine site 005	4.0	1.24	2.53	3.76	53.604	41.268	76.99
Turbine site 006	4.0	1.24	2.54	3.77	53.949	43.187	80.05
Turbine site 007	4.0	1.24	2.54	3.77	54.170	44.281	81.75
Turbine	4.0	1.24	2.55	3.77	54.307	45.055	82.96

site 008							
Turbine site 009	4.0	1.24	2.55	3.77	54.346	46.534	85.62
Turbine site 0010	4.0	1.24	2.55	3.77	54.457	54.457	100.0
Turbine site 0011	4.0	1.24	2.49	3.75	52.292	39.204	74.97
Turbine site 0012	4.1	1.24	2.55	3.82	56.128	43.486	77.48
Turbine site 0013	4.0	1.24	2.52	3.77	53.634	40.941	76.33
Turbine site 0014	4.0	1.24	2.53	3.75	53.116	41.527	78.18
Turbine site 0015	4.0	1.24	2.53	3.75	53.277	41.005	76.96
Turbine site 0016	4.0	1.24	2.54	3.74	53.287	42.495	79.75
Turbine site 0017	4.0	1.24	2.54	3.74	53.130	43.328	81.55
Turbine site 0018	4.0	1.24	2.54	3.75	53.546	44.346	82.82
Turbine site 0019	4.0	1.24	2.55	3.76	54.006	46.204	85.55
Turbine site 0020	4.0	1.24	2.55	3.77	54.450	54.450	100.0
Turbine site 0021	4.0	1.24	2.55	3.78	54.584	41.120	75.33
Turbine site 0022	4.1	1.24	2.56	3.79	55.265	42.432	76.78
Turbine site 0023	4.1	1.23	2.57	3.80	56.030	43.033	76.8
Turbine site 0024	4.1	1.23	2.58	3.81	56.505	44.583	78.9

Turbine site 0025	4.1	1.23	2.56	3.79	55.463	42.874	77.3
Turbine site 0026	4.0	1.24	2.55	3.78	54.677	43.874	80.24
Turbine site 0027	4.0	1.24	2.54	3.77	54.273	44.369	81.75
Turbine site 0028	4.0	1.24	2.55	3.77	54.307	45.044	82.94
Turbine site 0029	4.0	1.24	2.55	3.77	54.352	46.522	85.59
Turbine site 0030	4.0	1.24	2.55	3.77	54.416	54.416	100.0
Turbine site 0031	4.0	1.24	2.55	3.78	54.664	42.498	77.74
Turbine site 0032	4.0	1.24	2.55	3.78	54.698	43.983	80.41
Turbine site 0033	4.0	1.24	2.56	3.78	54.781	43.826	80.0
Turbine site 0034	4.1	1.24	2.56	3.78	54.908	44.843	81.67
Turbine site 0035	4.1	1.23	2.57	3.80	55.657	44.547	80.04
Turbine site 0036	4.1	1.24	2.56	3.79	55.219	45.116	81.7
Turbine site 0037	4.1	1.24	2.56	3.78	54.944	44.983	81.87
Turbine site 0038	4.0	1.24	2.55	3.78	54.726	45.421	83.0
Turbine site 0039	4.0	1.24	2.55	3.78	54.615	46.765	85.63
Turbine site 0040	4.0	1.24	2.55	3.78	54.566	54.566	100.0
Turbine site 0041	4.1	1.23	2.60	3.81	56.621	42.837	75.65

Turbine site 0042	4.1	1.23	2.60	3.81	56.897	43.916	77.18
Turbine site 0043	4.0	1.24	2.56	3.77	54.492	41.593	76.33
Turbine site 0044	4.0	1.24	2.55	3.76	53.903	42.181	78.25
Turbine site 0045	4.0	1.24	2.55	3.76	53.834	41.453	77.0
Turbine site 0046	4.0	1.24	2.55	3.76	54.081	43.229	79.93
Turbine site 0047	4.0	1.24	2.55	3.77	54.441	44.503	81.75
Turbine site 0048	4.0	1.24	2.55	3.77	54.507	45.229	82.98
Turbine site 0049	4.0	1.24	2.55	3.78	54.465	46.649	85.65
Turbine site 0050	4.0	1.24	2.55	3.78	54.522	54.522	100.0
Sector 11 total	-	-	-	-	2727.603	2231.405	81.81

Sector 12 (330°)

Turbine	A [m/s]	k	Freq. [%]	U [m/s]	MWh (free)	MWh (park)	Eff. [%]
Turbine site 001	3.2	1.57	2.21	2.91	16.546	12.726	76.91
Turbine site 002	3.3	1.56	2.24	2.95	17.805	13.398	75.25
Turbine site 003	3.3	1.55	2.25	2.97	18.410	14.515	78.84
Turbine site 004	3.3	1.55	2.24	2.95	17.933	13.663	76.19
Turbine	3.3	1.56	2.23	2.93	17.361	13.791	79.44

site 005							
Turbine site 006	3.3	1.56	2.22	2.93	17.096	13.320	77.92
Turbine site 007	3.3	1.56	2.22	2.93	17.104	14.065	82.23
Turbine site 008	3.3	1.56	2.22	2.93	17.144	14.329	83.58
Turbine site 009	3.3	1.56	2.22	2.93	17.156	14.747	85.96
Turbine site 0010	3.3	1.56	2.23	2.93	17.192	17.192	100.0
Turbine site 0011	3.3	1.56	2.19	2.93	16.869	12.746	75.56
Turbine site 0012	3.3	1.56	2.21	2.96	17.678	14.020	79.3
Turbine site 0013	3.2	1.57	2.19	2.92	16.493	12.485	75.7
Turbine site 0014	3.2	1.57	2.20	2.91	16.379	12.862	78.53
Turbine site 0015	3.2	1.57	2.21	2.91	16.607	12.695	76.44
Turbine site 0016	3.2	1.57	2.22	2.91	16.706	13.456	80.55
Turbine site 0017	3.2	1.57	2.23	2.92	16.802	13.359	79.51
Turbine site 0018	3.3	1.57	2.23	2.92	16.888	14.642	86.7
Turbine site 0019	3.3	1.57	2.23	2.93	16.994	14.568	85.72
Turbine site 0020	3.3	1.56	2.23	2.93	17.170	17.170	100.0
Turbine site 0021	3.3	1.56	2.23	2.93	17.203	15.145	88.03

Turbine site 0022	3.3	1.56	2.24	2.94	17.384	13.020	74.9
Turbine site 0023	3.3	1.56	2.24	2.94	17.566	13.728	78.15
Turbine site 0024	3.3	1.56	2.25	2.95	17.986	13.700	76.17
Turbine site 0025	3.3	1.56	2.24	2.95	17.785	14.182	79.74
Turbine site 0026	3.3	1.56	2.23	2.94	17.506	13.675	78.11
Turbine site 0027	3.3	1.56	2.23	2.94	17.388	14.327	82.4
Turbine site 0028	3.3	1.56	2.23	2.94	17.253	14.429	83.63
Turbine site 0029	3.3	1.56	2.23	2.93	17.238	14.842	86.1
Turbine site 0030	3.3	1.56	2.23	2.93	17.235	17.235	100.0
Turbine site 0031	3.3	1.56	2.23	2.93	17.261	15.199	88.05
Turbine site 0032	3.3	1.56	2.23	2.94	17.291	12.945	74.86
Turbine site 0033	3.3	1.56	2.23	2.94	17.311	13.505	78.01
Turbine site 0034	3.3	1.56	2.23	2.94	17.340	13.146	75.81
Turbine site 0035	3.3	1.56	2.24	2.94	17.532	13.954	79.59
Turbine site 0036	3.3	1.56	2.24	2.94	17.540	13.706	78.14
Turbine site 0037	3.3	1.56	2.23	2.94	17.474	14.398	82.4
Turbine site 0038	3.3	1.56	2.23	2.94	17.342	14.506	83.65

Turbine site 0039	3.3	1.56	2.23	2.94	17.289	14.893	86.14
Turbine site 0040	3.3	1.56	2.23	2.94	17.299	17.299	100.0
Turbine site 0041	3.3	1.56	2.26	2.95	17.839	15.310	85.82
Turbine site 0042	3.3	1.56	2.26	2.96	18.132	15.079	83.16
Turbine site 0043	3.3	1.56	2.23	2.94	17.394	14.922	85.79
Turbine site 0044	3.3	1.56	2.22	2.93	17.040	14.116	82.84
Turbine site 0045	3.3	1.56	2.22	2.93	16.955	14.502	85.53
Turbine site 0046	3.3	1.56	2.22	2.93	17.006	14.100	82.92
Turbine site 0047	3.3	1.56	2.22	2.93	17.072	14.646	85.79
Turbine site 0048	3.3	1.56	2.22	2.93	17.133	14.318	83.57
Turbine site 0049	3.3	1.56	2.22	2.93	17.157	14.744	85.94
Turbine site 0050	3.3	1.56	2.22	2.94	17.229	17.229	100.0
Sector 12 total	-	-	-	-	863.516	716.550	82.98

All Sectors

Turbine	Location [m]	Gross AEP [MWh]	Net AEP [MWh]	Efficiency [%]
Turbine site 001	(404000, 3690000)	8340.393	7874.252	94.41
Turbine site 002	(403678.4,3690297.0)	8345.183	7810.780	93.6

Turbine site 003	(403356.8,3690595.0)	8343.494	7778.620	93.23
Turbine site 004	(403035.1,3690892.0)	8343.562	7769.356	93.12
Turbine site 005	(402713.5,3691189.0)	8334.843	7758.015	93.08
Turbine site 006	(402391.8,3691487.0)	8321.250	7744.113	93.06
Turbine site 007	(402070.2,3691784.0)	8314.050	7741.802	93.12
Turbine site 008	(401748.6,3692081.0)	8307.434	7760.049	93.41
Turbine site 009	(401427.0,3692379.0)	8305.009	7798.448	93.9
Turbine site 0010	(401105.3,3692676.0)	8303.656	7987.604	96.19
Turbine site 0011	(404416.7,3690729.0)	8478.638	7986.757	94.2
Turbine site 0012	(404095.1,3691026.0)	8461.862	7908.548	93.46
Turbine site 0013	(403773.5,3691324.0)	8432.988	7854.436	93.14
Turbine site 0014	(403451.8,3691621.0)	8372.695	7789.088	93.03
Turbine site 0015	(403130.2,3691918.0)	8338.768	7749.280	92.93
Turbine site 0016	(402808.6,3692216.0)	8322.758	7737.506	92.97
Turbine site 0017	(402486.9,3692513.0)	8306.121	7726.814	93.03
Turbine site 0018	(402165.3,3692810.0)	8289.462	7742.845	93.41
Turbine site 0019	(401843.7,3693107.0)	8286.404	7782.850	93.92
Turbine site 0020	(401522.1,3693405.0)	8301.339	7991.722	96.27
Turbine site 0021	(403750.5,3689271.0)	8292.089	7967.201	96.08
Turbine site 0022	(403261.7,3689569.0)	8284.534	7871.522	95.01
Turbine site 0023	(402940.0,3689866.0)	8275.772	7845.878	94.81
Turbine site 0024	(402618.4,3690163.0)	8280.908	7844.098	94.73
Turbine site 0025	(402296.8,3690461.0)	8300.487	7859.297	94.68
Turbine site 0026	(401975.1,3690758.0)	8304.869	7863.728	94.69
Turbine site 0027	(401653.5,3691055.0)	8308.424	7870.610	94.73
Turbine site 0028	(401331.9,3691353.0)	8305.212	7874.786	94.82
Turbine site 0029	(401010.2,3691650.0)	8303.974	7891.329	95.03

Turbine site 0030	(400688.6,3691947.0)	8304.077	8037.081	96.78
Turbine site 0031	(403333.8,3688543.0)	8300.270	8233.811	99.2
Turbine site 0032	(402844.9,3688840.0)	8299.362	8192.501	98.71
Turbine site 0033	(402523.3,3689137.0)	8297.218	8172.165	98.49
Turbine site 0034	(402201.7,3689435.0)	8295.417	8163.740	98.41
Turbine site 0035	(401880.0,3689732.0)	8287.351	8150.806	98.35
Turbine site 0036	(401558.4,3690029.0)	8292.814	8155.018	98.34
Turbine site 0037	(401236.8,3690326.0)	8294.921	8157.941	98.35
Turbine site 0038	(400915.2,3690624.0)	8298.510	8161.544	98.35
Turbine site 0039	(400593.5,3690921.0)	8298.348	8166.679	98.41
Turbine site 0040	(400271.9,3691218.0)	8299.762	8190.589	98.68
Turbine site 0041	(404833.4,3691458.0)	8241.543	7750.735	94.04
Turbine site 0042	(404511.8,3691755.0)	8249.705	7705.646	93.41
Turbine site 0043	(404190.2,3692052.0)	8295.352	7751.750	93.45
Turbine site 0044	(403868.6,3692350.0)	8310.595	7766.629	93.45
Turbine site 0045	(403546.9,3692647.0)	8310.993	7768.865	93.48
Turbine site 0046	(403225.3,3692944.0)	8295.526	7757.094	93.51
Turbine site 0047	(402903.7,3693242.0)	8277.719	7749.318	93.62
Turbine site 0048	(402582.0,3693539.0)	8268.812	7772.578	94.0
Turbine site 0049	(402260.4,3693836.0)	8278.398	7831.274	94.6
Turbine site 0050	(401938.8,3694134.0)	8294.283	8037.895	96.91
Wind farm	-	415597.167	394855.023	95.01

Data origins information

The map was imported by 'Eng.Aubai' from a file called 'C:\Users\Eng.Aubai\Desktop\My Master thesis\Master Project\Wind Park design\wind data on wasp\My WASP Project\maps\Alhidjana7 28-9-2010.map', on a computer called 'ENGAUBAI-PC'. The map file data were last modified on the 9/28/2010 at 7:47:22 PM

There is no information about the origin of the wind atlas associated with this wind farm.

The wind turbine generator associated with this wind farm was imported by 'Eng.Aubai' from a file called 'C:\ProgramData\WAsP\Sample data\Wind turbine generators\V90-2MW.wtg', on a computer called 'ENGAUBAI-PC'. The wind turbine generator file was last modified on the 5/15/2007 at 1:00:30 PM

Project parameters

The wind farm is in a project called Project 1.

All of the parameters in the project are default values.