

Artificial Neural Networks Modelling for Monitoring and Performance Analysis of a Heat and Power Plant

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Thesis for the Degree of Master of Science

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To my family!!!

Preface

This master thesis has been carried out at the Department of Energy Science at (LTH), at Lund University. The study was carried out in cooperation with Öresundskraft, Västhamnsverket AB in Helsingborg, during fall and winter of 2005.

I would like to express my gratitude to all the people who has helped me to carry out this work. Thanks to my supervisors, Professor Tord Torisson, Associate Professor Mohsen Assadi and Dr. Jaime Arriagada for their precious guidance throughout this work. Special thanks to Ulrik Snygg, my contact person at Västhamnsverket, for providing me all information I needed.

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Last but not least, thanks to my parents who have always inspired and supported me throughout my studies.

Lund 2005-12-19

Mehrzad Kaiadi

Abstract

Öresundskraft AB has a number of plants that produces mainly electricity and district heat to the city of Helsingborg and its surroundings. Västhamnsverket is the main plant of the company, with an installed capacity of 126 MW electricity and 186 MW heat.

Västhamnsverket is a hybrid combined heat and power plant. In order to demonstrate an efficient control-monitoring model, several ANN models have been developed for different parts of Västhamnsverket. This master thesis is a part of a continuing ANN study applied at Västhamnsverket. The overall aim of this study is to develop an ANN simulator for the whole steam process at Västhamnsverket. In order to develop a better ANN model for the entire steam process, this process is divided into two sub-modules, called case 1 and case 2. Consequently two cases have been studied separately and two different ANN models have been developed. These are then linked to each other. The input and output parameters of each of these cases have been decided based on appropriate criteria as discussed later. Once the input and output parameters were decided, the dataset from the existing plant were obtained from the plant. Data preprocessing before using it for ANN training has been done in order to make the dataset as reliable as possible. Then properly screened dataset has been used for training of ANNs with cross validation and testing using a commercial neural program called NeuroSolutions.

A satisfactory accuracy has been obtained by trail and error. Some functions have been generated in Excel environment using the weight matrix of the trained ANNs in order to predict output parameters directly from input parameters by using a program called Formula Generator. These functions have been used in a user-friendly interface to obtain output parameters directly from input parameters in an easy and real time simulator. The detail of each steps of the development of this ANN simulator has been described in subsequent sections.

Regarding the work on ANNs, advanced commercial software specific for neural network implementations, viz. NeuroSolutions has been used.

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Nomenclature

b	Boiler	-
B	Biomass	-
C	Coal	-
d	Desired output or target	-
e	Error	-
E	Error function	-
F	Transfer function	-
f	Fuel	-
H	Number of hidden neurons	-
H_u	Heatings Value	kJ / kg. K
h	Enthalpy	kJ / kg. K
in	Inlet	-
\dot{m}	Mass flow rate	kg/s, ton/h
M	Number of input nodes	-
n	Iteration number	-
N	Number of output nodes	-
p	pressure	bar
P	Power/Effect	MW
\dot{Q}	Heat	MW
s	Summation	-
S	Steam	-
T	Temperature	°C
w	Water	-
w	Weight	-
\mathbf{w}	Weight vector	-
x	Input signal to neural network	-
\mathbf{x}	Input vector	-
y	Output signal from neural network	-

GREEK SYMBOLS

α	Alpha value	-
δ	Delta term	-
η	Efficiency	%
η	Learning rate	-
Σ	Summation function	-
Δ	Difference	-

SUPERSCRIPTS

T	Transposed (vector or matrix)	-
---	-------------------------------	---

SUBSCRIPTS

amb	Ambient
dh	District heating
i	Arbitrary node in the input layer
j	Arbitrary neuron in the hidden layer
k	Arbitrary neuron in the output layer

ABBREVIATIONS

ANN	Artificial Neural Network
CHP	Combined Heat and Power
HRSG	Heat Recovery Steam generator
LMS	Least Mean Square
MLP	Multi Layer Perceptron
MSE	Mean Square Error

1 Introduction

1.1 Background

The Division of Thermal Power Engineering at Lund University is the first in Sweden to introduce Artificial Neural Networks applications in the energy field, and several ANN models have been developed. One of the plants, which were involved in these projects, is Västhamnsverket. Västhamnsverket is a combined heat and power plant, which consists of a gas turbine, a coal and biomass fired boiler, a HRSG, preheaters, two condensers, a steam turbine and etc. Several ANN models have been developed for different parts of Västhamnsverket.

This master thesis is a continuing part of an ANN study applied at Västhamnsverket. The main focus of this study is on the steam cycle at Västhamnsverket.

ANN is the abbreviation for Artificial Neural Networks. It is a powerful method that can be used, among other methods, for solving non-linear multi dimensional problems. The overall aim by using ANN in energy field is to increase the availability and decrease the maintenance cost and to make an easier and more effective monitoring tool of the plant.

1.1.1 Previous Works at Västhamnsverket

The researchers in Division of Thermal Power Engineering at Lund University have performed several ANN models for different parts of this plant. The following points present the previous ANN experiences at Västhamnsverket:

- **Gas Turbine**

For the gas turbine two studies has been performed before:

1. ANN-model of gas turbine **SGT800** that is based on data generated by the heat and mass balance program **GT20**¹. The results showed that the ANN was successful in catching up the gas turbine's non-linear behavior.

¹ A design tool which is used in Siemens to generate data

2. ANN-model of the gas turbine for fault diagnosis purpose has been developed, which is based on data generated by GT20. The ANN model showed to be useful for fault diagnostics and early warning purposes in an industrial gas turbine.

- **Steam Cycle**

For the steam cycle two studies has been performed before:

- 1. Model development for fault diagnosing**

ANN-model of steam cycle, which is based on simulated data from IPSEpro². The simulation model in IPSEpro has produced data that has been used to develop ANN model for fault diagnosis. There have been 1000 simulations for different load cases, carried out with the IPSE model, which represent normal condition as well as three different faulty conditions. The ANN model, based on this data had high prediction accuracy.

- 2. Model development for performance prediction**

A simple ANN model of steam cycle has been performed in 2002. The aim of that ANN model was just to show the capability of ANNs to predict the power output. That ANN model had just a few input parameters, and thereby the accuracy of the ANN was not so high.

1.1.2 This work

Since in the pervious works, the boiler was assumed as a black box, no ANN model has been developed for this part, and since the relevant measured data were not provided in the previous work, the accuracy of predicting the power output was not good enough. In order to improve these two factors, this work has been performed.

Also no literature is still published on ANN application for prediction the performance of a biomass and coal-cofired boiler. At the same time, a research in this area is being carried out at the department of Energy Science. During this research work a physical model of such a plant has been developed and it was quite interesting to see the implementation of ANN on such a plant as well.

² IPSEpro is a flexible and comprehensive software environment for modeling and analyzing processes in energy engineering, chemical engineering and many other related areas.

1.2 Objectives

This study focuses mainly on Artificial Neural Networks modeling of the steam cycle at Västhamnsverket. The main objectives of this study are listed in following points:

- Understanding the theory of the ANN and implementing that knowledge to develop ANN models.
- Developing ANN models for monitoring and performance analysis of the plant at Västhamnsverket.
- Evaluating the models with the measured data.
- Investigate the predictability of the emissions based on fuels flow rate and operational parameters.
- Developing a friendly user interface.
- Presenting a base for future works.

1.3 Limitations

The limitations of this thesis are listed bellow:

- The main focus is on steam cycle and therefore the Gas Turbine is not included in the ANN model.
- Vast diversity of neural networks are available, but in this thesis only feed forward with back propagation algorithm (see section 2.4) is used. (Since previous studies showed that it was suitable for energy systems)
- Maximum two hidden layer were allowed to be used.

1.4 Methodology

The studies presented in this thesis were conducted following the methodology below:

- As introduction, literature studies on fundamentals conceptions and applications of ANNs have been performed in order to review the previous work and experiences in the field.
- Regarding the work on ANNs, advanced commercial software, specific for neural network implementations, viz. NeuroSolutions (See chapter 3) has been used. (An

introduction course from Jaime Arriagada³ was very helpful to learn the NeuroSolutions.)

- In order to model ANNs, the system has to be studied in details to collect theoretical, empirical knowledge and to select the input and output parameters. For this purpose the two previous master theses, which were performed in this heat and power plant, has been studied.
- In order to have a reliable dataset, a period of time was indicated to treat the provided data.
- By trial and error ANN models were trained to find out the best accurate solution.
- Making a user interface in excel environment.

1.5 Outline of the Thesis

Chapter one gives a background to subjects presented in this thesis outlines the objectives and limitations for these studies and describes the methodologies used. In chapter two a brief description of origin, fundamentals and methods of ANN are discussed. In chapter three descriptions and the instruction of NeuroSolutions is presented. In chapter four the characteristics of the heat and power plant are presented in brief in order to get some understanding needed to follow case studies. In chapter five the treatment of data is presented. In chapter six the case studies are presented, including modeling results and discussions. In chapter seven the developed interface is described. In chapter eight, the main conclusions of this thesis are discussed. In chapter nine suggested future works are listed follows by references.

³ Jaime Arriagada was a researcher at Lund Technology University who has a lot of experience in this field. In fact this master thesis is based on his Licentiate and Doctoral thesis.

2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are stimulated models based on the neural structure of the brain. The brain basically learns from experience. In contrary to traditional mathematical models, which are programmed, ANNs learn the relations between selected inputs and outputs. With *Neural Networks*, one will have access to a strong modeling environment that lets one test and explore simulated models faster and easier than ever before.

Training of the model is based on digital data⁴. The inputs and outputs data will be introduced to the network by using a neural networks program, viz. NeuroSolutions (see chapter 3). When the training is ready the model is ready to predict the performance of unseen data.

A brief comparison between brain and neural networks will be a good start to get some understanding about ANNs.

2.1 Analogy to the Brain

The most basic components of artificial neural networks are modeled based on the structure of the brain. Some neural network structures are not closely to the brain and some does not have a biological counterpart in the brain. However, neural networks have a strong similarity to the biological brain and therefore a great deal of the terminology is borrowed from neuroscience.

2.1.1 The biological Neuron

A brain is principally composed of a large number (circa 10 billion) of neurons, which are massively interconnected [1]. Neuron is the most basic element of a human brain. Neurons are specific cells, which control the abilities like identification, thinking, and applying previous experiences to every action. These neurons are interconnected with up to 200000 other neurons. This ability of the brain comes from the number of these components and multiple connections between them.

⁴ The symbolic data (if there is any) can be converted into digits

All natural neurons have four basic elements viz. dendrites, soma, axon, and synapses. Dendrites receive inputs from other sources, which is combined in some way in soma, performs a generally nonlinear operation on the results in axon and then outputs will be produced in the final stage viz. synapses. Figure 1 shows a simplified biological neuron and the relationship between these four components.

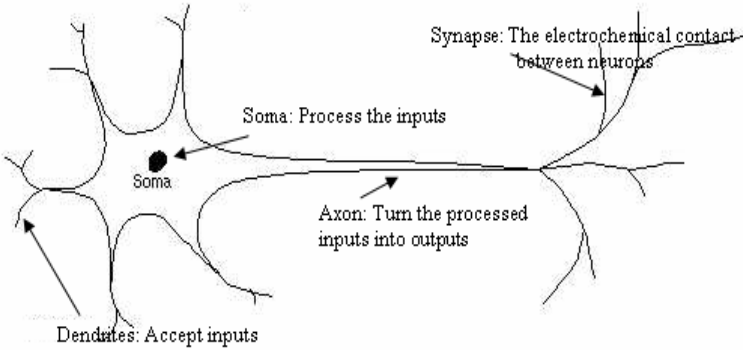


Figure 1: A biological neuron

2.1.2 The Artificial Neuron

Basic unit of the artificial neuron is simulated from the biological model but it is much simpler. Figure 2 shows the basics of an artificial neuron.

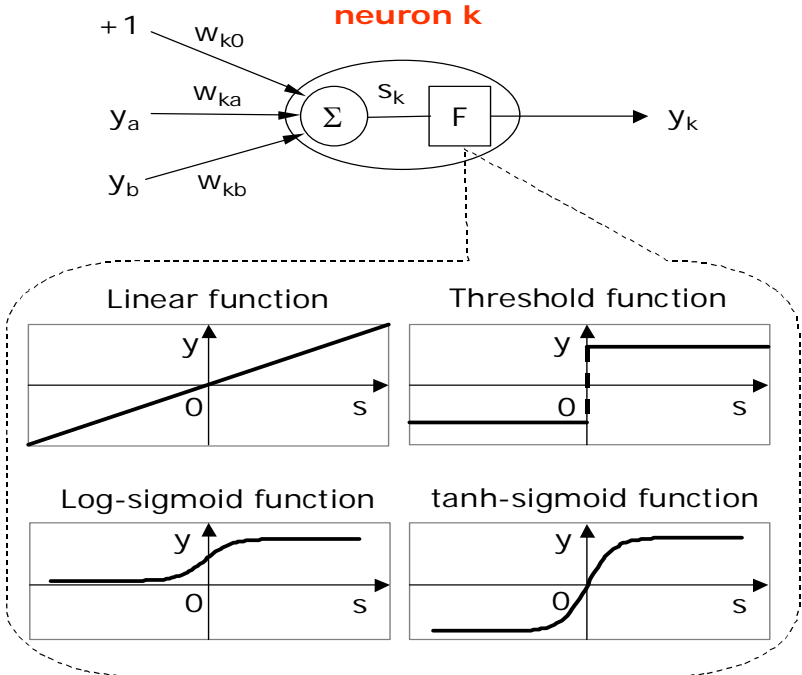


Figure 2: Basics of an artificial neuron and common transfer functions [2]

The inputs are represented by the mathematical symbol (y_a) , (y_b) . Each input is multiplied by its specified connection weights, which are represented by mathematical symbol (w_{kj}) . Besides that there is an extra input equal to +1 to each neuron and its corresponding weight by mathematical symbol (w_{k0}) is called the bias that introduce an off-set to the transfer function (see section 2.1.2.1), which allows the neuron to have an output, even if the output is equal to zero. In the next step some mathematical operations (mostly summation) are performed and the products of this operation are fed through nonlinear transfer functions in order to generate output. The construction of all artificial neural networks is the same but some fundamentals may vary in different ones.

2.1.2.1 Transfer Functions

The most used transfer functions are the linear function, the Threshold function, the Log-sigmoid function and the tanh-sigmoid function. Different transfer functions can be used depending on the applications; in this work tanh-sigmoid function has been used. In figure 2 the x-axis (S) of the charts represents the resulting weighted sum and the y-axis represents the output.

The **linear** transfer function: (c is constant)

$$y = c \cdot s \quad (2.1)$$

The **threshold** function: It only computes 1 and 0. This type of activation-function is called the McCulloch-Pitts model and reflects a sort of "all-or-nothing" ability with a neural network.

$$y = \begin{cases} +1, & \text{if } s \geq 0 \\ -1, & \text{otherwise} \end{cases} \quad (2.2)$$

The **logistic sigmoid** transfer function: When using the sigmoid activation function the artificial neuron will look more like the natural. The good thing about this function is that it makes a very soft transition (see figure 2). This gives outputs in the range [0, 1]:

$$y = \frac{1}{1 + e^{-s}} \quad (2.3)$$

The **tanh-sigmoid** transfer function: The tangents hyperbolic activation-function is a lot like the Sigmoid, except that it can give a negative output. This transfer function has been used during this work. This gives outputs that lie in the range $[-1, 1]$:

$$y = \frac{e^s - e^{-s}}{e^s + e^{-s}} \tag{2.4}$$

2.2 General Theory of Artificial Neural Networks (ANNs)

Artificial Neural Networks is no more than an interconnection of artificial neurons. ANNs learn the relations between selected inputs and outputs from the previous experiences. ANNs also perform their tasks simultaneously (i.e. parallel processing), which makes ANNs very fast. A typical ANN can identify and learn the relationships between the inputs and the outputs of a non-linear multi-dimensional system (see figure 3).

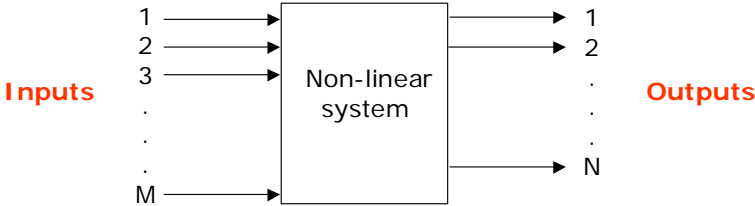


Figure 3: Non-linear multi-dimensional system [2]

2.2.1 ANNs Architecture

Mainly, ANNs are classified into two groups depending on the structure of the connections, *feed-forward* (are only allowed to pass in one direction, i.e. from input to output) and *recurrent* (feed-back) networks.

2.2.1.1 Recurrent Networks

When all units in all layers are connected to all units in all layers it is called *fully connected* which is the most general case of the recurrent networks. Figure 4 presents a fully connected ANN with its weights matrix.

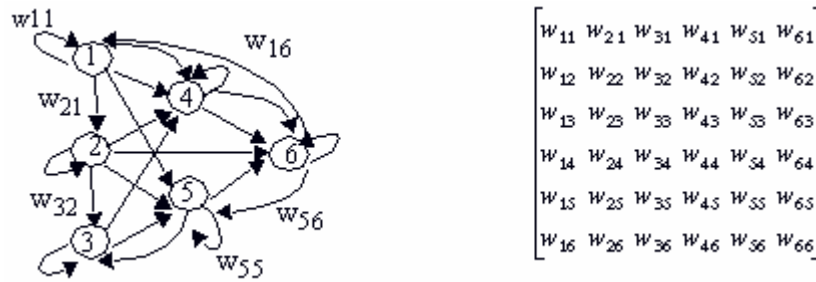


Figure 4: A fully connected ANN and the weight matrix [3]

In recurrent networks some of the connections may be absent, but there are feedback connections. “An input presented to a recurrent network at time t , will affect the networks output for future time steps greater than t ” [3]. Therefore, recurrent networks need to be operated over time.

2.2.1.2 Feed-Forward Networks

If the interconnection matrix is restricted to just one direction (neither feedback nor self connections), the neural network is defined as feed forward. A special group of feed forward networks is layered, which is called the multi-layer perceptron⁵ (MLP).

Layered ANNs, basically consist of a set of units that constitute the *input layer*, one (or more) *hidden layer(s)*⁶ and an *output layer*. No processing is done in the input layer and because of that its components are called *input nodes*.

Figure 5 presents a typical feed forward networks and its weight matrix.

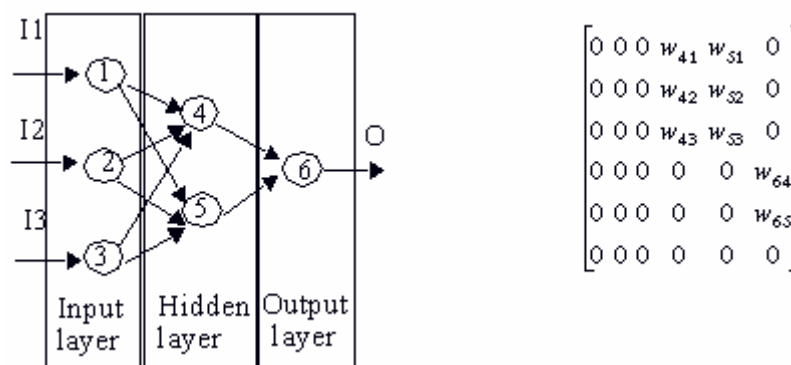


Figure 5: Multilayer perceptron and its weight matrix [3]

⁵ Perceptron consist of a single layer of nonlinear artificial neuron without feedback connections.

⁶ Hidden layer do not have direct contact with the environment, therefore it is called hidden.

2.3 Teaching an Artificial Neural Networks

The learning process is called *training* and is performed according to learning rules, which are classified into the two main following sorts:

- **Supervised learning:** where both inputs and outputs are known, this means the network can determine its predictive performance from given inputs.
- **Unsupervised learning:** where the outputs are not known and the neurons however have to find a way to manage them, this method is not considered in this study.

2.3.1 Learning rate

Most learning functions have some terms for a learning rate, or learning constant. Usually this term is positive and between zero and one.

By choosing a lower rate, more time is spent in training an ANN but the results will be more stable. With the faster learning rates, the training takes less time but the accuracy of the results will be worse. In order to get the highest accuracy learning rate $\eta = 0,1$ was chosen in this study.

Several other factors can play a role in determining how long it will take to train a network like: Network complexity (number of hidden neurons and layer), size of data, architecture and type of learning rule.

2.3.2 Learning Laws

Most of learning laws are some sort of variation of the best-known and oldest learning law, Hebb's Rule⁷. A few of the major learning laws are presented as examples.

Perceptron rule and the *delta* or *LMS (Least Mean Square error) rule*, both use supervised training, and work iteratively to update their weights.

⁷ Hebb published his book *The Organization of Behavior in 1949*, in which he proposed that the physiological learning is carried out through synaptic modifications in the brain, and thereby, he introduced the first known rule for self-organizing learning [2]

2.3.2.1 The perceptron Learning Law

Perceptron consists of a nonlinear artificial neuron, which has a threshold transfer function [2]. Figure 6 shows the perceptron with one neuron.

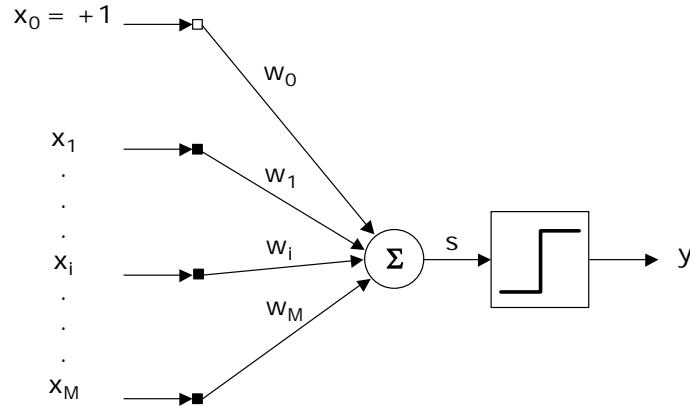


Figure 6: The Perceptron [2]

Equation (2.5) expresses the mathematical processes in the perceptron:

$$\begin{cases} s = \sum_{i=0}^M w_i \cdot x_i \\ y = F(s) \end{cases} \quad (2.5)$$

An error defined as a difference between the desired output (d) and the actual output; equation (2.6) expresses the error function:

$$e(n) = d(n) - y(n) \quad (2.6)$$

Where n is the iteration number and e is the error.

In the beginning of the training the weights are given random values, and by starting the process the errors will be generated. The perceptron has an algorithm to generate new set of weights with help of the calculated errors. Equation (2.7) expresses this algorithm:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \eta \cdot e(n) \cdot \mathbf{x}(n) \quad (2.7)$$

2.3.2.2 The Delta rule

The delta rule is one of the most commonly used. This rule changes the weights in the way that minimizes the mean squared error of the network. This rule is also referred to as the Least Mean Square (LMS) Learning Rule. Equation (2.8) expresses the error function:

$$E(\mathbf{w}) = \frac{1}{2} e^2(n) \quad (2.8)$$

The threshold function is replaced by a linear transfer function, and therefore the error can be expressed as

$$e(n) = d(n) - \mathbf{x}^T(n) \cdot \mathbf{w}(n) \quad (2.9)$$

Where \mathbf{x} and \mathbf{w} are input and weight vectors.

“The main assumption is that the optimal weights are to be found in the direction of the descent gradient of the error function with respect to the weights (steepest descent method), i.e. [2] “

$$\Delta \mathbf{w}(n) = -\eta \cdot \frac{\partial E(\mathbf{w})}{\partial \mathbf{w}(n)} \quad (2.10)$$

Differentiating equation (2.8) gives:

$$\frac{\partial E(\mathbf{w})}{\partial \mathbf{w}(n)} = e(n) \cdot \frac{\partial e(n)}{\partial \mathbf{w}(n)} \quad (2.11)$$

Putting equation (2.9) in (2.11) gives:

$$\frac{\partial e(n)}{\partial \mathbf{w}(n)} = \frac{\partial (d - \mathbf{x}^T \cdot \mathbf{w})}{\partial \mathbf{w}(n)} = -\mathbf{x}(n) \quad (2.12)$$

And finally, the new weight vector is equal to:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \Delta \mathbf{w}(n) = \mathbf{w}(n) + \eta \cdot e(n) \cdot \mathbf{x}(n) \quad (2.13)$$

When, between two repeated iterations, the error does not drop at least a given amount, training should be terminated and the weights will be frizzed.

Figure 7 demonstrates gradient descent learning rule:

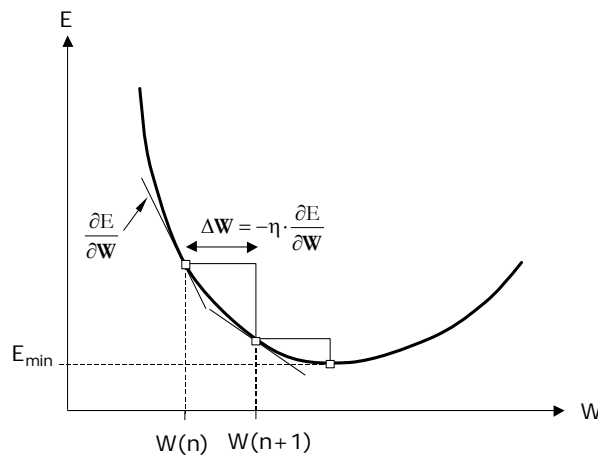


Figure 7: Gradient based updating of the weights [2]

2.3.2.2.1 Stop Criteria

NeuroSolutions is the software that has been used for training the data in this study (see chapter 3). There are two criteria in this software to stop the training which are listed below:

- An Option, which makes the operator able to choose the termination of the training if there is no improvement in the training.
- The data is divided into three groups in NeuroSolutions viz. *Training*, *Cross validation* and *Test* set. During training, when the training set is being trained the Cross validation set works as a supervisor and it stops the training when error in the Cross validation set starts increasing (see figure 8).

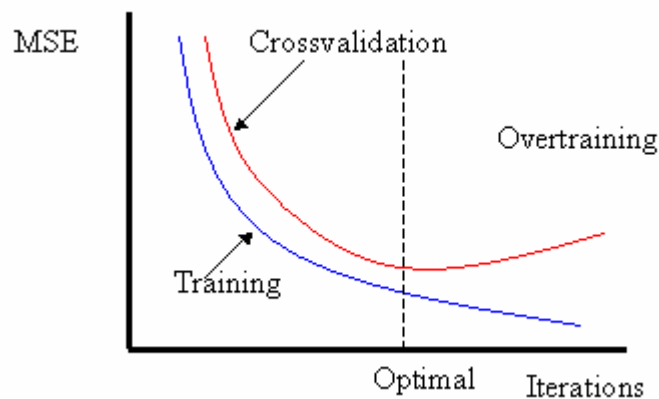


Figure 8: Behavior of MSE with overtraining

2.4 Feed-Forward Networks and Back propagation

The vast types of Artificial Neural Networks exist but the types of networks, which are focused in this study, are multi-layer feed-forward networks (MLP). In order to better understand and to know the advantages of multi-layer feed-forward networks, the single-layer feedforward networks has been discussed first.

2.4.1 Single-layer Feed-Forward Networks

Single-layer networks only consist of one layer of neurons, actually there are two, but as it is only the last of the layers that makes an actual calculation, it's called a single-

layer network. The reason why it is called a feed-forward system is because the information is only spread out from input to output (see figure 9).

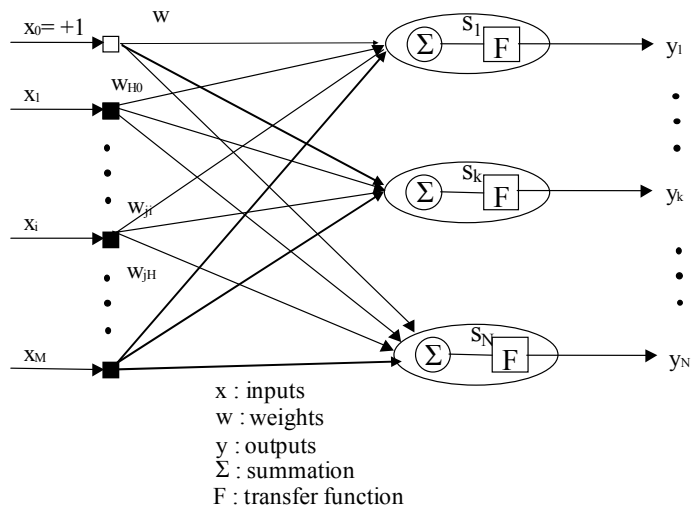


Figure 9: General structure of a single-layer feed-forward

The main problem with Single-layer networks is their disability of classifying non-linear functions (see figure10).

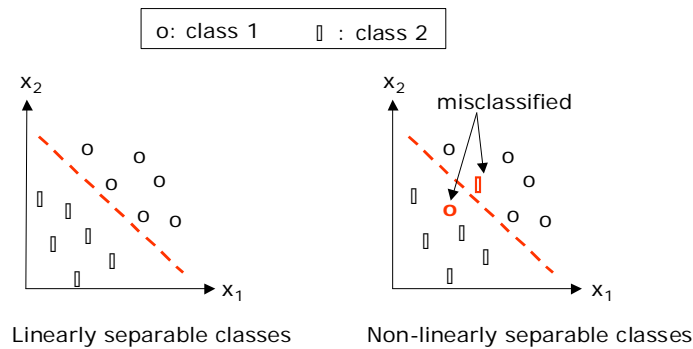


Figure 10: Disability of single-layer feed forward networks to classify non-linear functions [2]

The complexity of single-layer perceptrons is not big enough to handle greater categorization problems. The logical depth of these kinds of problems is too big for a single perceptron to handle. In order to solve this problem the networks in several layers have to be created. These are commonly referred to as MLP (Multi Layer Preceptrons).

2.4.2 Multi-layer Feed-Forward Networks

A typical MLP is presented in figure 11. In these types of networks, one or more hidden layers are between input and output layer and they will help the network to solve more

complex problems. Once the number of inputs and outputs has been decided, the number of the neurons in the input and the output layer is fixed. The optimum number of the hidden neurons in the hidden layer, however, has to be chosen. Finding the optimal number of hidden layer is the matter of trail and error, but here is a rule of thumb for beginning with a good start value and that is to begin with the number of the input parameters and thereby increase the number of hidden layers [2].

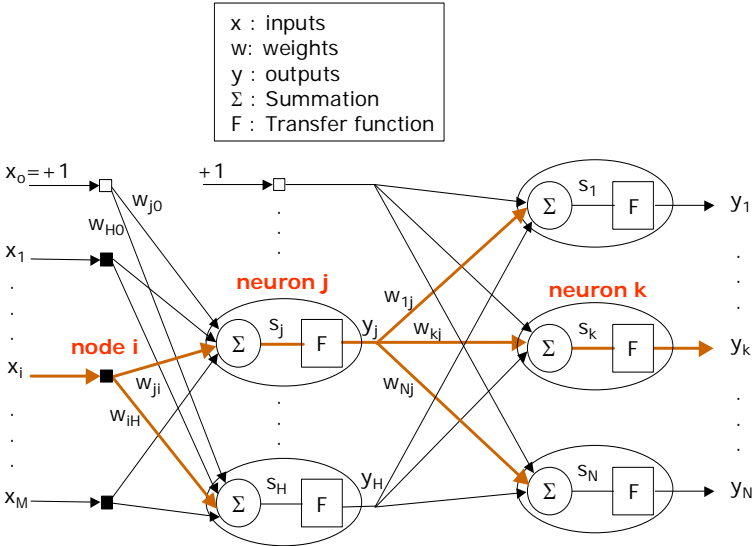


Figure 11: General structure of a feed-forward MLP with one hidden layer [2]

Using multi-layer feed forward networks will solve the disability of classifying non-linear functions (see figure 12).

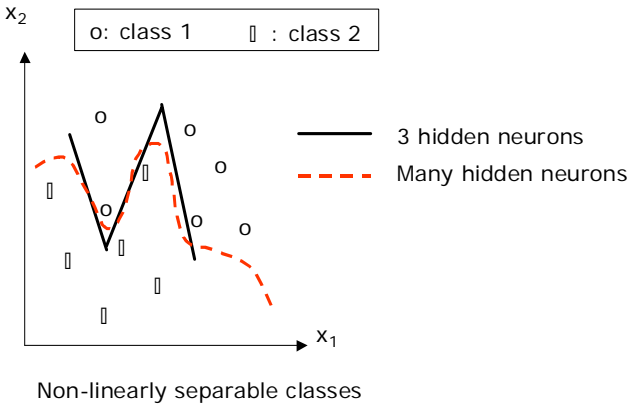


Figure 12: Capability of MLP to classify Non-linear functions [2]

2.4.3 Backpropagation Algorithm

Backpropagation is the basis for training a supervised neural network. The data used as inputs is transmitted through the network, layer by layer, and a set of outputs is

obtained. During this forward pass the weights of the network are set. The obtained outputs are compared with the desired outputs values and, as a backward pass; the difference between desired outputs and calculated outputs (error) is used to adjust the weights of the net in order to reduce the level of the error (see figure 13). This is an iterative process, which continues until an acceptable level of errors will be obtained. Each time the network processes the whole set of data (both a forward and a backward pass), is called an epoch. The network is in this way trained and the error is reduced by every epoch until an acceptable level of error will be gained. This method is called *error back-propagation* training.

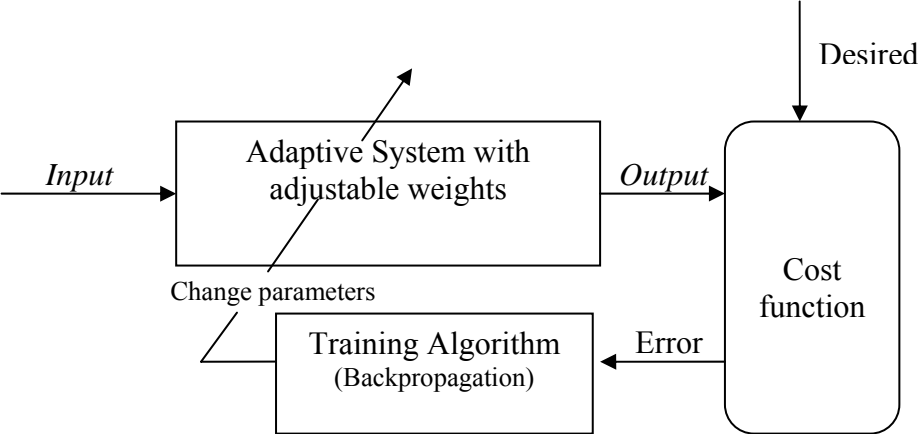


Figure 13: Training a network with Backpropagation algorithm

2.5 Concluding Remarks

The objective of this chapter is to provide a basic knowledge about ANNs (especially multi layer perceptron with Backpropagation algorithm). The stimulation, structure, learning rules and the functions of ANNs have been explained in different sections.

3 NeuroSolutions

As it was mentioned in the objectives section, the main objective of this master thesis is to develop an ANN model of the steam cycle at Västhamnsverket. All the models have been developed in the commercial neural network program NeuroSolutions. A short background and instruction of using NeuroSolutions is presented in this chapter.

3.1 Features of the NeuroSolutions

There are six levels of NeuroSolutions, viz.; *Educator*, *User*, *Consultants*, *Professional*, *Developer* and *Developer Lite* [4]. The *Educator* level is used in this work. The *Educator* is an entry level version, which is intended for those who want to learn about neural networks and work with MLPs. Regarding the implementation of ANN in energy-field the MLPs are the best type of the neural networks. The *Educator* features are summarized in points:

- Multi-layer perceptrons (MLPs)
- Generalized feedforward networks
- User-defined network topologies
- Up to 50 neurons per layer
- Up to 2 hidden layers
- Learning Paradigms is Backpropagation

The flexibility of the NeuroSolutions makes it more powerful. NeuroSolutions can be connected to Excel, Matlab and Visual basic. The NeuroSolutions for excel has been used in this study.

3.2 NeuroSolutions for Excel

NeuroSolutions for Excel is an Excel Added NeuroSolutions that provides a very powerful environment for manipulating the data and generating the reports.

Data processing is very advanced in *NeuroSolutions for Excel*, in comparison to Microsoft Excel e.g. extra options like randomizing, sampling and etc.

3.3 A Brief Instruction for Using NeuroSolutions

Since the data has been provided in excel-files and working with Microsoft Excel is relatively easier than Matlab, NeuroSolutions for Excel has been used. Detailed instruction of using this program is available at the Department of Energy Science for those who are interested, but the following descriptions are listed in order to clarify the process. The processes are listed below:

- Open the data-file
- Select the inputs and outputs
- Share the data into three parts, viz. *Training*, *Cross validation* and *testing*
- Save all the files
- Create a neural network
- Specify the settings of the network, like: number of the hidden layers, number of hidden neurons, type of transfer function, learning rate, number of iterations
- Save the network
- Start the training of the network
- Test the network
- Generate a formulation with the help of the saved weights
- Use the formulation in the final interface

The two last points are not done directly in the NeuroSolutions, but the formula is generated with another program viz. *formula Generator* and will be used in Microsoft excel.

3.4 Advantages of ANN Compared to IPSEpro (Heat & Mass balance programs)

Regarding the predicting capacity and using the named programs, a comparison has been done. IPSEpro is a commercial heat and mass program with a semi parallel solver, which make it very fast. Advantages of ANN compared to IPSEpro are listed below:

- Using ANN is easier than IPSEpro.
- From an end users perspective ANN models are much easier to use compare to IPSEpro models.
- That's true that one can define all losses in an IPSEpro model but despite that the model would never be like a real system. By using ANN, the ANN model takes care of everything in the system i.e. the ANN model can work like the real system.
- Detecting the degradation is possible with ANN model but not with IPSEpro model.

4 Öresunds AB

4.1 Company Description [5]

Öresunds AB consists of a number of utility plants, which produce electricity, district heat and district cold. The largest amount of the utility is provided by the heat and power plant at Västhamnsverket.

1. Västhamnsverket

Steam-boiler/steam-turbine has a capacity of 69 MW electricity and 138 MW district heat. The main fuel is wood pellet and coal.

2. Västhamnsverket's Gas turbine

This part of the plant is connected in parallel with the steam turbine and it has a capacity of 56 MW electricity and 53 MW district heat just by itself. The main fuel is natural gas but the plant can also run by oil.

3. Heat-pump

The clean water from Helsingborg's outflow system is used in a heat pump, whose capacities are on 30 MW district heat and 10 MW district cold.

4. Biogas-plant at Filborna

The biogas is used to run a small CHP whose capacities are of 1,9 MW electricity and 11,9 MW district heat.

5. Heat-water-Boiler

Four boilers exist in the district-heat centre Israel, which is used as reserved plant. Three of them run with natural gas and oil but the fourth one runs with biomass. Totally they have a capacity of 400 MW to produce district heat.

6. Waste-Heat

By using the heat from industries around the city 35 MW district heat can be collected.

7. Wind-power

A wind-power plant has a capacity of 200 kW, electricity. As soon as the wind's speed exceeds 6 m/s it produces electricity.

8. District cold

The heat pumps together with four refrigerating-machines produce district cold. The capacity of the heat pump is 10 MW district cold and the refrigerators capacity is 11 MW.

9. Bjällerforsen Water-Power

On the boundary between Skåne and Blekinge are three water-turbines, which produce electricity. Totally they have a capacity on 2,7 MW electricity.

4.2 Västhamnsverket

Västhamnsverket, a hybrid combined heat and power plant, is the main power plant in the Öresunds AB Company. Figure 14 presents a schematic figure of Västhamnsverket.

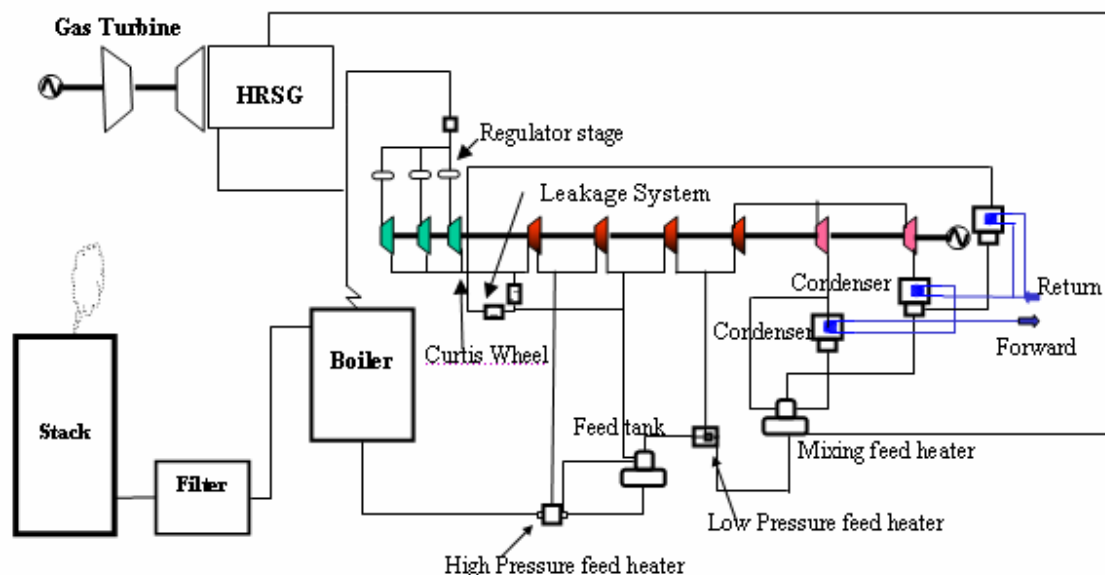


Figure 14: A simple schematic figure of Västhamnsverket

Västhamsverket consists of a boiler, built in 1982 [5]. The boiler has capability to use oil, coal or biomass as a fuel. The boiler produces steam, which expands in the steam turbine. By conversion of the heat-energy to movement-energy the electricity will be produced in the generator.

A topping-cycle (Gas turbine + Heat Recovery Steam Generator) has been added into the bottoming-cycle (steam cycle) in 1999. The gas turbine can generate electricity by itself and the high temperature, exhaust gas leaving the gas turbine, is taken care of by HRSG. A flow of steam can be generated in HRSG and it will be sent into the steam turbine. By adding a topping cycle to the bottoming cycle total efficiency of the heat and power plant was increased significantly.

4.2.1 Steam-Boiler

The steam boiler is constructed and manufactured by Götaverken Ångteknik. The construction data [6] of the boiler is:

Pressure: 130 bar

Temperature: 540°C

Steam-flow: 82 kg/s

The steam-boiler's heat transfer areas consist of up-righted tubes which are weld attached with flat iron. The water circulates through the tubes with self-circulation. Superheating occurs in four superheating's part.

Air preheating occurs in three stages: two in finned-batteries and one in rotating air preheater.

4.2.2 Steam Turbine

This unit of steam turbine (See figure 15) is from a series of ATM (The Axial flow Turbine series of Medium size) [7]. The steam turbine consists of three modules: Inlets-Regulator, TMI- module and TME- module. The Inlets-Regulator is a Curtis-type (two rotors and two stators). TMI module (With 16 stages) is a power part of the turbine and has three drains. TME-module (With 5 stages) is called power and heat part and has two drains to the condensers; these two drains are after stage 4 and 5. Totally the number of stages is 25.

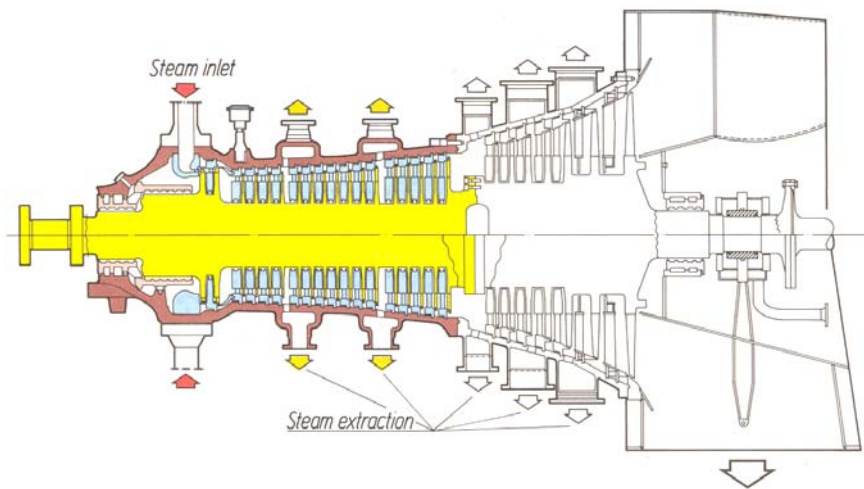


Figure 15: Steam turbine [8]

Some reconstruction was performed in the steam turbine in 1999 after adding the topping cycle. The reason for reconstructing was to make the steam turbine able to handle higher steam flows.

4.2.3 Condensers

Västhamsverket have two heat-condensers (E001 and E002) [9]. The heat transfer area of these condensers is 1980 m². These condensers condense the drain steam from the TME-module and the steam is being converted into saturated water when it leaves the condensers. The heat-energy is captured from the district heat part and thereby the temperature of the district heat increases.

4.2.4 Feed-heaters Chain

Feed-heaters chain consist of one mixing-feed-heater which, mix the condensated water with the drain steam from the drains, one Low-pressure feed-heater, one feed-tank that works like a mixing-feed-heater and one High-pressure feed –heater (see figure 14). The number of the connections and the connections places of the feed-heaters are clear in figure 14.

4.2.5 Leakage Steam

By running the steam turbine the steam leakage is inevitable, in other words; it is not possible to keep everything leak proof. In order to prevent the suction pressure

(negative pressure) it is necessary to have leakage steam. One part of this leakage steam is used to heat up the water in district heat (see figure 14), and the other part of leakage steam goes to drains.

4.2.6 Exhaust-Cleaning System

Exhaust gases are cleaned in three stages:

1. Electro-filters
2. Sulfur-Cleaning
3. Textile Tube-filters

Electro-filters capture the particles like the flying-ashes. Sulfur Cleaning is a wet-dry SO_2 –box that with help of, for example NaOH absorbs the sulfur. In the final stage the smallest particles will be separated in the textile Tube-filters.

4.2.7 Gas Turbine

The gas turbine (SGT800) [7] is manufactured by Alstom Power AB in Finspång (see figure 16). The gas turbine can produce up to 43 MW electricity and its thermal efficiency is 37 %. The gas turbine also has very low emissions level (less than 15 ppm NO_x with gas fuel).

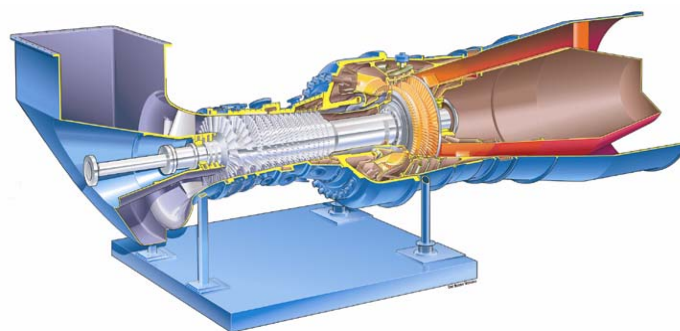


Figure 16: Gas Turbine SGT800 [8]

The gas turbine is uniaxial and runs the generator with the “cold” side (this implies that one for instance can have an efficient long conical diffuser after the turbine, see figure 16). The compressor is consisted of 15 stages and the pressure ratio is ca 20 with a flow rate of ca 130 kg/s.

The gas expands in three stages and generates 100 MW turbine-work. Since the machine is optimized for a combined-cycle the outlet temperature is relatively high and the two first turbine stages are air-cooled.

4.2.8 HRSG (Heat Recovery Steam Generator)

The HRSG [10] consists of two superheaters, one evaporator, one economizer and one district-heat economizer. The effect of the district-heat economizer is ca 20 MW. The effect that is produced in form of steam by HRSG (except the district-heat economizer) is ca 45 MW.

4.2.9 Heat-pump

Helsingborgs exhaust-system delivers purified exhaust-water to Västhamnsverket's electrically driven heat pump. Heat pump increases the water temperature and this heat can be transferred towards the district-heat water. After this heat exchanging the exhaust-waters temperature is decreased to ca 6 °C and thereby it can be used in district-cold system.

4.2.10 Safety and Reserves [5]

In cooperation with "Svenska Kraftnät" a stand by diesel unit, has been installed. Its duty is to start the gas turbine and thereby Västhamnsverket's steam boiler and steam turbine can be started.

4.2.10.1 Accumulator Tanks

Two accumulator tanks have been installed in the plant;

1. District-heat with 36 000 m³ capacity
2. District-cold with 5000 m³ capacity

The functions of these accumulators are acting as buffers for varying the consuming and maintain the pressure in the grid. In 2003 installing a new liquid-cooler has extended the production capacity of the district-cold.

5 Data Treatment

This chapter is divided into three main sections. In the first section, measured parameters, which have been used for ANN modeling is presented. In the second section, data treatment before usage in NeuroSolutions is presented and in the last section, data treatment during using in NeuroSolutions has been discussed.

5.1 Parameters

An intensive work was indicated to data analysis. Only a part of the data has been considered meaningful, in particular, the parameters chosen for training were divided into 5 different blocks, each one containing a different number of parameters. Data were provided in five minutes average for one month (February 2005). See figure 17 to get better understanding about the parameters (The corresponding number of the index number of each parameter is presented at the figure).

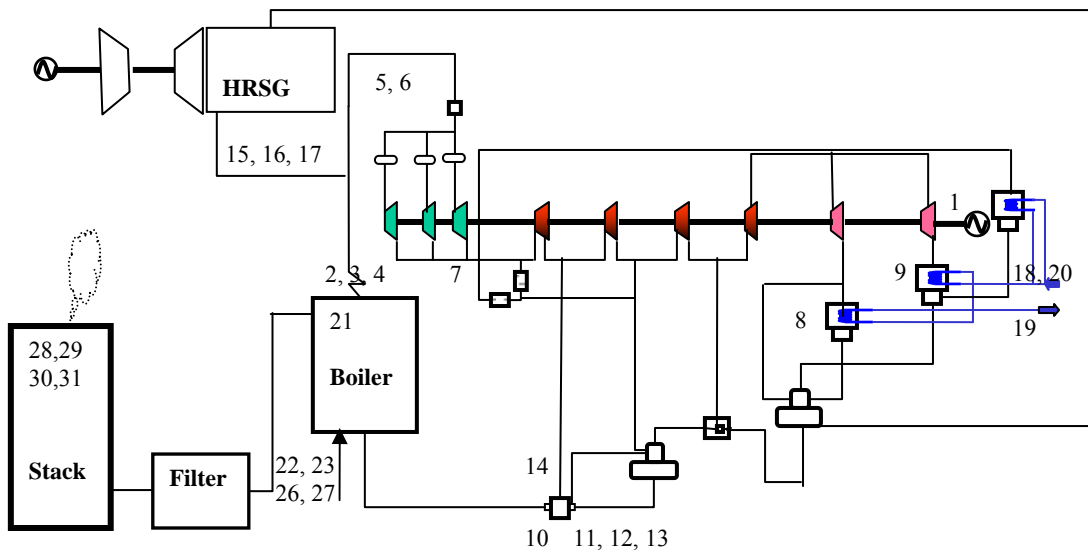


Figure 17: Schematic figure of the heat and power plant

1 Steam-Cycle:

Table 1 presents the steam-cycle (without boiler) parameters, which are used in this study. The *Measurements code* column presents the corresponding identification code in the plants measurements list.

Index	Descriptions	Units	Measurements code
1	Power	MW	605.K806
2	Mass flow steam Boiler	Kg/s	721.K301
3	Temperature steam Boiler	°C	321.K590
4	Pressure steam Boiler	MPa	321.K101
5	Pressure steam before regulator	MPa	421.K101
6	Temperature steam before regulator	°C	421.K501
7	Pressure after Curtis	Bar	403.K101
8	Pressure Condenser E001	Bar	461.K101
9	Pressure Condenser E002	Bar	461.K104
10	Temperature water after HPFH	°C	763.K503
11	Mass flow water before HPFH	Kg/s	763.K301
12	Temperature water before HPFH	°C	763.K501
13	Pressure water before HPFH	MPa	763.K103
14	Drain Pressure	MPa	423.k101

Table 1: Steam-cycle parameters

2 HRSG (Heat Recovery Steam Generator)

Index	Descriptions	Units	Measurements code
15	Mass flow HRSG	Kg/s	LBA60.CF901
16	Steam Temperature HRSG	°C	LBA60.CT015
17	Steam Pressure HRSG	MPa	LBA60.CP001

Table 2: HRSG parameters

3 District heating system water

Index	Descriptions	Units	Measurements code
18	Flow rate of the water	[m ³ /hour]	744.K302
19	Temperature of the forwarding flow	°C	744.K571
20	Temperature of the returning flow	°C	744.K501

Table 3: District heating system parameters

4 Boiler

In this part the data is divided into two groups the measured data and the calculated data. The first 4 rows in table 4 are measured data and rows 5 and 6 are constant value, which is provided by the plant. Rows 7 and 8 are calculated data and the process of calculation is described below.

Index	Descriptions	Units	Measurements code
21	Burner Temperature	°C	301.K530
22	Total air flow rate	[Nm ³ /s]	331.K305
23	Air Temperature	°C	331.K501
24	Coal Heating value	[MJ/Kg]
25	Biomass Heating value	[MJ/Kg]
26	Coal flow rate	[ton/h]
27	Biomass flow rate	[ton/h]

Table 4: Boiler parameters

4.1 Calculation of the Flow Rate of the Fuels

Usually it is very difficult to measure the flow rate of the solid fuels and the Västhamnsverket is no exception. However with respect to the main objectives of this ANN modeling of the boiler, it was needed to calculate the fuel flow rate in better way. Different approaches have been tested and one providing the best result has been chosen which is presented below.

This approach is based on the definition of the boiler efficiency (the sensible heats are included in the boiler efficiency). The boiler efficiency is defined as the division of the useful effect of the boiler by the fuel efficiency.

In this method the boilers effect (useful effect) is calculated according to the following formulation (see also figure 18):

$$\dot{Q}_b = \dot{m}_s * (h_{steam_out} - h_{Water_in}) \quad (4.1)$$

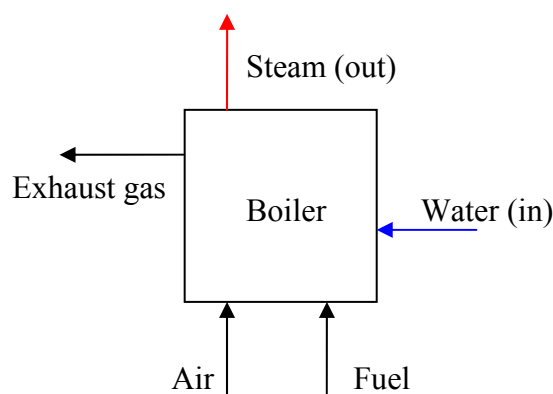


Figure 18: Demonstration of the inputs and outputs of the boiler

Both, pressure and temperature as well as the mass flow of the steam and water were measured. The enthalpies of each specific temperature and pressure could be read from the steam table. With respect to the amount of data, a program has been developed in

MATLAB reading the temperature and pressure from an Excel file and providing the corresponding enthalpies.

When the boiler effect is calculated, the fuel-effect can be calculated with respect to the boiler efficiency (see equation 4.2)

$$P_f = \frac{\dot{Q}_b}{\eta_b} \quad (4.2)$$

The calculation of the boiler efficiency is based on the charts and values from “Svenska Maskinverken” provided by Claes Hellberg⁸. The variation of the boiler efficiency was very small. Therefore an average value has been taken into account.

At the last step the flow rate of the fuels are calculated according to the fuel effect and the heating value of the respective fuel.

$$\dot{m}_f = \frac{P_f}{H_u} \quad (4.3)$$

In this case study two types of fuels are feed into the boiler viz. coal and biomass. Since the fuel flow rate cannot be measured accurately, the total deliveries of respective fuels to the burner are measured monthly. Mass fractions have been calculated for the fuels and it was assumed as uniform fuels flow rates during the plant operation. Table 5 shows the total fuel consumption in the boiler and the average value of calorific value of the fuels in February 2005.

Fuel	Mass (ton)	Mass fraction	Heating value (MWh/ton)
Coal	5994	0,221024951	7,256
Biomass	21125,11023	0,778975049	4,768
Sum	27119,11023	1	-----

Table 5: Total fuel consumption and the calorific value of the fuels in February

Providing the fuels mass fraction it is possible to calculate the fuel rate of each fuel types.

Some assumptions have been made in these processes, which are listed below:

- Since the boiler efficiency does not vary so much, an average value has been used.

⁸ Clase Hellberg has performed his Master thesis at Västhamnsverket

- Since the data for fuels flow rate has not been provided from the plant, and with respect to the variation of the power which was not too much, it was assumed a uniform fuels flow rate whole the production.

Table 6 presents the results of the calculation.

Index	\dot{m}_s [kg/s]	h_s [kJ/kg]	h_w [kJ/kg]	\dot{Q}_b [kW]	η_b [%]	P_f [kW]	Total \dot{m}_f [ton/h]	\dot{m}_C [ton/h]	\dot{m}_B [ton/h]
1	69,7	3439,7	929,9	175035,4	92,4	189515,7	35,6	7,9	27,8
2	66,5	3454,9	915,9	168903,3	92,4	182876,2	34,4	7,6	26,8
3	80,9	3464,8	926,1	205439,2	92,4	222434,7	41,8	9,2	32,6
4	49,0	3440,7	917,0	123678,0	92,4	133909,6	25,2	5,6	19,6
5	80,8	3463,5	925,2	205067,9	92,4	222032,7	41,8	9,2	32,5
6	56,3	3449,7	938,2	141357,6	92,4	153051,8	28,8	6,4	22,4
.
.
1000	83,5205	3452	1013,2	203689,8	92,4	220540,6	41,5	9,2	32,3

Table 6: Fuel rate has been calculated for each measurement point.

A comparison has been performed in order to evaluate the accuracy of the calculation. The result is shown in table 7. Mass of the fuels has been calculated (in table 7) with respect to 660 hours operation time of the boiler in February 2005.

Fuel	Mass measured (ton)	Mass calculated (ton)	Differences (%)
Coal	5994,00	5783,35	3,51
Biomass	21125,11	20382,72	3,51
Sum	27119,11	26166,07	3,51

Table 7: Comparison between the total measured masses of fuel in February with the calculated one

The difference between the calculated and the measured fuels flow rates are only 3,51 %, which can assure the accuracy of the approach. The difference has been generated due to the assumptions, which have been made for calculation of the mass of the fuels.

5 Exhaust gas

Index	Descriptions	Units	Measurements code
28	Mass flow exhaust gas	[kNm ³ /h]	341.K301
29	Temperature in the stack	°C	341.K565
30	O ₂	%	341.K865
31	NO _x	ppm	341.____.XP10G

Table 8: Exhaust gas parameters

As it was mentioned before, the data (in 5-minutes average) provided by Västhamnsverket for one month. In order to prepare the dataset for ANN training, the following processes (section 5.2 & 5.3) have been performed.

5.2 Data Treatment before Using in NeuroSolutions

ANN is a statistical program that can learn from the experiences (data) and the results of the ANN can never be better than the initial data. In order to get a good result from ANN the Initial data has to be very reliable.

A review of the dataset is necessary in order to remove outliers. By removing the outliers from the dataset, their negative effect on the predictive performance of the ANN model will be eliminated.

5.2.1 Data Filtering

In order to investigate the reliability of the measured data, power output is plotted against time. (See chart 1)

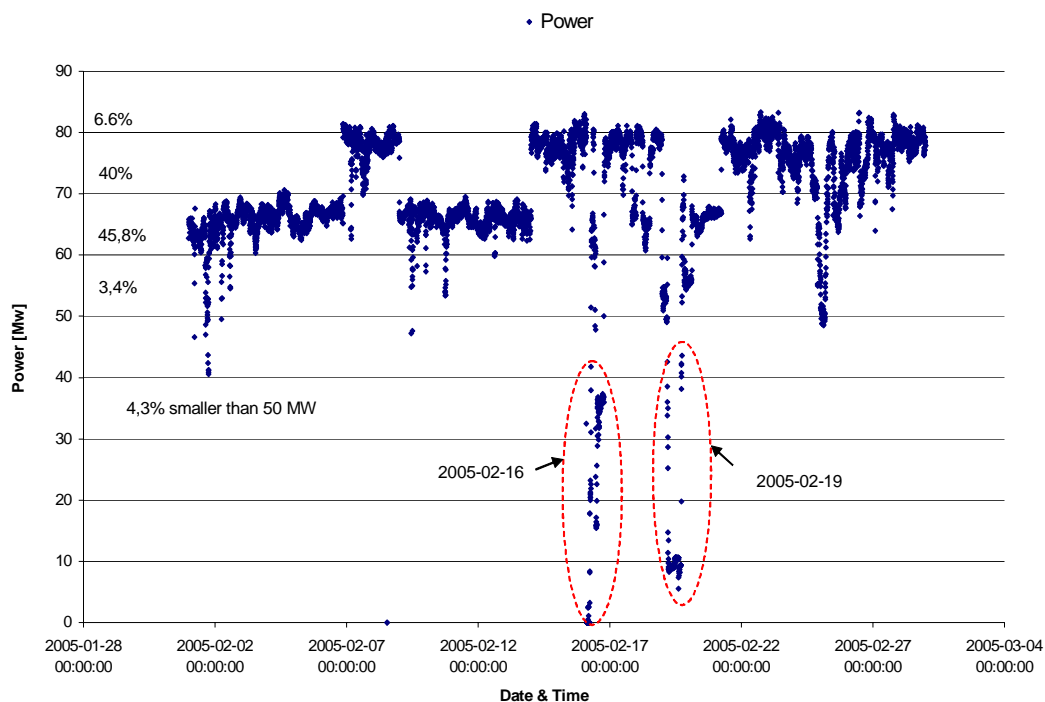


Chart 1: Power distribution as a function of time in February

As it is seen in the chart 1 the provided measured power output varies dramatically for two days (2005-02-16 and 2005-02-19). After discussing with the plant's

operator, it was clarified that in these days the steam turbine has had some problems and consequently these data are not reliable. The data for these days has been omitted from the list. Chart 2 shows the power after deleting those data.

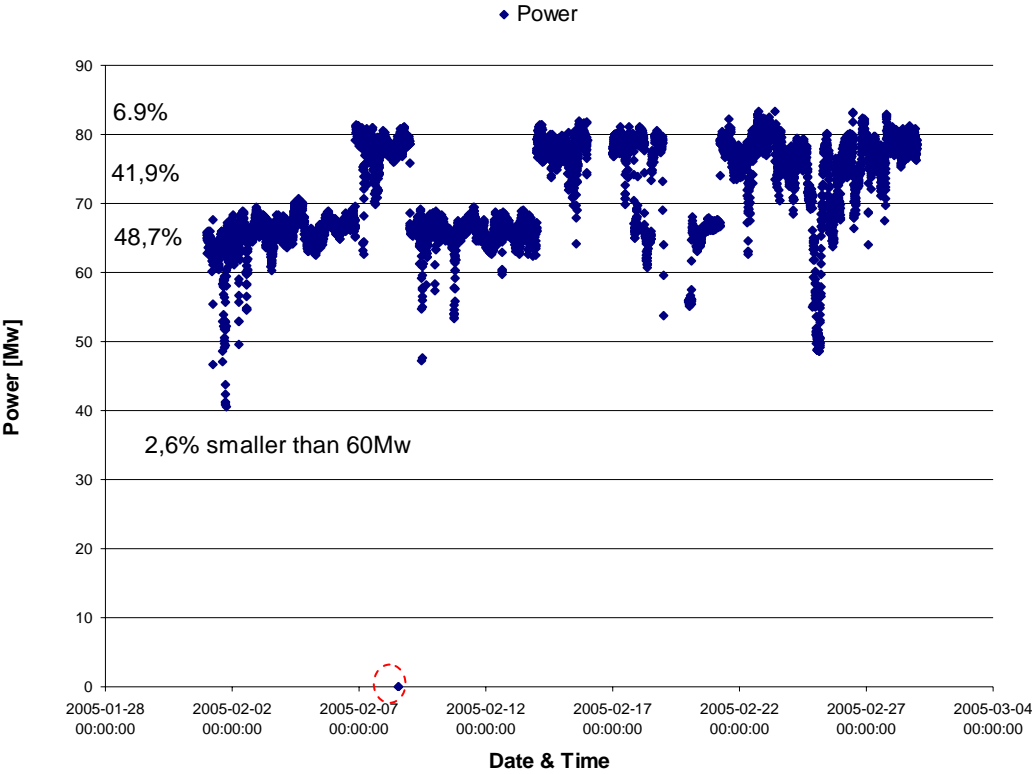


Chart 2: Power distribution after deleting the data from 2005-02-16 and 2005-02-19

As it is seen in chart 2 (specified in the circle) there is still some data, for where the power is zero in the corresponding points (2005-02-08 13:05 and 2005-02-08 13:10). These data has been omitted from the dataset as well.

After data filtering process, the number of dataset has been reduced from 8064 points to 7486 points.

5.2.2 Data compression

In the second step it was decided to decrease the volume of measured data, because of 2 reasons:

1. As it is experienced by the author: the Microsoft Excel and the NeuroSolutions cannot handle the large amount of the data. (More than 30MB)
2. The training process takes significantly less time with smaller number of data.

It is desired to decrease the dataset from 7486 to 1000 points. In order to decrease the amount of the dataset, a proper representative group of the dataset has to be found.

In order to find a proper representative group, the distribution of the power is examined and the dataset was classified into 4 categories (based on power distribution). The first column in table 9 shows the data categories, the second column presents a proportion of each category and in the third column the number of data has been calculated in the new dataset.

Data categories	The proportion (%)	The proportion in 1000 points
Larger than 80 MW	6,9	69
Between (70-80)MW	41,9	419
Between (60-70)MW	48,7	487
Between (40-60)MW	2,6	26
Sum	100	1000

Table 9: Classification of dataset into different categories

After classifying the data, the respective category has been gathered in a separate excel-sheet. The dataset of each category has been randomized and the proportion of each category was picked out (for example the dataset of category “Larger than 80 MW” has been randomized and 69 points, which is the proportion of this category, picked out).

Chart 3 shows the distribution of the prepared data.

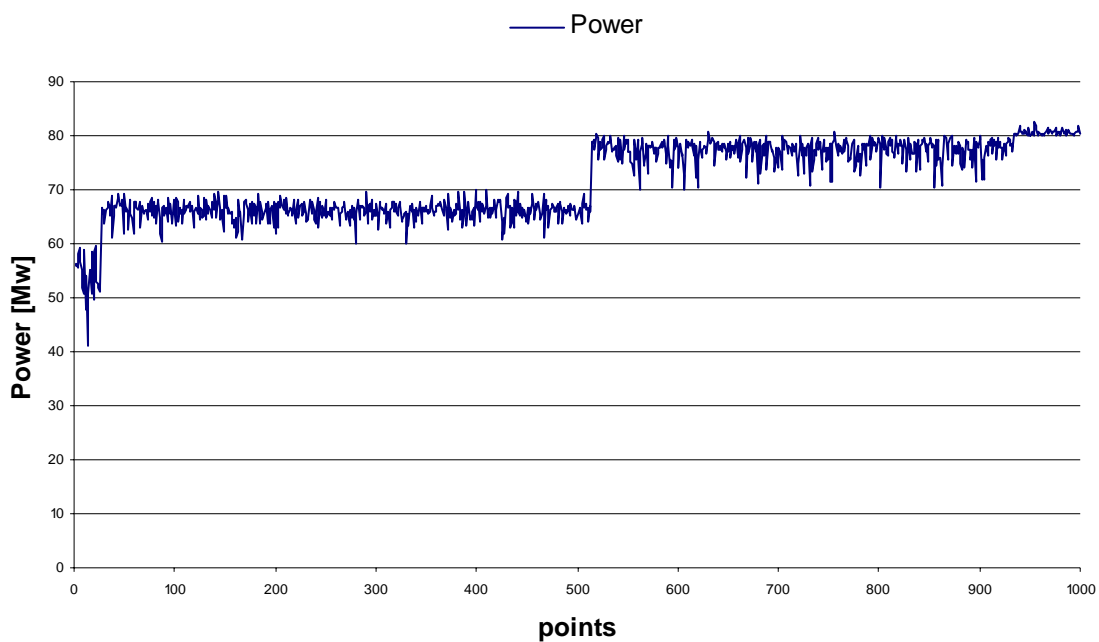


Chart 3: Power distribution after data compression

5.2.2.1 Testing the approach

In order to examine if this selection of data is good enough, an ANN model for predicting of power has been created. Chart 4 presents the results of this experience:

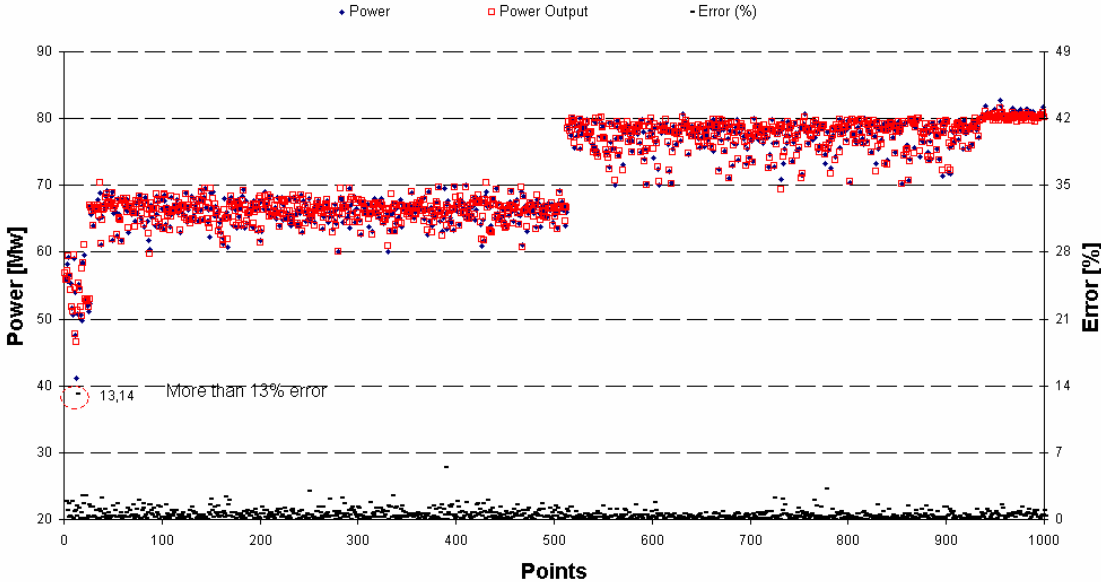


Chart 4: ANN results after using the compressed data

As it is seen in chart 4 the accuracy of the ANN is not good in one point (more than 13% error). As it was mentioned previously, ANN learns from the data. In order to increase the learning ability of the ANN, the dataset has to be as uniform and as *tight* as possible.

With these clarifications in mind and after investigating the data distribution (chart 3) and the ANN result (chart 4), the following conclusions have been made.

1. The proportion of the dataset was very low in category “smaller than 60 MW” (26 points).
2. The interval between this specific point and the other points in same category is too large.
3. When the data has been shared by NeuroSolutions into three parts; training, cross validation and test set, these points were placed in the test dataset, which explains the large error.

In order to overcome this problem following measure was taken:

1. Increase the data portion of category “Between (40-60) MW” by decreasing the data portion of other categories. Table 10 shows the new proportion:

Data categories	The proportion (%)	The proportion in 1000 points
Larger than 80 MW	6,9	69
Between (70-80)MW	40,0	400
Between (60-70)MW	46,0	460
Between (40-60)MW	7,1	71
Sum	100,0	1000

Table 10: New proportion set of the data

The distribution of the new dataset is also illustrated in chart 5:

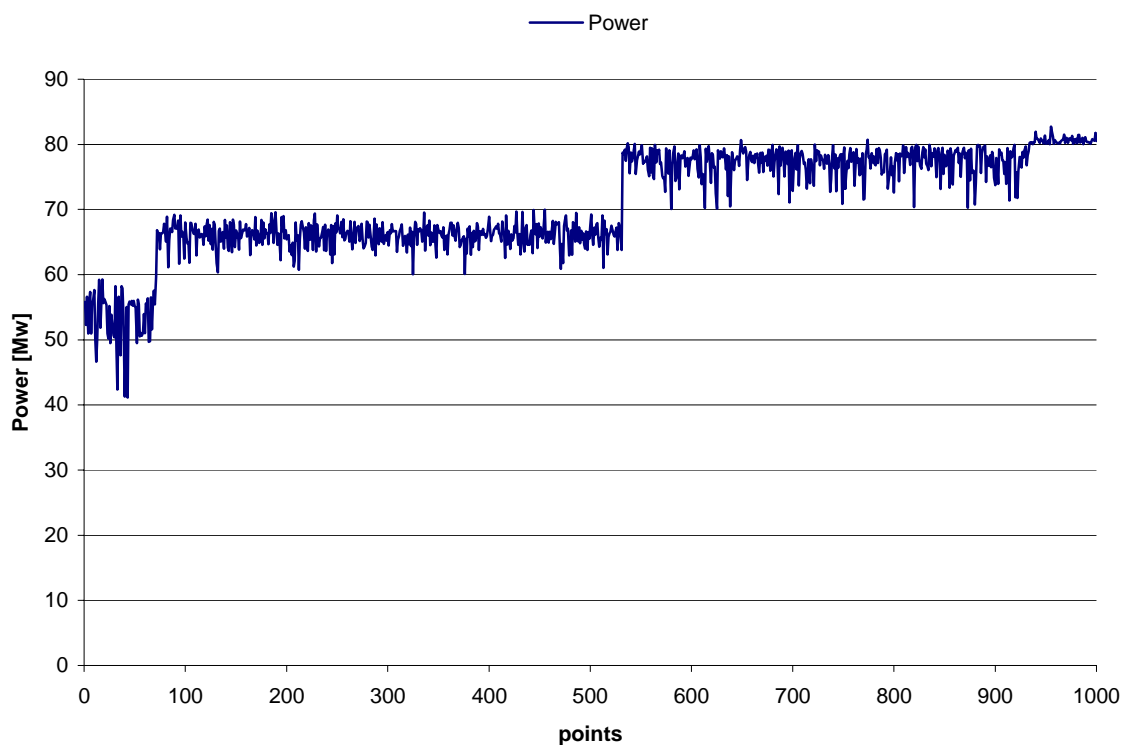


Chart 5: Power distribution after changing the data proportion

2. Ensure that the minimum value of this category will be in the training set when the ANN will be trained.

An Ann model was created again with this new dataset in order to find out if the problem is still remaining or not. Chart 6 presents the ANN accuracy with the second dataset.

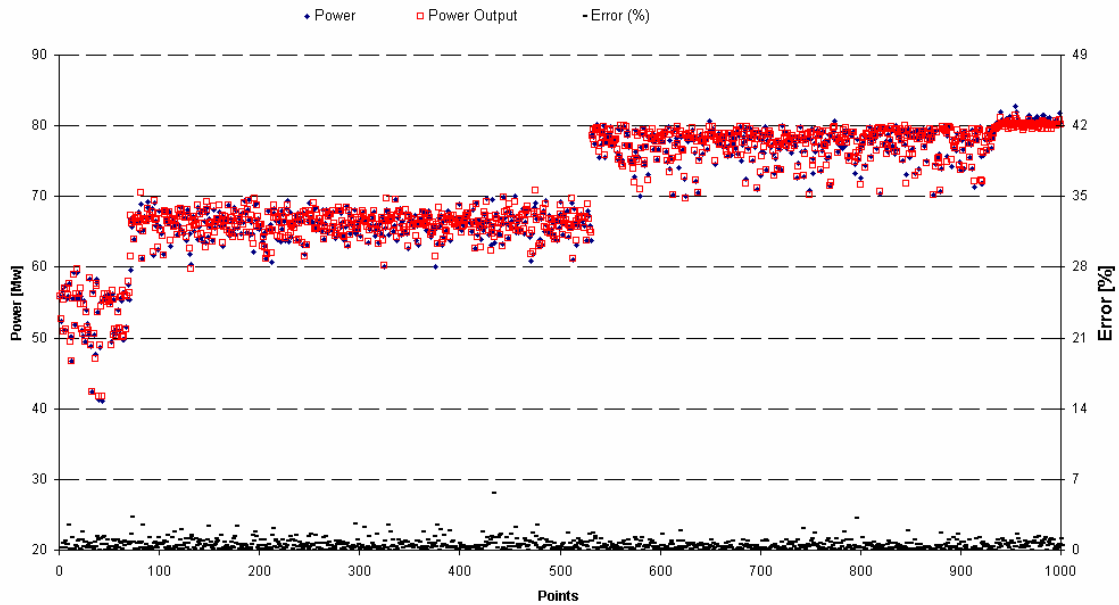


Chart 6: ANN results after using the new compressed dataset

The problem has been solved after implementing the suggested measures, and it is assured that ANN models are directly dependent on the *smoothness* and the *tightness* of data.

5.3 Data Treatment during Using in NeuroSolutions

As it was mentioned before, an ANN model cannot be better than the accuracy of the available data. In order to have a reliable ANN model, the processes presented in the pervious sections should be done before using data in NeuroSolutions.

After it will be assured that the data is reliable, the data can be used in NeuroSolutions for training an ANN model. Some other data processing have to be done during and after training, in order to have a more meaningful model.

In this section these processes, are presented in following points:

- The whole dataset should be randomized and divided into three parts viz. *training set*, *cross validation set* and *test set*. An option is available to decide the proportion of these three datasets, in this work 60 percent of the whole data is used for training, 15 percent for cross validation and 25 percent for testing the network. The training set is used to generate errors and thereby to update the weights, while the cross validation set is worked as a supervisor to training set, as stop criteria (see stop criteria section).

The test set is an unseen dataset, which will be used in order to find out the accuracy of the ANN. This method is called cross validation method (see figure 19).

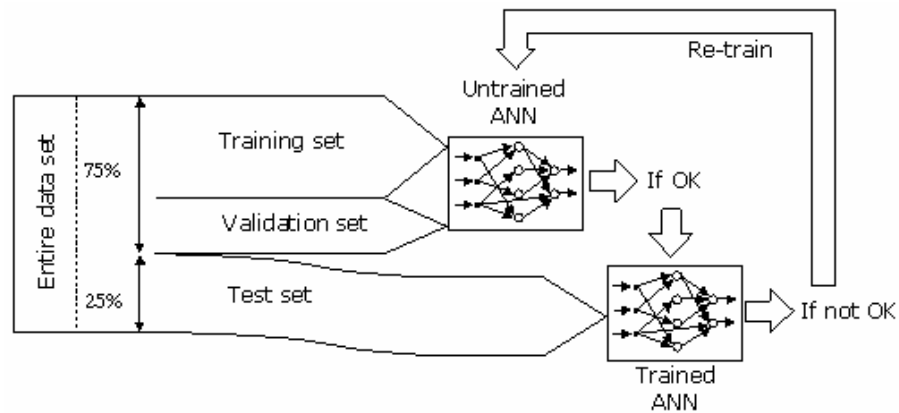


Figure 19: The cross validation process [2]

- In order to avoid that a signal with a value greater than the others becomes dominant the dataset has to be normalized. Regarding the choice of transfer function and its boundaries, the normalization has to be done within the boundaries of the transfer function. In order to have meaningful outputs, they have to be denormalized within the same boundaries (see figure 20).

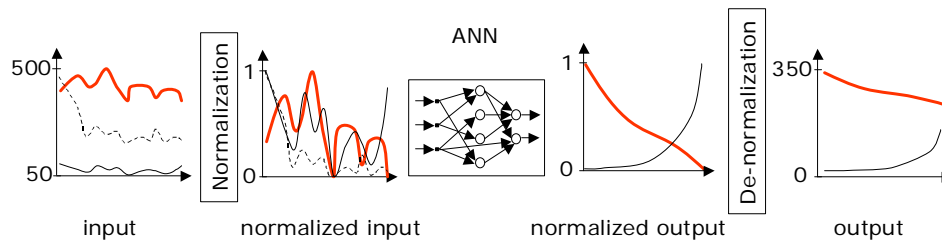


Figure 20: Normalization and Denormalization of the dataset [2]

6 Case studies

The overall aim of this study is to develop an ANN simulator for the whole steam process at Västhamnsverket. In order to develop a better ANN model for the entire steam process, this process is divided into two sub-modules, called case 1 and case 2 (refer to Figure 21). Consequently two cases have been studied separately and two different ANN models have been developed. These are then linked to each other by the parameter steam flow rate from the boiler sub-module (case 1) to the steam turbine sub-module (case 2). The input and output parameters of each of these cases have been decided based on appropriate criteria as discussed later.

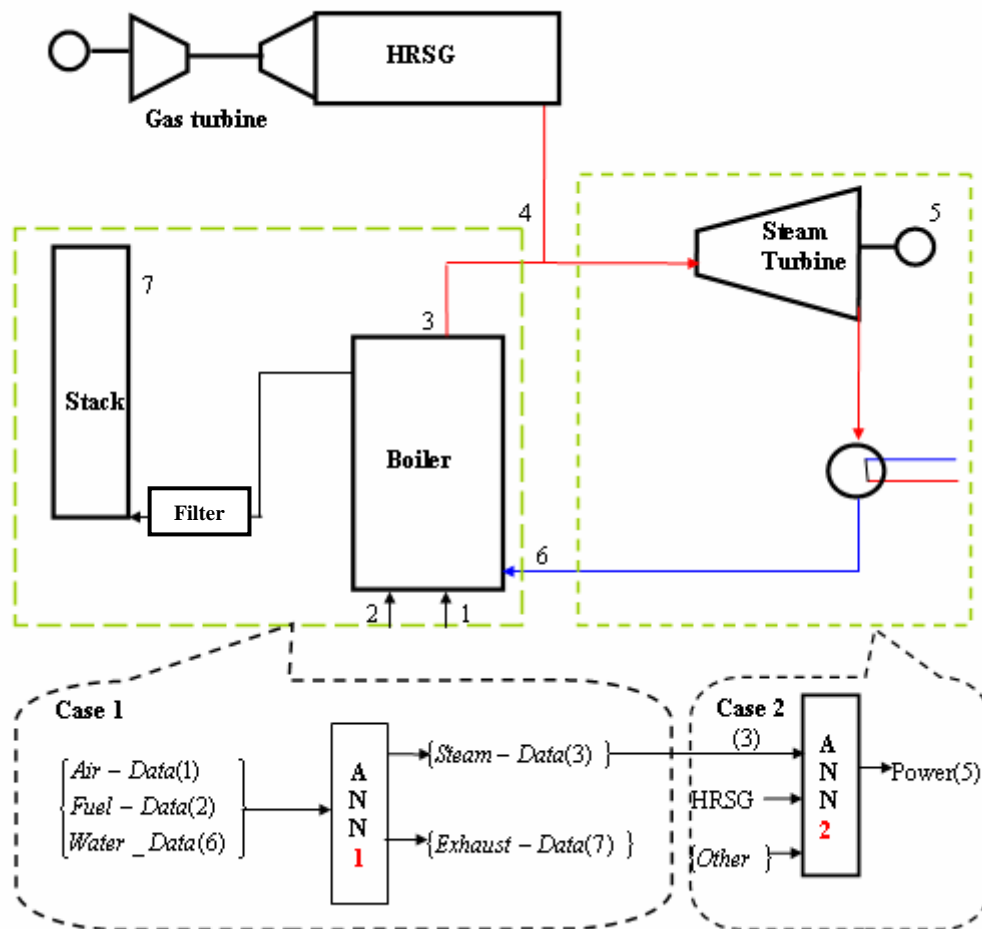


Figure 21: Case Studies

This ANN modeling has several advantages and applications area, which are studied in this thesis and they are listed below:

- Sensitivity analysis of the inputs: The best inputs are well correlated with the intended outputs. With this clarification in mind, and by adding or omitting each input parameters it can be seen the impact of the parameters on the accuracy of the ANN, thereby the best inputs can be found and unnecessary inputs can be removed in the model.
- Making a friendly user interface in excel environment to see how the output power can be affected by changing each input parameters⁹ (see chapter 7).
- Degrading of the plant performance can be observed: The conventional maintenance approaches seems to be costly when compared to predictive approaches. An ANN model can be created when the plant is healthy. After a period of time the model can detect the degradation during the specific time by feeding the model with the new data (see section 6.2.6).
- This model has the capability to work as a supervisor by working online: when the plant is running, the measured data can be feed into ANN model in the same time and by checking the differences between the measured data and the predicted one the plant can be supervised. Figure 22 presents a supervising ANN model.

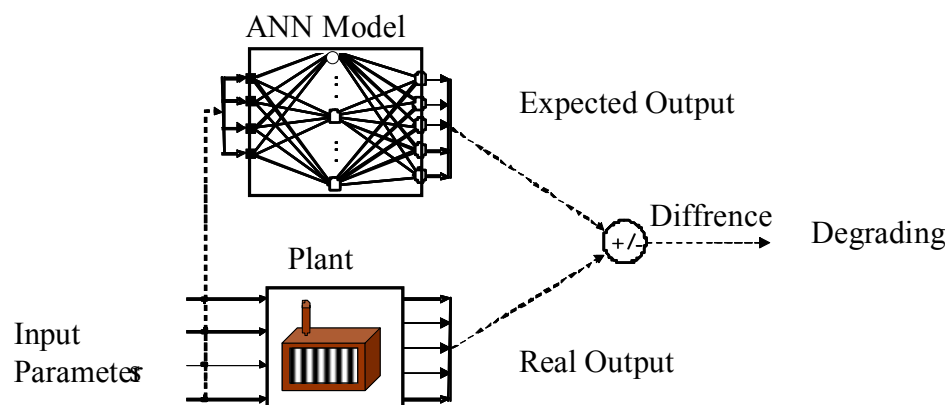


Figure 22: Principal for online supervising and degrading of the ANN model [8]

⁹ Especially interesting to see how the district heat and HRSG parameters can affect the output power

6.1 Case 1 (ANN Modeling of the Boiler)

In this section an ANN model of the boiler is developed. Figure 23 shows the whole plant, and the highlighted part in the figure is the studied part in this section.

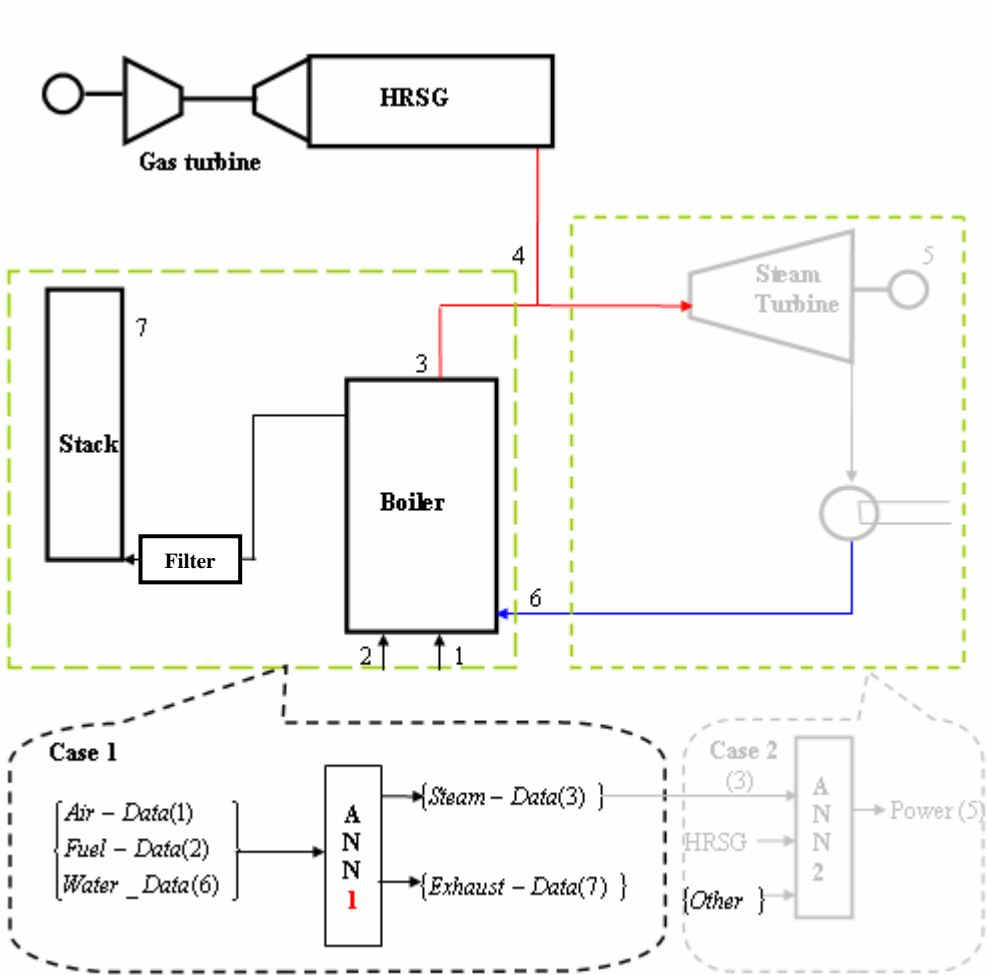


Figure 23: Case study 1

6.1.1 Objectives

The main objectives of ANN modelling of this part are explained in following points:

1. To perform a sensitivity analysis
2. To predict the emissions and the exhaust data in the stack
3. To provide the input parameters for Case study 2 (see figure 23)

6.1.2 Background

There is still no published literature on ANN application for prediction of the performance of a biomass and coal-cofired boiler. At the same time, a research in this area is being carried out at the department of Energy Sciences. During this research work a physical model of such a plant has been developed and it was quite interesting to see the implementation of ANN on such a plant as well.

6.1.3 Input and Output Parameters

Regarding the objective of the ANN models the following criteria for choosing the input and output parameter has been used:

6.1.3.1 Input parameters criteria:

- Parameters that can be controlled by the operator are suitable as input parameters e.g. the flow rate of the fuels in this case. The boiler uses two kinds of fuels simultaneously, viz. Biomass and Coal.
 1. Biomass flow rate
 2. Coal flow rate
- Parameters that may not be controlled directly by the operator but are input parameters to the system like the ambient conditions.
 3. Air flow rate
 4. Air temperature
- Parameters, which are highly correlated with the output parameters like the data incoming water to the boiler inlet and the maximum temperature in the boiler.
 5. Maximum temperature in the boiler
 6. Water flow rate
 7. Water temperature
 8. Water pressure

Totally eight input parameters has been specified. A sensitivity analysis is performed later in the thesis, in order to omit the unnecessary inputs.

6.1.3.2 Output parameters criteria:

- The steam data, which can be the input parameters for the next ANN model (case 2), like the steam data leaving the boiler.
 1. Steam flow rate
 2. Steam temperature
 3. Steam pressure
- Emissions: it was desired to investigate the predictability of all emissions but suitable data for some of the emissions were not available: (It has to be mentioned that all of the emissions are measured in the stack).
 - CO₂ is not measured but by using of other parameters, the amount of the CO₂ can be calculated [11].
 - SO_x: after controlling the measured data and seeing the plant schematic figure it is clear that between the boiler and the stack are some filters. The filters take care of the exceeding amount of SO_x and thereby the measured data shows a constant value of SO_x, which make this data not suitable for ANN study.
 - CO: The measurements data of CO were zero because of the exceeds oxygen in combustion.

With these clarifications, only two emissions were studied:

4. O₂
 5. NO_x
- The exhaust data:
 6. Flow rate of the exhaust gas
 7. Temperature of the exhaust gas (in the stack)

Figure 24 presents the input and output parameters, which have been chosen for training the ANN model. In figure 24 (8 H 7), 8 represents the number of inputs, H number of hidden neurons and 7 represents the number of outputs.

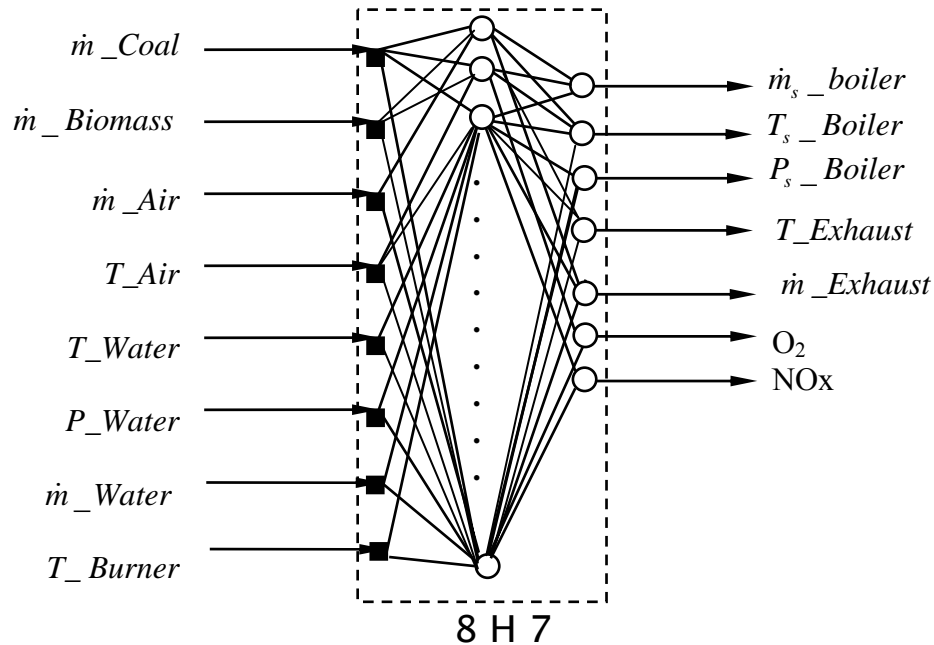


Figure 24: Input and output parameters of the ANN model of the Boiler

6.1.4 Sensitivity Analysis

In order to see the effect of each input on each output parameter, and to remove the unnecessary input parameters, sensitivity analysis was performed. Different input parameters has been omitted in order to see how much those specific parameters can affect the accuracy of the ANN.

In order to compare ANN models fairly the following criteria were performed

- The same randomized dataset is used in each ANN model: By using the same randomized dataset it will be assured that the same data is used in training, cross validation and testing dataset.
- Same portion of data for training, testing and cross validation is used for each ANN. (60 % training, 15 % cross-validation and 25 % testing)
- The same ANN structure is chosen for each ANN training:
 - ✓ Number of runs = 3
 - ✓ Number of epochs = 10000

- ✓ Variation of hidden neurons from 5 to 30
- ✓ Normalization range [-0,8 0,8]
- ✓ Denormalization range [-0,8 0,8]
- ✓ Transfer function = tanh

6.1.4.1 Reference case

As a reference case ANNs have been trained with all the input and output parameters. The best result of the ANNs has been selected for presentation. Table 11 presents the results of this ANN.

All	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	1,110	0,757	1,960	3,859	0,333	0,277	0,095
Max error %	4,992	3,385	13,886	27,687	3,657	2,658	0,487

Table 11: Results of ANN with all parameters

The mean error shows the average error of the predicted output from the real output. As it is seen in table 11 the mean error is in acceptable range for all the outputs, which means that the ANN has a capability to predict these parameters, based on defined input parameters with very good accuracy.

6.1.4.2 The ANN without the Fuels flow rate

In order to find out the effect of the fuels flow rate (biomass and coal flow rate) on the output parameters, they have been eliminated from the input parameters. Table 12 presents the results.

Without Fuel	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	1,082	0,803	3,546	4,340	1,090	0,368	0,157
Max error %	5,349	6,181	18,123	37,493	7,805	2,521	0,828

Table 12: results of the ANN without the fuels flow rate

In order to find out the amount of change in the accuracy of the reference ANN, a comparison has been done between this ANN and the reference one. Table 13 presents the results of this comparison.

	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	2,56	-6,01	-80,89	-12,47	-227,86	-32,94	-64,33
Max error %	-7,16	-82,58	-30,51	-35,42	-113,40	5,17	-69,77

Table 13: Comparison between the reference ANN and the ANN without fuels flow rate

In table 13, if a value has a negative sign it means that the results have got worse but if some value has a positive sign it means that the results are improved. As table 13 shows, the accuracy of the ANN with fuels flow rate is definitely better than without that. Table 13 also shows that the effect of the fuels flow rate is different on each output parameter.

6.1.4.3 The ANN without Burner Temperature

Because of the high correlation between the burner temperature (maximum temperature in the boiler) and the exhaust products and the emission this parameter has been used. In order to see the effect of the burner temperature on the ANN accuracy, this parameter has been omitted from the reference ANN. An ANN has been trained without burner temperature and the results are shown in table 14.

Without burner	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	1,056	0,841	2,189	4,445	0,355	0,282	0,108
Max error %	6,448	4,304	14,385	36,324	3,767	2,647	0,488

Table 14: Results of the ANN without the burner temperature

In order to find out the amount of changes in the accuracy of the reference ANN, a comparison has been performed between this ANN with the reference one. Table 15 presents the results of this comparison.

	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	4,88	-11,05	-11,65	-15,20	-6,80	-1,94	-13,84
Max error %	-29,18	-27,14	-3,59	-31,19	-3,00	0,42	-0,02

Table 15: Comparison between the reference ANN and the ANN without burner temperature

Table 15 presents the comparison and it can apparently be seen that the accuracy of the reference ANN has got worse by omitting the burner temperature.

6.1.4.4 The ANN without Air Temperature

Temperature of air has been omitted from the input parameters and an ANN has been trained without this parameters. Table 16 shows the obtained results.

Without air temperature	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	1,131	0,715	2,732	4,120	0,401	0,272	0,099
Max error %	6,302	4,724	16,377	34,806	4,428	2,850	0,554

Table 16: Results of the ANN without the air temperature

A comparison has been performed in order to find out the importance of this parameter for prediction of the outputs. Table 17 presents the results of this comparison.

	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	-1,92	5,57	-39,35	-6,78	-20,57	1,66	-3,99
Max error %	-26,26	-39,53	-17,94	-25,71	-21,06	-7,23	-13,59

Table 17: Comparison between the reference ANN and the ANN without air temperature

As table 17 shows the accuracy of the reference ANN has got worse by omitting the air temperature.

6.1.4.5 The ANN without Water Parameters

Three water parameters were used to train the reference ANN viz. flow rate, temperature and the pressure. In order to see the effect of these parameters on each output parameter, they have been omitted from the input parameters and an ANN model has been trained without them. Table 18 shows the results of this experience.

Without water	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	1,478	1,344	3,476	7,652	1,067	0,392	0,520
Max error %	13,273	5,783	19,480	38,502	3,849	3,416	1,744

Table 18: Results of the ANN without the water parameters

Table 19 shows a comparison between the results of this ANN and the reference ANN.

	Flow exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	-33,20	-77,45	-77,33	-98,30	-220,98	-41,39	-446,29
Max error %	-165,91	-70,83	-40,28	-39,06	-5,23	-28,53	-257,75

Table 19: Comparison between the reference ANN and the ANN without water parameters

As table 19 shows the results are much worse without the water parameters.

6.1.5 Final results of the ANN Model

Concerning the sensitivity analysis, the reference ANN (with all input parameters) gave the best accuracy. The reference ANN was accepted as a final model and thereby the results will be discussed closer in this section.

The obtained results in this study are summarized in table 20. The first row in table 20 presents the output parameters, which have been predicted by the ANN. The second row in table 20 shows the percentage of the average error of each predicted output. The third and the last line show the maximum error of the each predicted output parameter.

	Flow rate Exhaust	T_stack	O2	NOx	Steam flow	T_Steam	P_Steam
Mean error %	1,110	0,757	1,960	3,859	0,333	0,277	0,095
Max error %	4,992	3,385	13,886	27,687	3,657	2,658	0,487

Table 20: Results of the ANN model of the boiler

Table 20 shows that the mean errors for prediction of all the output parameters are in acceptable ranges. As it is seen in the table, the prediction of the steam condition is much better than the prediction of exhaust and emissions. Due to the close relation of input parameters (especially water parameters) the prediction of the steam conditions are much better. In the following subsections the predictability of each output parameter are discussed in details.

6.1.5.1 Flow rate of the Exhaust-gas

Chart 7 shows the capability of the ANN to predict the flow rate of the exhaust gas. The right y-axis presents the amount of the exhaust flow rate and the left y-axis presents the error in prediction in percentage. X-axis presents the number of measurement points.

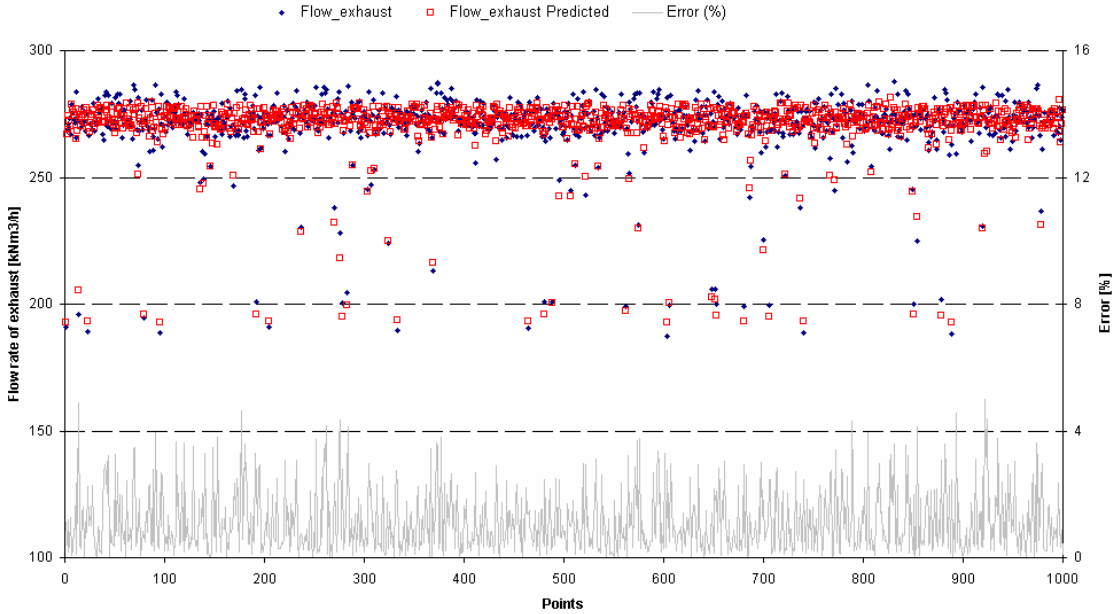


Chart 7: Prediction of the flow rate of exhaust gas

The mean error of the ANN for predicting the flow rate of the exhaust gas was 1,1 % and the max error was 4,9 %. In order to see the distribution of the errors, table 21 has been created.

	Larger than 4 %	Between 2 & 4%	Smaller than 2%	Sum
Number of errors	10	170	820	1000
Percentage	1	17	82	100

Table 21: Distribution of the errors of predicted exhaust flow rate

As table 21 shows 82 % of the errors are smaller than 2 % and that can confirm the stability of the result.

6.1.5.2 Temperature of the Exhaust-Gas in the Stack

Chart 8 shows the capability of the ANN to predict the temperature of the exhaust gas in the stack. The right y-axis presents the temperature of the exhaust gas (for both the measured and predicted data) and the left y-axis presents the error of prediction in percentage form. X-axis presents the number of measurement points.

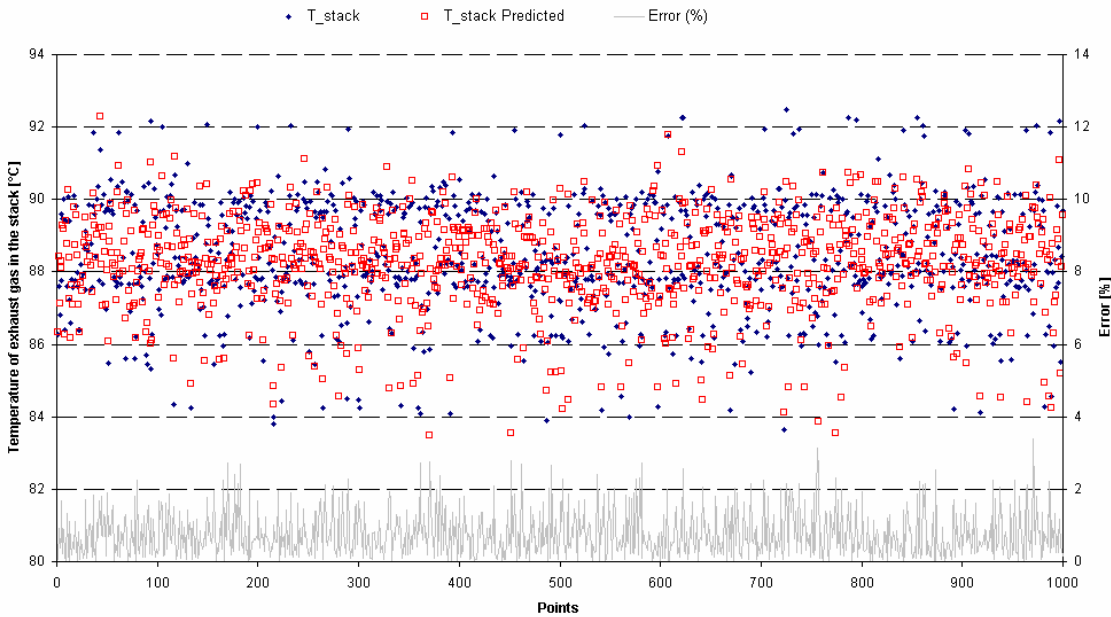


Chart 8: Prediction of the temperature of the exhaust gas

The mean error of the ANN for predicting the temperature of the exhaust gas was 0,75 % and the max error was 3,38 %. The difference between the mean error and the max error is not too much but in order to see the distribution of the errors, table 22 has been created.

	Larger than 3 %	Between 1 & 3%	Smaller than 1%	Sum
Number of errors	2	280	718	1000
Percentage	0,2	28	71,8	100

Table 22: Distribution of the errors of predicted temperature of the exhaust

6.1.5.3 O₂

Chart 9 shows the capability of the ANN to predict the O₂ in the stack. The right y-axis presents the O₂ (for both the measured and predicted data) and the left y-axis presents the error of prediction in percentage form. X-axis presents the number of measurement points.

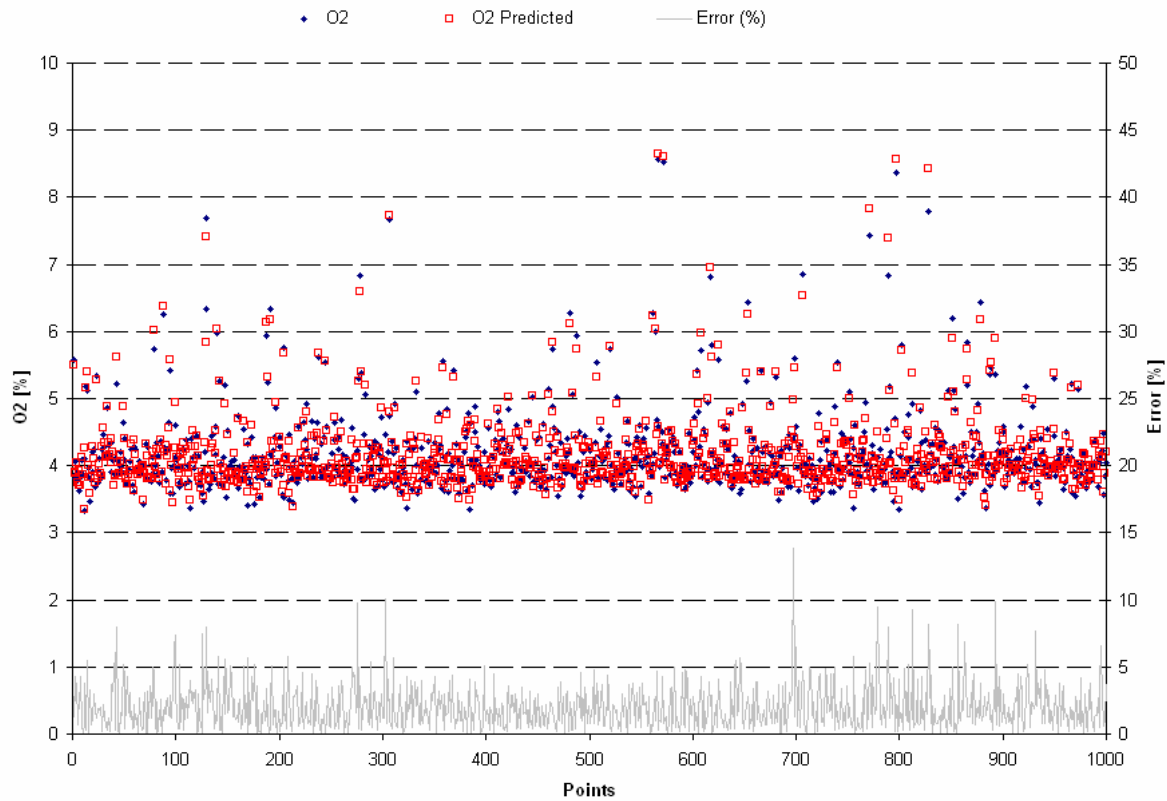


Chart 9: Prediction of the O₂

The mean error of the ANN for predicting the O₂ was 1,98 % and the max error was 13,88 %. The difference between the mean error and the max error is too much in this case. In order to see the distribution of the errors, table 23 has been created.

	Larger than 10 %	Between 5 & 10%	Smaller than 5%	Sum
Number of errors	2	39	959	1000
Percentage	0,2	3,9	95,9	100

Table 23: Distribution of the errors of predicted O₂

Table 23 shows that the absolute majority of the errors (96 %) are smaller than 5 %, this confirms the reliability of the ANN model.

6.1.5.4 NOx

Chart 10 shows the capability of the ANN to predict the NOx in the stack. The right y-axis presents the amount of NOx emissions (for both the measured and predicted data) and the left y-axis presents the error of prediction in percentage form. X-axis presents the number of measurement points.

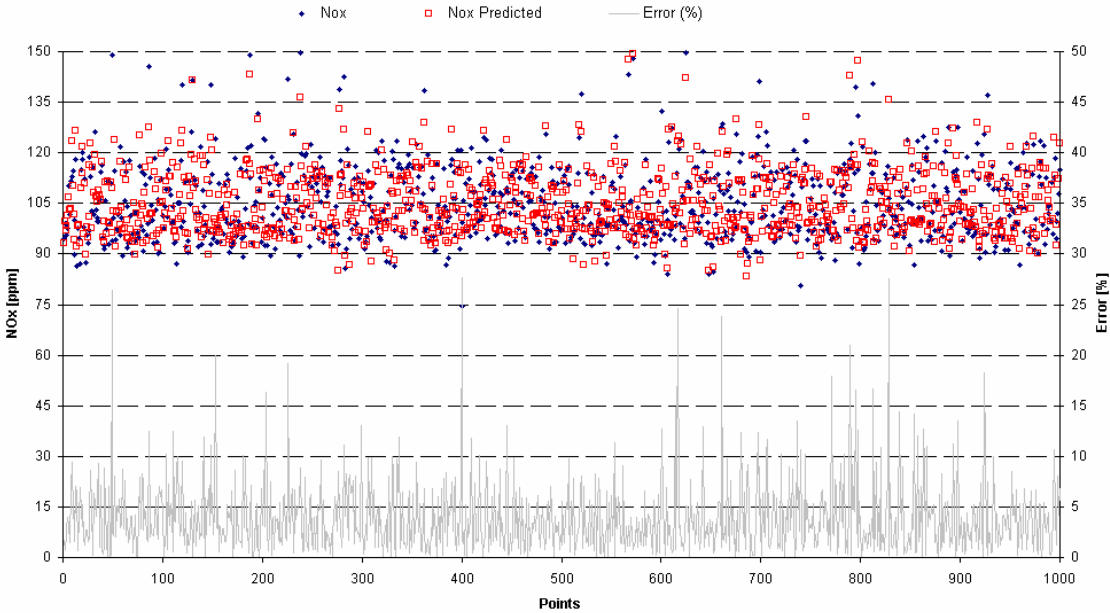


Chart 10: Prediction of the NOx

Due to the complexity of the emissions production, the accuracy of NOx prediction was not as good as the other output parameters. Production of emissions data is depended based on many parameters in combustor and measuring those parameters is very difficult. It is known that if the more related input parameters are available the better accuracy will be obtained, but in this study more related inputs than the used inputs were not available.

The mean error of the ANN for predicting the NOx was 3,85 % and the max error was 27,68 %. The difference between the mean error and the max error is too much in this case. In order to see the distribution of the errors, table 24 has been created.

	Larger than 10 %	Between 5 & 10%	Smaller than 5%	Sum
Number of errors	50	222	728	1000
Percentage	5	22,2	72,8	100

Table 24: Distribution of the errors of predicted NOx

Table 24 shows that the majority of the errors (72,8 %) are smaller than 5 %, which can confirm the reliability of the ANN model.

6.1.5.5 Flow Rate of the Steam after the Boiler

As it was mentioned before, the results of the prediction of the steam condition were much better than the prediction of the exhausts data and the emissions.

Chart 11 shows the capability of the ANN to predict the flow rate of the steam after boiler. The right y-axis presents the flow rate of the steam (for both the measured and predicted data) and the left y-axis presents the error of prediction in percentage form. X-axis presents the number of measurement points.

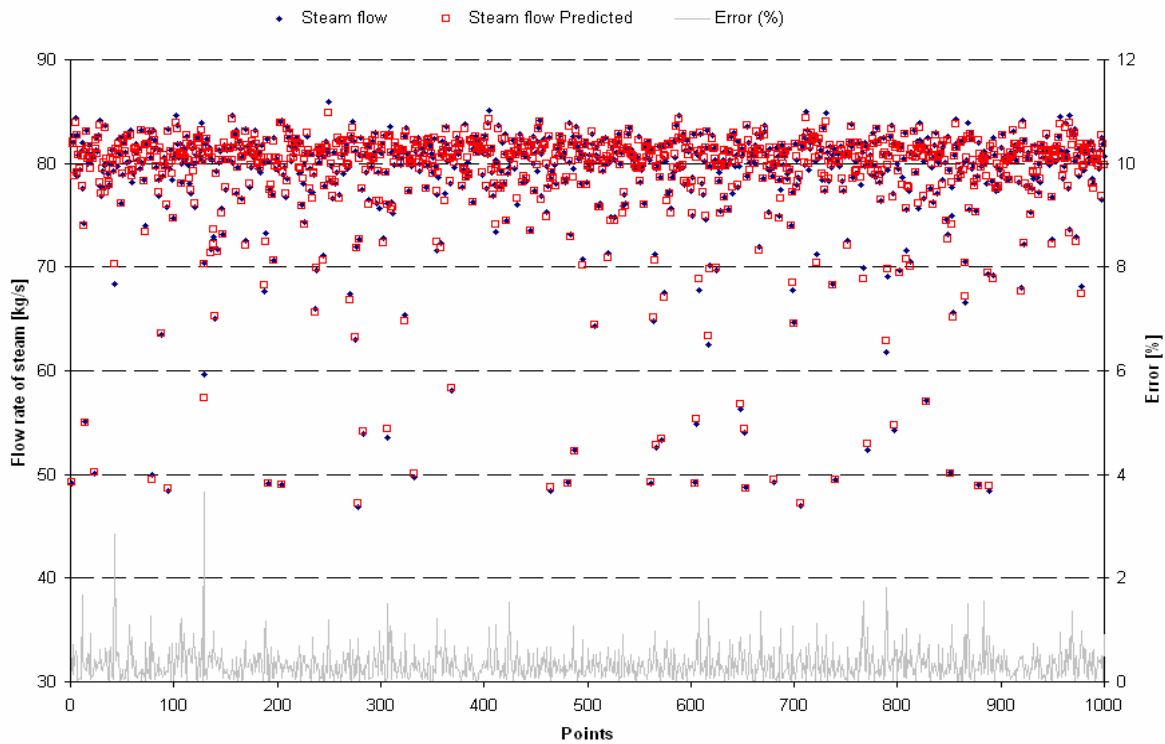


Chart 11: Prediction of the flow rate of the steam

The mean error of the ANN for predicting the flow rate of the steam was 0,33 % and the max error was 3,67 %. The difference between the mean error and the max error is not too much in this case. In order to see the distribution of the errors, table 25 has been created.

	Larger than 3 %	Between 1 & 3%	Smaller than 1%	Sum
Number of errors	1	31	968	1000
Percentage	0,1	3,1	96,8	100

Table 25: Distribution of the errors of predicted steam flow rate

6.1.5.6 Steam Temperature after the Boiler

Chart 12 shows the capability of the ANN to predict the temperature of the steam after boiler. The right y-axis presents the temperature of the steam (for both the measured and predicted data) and the left y-axis presents the error of prediction in percentage form. X-axis presents the number of measurement points.

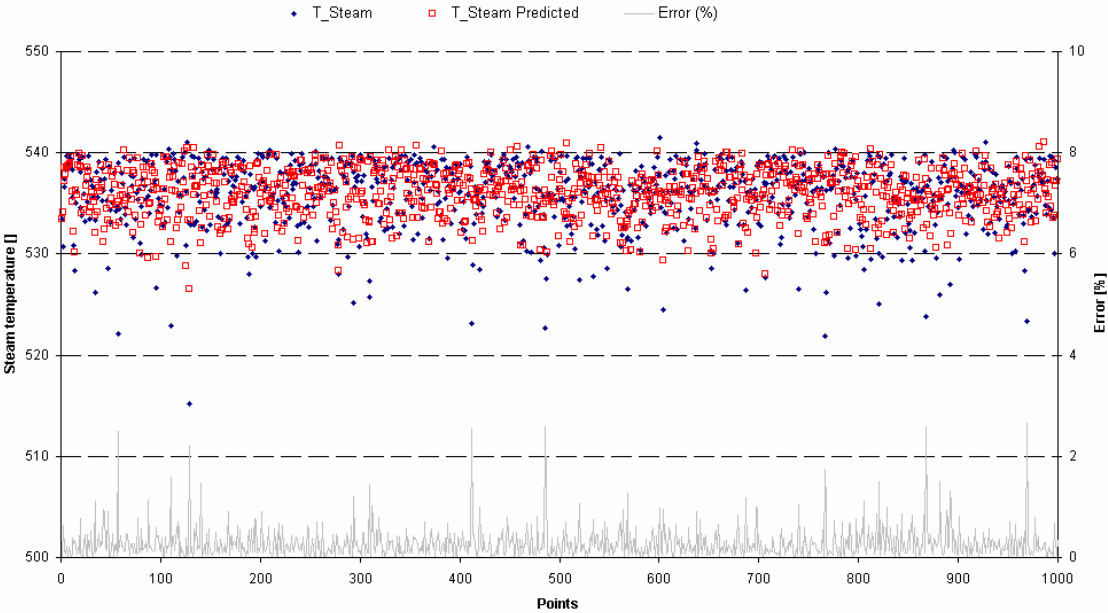


Chart 12: Prediction of the temperature of the steam

The mean error of the ANN for predicting the flow rate of the steam was 0,27 % and the max error was 2,66 %. The difference between the mean error and the max error is not too much in this case. In order to see the distribution of the errors, table 26 has been created.

	Between 1 & 3%	Smaller than 1%	Sum
Number of errors	26	974	1000
Percentage	2,6	97,4	100

Table 26: Distribution of the errors of predicted steam temperature

6.1.5.7 Steam Pressure

Chart 13 shows the capability of the ANN to predict the pressure of the steam after boiler. The right y-axis presents the pressure of the steam (for both the measured and predicted data) and the left y-axis presents the error of prediction in percentage form. X-axis presents the number of measurement points.

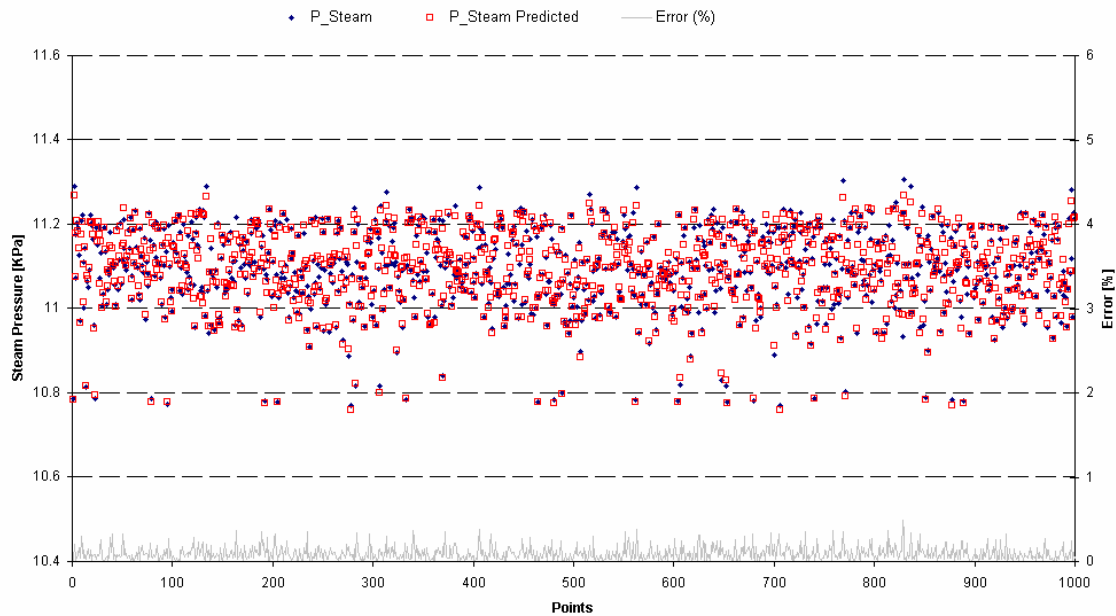


Chart 13: Prediction of the steam pressure

The mean error of the ANN for predicting the flow rate of the steam was 0,095 % and the max error was 0,487 %. The accuracy of the ANN to predict the steam pressure is excellent.

6.1.6 Concluding Remarks

Concerning the objective of this section, a sensitivity analysis has been performed in order to find out the impact of the input parameters and to remove unnecessary inputs. After performing a sensitivity analysis, it was concluded that all the selected input parameters in figure 24 were necessary for the ANN modelling. Furthermore, the other objectives of this section are fulfilled and the all selected output parameters (Exhaust data and input parameters for case 2, see even figure 24) were predicted with good accuracy.

6.2 Case 2 (ANN Modeling of the Steam Turbine)

In this section an ANN model of the steam turbine is created. Figure 25 shows the whole plant, and the highlighted part is the studied part in this section.

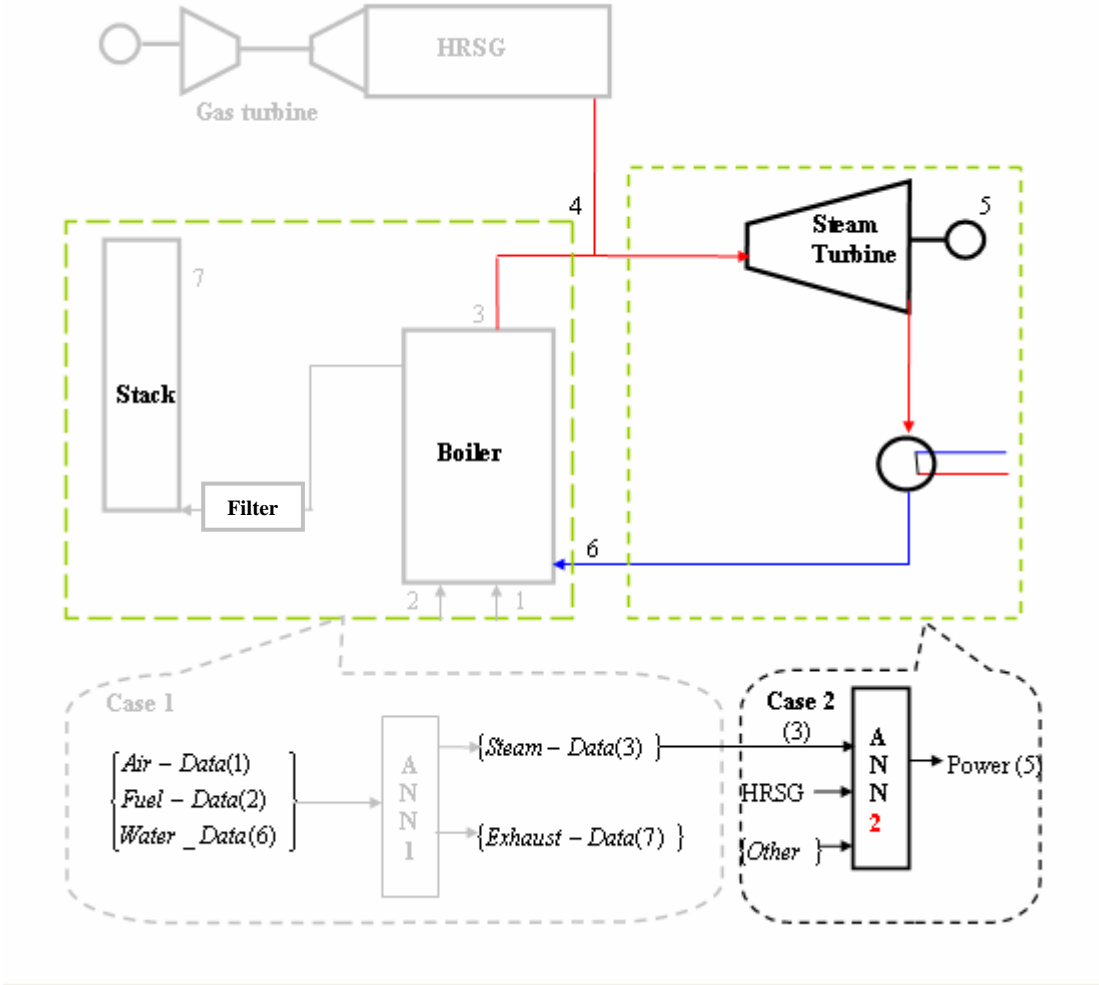


Figure 25: Case study 2

6.2.1 Objective

The main aim with this model is

1. Predicting the power output from the generator.
2. Finding out the impact of each input parameter on the output (sensitivity analysis).
3. Tracking the degradation.

6.2.2 Background

An ANN model of this part was created at Department of Energy Science in 2002. The aim of that ANN model was to show the capability of ANNs to capture the plants performance. That ANN model had just a few input parameters. In order to see the affect of the other parameters and to obtain a better accuracy this model has been created. This study is a supplementary of the previous study.

6.2.3 Input Parameters

In order to find out the suitable input parameters the following criteria have been intended: (See figure 25 & 26)

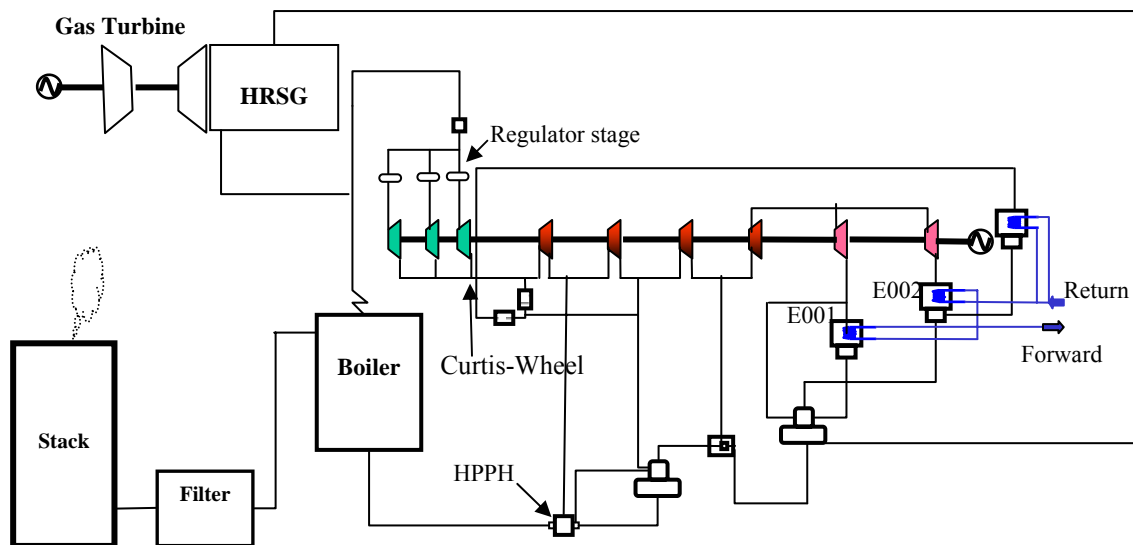


Figure 26: Schematic figure of the heat and power plant

- The parameters, which will be provided by created ANN in case 1
 - Steam flow rate after boiler
 - Steam temperature after boiler
 - Steam pressure after boiler
- The parameters which will be provided by HRSG: it is desired to see the affect of the HRSG in the system
 - Steam flow rate after HRSG
 - Steam temperature after HRSG

- Steam pressure after HRSG
- Steams condition after mixturing the steam flow rate from the boiler and HRSG: steams condition before Regulator-stage¹⁰, like pressure and temperature.
- The parameters, which can show the relation between the district heat and the electricity. By the way, the operators can control these parameters.
 - Flow rate
 - Temperature of the return water
 - Temperature of the forward water
 - Pressure of the condensers
- The parameters, which are highly correlated with the output parameter like the drain pressures, the pressure after Curtis-wheel and the water condition before and after HPPH (high pressure preheater). These parameters should be included in the ANN model in order to reach higher accuracy.

In order to see the relation between input and output parameters chart 14 has been plotted. The plots of some pressures are not included in the chart. The values of condensers pressures are too small in comparison with the other parameters and they are hardly seen.

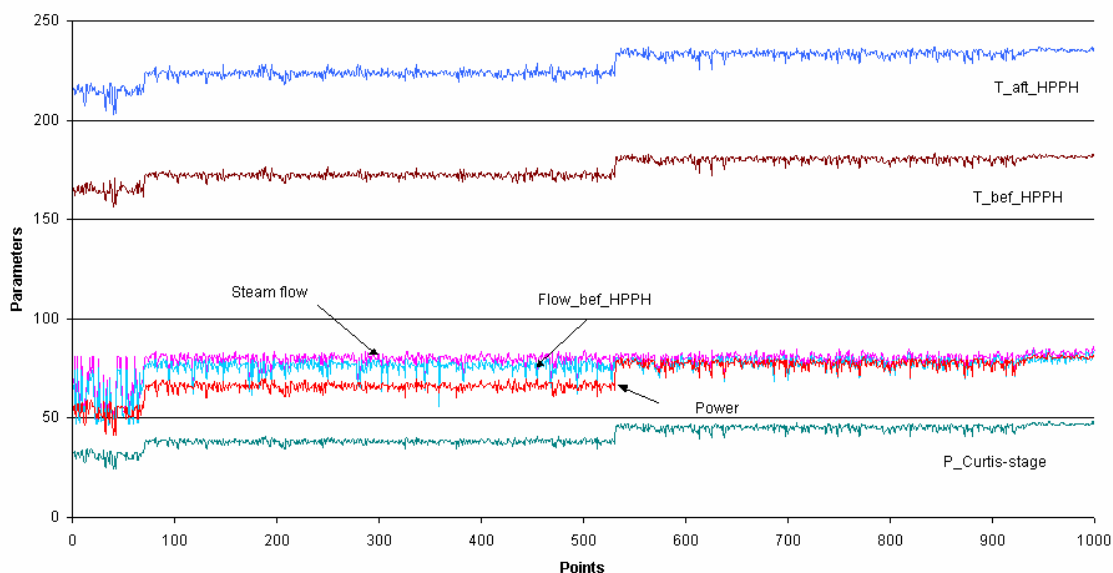


Chart 14: Correlation of some input parameters with output parameter

¹⁰ The position of the valves was interesting for this study, but the measurement points were not available

Totally 19 input have been considered to predict the output power. Figure 27 presents the input parameters of the ANN model.

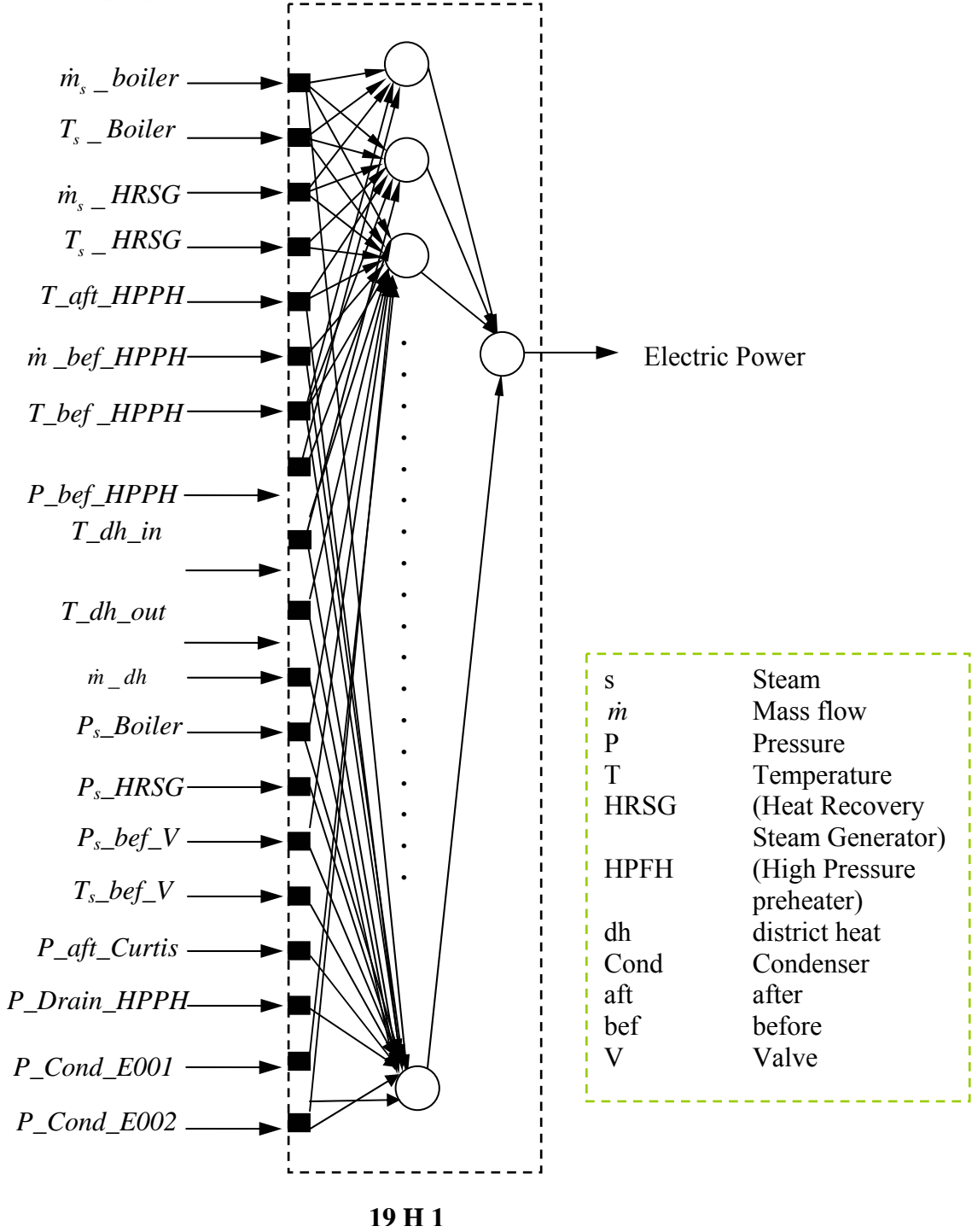


Figure 27: Demonstration of inputs and output parameters of the ANN model (19 H 1)¹¹

¹¹ (19 H 1) 19 represents the number of inputs, H the hidden neurons and 1 represents the number of outputs

6.2.4 Results and Structure of the ANN Model with 19 Inputs

The results obtained in this study are summarized in table 15. It can be seen from the results that it is possible to train an ANN model for approximating the output power with a very good accuracy.

Number of hidden neuron	Mean Error (%)	Max Error (%)	Min Error (%)
17	0,250	1,931	0,000

Chart 15: Results of the ANN model (19 H 1) for predicting of the electricity power

Chart 16 expresses the capability of ANN to predict the electricity power with very good accuracy. The x-axis represents the points (date & time), y-axis at the left side represents the difference between the real output and the predicted one and the right axis represents the electric power.

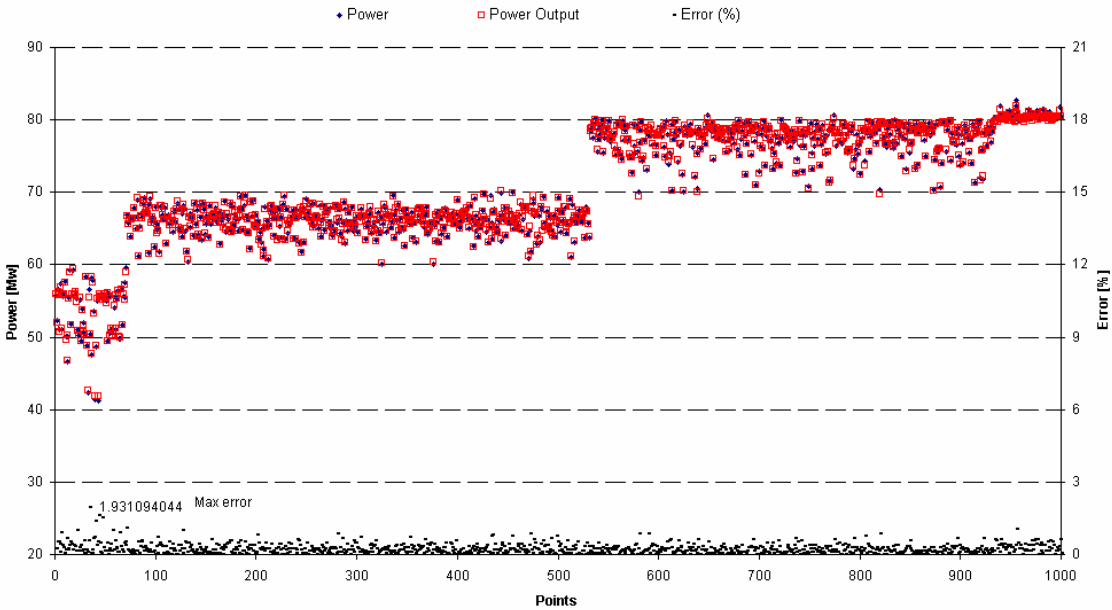


Chart 16: Prediction of power output with 19 inputs

6.2.5 Sensitivity Analysis

In order to see how much each input parameter can affect the output parameters, sensitivity analysis is performed. Different parameters has been omitted in order to see how much those specific parameters can change the accuracy of the ANN.

In order to compare ANN models fairly, the following criteria were performed

- The same randomized dataset is used in each ANN model: By using the same randomized dataset it will be assured that the same data is used in training, cross validation and testing dataset for all ANNs.
- Same proportion of data for training, testing and cross validation is used for each ANN. (60 % training, 15 % cross-validation and 25 % testing)
- The same ANN structure is chosen for all ANN trainings:
 - ✓ Number of runs = 3
 - ✓ Number of epochs = 8000
 - ✓ Variation of hidden neurons from 5 to 20
 - ✓ Normalization range [-0,8 0,8]
 - ✓ Denormalization range [-0,8 0,8]
 - ✓ Transfer function = tanh
- “Mean error” is the main criteria for comparing different ANNs with each other in this study. According to “Appendix C”, the max error can occur by accident.

6.2.5.1 ANN without the Parameters before Regulator-Stage

The temperature and pressure before the regulator-stage represents the condition of the steam after the steam flow rate from HRSG and the boiler are mixed. Table 27 presents the results, which are obtained after the training of this ANN model.

ANN	Mean error (%)	Max error (%)	Min error (%)
With Regulator parameters (19H1)	0,250	1,931	0,000
Without Regulator parameters (17H1)	0,251	2,087	0,000

Table 27: ANN results with and without Regulator temperature and pressure

It is seen in table 27 that the differences are very small (less than 1 %), and these parameters can be assumed as “redundant” parameters in this model. In fact these two parameters represent the same thing as the pressure and temperature after the HRSG and the boiler do.

It is decided to omit these parameters from the total input parameters.

6.2.5.2 ANN without Curtis-Wheel Pressure

The pressure after the Curtis-Wheel is omitted from the input parameters, and the obtained result is compared in table 28 with the ANN, which has this parameter as an input parameter.

ANN	Mean error (%)	Max error (%)	Min error (%)
With Curtis-Wheel Pressure (17H1)	0,251	2,087	0,000
Without Curtis-Wheel Pressure (16H1)	0,354	2,545	0,000

Table 28: ANN results with and without Curtis-Wheel pressure

It is seen in table 28 that, the average error is increased more than 40 % by omitting the Curtis-Wheel pressure. This result assures the close relation between this parameter and the output power. The interdependence between this parameter and the power is also shown in chart 14.

6.2.5.3 ANN without Condensers Pressures/District Heat Parameters

In fact the pressure of the condensers and the temperature of the district heating represent the same thing. Figure 28 shows the thermodynamic relationship between the condensers pressure and district heat temperature. In the condensers the steam is converted to the saturated water and the pressure can give the saturation temperature (the temperature and pressure is constant during the phase-changing). The pinch point is always between 3-5 °C [12] and thereby the temperature of the forward district heat is calculated by subtracting the pinch point from saturation temperature.

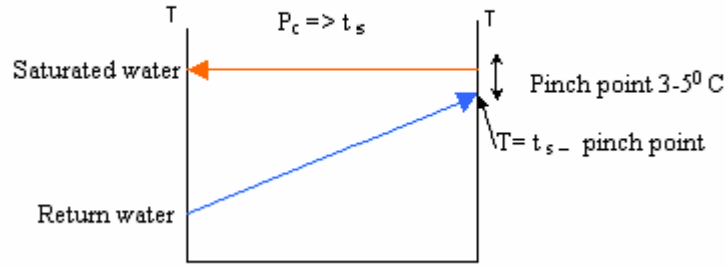


Figure 28: connection between condensers Pressure and district heat temperature

In order to find out the impact of each of these parameters on the accuracy of ANN models, different ANN has been trained and the results have been compared to each other (see table 29).

ANN	Mean error (%)	Max error (%)	Min error (%)
With Condensers & District heat parameters (17H1)	0,251	2,087	0,000
Without Condensers pressure (15H1)	0,375	2,639	0,000
Without District heat parameters (14H1)	0,241	2,359	0,000
Without Condensers & District heat parameters (12H1)	0,640	3,193	0,000

Table 29: ANN results with and without Condensers pressure

The first row in table 29 presents the reference ANN, with 17 input parameters. The second line shows the result of an ANN without the pressures of the two condensers actually with 15 input parameters. The mean error is increased by more than 40 % by omitting the condensers pressure, which means that these two pressures are closely related to the output.

In the second attempt, the condensers pressure is kept as input parameters but the district heat parameters (water flow rate, return and forward temperature) have been omitted. Line 3 in table 29 shows the result of this ANN and as it is seen the accuracy of the ANN is getting better with almost 4 %.

In the third attempt, both parameters from condensers and district heat were omitted. Line 4 in table 29 shows the result. The accuracy of ANN is much worse (more than 150 %) by omitting both condensers and district heat parameters.

After a comparison between these three ANN, it was decided to keep the condensers pressure as input parameters and omitting the district heat parameters.

6.2.5.4 ANN without the Drain Pressure

Table 30 shows the results of the ANN without the drain pressure compare to the ANN with drain pressure:

ANN	Mean error (%)	Max error (%)	Min error (%)
With Drain pressure (14H1)	0,241	2,359	0,000
Without Drain pressure (13H1)	0,252	2,023	0,000

Table 30: ANN results with and without drain pressure

The table 30 shows that the average error is in the same range for both of ANN models (only 4 % difference). It was expected to see a larger difference by omitting this parameter because the drain pressure is highly correlated to the power. In order to find out the reason a plot has been created. Chart 17 shows the variation of power and the drain-pressure.

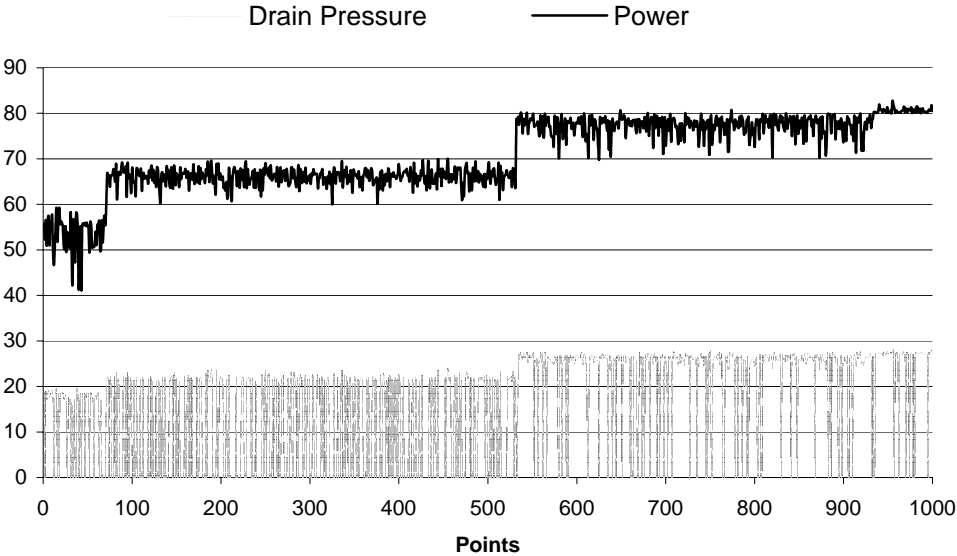


Chart 17: Correlation of the drain-pressure and power after data compression

When the drain-pressures data was studied closely, it became clear that maybe one third of the data is zero and the rest varies between 18 to 28 bar. The interval between the values is too much and it can be a good reason for ANN not to be able to predict very good. Chart 18 presents the variation of power and the drain-pressure before data compression. Chart 18 shows that the drain-pressure from the first of February until 2005-02-10 14:15:00 was zero.

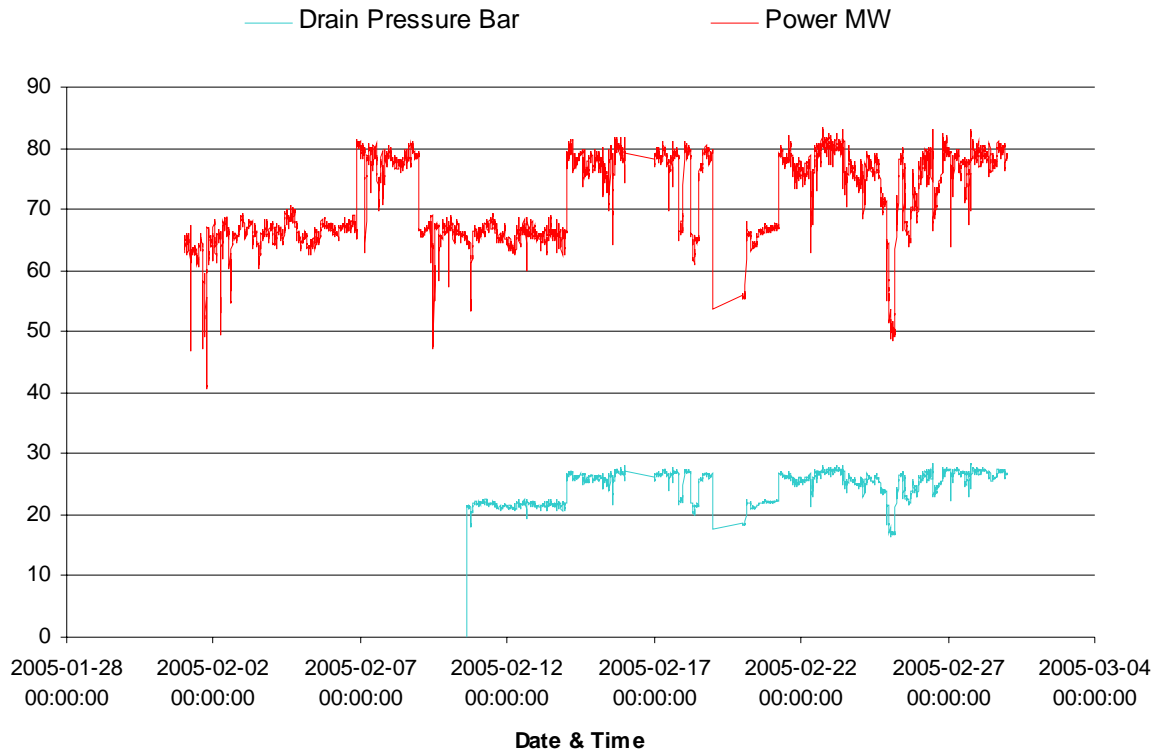


Chart 18: Correlation of the drain-pressure and power before data compression

6.2.5.5 ANN without the HPFH Parameters

Four parameters had been chosen from HPFH, viz., temperature before and after, pressure before and the mass flow of water before HPFH. In the first attempt all the parameters of HPFH have been omitted in order to see how important these parameters are for the accuracy of the ANN.

Table 31 presents the result of this ANN in compare with an ANN with HPFH parameters:

ANN	Mean error (%)	Max error (%)	Min error (%)
With HPFH Parameters (14H1)	0,241	2,359	0,000
Without HPFH Parameters (10H1)	0,263	3,202	0,000

Table 31: ANN results with and without HPFH parameters

Table 31 shows that the accuracy of the ANN decreases by 9.6 % if all HPFH parameters omitted as inputs.

In order to see how much each of HPFH parameters can affect the ANNs accuracy, four ANN has been trained. Table 32 presents the results of this study:

ANN	Mean error (%)	Max error (%)	Min error (%)
With all HPFH parameters	0,241	2,359	0,000
Without all HPFH parameters	0,263	3,202	0,000
Without T-after HPFH	0,276	2,811	0,000
Without T-before HPFH	0,274	2,211	0,000
Without P-before HPFH	0,251	2,822	0,001
Without flow rate	0,237	3,623	0,001

Table 32: Affect of each HPFH parameters on ANN accuracy

Table 32 shows that the temperatures (before and after HPFH) are much more closely correlated to the output than the pressure or flow rate of water. As it is seen in table 32 by omitting the flow rate of water, or the pressure before HPFH, the mean error is decreased.

Chart 19 has created in order to assure the obtained results. Chart 19 shows that the temperatures have better correlation with output than the flow rate and the pressure have.

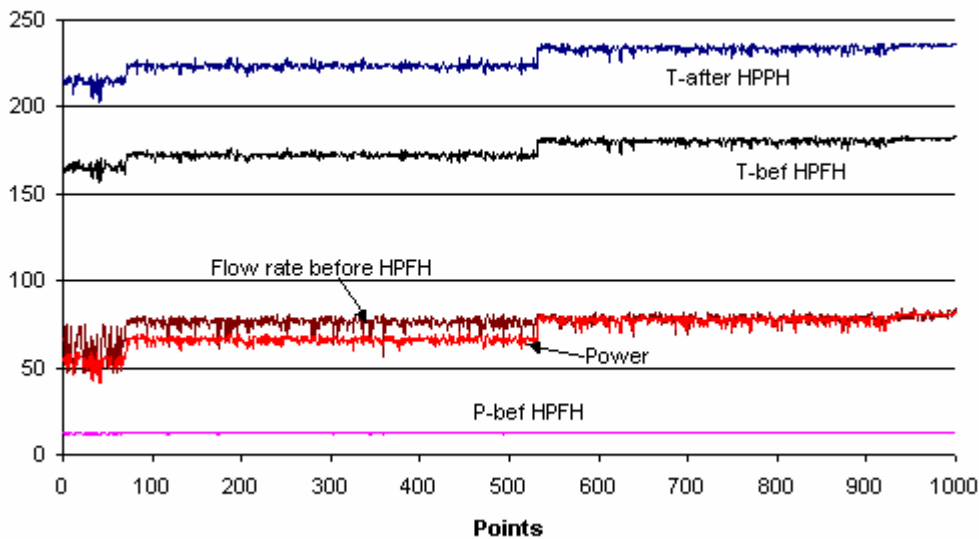


Chart 19: Correlation of HPFH parameters with output power

It is decided to train an ANN without flow rate and pressure before HPFH in order to test if it gives higher accuracy.

ANN	Mean error (%)	Max error (%)	Min error (%)
With P-before & flow rate parameters	0,254	2,605	0,001

Table 33: ANN results without Pressure and flow rate before HPFH

After a comparison between all these cases it is decided to keep all the HPFH parameters.

6.2.5.6 ANN without HRSG Pressure/Temperature

Three parameters have been chosen from HRSG viz., steam flow rate, temperature and pressure. In order to find out what temperature and pressure of HRSG can affect the accuracy of The ANN; two different attempts have been performed and the results of this ANN are presented in table 34:

ANN	Mean error (%)	Max error (%)	Min error (%)
With all HRSG parameters	0,241	2,359	0,000
Without all HRSG parameters	0,255	2,484	0,000
Without T & P HRSG	0,252	2,825	0,000

Table 34: ANN results without the HRSG parameters

The first row in table 34 represents the results of the reference ANN with all these three parameters. Line 2 in the table all the parameters from HRSG has been omitted. As it was expected the accuracy of the ANN without HRSG parameters has not been affected so much (only 6 %). The reason is the low flow rate from the HRSG. Chart 20 shows the variation of the HRSG flow rate in compare with the output power.

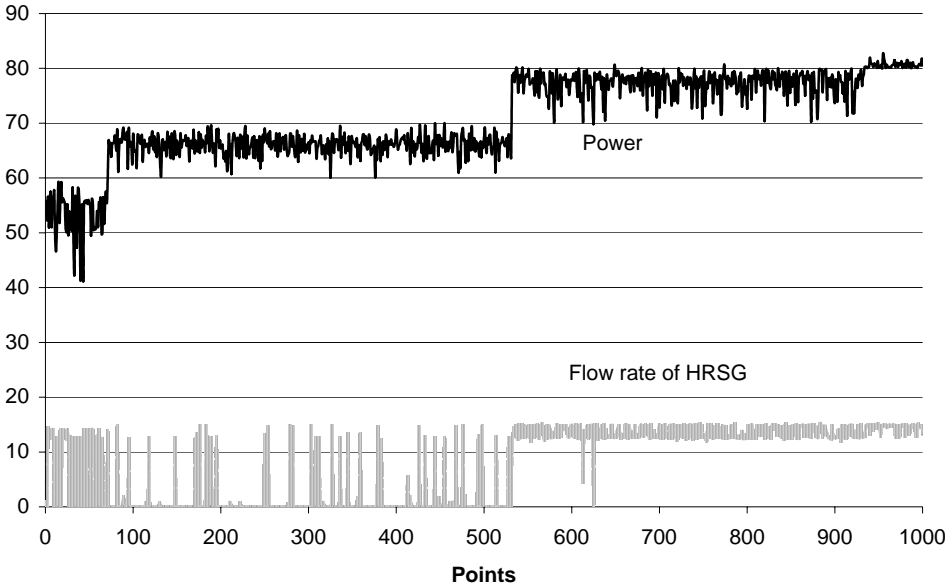


Chart 20: Flow rate of the HRSG

Another ANN has been trained, with flow rate but without temperature and pressure of the HRSG in order to see which one of these parameters has more consequence on the ANN. Line 3 in table 34 represents the result of this ANN and as it is seen by omitting the

temperature and pressure the mean error dose not varies from line 2 and it means that they have lesser consequence on the ANN than the flow rate.

6.2.6 Degradation at Västhamnsverket

In order to find out the degradation of a plant, complete information of the plant’s maintenance history must be available. With access to that information and with help of ANN the degradation can be detected. The objective of this section is not to find out the exact amount of the degradation in the system but it will be established that the ANN is capable to track the degradation in a system.

A previously developed ANN from 2002 was tested with the new data (from 2005) in order to find out the degradation of the plant during these three years operation. Testing of this ANN model with 1000 points of the new data (from 2005) has been performed. In order to get a more reliable response, it was considered that the ranges of all new data lie in the corresponding ranges of old data. Chart 21 presents the result of this testing. The right y-axis presents the difference between the real data and the predicted one in percentage. The left y-axis presents the power in MW.

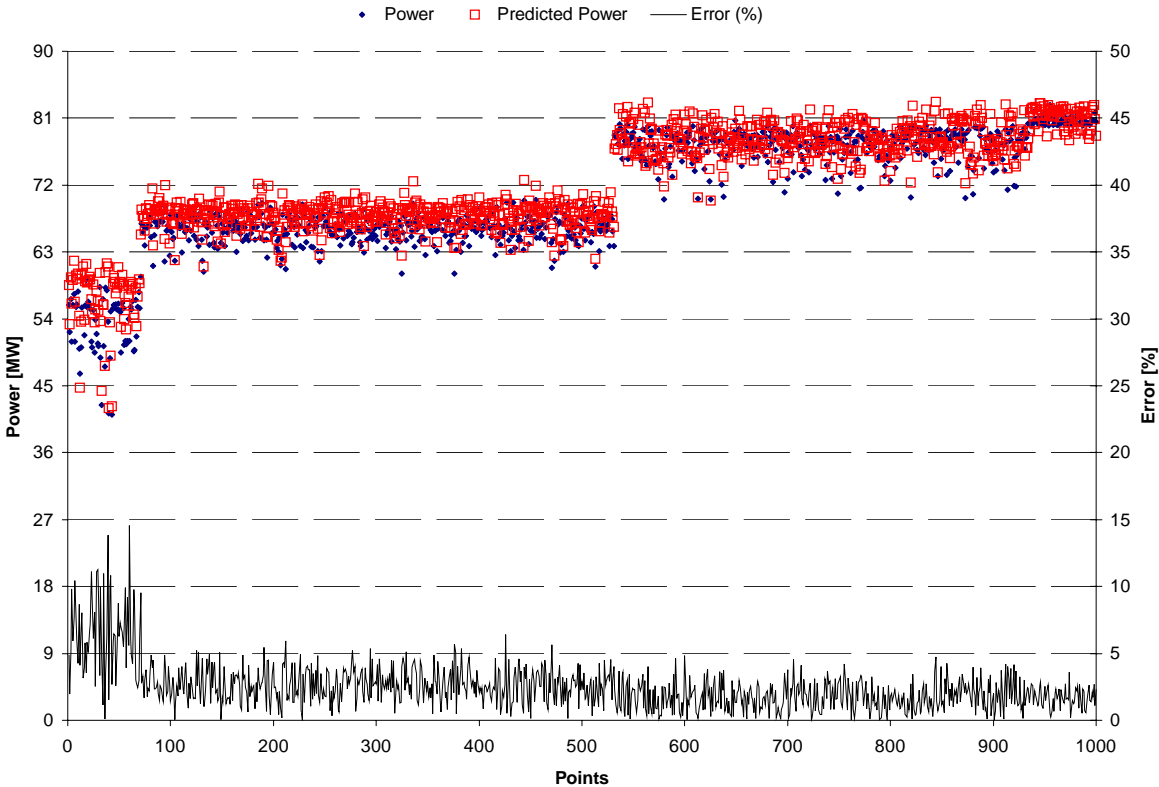


Chart 21: Validating of the “old ANN” model with the new data (Degradation)

As it is seen in chart 21 the trend of the predicted power are higher than the real one, which assures the degradation in the system. Table 35 presents the results of this test and it shows that the accuracy of the ANN with new data (2005) is 1,4 % worse than 2002 (after three years operation), which can be the results of the degradation, but as it was mentioned before a more detailed study must be done in order to find out the degradation.

	Mean error (%)	Max error (%)	Min error (%)
Year 2005	2,51	14,56	0,001
Year 2002	1,18	10,45	0,000

Table 35: Difference of errors from 2002 to 2005

6.2.7 Concluding Remarks

Concerning the objective of this section, a sensitivity analysis has been performed in order to find out the impact of the input parameters and to remove unnecessary inputs. After a comparison between the results (mean error) of the sensitivity analysis section, and with respect to an objective of the study (making a user interface which can show the relation between electricity and heat production) it was decided to use ANN (17H1) as a final model and use it in the user interface for predicting the electric power. This ANN has 17 inputs, in the other words, apart from temperature and pressure before regulator all the presented inputs in Figure 27 has been used.

7 Interface

The main objective of this interface is, to find out the relationships between the input and the output parameters quickly and very simple.

Once the training of the model is ready, a function can be generated, which will be later used in the interface. In order to generate a function, a program “*Formula Generator*” has been used to take the frizzed weights into the *visual basic* environment (see appendix A). After some manipulation in visual basic the function is ready to use in excel environment (see appendix B). An interface has been developed in excel environment (see Figure 29).

7.1 Inputs parameters in the interface

The input parameters (which can be controlled by the operator) of the interface are:

1. District heat parameters (flow rate, return temperature and forward temperature)
2. HRSG parameters (flow rate, temperature and pressure)
3. Fuels flow rate (Biomass and Coal)
4. Air conditions (flow rate and temperature)

By changing each of above parameters the corresponding changes in the outputs will be seen.

7.2 Outputs parameters in the interface

The output parameters are:

1. Power output
2. Steam condition after the boiler (temperature, flow rate and pressure)
3. Exhaust gas condition (flow rate and temperature in the stack)
4. Emissions (NO_x and O₂)

7.3 Limitations

The limitations of the developed interface are listed below:

1. It was desired to train an ANN with only these input parameters, which can be controlled by operators. The outputs were highly correlated to the other parameters and without the other inputs the accuracy of the ANN will not be good enough. These parameters are:

{ Burner temperature
Water conditions as incoming to the boiler
Drain pressure (the first one)
Curtis stage pressure
Condensers pressure

The values of these parameters are fixed in this interface and they are assumed to be unchangeable values.

Another option has been intended in this interface which makes it possible for the operator to change these parameters if they are known to him: These parameters can be changed in another page in the same excel-workbook which name is input (see Figure 32).

2. The training of the ANN has been performed in specific ranges of the data: the accuracy of the ANN will not be guaranteed if the inputs are out of these ranges (see Figure 31).

7.4 Excel-Workbook (Interface) description

This Workbook consists of four pages:

Page one “Model”: In this page one can see the results of the ANN by changing the input parameters (see Figure 29).

Page two “Reference”: In this page some information about the parameters localization and reference values can be found (see Figure 30).

Page three “Important to know”: In this page some information about the data ranges will be found (see Figure 31).

Page four “Inputs”: This page is open for those who will change the other intern input parameters otherwise it can be hidid (see Figure 32).

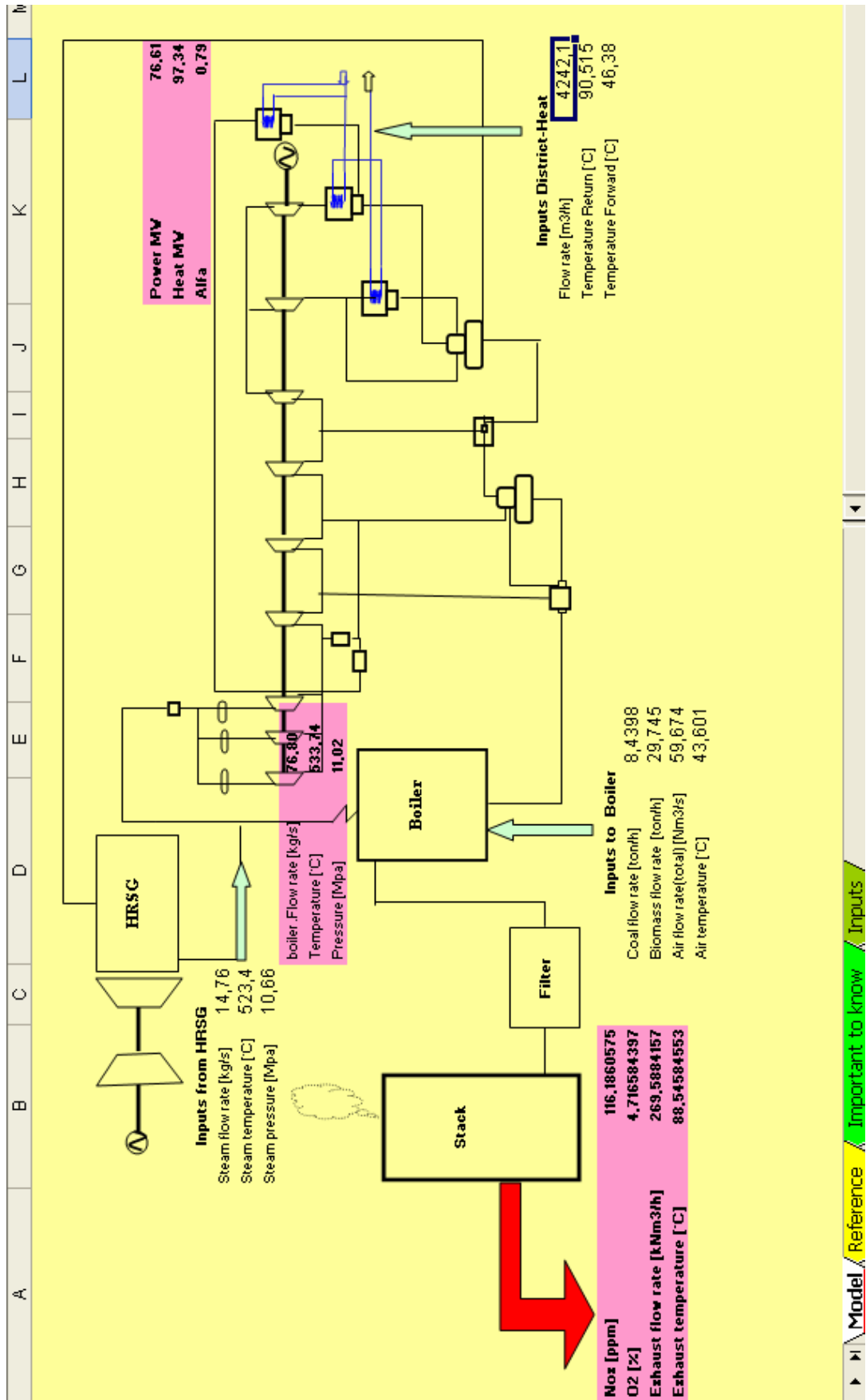


Figure 29: Developed interface in excel environment (model page)

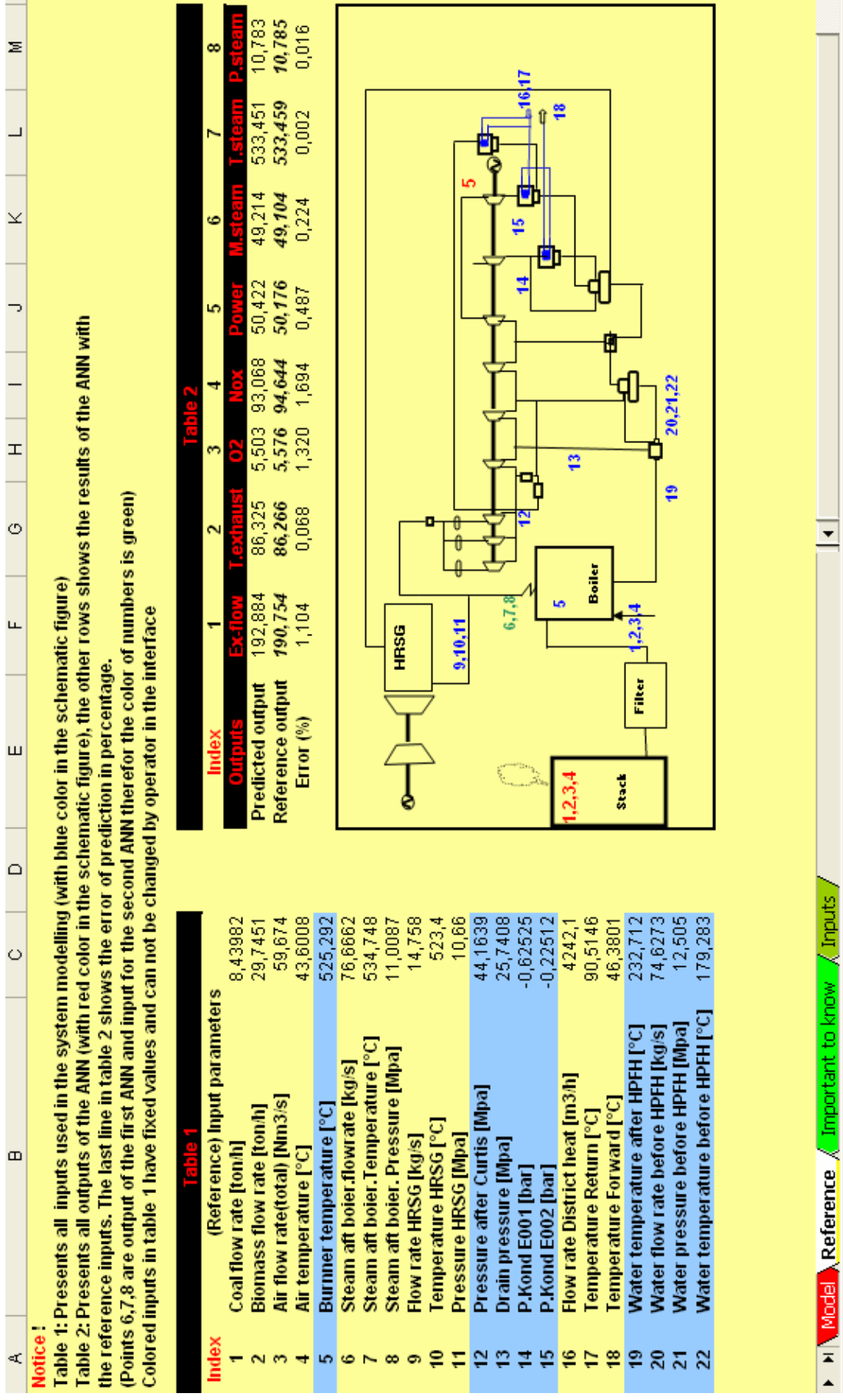


Figure 30: Developed interface in excel environment (Reference page)

Index	Input parameters	Min	Max
1	Coal flow rate [ton/h]	5,324	9,421
2	Biomass flow rate [ton/h]	18,763	33,204
3	Air flow rate(total) [Nm ³ /s]	42,214	61,056
4	Air temperature [°C]	31,637	43,828
5	Burner temperature [°C]	408,113	760,457
6	Steam aft boiler.flowrate [kg/s]	46,807	85,914
7	Steam aft boiler.Temperature [°C]	515,138	541,491
8	Steam aft boiler. Pressure [Mpa]	10,769	11,307
9	Flow rate HRSG [kg/s]	0,000	15,216
10	Temperature HRSG [°C]	0,000	523,500
11	Pressure HRSG [Mpa]	0,000	10,920
12	Pressure after Curtis [Mpa]	24,548	48,588
13	Drain pressure [Mpa]	0,000	28,018
14	P.Kond E001 [bar]	-0,716	-0,370
15	P.Kond E002 [bar]	-0,444	0,364
16	Flow rate District heat [m ³ /h]	2119,100	5049,220
17	Temperature Return [°C]	43,358	52,586
18	Temperature Forward [°C]	81,100	103,702
19	Water temperature after HPFH [°C]	203,122	236,677
20	Water flow rate before HPFH [kg/s]	44,956	84,392
21	Water pressure before HPFH [Mpa]	11,437	12,985
22	Water temperature before HPFH [°C]	156,572	183,346

Table 1
This table shows the Min and Max values of each input parameter.

The training of this ANN model has been performed in these ranges. Changing of each input parameter within corresponding range, can give guaranteed results according to table 2.

Accuracy of the results (according to table2), cannot be guaranteed by changing the inputs out of the specified ranges.

Table 2
The first line presents the output parameters of the ANN
The second line presents the mean error of the prediction
The third line shows the accuracy of the ANN to predict the respective output

Outputs	Flow rate_exhaust	Temperature_stack	O2	NOX	Steamflow	I	Steam	P	Steam	Power
Mean error (%)	1,11	0,757	1,96	3,859	0,333	0,277	0,095	0,25		
Mean accuracy (%)	98,89	99,243	98,04	96,14	99,667	99,723	99,905	99,75		

Table 2

Figure 31: Developed interface in excel environment (Ranges page)

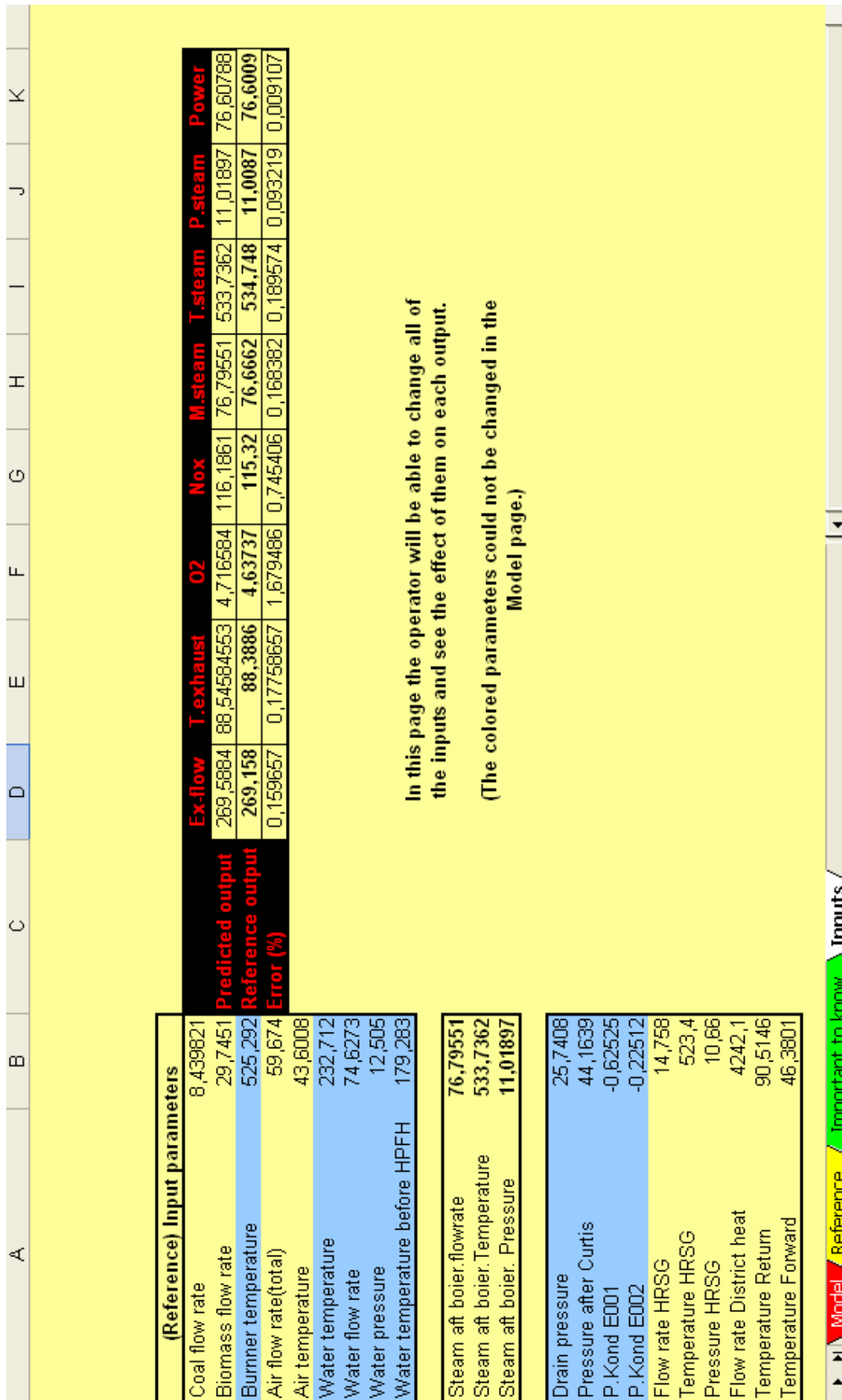


Figure 32: Developed interface in excel environment (Inputs page)

8 Conclusions

The overall aim of this study is to develop an ANN simulator for the whole steam process at Västhamnsverket. In order to have more efficient ANN model, the plant was divided into two parts and an ANN model were created for each part, which were linked to each other subsequently. The ANN models are found to have very good prediction accuracy. In case 1, the prediction of emissions (i.e., NO_x, O₂) and in case 2, the prediction of power output was estimated.

At present, it is very difficult and complex to evaluate emissions (especially NO_x) from biomass-coal cofired boilers. By using the ANN technology, it was confirmed (results of the case study 1) that it would be very easy and simple to predict the emissions with an acceptable accuracy. Since the amount of NO_x depends on the fuel/air ratio, fuel flow rates, airflow rate and air temperature, these were used as input parameters for the ANN model. Also, other parameter like maximum temperature in the furnace is used as an input parameter in order to increase the accuracy of the model.

In case 2 it was also established that the power output can be predicted with very good accuracy based on the developed model. Since it was desired to see the affect of the parameters of HRSG, district heat and input parameters of the boiler e.g. fuel and air flow rates and air temperature on the power output, these parameters were used as input parameters for this ANN model. Other parameters like drain pressure and the Curtis pressure have been used as input parameters in order to increase the accuracy of the ANN model. By predicting the power output with good accuracy, online-monitoring system and the assessment of degradation of the performance of the plant can be implemented. In order to find out the degradation of the plant, more detailed studies must be done i.e. complete information of the plant's maintenance history must be available.

It was also confirmed that a user interface can be implemented in excel environment which is very easy for everyone to use. In this interface calculation can be performed quickly due to the fact that there is no iterative calculation. It must be clarified that if any changes occur in the system, a retraining of the ANN is required.

Other conclusions, which have been drawn during this study, are listed in following points:

- Because the accuracy of an ANN model depends highly on the availability of the training data it is important that the training data has as much variation as possible.
- ANN provides an approximation in the range of variation and can only be trusted in that range.
- ANN can be applied to any technology or process from which data is available.

The objectives of this master thesis were fulfilled and other possibility for ANN studies have been identified which are presented in the next chapter (Future works).

9 Future Works

Several fields of future ANN studies have been identified at Västhamnsverket which are listed below:

- Making an ANN model for the Gas Turbine with real data and integrate that model with the model, which has been implemented in this master thesis.
- Making ANN models for each component and connect them together in order to make a control panel system for the entire plant.
- Making a sensor validation model for the plant, in order to detect the faults when they are not progressed.
- Making a fault diagnosis model in order to increase the availability of the plant.
- Performing a complete degradation study at the plant.

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- [11] Ulrik Snygg: Investigating engineer at Västhamnsverket (Ulrik.Snygg@oresundskraft.se)
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Appendix

Once the training is ready, the weights are frizzed and in order to generate a function, a program “*Formula Generator*” has been used to take the frizzed weights into the *visual basic* environment (see appendix A). After some manipulation in visual basic the function is ready to use in excel environment (see appendix B). In order to get a better understanding about this topic an example has been presented, Appendix A shows the code before manipulation and Appendix B shows the code after the manipulation. Appendix C shows the results of experiments for finding out the reliability of ANN models.

Appendix A

Sub NSMacro1()

Dim hidden1AxonPE1 As Double

```
hidden1AxonPE1 = tanh( ( (Range ("A1")*3.904823362827301e-001 + -2.878804683685303e+000
)*3.073940752074122e-003 )+ ((Range ("B1")*1.107947304844856e-001 + -2.878804445266724e+000
)*2.553728222846985e-001 )+ ((Range ("C1")*4.666981752961874e-003 + -2.713681936264038e+000 )*-
1.153101697564125e-001 )+ ((Range ("D1")*8.719250559806824e-002 + -4.483970642089844e+000 )*-
3.731006681919098e-001 )+ ((Range ("E1")*7.310476154088974e-002 + -2.778317213058472e+000 )*-
7.472507953643799e-001 )+ ((Range ("F1")*4.768289625644684e-002 + -1.048544502258301e+001 )*-
1.365749478340149e+000 )+ ((Range ("G1")*4.057217016816139e-002 + -2.623974800109863e+000 )*-
1.984714567661285e-001 )+ ((Range ("H1")*1.035867214202881e+000 + -1.265094280242920e+001 )*-
2.352578938007355e-001 )+(-7.934687733650208e-001 )
.
```

.

.

.

Dim outputAxonPE1 As Double

```
outputAxonPE1 = tanh( ( hidden1AxonPE1*-4.509064853191376e-001 )+ ( hidden1AxonPE2*-
5.644919350743294e-002 )+ ( hidden1AxonPE3*2.776071988046169e-002 )+ (
hidden1AxonPE4*2.379684597253799e-001 )+ ( hidden1AxonPE5*-1.813749223947525e-001 )+ (
hidden1AxonPE6*-5.856658220291138e-001 )+ ( hidden1AxonPE7*2.023218274116516e-001 )+ (
hidden1AxonPE8*-2.914870083332062e-001 )+ ( hidden1AxonPE9*5.347039923071861e-002 )+ (
hidden1AxonPE10*2.246066480875015e-001 )+ ( hidden1AxonPE11*-8.500406891107559e-002 )+ (
hidden1AxonPE12*1.444311589002609e-001 )+ ( hidden1AxonPE13*4.803305864334106e-002 )+ (
hidden1AxonPE14*-1.919715255498886e-001 )+ ( hidden1AxonPE15*-5.030149221420288e-001 )+ (
hidden1AxonPE16*-1.659857928752899e-001 )+(-1.768327504396439e-001 )
```

```
Range ("I1") = ( outputAxonPE1)--3.860209465026856e+000) / 1.621698215603828e-002
Range ("J1") = ( outputAxonPE2)--1.685128211975098e+001) / 1.915525645017624e-001
Range ("K1") = ( outputAxonPE3)--1.814493775367737e+000) / 3.048844337463379e-001
Range ("L1") = ( outputAxonPE4)--2.394266366958618e+000) / 2.136218547821045e-002
End Sub
```

Function tanh(x As Double) As Double

```
tanh = (Exp(x) - Exp(-x)) / (Exp(x) + Exp(-x))
```

End Function

Appendix B

Function ANN_emission(Coal As Double, Biomass As Double, TBurnner As Double, Airflow As Double, TAir As Double, Twater As Double, Mwater As Double, Pwater As Double) As Double()

'-----

'HIDDEN LAYER

Dim hidden1AxonPE1 As Double

hidden1AxonPE1 = tanh(((Coal * 0.39048233628273 + -2.8788046836853) * 3.07394075207412E-03) + ((Biomass * 0.110794730484486 + -2.87880444526672) * 0.255372822284698) + ((TBurnner * 4.66698175296187E-03 + -2.71368193626404) * -0.115310169756413) + ((Airflow * 8.71925055980682E-02 + -4.48397064208984) * -0.37310066819191) + ((TAir * 7.31047615408897E-02 + -2.77831721305847) * -0.74725079536438) + ((Twater * 4.76828962564468E-02 + -10.485445022583) * -1.36574947834015) + ((Mwater * 4.05721701681614E-02 + -2.62397480010986) * -0.198471456766129) + ((Pwater * 1.03586721420288 + -12.6509428024292) * -0.235257893800736) + -0.793468773365021)

.

.

'-----

'OUTPUT LAYER

Dim outputAxonPE1 As Double

outputAxonPE1 = tanh((hidden1AxonPE1 * -0.450906485319138) + (hidden1AxonPE2 * -5.64491935074329E-02) + (hidden1AxonPE3 * 2.77607198804617E-02) + (hidden1AxonPE4 * 0.23796845972538) + (hidden1AxonPE5 * -0.181374922394753) + (hidden1AxonPE6 * -0.585665822029114) + (hidden1AxonPE7 * 0.202321827411652) + (hidden1AxonPE8 * -0.291487008333206) + (hidden1AxonPE9 * 5.34703992307186E-02) + (hidden1AxonPE10 * 0.224606648087501) + (hidden1AxonPE11 * -8.50040689110756E-02) + (hidden1AxonPE12 * 0.144431158900261) + (hidden1AxonPE13 * 4.80330586433411E-02) + (hidden1AxonPE14 * -0.191971525549889) + (hidden1AxonPE15 * -0.503014922142029) + (hidden1AxonPE16 * -0.16598579287529) + -0.176832750439644)

.

'-----

'DENORMALIZATION

Dim Exhaust_flow As Double

Exhaust_flow = ((outputAxonPE1) - -3.86020946502686) / 1.62169821560383E-02

Dim Exhaust_Tem As Double

Exhaust_Tem = ((outputAxonPE2) - -16.851282119751) / 0.191552564501762

Dim O As Double

O = ((outputAxonPE3) - -1.81449377536774) / 0.304884433746338

Dim Nox As Double

Nox = ((outputAxonPE4) - -2.39426636695862) / 2.13621854782104E-02

'-----

'BUILD UP AN OUTPUT VECTOR

Dim temp(3) As Double

temp(0) = Exhaust_flow

temp(1) = Exhaust_Tem

temp(2) = O

temp(3) = Nox

'-----

'THE FINAL FUNCTION

ANN_emission = temp

End Function

Function tanh(x As Double) As Double
tanh = (Exp(x) - Exp(-x)) / (Exp(x) + Exp(-x))
End Function

Appendix C

ANNs Reliability

In order to find out the reliability of the ANN models, a dataset (with 1000 points) has been trained 5 times with the same ANN structure. The dataset has been randomized first before using in the ANNs; it means that the dataset has same order in all ANN models.

ANN settings are chosen as below:

- ✓ Number of runs 3
- ✓ Number of epoch 5000
- ✓ Variation of hidden neuron from 5 to 20
- ✓ Transfer function: Tanh
- ✓ Other details like step size and etc were the same in all ANNs

Table 1 presents the error conditions in each ANN model.

10 H 1	Mean error (%)	Max error (%)	Min error (%)	Max point
ANN 1	0,6389540	8,3406825	0,0011693	691
ANN 2	0,5705044	7,7144537	0,0003849	691
ANN 3	0,5903079	10,3014291	0,0003496	691
ANN 4	0,5993469	7,5787314	0,0013848	691
ANN 5	0,580008856	8,029584618	2,03659E-05	691

Table 36: Results of the ANN (10 H 1) after each training

As it is seen in table 36 the response of each ANN varies from the others. ANN 1, 2 and 3 in table 1 has been studied closer and the results are presented below.

ANN 1 is compared with ANN 2 in table 36. Mean error is decreased by 10 %, and Max error is decreased by almost 7, 5 %.

ANN 2 is compared with ANN 3 in table 1. Mean error is increased by almost 3, 5 % but the max error is increased by 33, 5 %, which can be considered as a large difference.

One interesting point was that all of the max errors have occurred in one point in this model but surprisingly it was seen that the prediction of each single points varies significantly, with each ANN. Table 37 shows an example. By accident point 163 has been chosen and the error percentage has been calculated. It is seen that the differences between the predictions of this point by each ANN are almost high which means that each point can be predicted very different in each ANN.

Index	ANN 1 Error (%)	ANN 2 Error (%)	ANN 3 Error (%)	ANN 4 Error (%)	ANN 5 Error (%)
163	0,08185675	0,224012384	1,025540427	0,159838339	0,390915648

Table 37: Each ANN predict differently in each single point

With this clarification in mind it was decided to examine, if the max errors always occurs in the same point or it was just by accident in the last example.

Another ANN has been trained with two more input parameters (Drain pressure and pressure after Curtis-wheel) and as it is obvious in table 38 that the max points are not the same in this model. It means that the max error can occurs just by accident.

12 H 1	Mean error (%)	Max error (%)	Min error (%)	Max point
ANN 1	0,56180729	6,082795952	0,00151844	835
ANN 2	0,612348097	4,92007042	0,000517022	49
ANN 3	0,615840115	4,001304261	0,000285808	263
ANN 4	0,592186742	4,987334176	0,000565822	702
ANN 5	0,559189472	4,12184943	0,000438438	835

Table 38: Results of the ANN (12 H 1) after each time training

ANN 1 is compared with ANN 2, the mean error is increased by 9 %, but max error decreased by more than 19 %.

In another attempt the number of runs in NeuroSolutions is increased from 3 to 10 in order to overcome the differences between max errors in the previous ANN (12 H 1). As the results present in table 39, the problem is still remaining.

12 H 1	Mean error (%)	Max error (%)	Min error (%)
ANN 1	0,550117439	4,489233892	3,60937E-05
ANN 2	0,582832955	6,063367972	0,000695098

Table 39: Results of the ANNs after the number of the runs is increased from 3 to 10

ANN 1 and 2 in table 39 is compared and it is seen that mean error is increased by 6 %, but max error is increased by 35,4 %.

Conclusion

The following points have been concluded after this part of this study:

- ✓ After this study it has been concluded that the max error shall not be a good factor for judging the ANNs accuracy.
- ✓ Mean error can vary up to 10 % according to my study (maybe it can be more)
- ✓ There is no specific relationship between max error and the mean error. Sometimes from one ANN to another one both mean and max errors increase or decrease simultaneously, but sometimes one of them increases while the other one decreases or on the contrary.

ANN is based on statistical methods and obviously it is not exactly a mathematical calculation. It is expected not to get the same result from two same ANNs, but the question is how acceptable these differences should be.

With these clarifications in mind this question is still not answered that if ANN is reliable enough especially in some applications fields like sensitivity analysis.