Rapport SGC 184

Condition monitoring and thermoeconomic optimization of operation for a hybrid plant using artificial neural networks

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INSTITUTIONEN FÖR ENERGIVETENSKAPER
LUNDS TEKNISKA HÖGSKOLA

Rapport SGC 184 • ISSN 1102-7371 • ISRN SGC-R--184-SE

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Energimyndigheten
Värmeforsk AB
Siemens Industrial Turbomachinery AB
Öresundskraft Produktion AB

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Jörgen Held

Abstract

Artificial neural networks have been integrated and tested for online condition monitoring in the computer system of an existing combined heat- and power plant. An accompanying graphical user interface has also been developed including an economics part for thermoeconomic optimization of operation.

Summary

The project aim is to model the hybrid plant at Västhamnsverket in Helsingborg using artificial neural networks (ANN) and integrating the ANN models, for online condition monitoring and thermoeconomic optimization, on site. The definition of a hybrid plant is that it uses more than one fuel, in this case a natural gas fuelled gas turbine with heat recovery steam generator (HRSG) and a biomass fuelled steam boiler with steam turbine. The thermoeconomic optimization takes into account current electricity prices, taxes, fuel prices etc. and calculates the current production cost along with the "predicted" production cost. The tool also has a built in feature of predicting when a compressor wash is economically beneficial. The user interface is developed together with co-workers at Västhamnsverket to ensure its usefulness. The user interface includes functions for warnings and alarms when possible deviations in operation occur and also includes a feature for plotting parameter trends (both measured and predicted values) in selected time intervals.

The target group is the plant owners and the original equipment manufacturers (OEM). The power plant owners want to acquire a product for condition monitoring and thermoeconomic optimization of e.g. maintenance. The OEMs main interest lies in investigating the possibilities of delivering ANN models, for condition monitoring, along with their new gas turbines.

The project has been carried out at Lund University, Department of Energy Sciences, with support from Västhamnsverket AB and Siemens Industrial Turbomachinery AB. Västhamnsverket has contributed with operational data from the plant as well as support in plant related questions. They have also been involved in the implementation of the ANN models in their computer system and the development of the user interface. Siemens have contributed with expert knowledge about their SGT800 gas turbine.

The implementation of the ANN models, and the accompanying user interface, in Västhamnsverkets computer system was carried out successfully. With the developed tool plant condition can be monitored while at the same time possible deviations, such as degradation, are economically evaluated.

Keywords: ANN modelling, thermal power plants, condition monitoring, thermoeconomic optimization, gas turbine

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1 Introduction

1.1 Background

The project, which is co-financed by Värmeforsk and Svenskt Gastekniskt Center (SGC), concerns online condition monitoring and thermoeconomic optimization of operation for the hybrid plant at Västhamnsverket in Helsingborg, Sweden. For this purpose artificial neural network (ANN) models have been integrated in Västhamnsverkets computer system together with the development of a graphical user interface (GUI). The GUI includes a tool for parameter analysis, warning- and alarm indicators, analysis of production cost and a tool for economic evaluation of compressor washes.

The combined heat- and power (CHP) plant consists of a modern Siemens gas turbine (SGT800), a heat recovery steam generator (HRSG) and a biomass fuelled boiler. Steam generated by the boiler and HRSG expands in one common steam turbine.

Condition based maintenance requires continuous monitoring of the CHP plant components. Deviations from expected data pattern could indicate e.g. a faulty component or degradation whereupon the operators are alerted to take action. Early detection of faults leads to reduced costs for maintenance.

This project forms a part of a series of projects conducted in collaboration between Lund University, Västhamnsverket and Siemens Industrial Turbomachinery AB.

1.2 Description of the research area

ANN modelling of power plant systems is a relatively new area although ANN has been used within other disciplines for some time. The past years research studies, within in this field, have been conducted at the division of Thermal Power Engineering at Lund University. Several areas of implementation have been identified, e.g. simulation of operation, condition monitoring, thermoeconomic analysis, sensor validation and fault diagnosis. The present project is a continuation of previous studies.

1.3 The purpose of the research assignment and its role within the research area

Increased availability, reduced cost for maintenance and more efficient maintenance is the main interest for this research. By linking historical operational data to analysis of plant condition, optimization of maintenance and performance of the plant is possible.

1.4 Goal and audience

The goal of the project is to create a product fully integrated at the plant (Västhamnsverket) together with a graphical user interface, for condition monitoring and thermoeconomic optimization of operation. The product can be used as a basis for transition from time based maintenance to condition based maintenance.

The target groups are the power plant owners and the OEMs. The power plant owner's interest lies in receiving a product that can be used for condition monitoring and thermoeconomic optimization of e.g. maintenance. The OEMs are interested in investigating the possibility integrating ANN models in the control system of new gas turbines.

2 The CHP plant

The plant, Västhamnsverket, is located in Helsingborg, Sweden and is owned by Öresundskraft AB. It is a unique multi-fuel CHP plant. The plant consists of a gas turbine, a heat recovery steam generator (HRSG) and a steam cycle consisting of a biomass fired boiler, a steam turbine, pre-heaters and two condensers. These are the main components of the plant as shown in Figure 1.

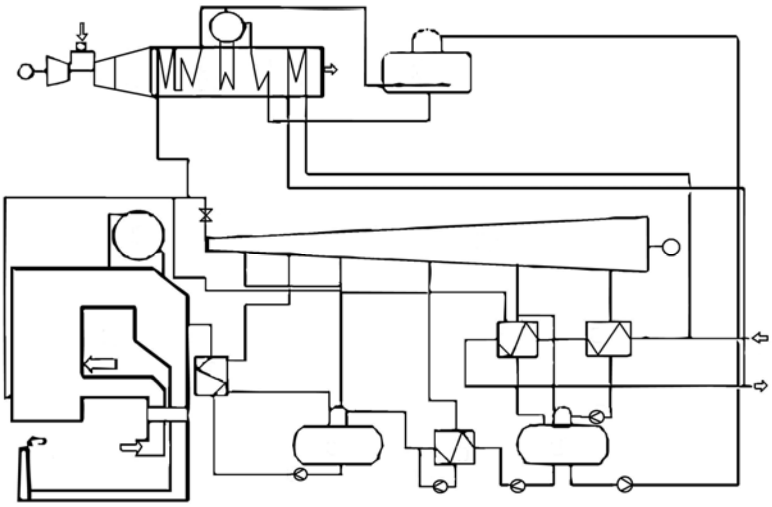

Figure 1. Schematic layout of the hybrid plant

The boiler was installed by Götaverken Ångteknik, Sweden in 1982. The boiler has the capability to use oil, coal and biomass as fuels. The main operating parameters of the boiler are, maximum pressure: 130 bar, maximum temperature: 540°C and steam-flow rate: 82 kg/s. It delivers power as well as district heat. In the year 1999, a gas power plant consisting of a gas turbine and a heat recovery steam generator was added to the existing steam plant. Thus the CHP plant presently operates as a ‘hybrid’ one. It generates steam from the waste heat of the gas turbine in the HRSG as well as in the boiler using biomass as fuel. The steam from the HRSG and the boiler expands in one common steam turbine. By adding a gas power cycle to the existing steam cycle, total power output and district heat were increased significantly. The system solution is unique and has a high alpha-value (ratio between produced electricity and heat) of 0,68. In total approximately 125 MW_e and 186 MW_{th} are produced.

The SGT800 (formerly known as GTX100) gas turbine was manufactured by Alstom Power AB (presently Siemens Industrial Turbomachinery AB) in Sweden. Its pictorial view is shown in Figure 2. The gas turbine was designed to produce up to 44 MW power with a thermal efficiency of 37 %. It is uniaxial with the generator on the ‘cold’ side (i.e., cold end drive). The compressor consists of 15 stages with a pressure ratio of around 20 and a mass flow of 130 kg/s. In the combustion chamber 120 MW fuel is burned, generating 100 MW of turbine work. Due to the very high temperatures after the combustion chamber the first two stages of the turbine are cooled with compressor air. The gas turbine is optimized for combined cycle operation and therefore a relatively high exhaust gas temperature is maintained.

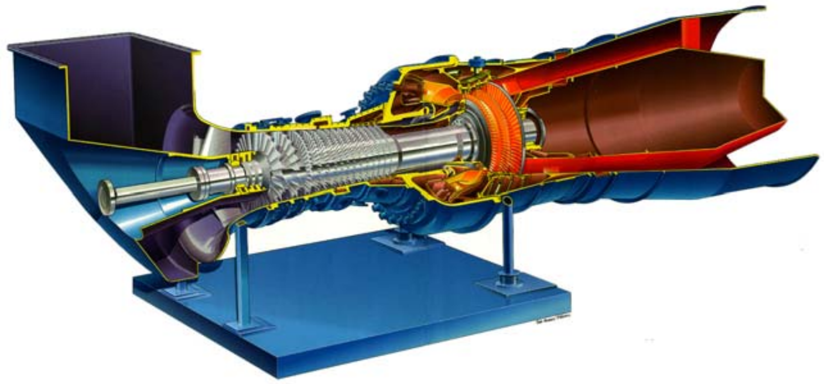

Figure 2. Siemens SGT800 gas turbine

The SGT800 gas turbine at Västhamnsverket was the production prototype, co-owned by Öresundskraft and Siemens, and has been used for component test and development. Due to this it has been subject to many component exchanges etc., thus a change in behavior during its years of operation might be expected. Natural gas is the main fuel used in this gas turbine. The gas turbine runs at full load during most of the time of its operation otherwise its power output is set to 30 MW. The gas turbine is limited to a lower power output when only the generated heat is desired. It is however only economically beneficial to operate the gas turbine during the winter months due to local conditions, such as ambient temperature, electricity and gas prices. The gas turbine is also equipped with an anti-icing system which preheats the inlet air to avoid harmful ice formation during simultaneous cold and humid conditions. The anti-icing system is normally in operation when the ambient temperature is somewhere between -5°C and +5°C while at the same time the relative humidity exceeds 80%. When preheating the air the gas turbine efficiency and power output decreases due to decreasing air density. In this power plant the inlet air for the gas turbine is preheated in a heat exchanger using district heating water.

Till May, 2007, fifty two such SGT800 machines were sold of which 24 are in commercial operation. Two of these machines have more than 45 000 EOHs and 17 machines have more than 20 000 EOHs. Out of the total fifty two machines, ten machines are operating in gas turbine power plants, seventeen in co-generation plants and twenty five in gas-steam combined power plants.

3 Brief basics of Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a simulation tool that mimics the neural structure of the human brain which basically learns from experience. In contrary to traditional mathematical models, which are programmed, ANN learns the relations between selected input and output parameters through an iterative process called training. The basic requirement is that reliable data, for selected input- and output parameters, is available for training.

ANN consists of a number of interconnected artificial neurons with linear or non-linear transfer functions and is well capable of predicting non-linear behaviour of a system. The multi-layer feed forward network is the type of network which has been used during this study. It consists of an input layer, one or more hidden layer(s) and an output layer. However, there is no impediment to having more than one hidden layer, since it has been proved that one layer with hidden neurons is enough to approximate any continuous function if it only has a sufficient number of units.

Once the inputs are presented to the network they will be multiplied by their adjustable weights and in each processing element summed and passed through a transfer function in order to produce outputs. The data used as inputs is transmitted through the network, layer by layer, and a set of outputs is obtained. Errors are generated by comparing these outputs with the desired outputs. The errors are then used for updating the weights before another set of inputs are transmitted through the network. The mean squared error (MSE) is calculated between each epoch (iteration) and the training is terminated when the MSE is satisfactory low. When training is completed the weights are fixed and the model is ready to predict outputs from previously unseen data, i.e., generalization.

Experience accumulated at the department over the years has shown that using the non-linear tangent hyperbolicus transfer function is suitable when modeling power plant systems. When training, all neural networks have been optimized regarding the number of neurons in the hidden layer.

4 ANN modeling of the hybrid plant

The system was divided into its basic components, i.e. gas turbine, HRSG, boiler and steam turbine, where each component was modeled separately. Data from the hybrid plant was delivered as five minute averages, covering three months of operation. A baseline was established and data recorded after this was considered as healthy and thereby suitable for ANN training. However, before using any data for training it has to be filtered and outliers, etc. removed. Furthermore, all transient operation was also removed since five minute average data only allows the steady state operation to be modeled. Selection of input and output parameters, for the individual models, was based on the availability of reliable plant data as well as real life needs. All ANN models have been subject to a sensitivity analysis in order to assess which input parameters that are of significance to respective model.

4.1 Gas turbine model; structure and performance

When operating at full load the ambient conditions (temperature, pressure) determines the gas turbine's performance. Hence, using the ambient conditions as input parameters to the gas turbine ANN model is natural. However, since the gas turbine is set to run at either full load or limited to 30 MW an input parameter representing these modes is necessary. The two discrete load cases were represented by two 'switches', i.e., '1' and '0'. This enabled the neural network to differentiate between the two modes of operation based on load. Another 'real life' issue was that of harmful ice formation in the intake manifold during simultaneous cold and humid local ambient conditions. To avoid this, an anti-icing system is used to preheat the air before the compressor. The anti-icing operation is also a discrete mode and represented by another set of switches of '1' and '0' in the ANN model. A complete list of input and output parameters for this ANN is shown in Table 1. The use of relative humidity as an input was redundant since its effects on gas turbine performance was marginal. It should be reminded however, that the relative humidity has large effect on ice formation. This ANN model was successful in prediction of all output parameters with very small errors, seen in Table 2.

Table 1. Input and output parameters for the gas turbine model

Inputs		*Outputs*	
Operation mode	[1 or 0]	Power output	[MW]
Anti-icing mode	[1 or 0]	Compressor inlet pressure	[kPa]
Ambient temperature	[°C]	Inlet guide vanes angle	[%]
Ambient pressure	[kPa]	Bleed temperature	[°C]
		Compressor outlet pressure	[MPa]
		Compressor outlet temperature	[°C]
		Mass flow rate of fuel	[MJ/s]
		Mass flow rate through turbine	[kg/s]
		Exhaust gas temperature	[°C]

Table 2. Error distribution for predictions

Parameter	<1%	1-2%	2-4%	>4%
Power output	7179	58	1	1
Compressor inlet pressure	7239	0	0	0
Inlet guide vanes angle	6489	558	183	9
Bleed temperature	7142	90	6	1
Compressor outlet pressure	7234	3	2	0
Compressor outlet temperature	7223	16	0	0
Mass flow rate of fuel	6649	579	8	3
Mass flow rate through turbine	7229	8	2	0
Exhaust gas temperature	7239	0	0	0

To further visualize the prediction accuracy of the gas turbine ANN a number of plots are shown in Figure 3, Figure 4 and Figure 5. In all figures the color black represents measured values, green predicted values and blue the prediction error. The measured and predicted values are read of the left y-axis and the error of the right y-axis. The number of data points is seen on the x-axis, where each point represents five minutes.

For the full load case the IGVs are fully opened and hence the angle is constant, the power varies with the ambient conditions as well as the compressor outlet pressure. When the gas turbine is set to run at 30 MW the power output is instead constant while the IGV angle and compressor outlet pressure varies with the ambient. Despite these differences the prediction accuracy, of the ANN, is very high in every case.

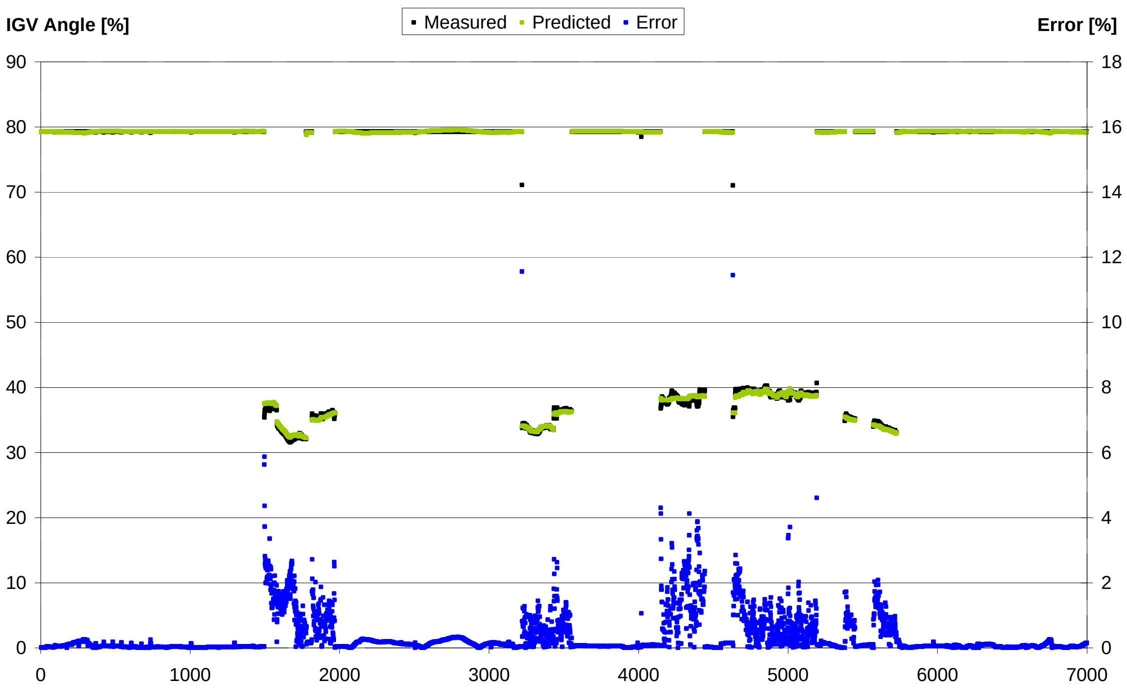

Figure 3. IGV Angle; prediction accuracy

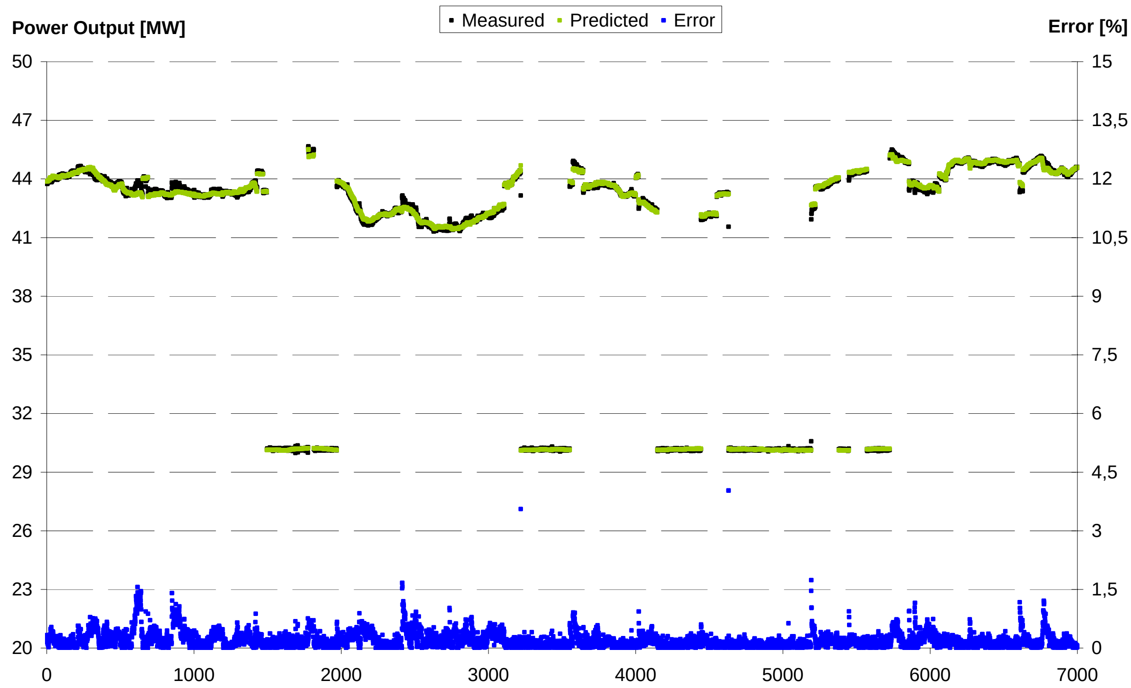

Figure 4. *Power output; prediction accuracy*

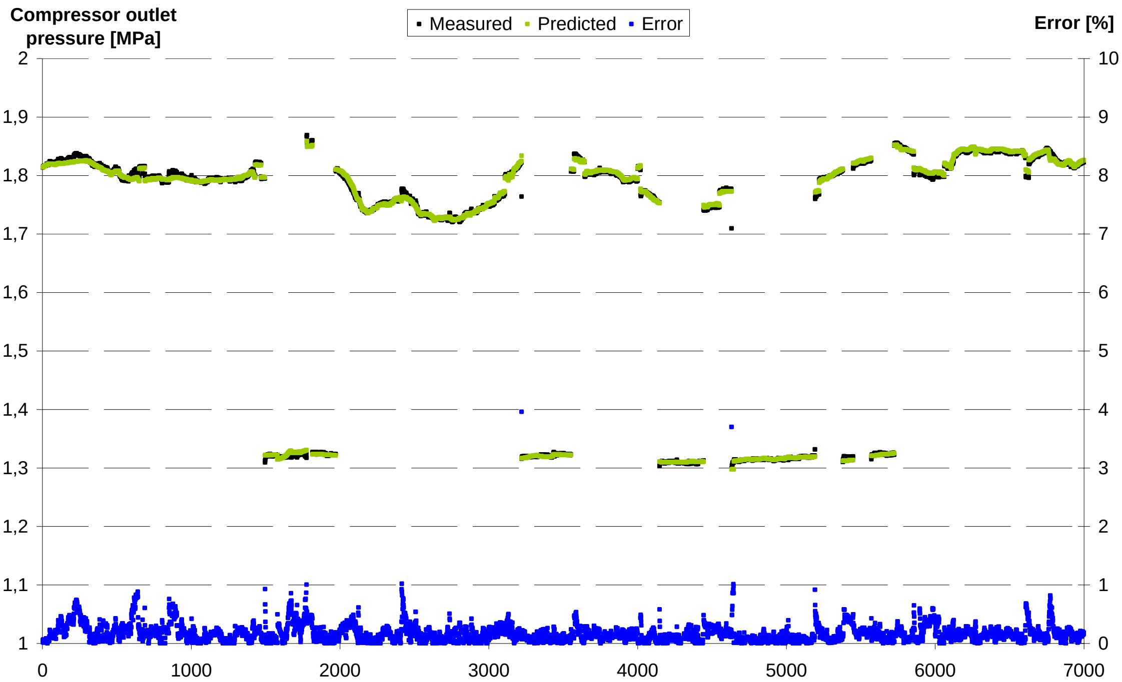

Figure 5. *Compressor outlet pressure; prediction accuracy*

4.1.1 Comparison of different gas turbine models

In previous projects (year 2001) a gas turbine model based on simulation data was developed. In this section a comparison between that ANN model and the ANN model described in chapter 4.1 is performed to assess whether using simulation data instead of operational data is suitable for ANN training. This could be a way to tackle the problem of non-availability of data for ANN training, especially at the beginning of gas turbine operation. The data was produced, in defined intervals and resolution, using Siemens gas turbine design program.

For the comparison values of input parameters from the plant was presented to both ANN models and values of common outputs parameters were compared. Predictions of power output and exhaust gas temperature by these two ANNs along with measured values of them are shown in Figure 6 and Figure 7 respectively. The first ANN model, based on simulation data is referred to as ANN 1 and the second model based on operational data as ANN 2. On the x-axis the number of data points was used as parameter where each point represents a five minute average value. As expected, the ANN model based on operational data predicted the power and the exhaust gas temperature with better accuracy as shown in Figure 6 and Figure 7. The prediction of the ANN model based on simulation data was not impressive apparently. The difference in predictions by these models was however expected since the gas turbine had been operating for several years while the simulation data represented the performance of a new gas turbine. The ANN based on simulation data predicted higher power outputs than those actually measured and for exhaust gas temperature it was just the opposite. During the years (2001-2006) when simulation data was generated (2001) and the operational data was collected (2006) several overhauls, replacements of components etc. occurred. The gas turbine performance degradation was thus expected which partly corresponds to the results shown in these figures. To compare the trends of predictions by these two ANNs, plots of predictions by one model is shifted vertically to check the matching of these two plots. These plots are shown in Figure 8 and Figure 9. Obviously for these figures, plots of predictions by two ANNs are represented by different axes in vertical directions as shown. Even for these plots, predictions by the two ANNs did not overlap. Apparently this seemed to be a failure of the use of synthetic data. However, it was revealed that the mode of operation changed with respect to anti-icing during this period. There was no consideration of anti-icing in the simulated data. Moreover effect of ambient pressure was not considered in simulated data either. Thus comparison of predictions by the two models during normal mode of operation without anti-icing would be more meaningful. It was identified that a section of data points, i.e., data points 4050 to 5200 were during operation without anti-icing. Plots were made for these data points only as shown in Figure 10 and Figure 11, also with vertical shifting. In these plots, predictions by the two models match very closely for exhaust gas temperature. However, there exists still some difference for power predictions. The reason behind this difference for power and exhaust gas temperature plots are due to the consideration of ambient pressure as one input parameter for the second model though it was not used for the first one. Variations of ambient pressure do not affect the exhaust gas temperature significantly though it was expected to influence power output. This can be demonstrated through adjusting the power output predictions from ANN 1 according to variations in ambient pressure by applying Equation 1. The results are shown in the final figure, Figure 12, and confirm that the difference in power output predictions (seen in Figure 11) between the two ANNs is due to the fact that ambient pressure was not included as an input to the first ANN (based on synthetic data). Index i in Equation 1 represents the data points, p_{ISO} is the constant atmospheric ISO pressure (1,013bar).

$$P_{adjusted,i} = P_{ANN\,1,i} \cdot \frac{p_{ambient,i}}{p_{ISO}} \qquad (1)$$

Thus it was concluded that the model developed using synthetic data was equivalent to that using operational data under identical operational condition. However, the vertical shift in prediction by one model was partly due to the degradation of the plant as the second model was developed using data after about five years of operation. Another reason for the vertical shift is the fact that this gas turbine was, as mentioned earlier, the production prototype and thereby subject to many component exchanges etc. However, interesting to notice is, despite the circumstances, that the generalization capability of the ANN based on synthetic data is very accurate. This indicates that no retraining of ANN models is needed due to e.g., overhauls or component exchanges. This study was successful to establish the possibility of using synthetic data for developing ANN model for condition based maintenance of gas turbines from the beginning of its operation. Furthermore, the results of this study add value to previous studies regarding fault diagnosis tools based on ANN and simulated faults.

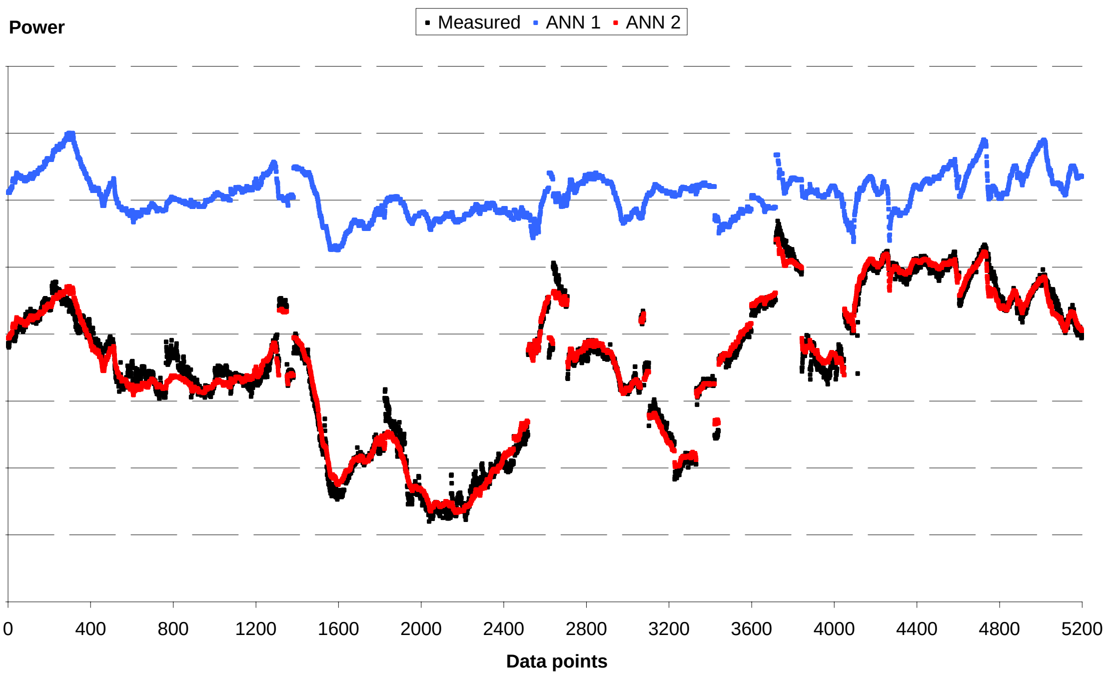

Figure 6. Measured and predicted values of power

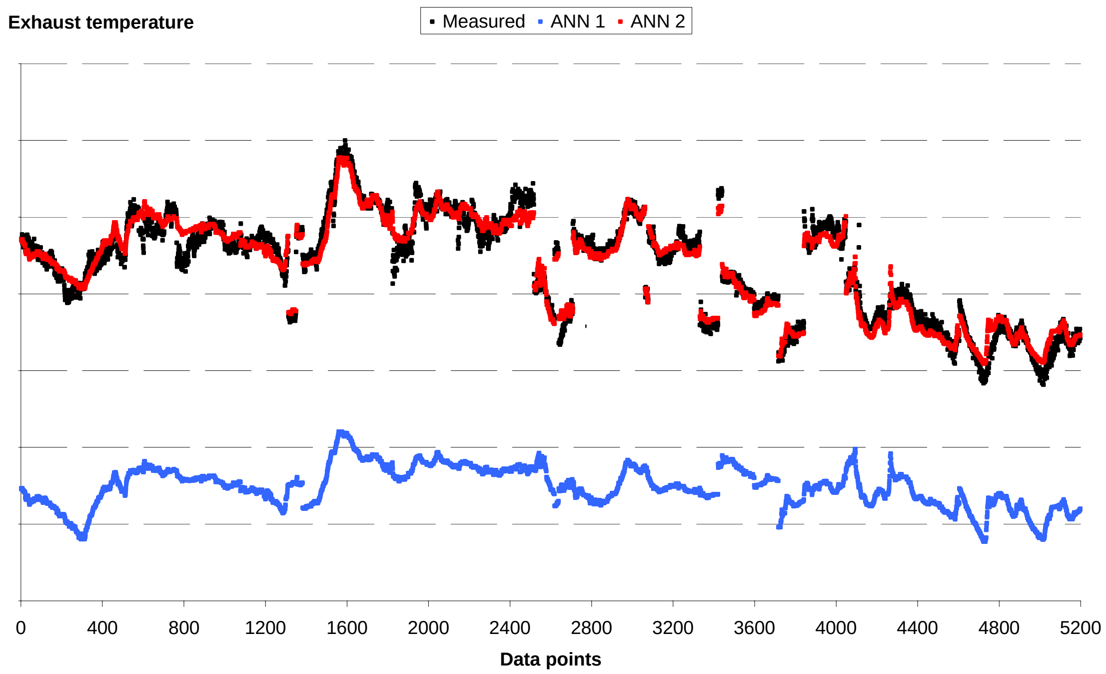

Figure 7. Measured and predicted values of exhaust gas temperature

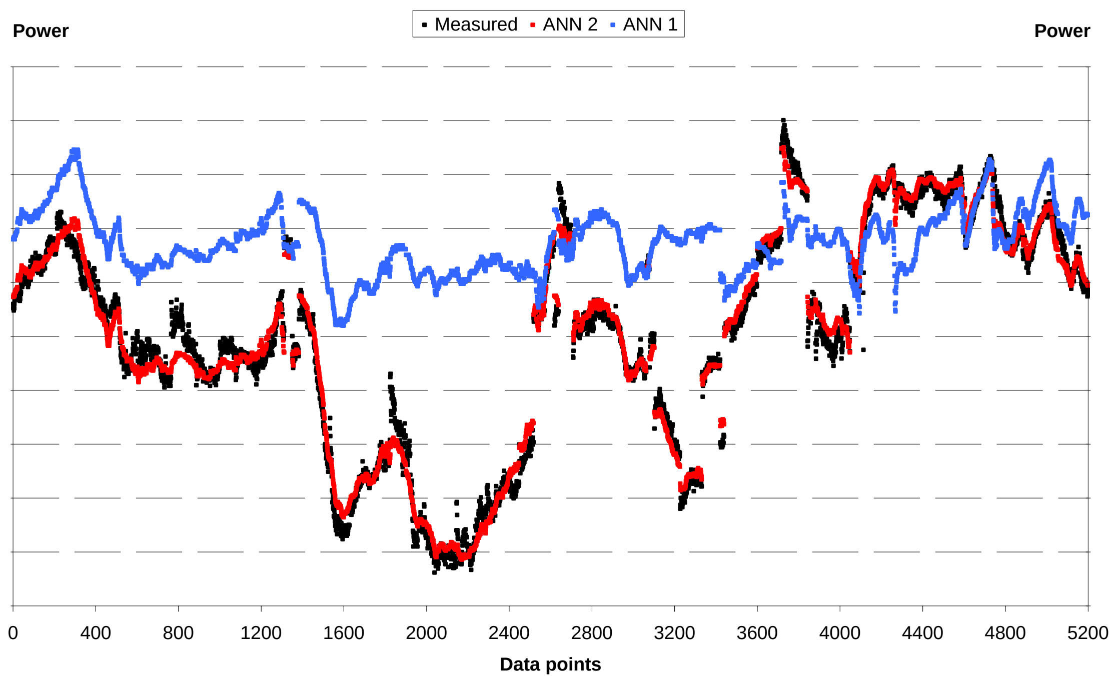

Figure 8. Measured and predicted values of power, with a vertical shift

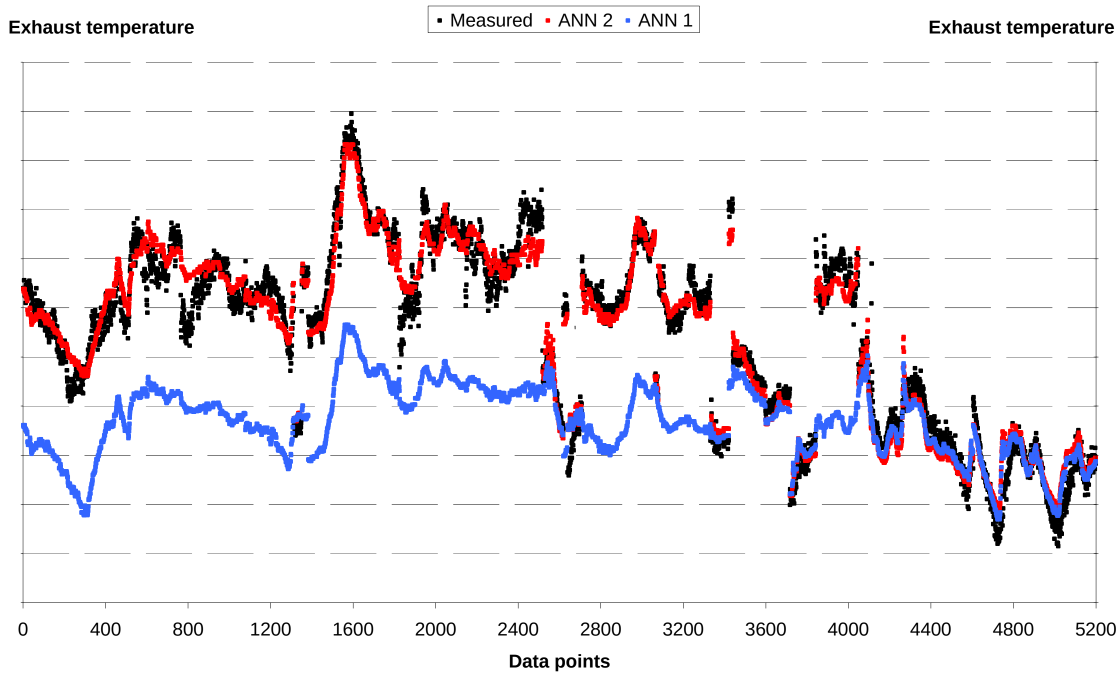

Figure 9. Measured and predicted values of exhaust gas temperature, with a vertical shift

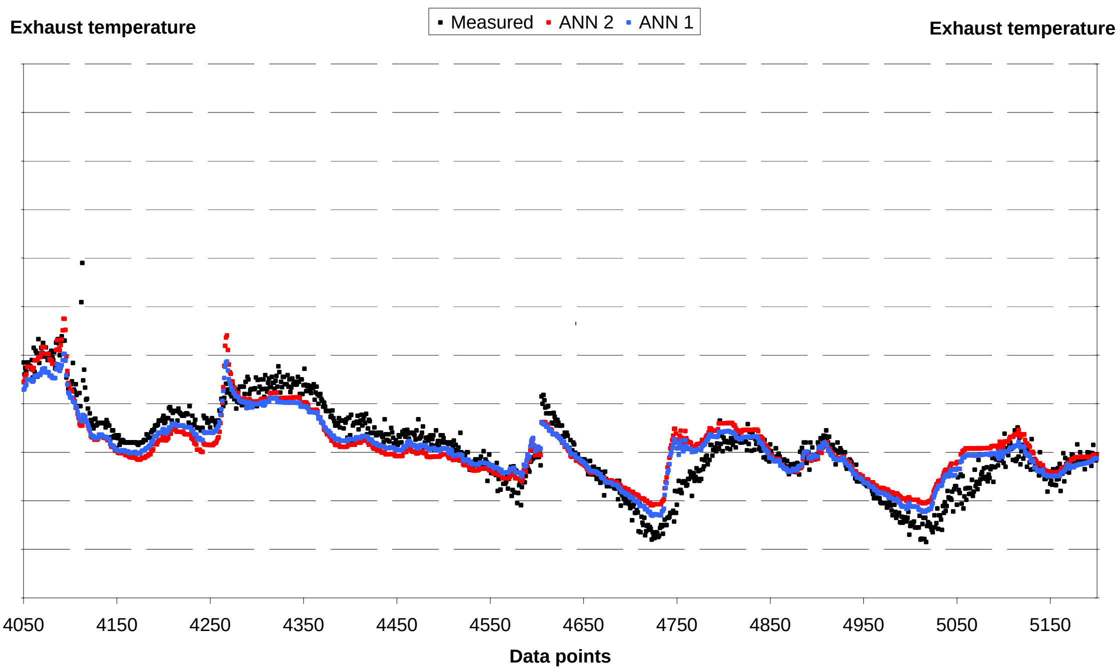

Figure 10. Measured and predicted values of exhaust gas temperature, with a vertical shift and without anti icing operation

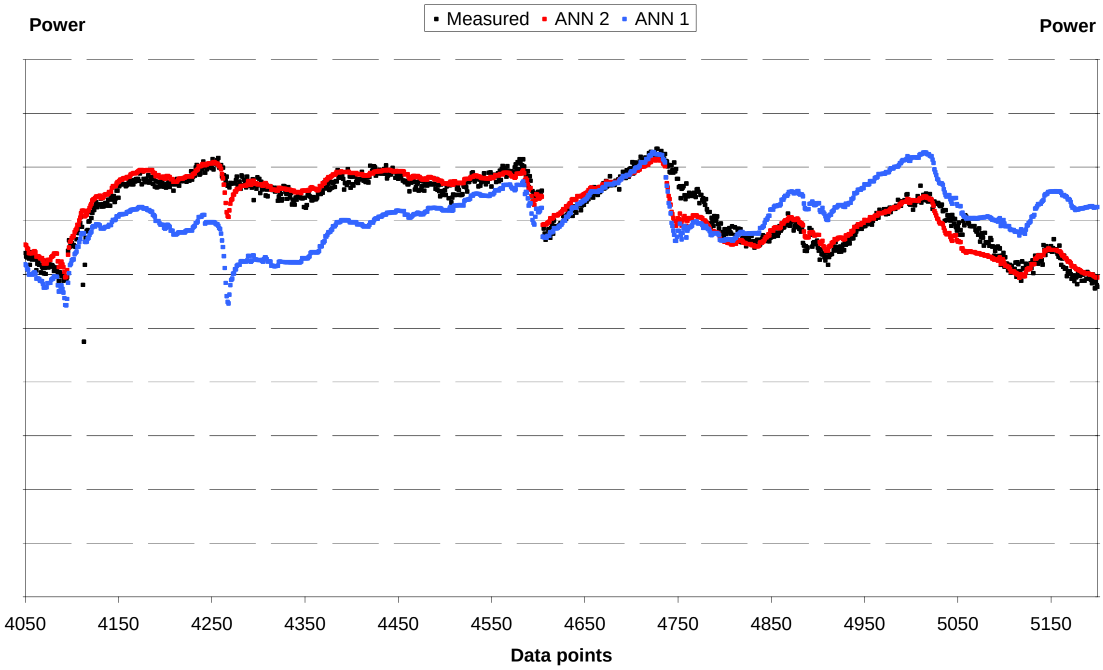

Figure 11. Measured and predicted values of power, with a vertical shift and without anti icing operation

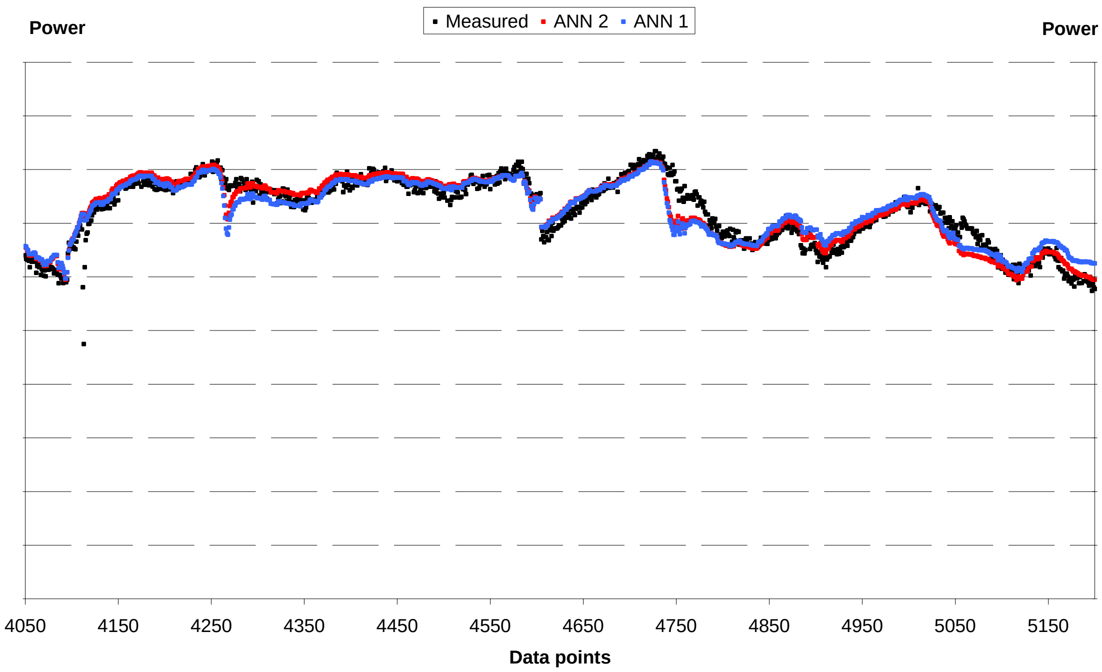

Figure 12. Measured and predicted values of power, with a vertical shift, without anti icing operation and with ISO corrected predictions from ANN 1

4.2 HRSG model; structure and performance

The input parameters for the HRSG ANN are very much similar to the ones in the gas turbine ANN due to the fact that the gas turbine governs the performance of the HRSG. The only difference is that the HRSG is also affected by the district heating return- and delivery temperatures. Both steam, for the steam turbine, and heat, for the district heating grid, is produced in the HRSG.

Table 3. Input and output parameters for the HRSG model

Inputs		*Outputs*	
Operation mode	[1 or 0]	Volume flow rate of district heating water	[m^3/h]
Anti-icing mode	[1 or 0]	Mass flow rate of steam	[kg/s]
Ambient temperature	[°C]	Superheater 1 steam exit temperature	[°C]
Ambient pressure	[kPa]	Superheater 2 steam exit temperature	[°C]
District heating return temperature	[°C]	Stack exhaust gas exit temperature	[°C]
District heating delivery temperature	[°C]	District heating economizer heat	[MW]

The prediction accuracy is seen in Table 4, Figure 13 and Figure 14. The errors are slightly higher than for the gas turbine model but still very acceptable. The reason for the slightly higher prediction errors could e.g. be lower sensor accuracy.

Table 4. Error distribution for predictions

Parameter	<1%	1-2%	2-4%	>4%
Volume flow rate of district heating water	3387	2225	1188	165
Mass flow rate of steam	5757	1019	165	24
Superheater 1 steam exit temperature	6949	16	0	0
Superheater 2 steam exit temperature	6965	0	0	0
Stack exhaust gas exit temperature	6481	464	17	3
District heating economizer heat	4729	1711	453	72

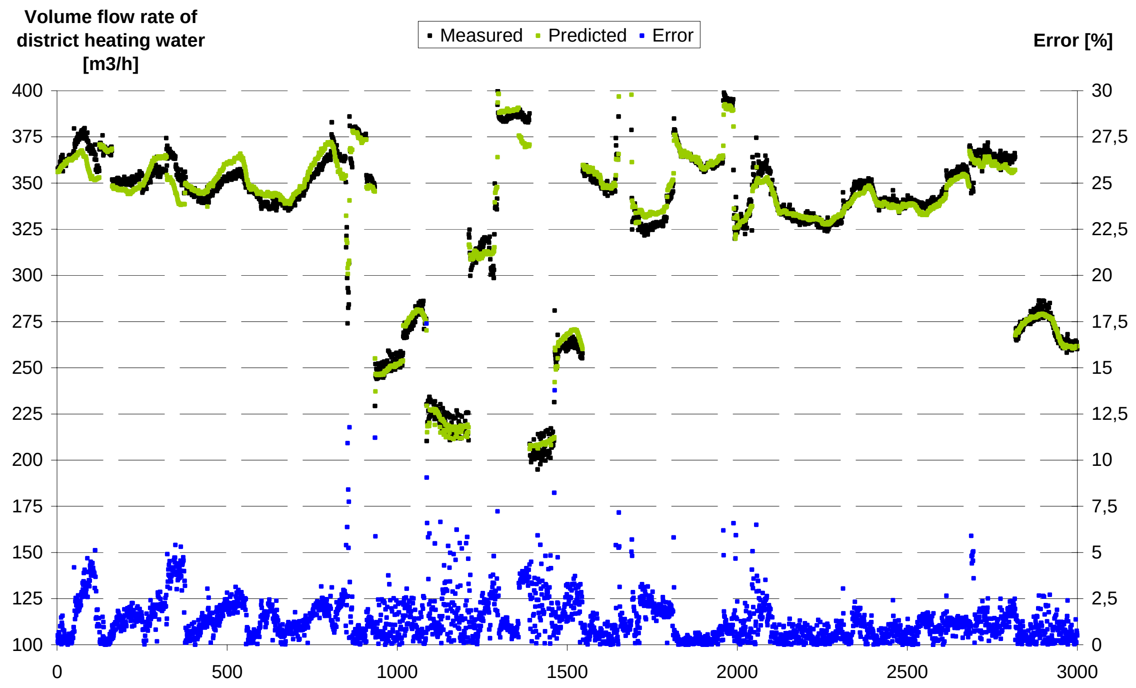

Figure 13. Volume flow rate of district heating water; prediction accuracy

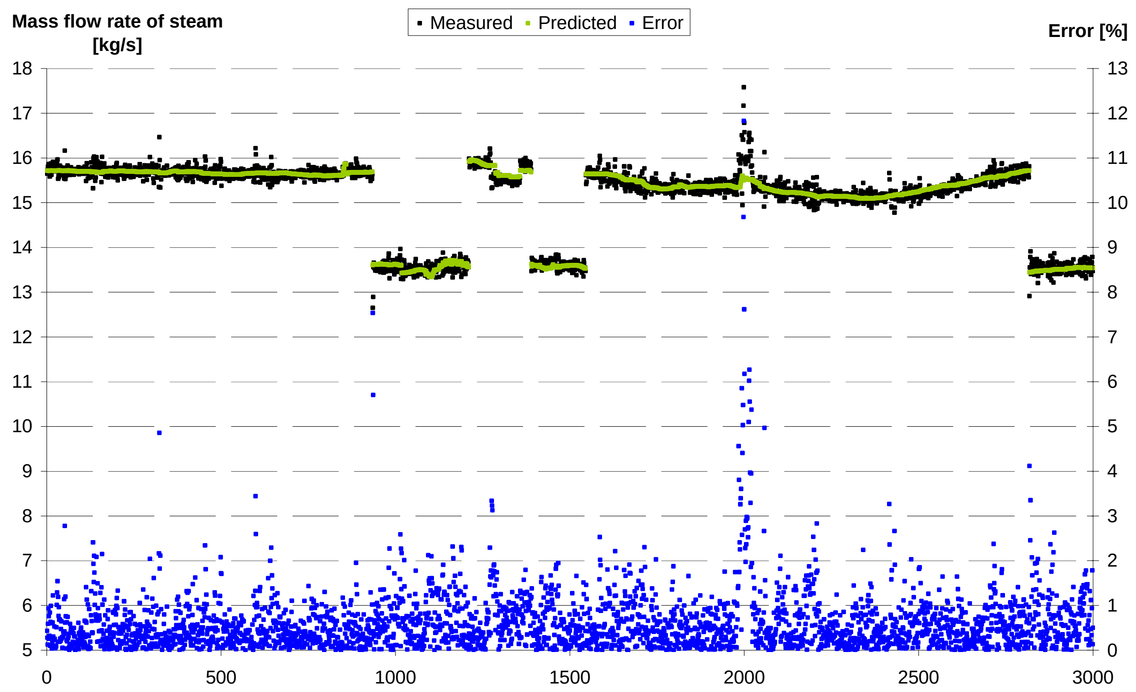

Figure 14. Mass flow rate of steam; prediction accuracy

4.3 Boiler model; structure and performance

Only two input parameters, temperature and pressure of the feedwater, are needed for the boiler model to predict e.g. the steam properties and mass flow rate of pellets.

Table 5. Input and output parameters for the boiler model

Inputs		Outputs	
Feedwater temperature	[°C]	Mass flow rate of steam	[kg/s]
Feedwater pressure	[MPa]	Steam temperature	[°C]
		Mass flow rate of pellets	[kg/s]
		Economizer heat	[MW]

The prediction accuracy is seen in Table 6 and Figure 15.

Table 6. Error distribution for predictions

Parameter	<1%	1-2%	2-4%	>4%
Mass flow rate of steam	2628	229	25	18
Steam temperature	2332	517	51	0
Mass flow rate of pellets	2462	400	30	8
Economizer heat	157	168	389	2186

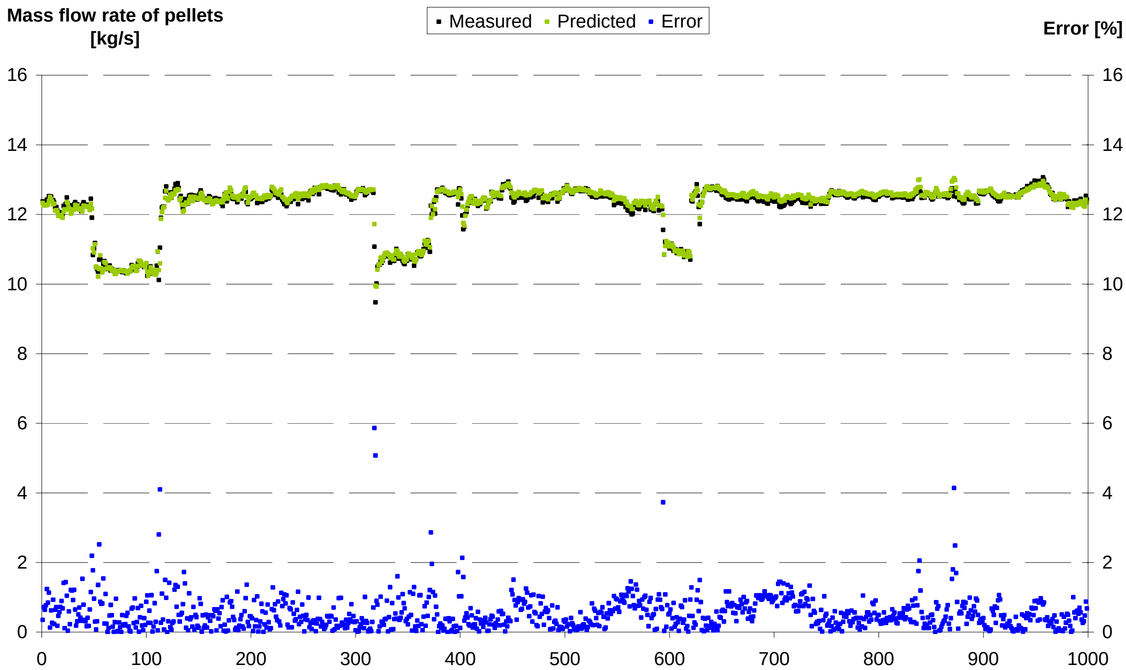

Figure 15. Mass flow rate of pellets; prediction accuracy

4.4 Steam turbine model; structure and performance

For prediction of power output and produced heat in the district heating condensers a number of input parameters are needed. The most obvious input parameters are the steam properties, both from the HRSG and the boiler, along with district heating return- and delivery temperatures. The heat generated in the economizer and heat pump are added as inputs since they are located on the same districts heating circuit as the condensers and thereby also affect the system. The complete list of input and output parameters is seen in Table 7

Table 7. Input and output parameters for the steam turbine model

Inputs		Outputs	
Mass flow rate of steam, HRSG	[kg/s]	Power output	[MW]
Mass flow rate of steam, boiler	[kg/s]	Feedwater temperature	[°C]
Steam temperature, boiler	[°C]	Condenser heat	[MW]
District heating return temperature	[°C]		
District heating delivery temperature	[°C]		
Heat pump heat	[MW]		
Economizer heat	[MW]		

The prediction accuracy is slightly worse for the condenser heat which could be derived from the fact that it is calculated and thereby dependent on several sensors. However, the accuracy is still acceptable which can be seen in Figure 16.

Table 8. Error distribution for predictions

Parameter	<1%	1-2%	2-4%	>4%
Power output	2795	94	10	1
Feedwater temperature	2900	0	0	0
Condenser heat	1655	736	354	155

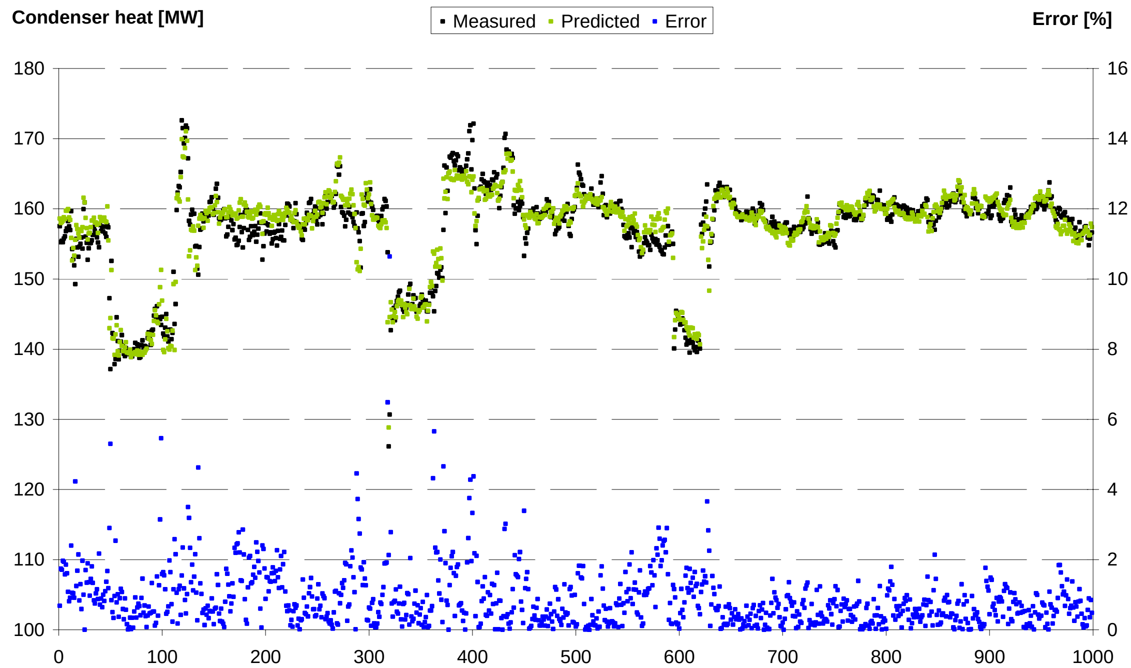

Figure 16. Condenser heat; prediction accuracy

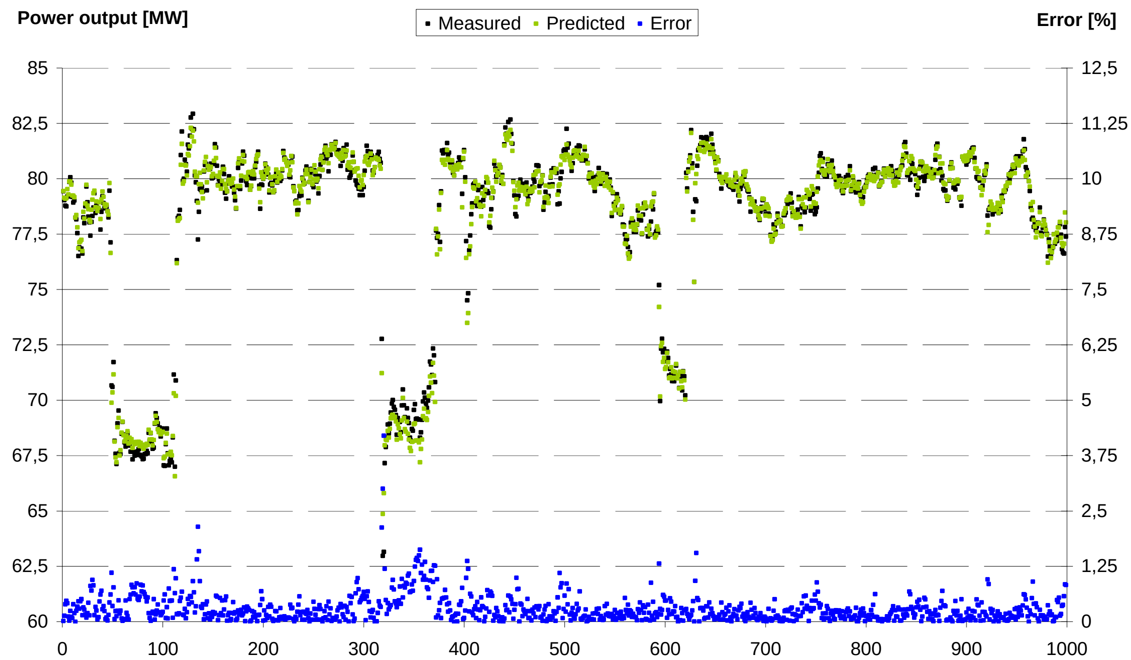

Figure 17. Power output; prediction accuracy

5 Means of controlling the energy sector (in Sweden)

Since a big part of this project is about connecting thermoeconomic calculations to developed ANN models, a description of the means of controlling the energy sector is necessary. The goal is to have a measurement of the production cost, both current and “predicted”, which allows e.g. plant degradation to be economically evaluated. This is possible since the ANN models always predict the performance of a healthy plant and thermoeconomic calculations based on these predictions will indicate what the production cost should be. Not only will the fuel prices and electricity prices affect the production cost but also taxes on fuels and energy production. The different taxes and fees are described in this chapter.

The sulphur tax and NO_x fee will not be described in detail as they do not affect the power plant at Västhamnsverket significantly since it operates on low sulphur fuels (pellets and natural gas) and is state financially neutral regarding NO_x emissions

5.1 Carbon dioxide tax

To reduce carbon dioxide emissions all fossil fuels, such as coal, oil and natural gas, are subject to carbon dioxide tax. However, electricity production is freed of the tax and heat produced in combined heat- and power plants is only subject to 21 % of the tax. Pure heat production is subject to full, 100 %, carbon dioxide tax. Different fuels have different compositions and thereby the carbon dioxide tax varies depending on the fuel.

Table 9. Carbon dioxide tax on various fuels

Fuel type	Carbon dioxide tax
Coal	2317 SEK/tonne
Oil (EO5)	2663 SEK/m^3
Natural gas	1994 SEK/km^3

5.2 Energy tax

Fossil fuels are also subject to energy tax. However, this tax is not based on the carbon content of the fuel but instead on current tax policies. Both electricity production and heat production, in heat- and power plants, is freed of this tax while pure heat production is subject to full energy tax.

Table 10. Energy tax on various fuels

Fuel type	Energy tax
Coal	319 SEK/tonne
Oil (EO5)	750 SEK/m3
Natural gas	243 SEK/km3

5.3 Emission trading

The emission trading is a mean to reduce the emission of greenhouse gases into the atmosphere, in accordance with the Kyoto protocol. At present time only carbon dioxide is included in the system, but more greenhouse gases could be included in the future. The trading is done with carbon contracts where each contract represents the right of emitting one tonne of “fossil” carbon dioxide.

5.4 Green Certificates

Producers of electricity are awarded one green certificate for every megawatt hour of electricity generated with renewable energy sources. “Renewables” include wind-, solar-, wave- and geothermal energy along with certain types of bio fuels and hydro energy. The demand for green certificates is created through a quota system which states the proportion of renewable sources in the energy mix from year to year.

Table 11. Quotation levels for renewable fuels year 2003 – 2015

Year	Quota [%]
2003	7,4
2004	8,1
2005	10,4
2006	12,6
2007	15,1
2008	16,3
2009	17,0
2010	17,9
2011	17,9
2012	17,9
2013	8,9
2014	9,4
2015	9,7

6 Thermoeconomic analysis

The production cost is divided between the two different means of production, i.e. gas turbine/natural gas and solid fuel boiler/pellets. Since these are closely connected through the hybrid configuration, special consideration is needed when calculating the production cost. The method is explained in detail in chapter 6.1 and chapter 6.2.

Generally, electricity and heat production is much more profitable for the solid fuel boiler than for the gas turbine. The gas turbine is only profitable during the coldest winter months when the efficiency is high as well as the electricity prices. To exemplify this, the production cost is calculated, based both on measurements and predictions, for a period with varying operational conditions (such as ambient, district heating, etc.). The price of electricity was varied between 140 and 1000 SEK per megawatt hour and the results are shown in Figure 18. Some incomes are included in the calculations and hence the value for “production cost” turns negative at a certain point.

The gas turbine process reacts faster to change in electricity price thanks to a higher alpha value and with given prerequisites there is a breaking point at 630 SEK per megawatt hour when production becomes more profitable in the gas turbine. However, important to point out is that the gas turbine can not operate in combined cycle without the solid fuel boiler since the amount of steam produced in the HRSG is too small to alone expand in the steam turbine.

Table 12. Inputs for calculation of production cost

Inputs	Price	
Gas price	185	SEK/MWh
Gas grid	35	SEK/MWh
Electric grid	13	SEK/MWh
Carbon dioxide tax	1994	SEK/kNm^3
Energy tax	243	SEK/kNm^3
Carbon contracts	200	SEK/tonne
Pellets price	225	SEK/MWh
Green certificates	170	SEK/MWh

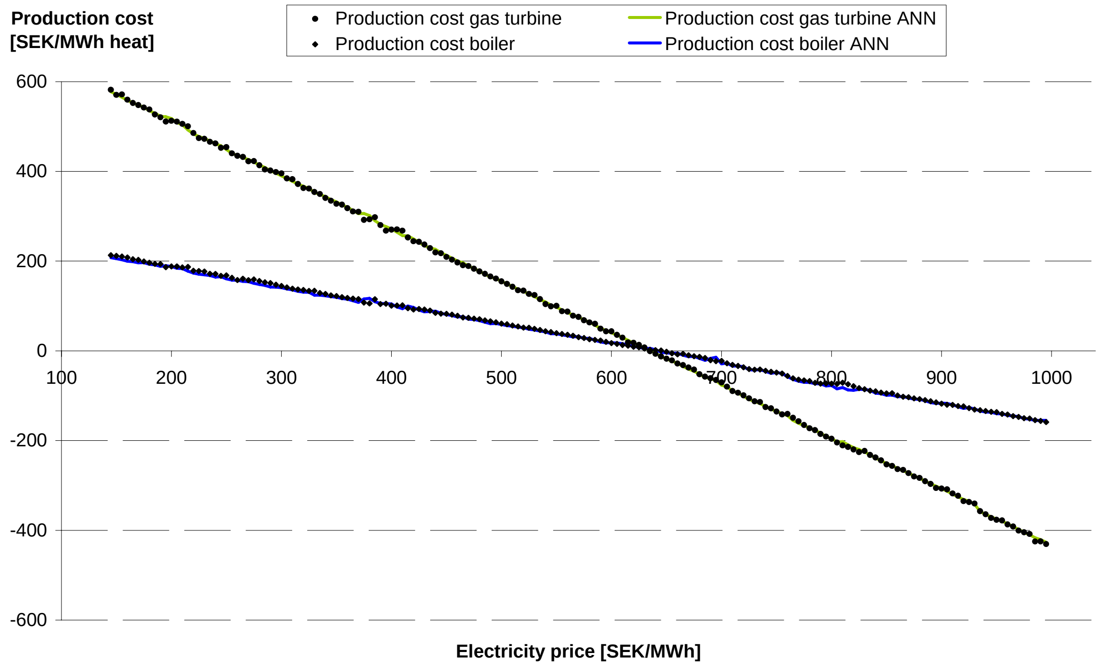

Figure 18. Production cost at varying price of electricity

6.1 Gas turbine

Four larger posts are used to calculate the production cost, i.e. cost of fuel (natural gas), cost of taxes, cost of carbon contracts and income of electricity. The smaller posts are cost of maintenance and cost of tax for auxiliary power used for electricity production. Everything is calculated in SEK per megawatt hour of produced heat.

$$C_{production}\left[\frac{SEK}{MWh_{heat}}\right] = C_{NG} + C_{tax} + C_{cc} - I_e + C_{maintenance} + C_{aux}$$

When calculating the production cost all plant specific parameters are available both as measurements and predictions which enables comparison of “optimal” production cost with actual production cost. Example of parameters used is fuel flow, condenser heat and power output.

6.1.1 Cost of fuel

The cost of fuel is calculated with current gas and grid prices. Heat is produced both directly in the HRSG but also through the condensers connected to the steam turbine since part of the steam is generated in the HRSG.

$$C_{NG}\left[\frac{SEK}{MWh_{heat}}\right] = \frac{\dot{m}_{NG}\left[\frac{MJ}{s}\right]\cdot\left(price_{NG}\left[\frac{SEK}{MWh}\right] + price_{\text{gasgrid}}\left[\frac{SEK}{MWh}\right]\right)}{\dot{Q}_{eco}[MW_{heat}] + \left(\frac{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right] + \dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}\right)\cdot\dot{Q}_{cond}[MW_{heat}]}$$

6.1.2 Cost of carbon dioxide tax

21 % of the heat production is subject to carbon dioxide tax. The amount of fuel used for heat production is calculated by using the alpha value

$$C_{tax}\left[\frac{SEK}{MWh_{vä}}\right]=0.21\cdot\frac{\left(\frac{1}{1+\alpha}\right)\cdot\dot{m}_{NG}\left[\frac{MJ}{s}\right]\cdot tax_{CO_2}\left[\frac{SEK}{kNm^3}\right]}{H_u\left[\frac{kWh}{Nm^3}\right]\cdot\left(\dot{Q}_{eco}\left[MW_{heat}\right]+\left(\frac{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]+\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}\right)\cdot\dot{Q}_{cond}\left[MW_{heat}\right]\right)}$$

The alpha value is calculated as follows:

$$\alpha=\frac{P_{GT}\left[MW\right]+P_{ST}\left[MW\right]\cdot\left(\frac{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]+\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}\right)}{\dot{Q}_{eco}\left[MW_{heat}\right]+\left(\frac{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]+\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}\right)\cdot\dot{Q}_{cond}\left[MW_{heat}\right]}$$

6.1.3 Cost of carbon contracts

An emission factor is used to calculate the amount of carbon dioxide formed when burning natural gas.

$$C_{cc}\left[\frac{SEK}{MWh_{heat}}\right]=\frac{\dot{m}_{NG}\left[\frac{GJ}{s}\right]\cdot emissionfactor\left[\frac{tonne}{GWh}\right]\cdot price_{cc}\left[\frac{SEK}{tonne}\right]}{\left(\dot{Q}_{eco}\left[MW_{heat}\right]+\left(\frac{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]+\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}\right)\cdot\dot{Q}_{cond}\left[MW_{heat}\right]\right)}$$

6.1.4 Income of electricity

The auxiliary consumption is estimated to 3 % when calculating the income of electricity.

$$I_e\left[\frac{SEK}{MWh_{heat}}\right]=0.97\cdot\frac{\left(price_{electricity}\left[\frac{SEK}{MWh}\right]+price_{grid}\left[\frac{SEK}{MWh}\right]\right)\cdot\left(P_{GT}\left[MW\right]+P_{ST}\left[MW\right]\cdot\left(\frac{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]+\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}\right)\right)}{\dot{Q}_{eco}\left[MW_{heat}\right]+\left(\frac{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]+\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}\right)\cdot\dot{Q}_{cond}\left[MW_{heat}\right]}$$

6.1.5 Other posts

The maintenance cost for heat production is estimated to be 4 SEK per megawatt hour of produced heat and for power production 4 times alpha per megawatt hour of produced heat.

$$C_{maintenance}\left[\frac{SEK}{MWh_{heat}}\right] = 4\left[\frac{SEK}{MWh_{heat}}\right] + 4\left[\frac{SEK}{MWh_{heat}}\right]\cdot\alpha$$

Also, full carbon dioxide tax and energy tax has to be paid for 1.5 % of the consumed gas.

$$C_{aux}\left[\frac{SEK}{MWh_{heat}}\right] = 0.015\cdot\frac{\left(\frac{\alpha}{1+\alpha}\right)\cdot\dot{m}_{NG}\left[\frac{MJ}{s}\right]\cdot\left(tax_{CO_2}\left[\frac{SEK}{kNm^3}\right]+tax_{energy}\left[\frac{SEK}{kNm^3}\right]\right)}{H_u\left[\frac{kWh}{Nm^3}\right]\cdot\left(\dot{Q}_{eco}\left[MW_{heat}\right]+\left(\frac{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}{\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]+\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}\right)\cdot\dot{Q}_{cond}\left[MW_{heat}\right]\right)}$$

6.2 Solid fuel boiler

Three larger posts and one smaller are used to calculate the production cost. The larger posts include cost of fuel, income of electricity and income of green certificates. The smaller post is cost of maintenance.

$$C_{production}\left[\frac{SEK}{MWh_{heat}}\right] = C_{pellets} - I_e - I_{greencert} + C_{maintenance}$$

6.2.1 Cost of fuel

$$C_{pellets}\left[\frac{SEK}{MWh_{heat}}\right] = \frac{\dot{m}_{pellets}\left[\frac{kg}{s}\right]\cdot H_u\left[\frac{MJ}{kg}\right]\cdot price_{pellets}\left[\frac{SEK}{MWh}\right]}{\dot{Q}_{cond}\left[MW_{heat}\right]\cdot\left(\frac{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]+\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}\right)+\dot{Q}_{eco}\left[MW_{heat}\right]}$$

6.2.2 Income of electricity

The auxiliary consumption is estimated to 10 % when calculating the income of electricity.

$$I_e\left[\frac{SEK}{MWh_{heat}}\right] = 0.90\cdot\frac{\left(price_{electricity}\left[\frac{SEK}{MWh}\right]+price_{grid}\left[\frac{SEK}{MWh}\right]\right)\cdot P_{ST}\left[MW\right]\cdot\left(\frac{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]+\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}\right)}{\dot{Q}_{cond}\left[MW_{heat}\right]\cdot\left(\frac{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]+\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}\right)+\dot{Q}_{eco}\left[MW_{heat}\right]}$$

6.2.3 Income of green certificates

$$I_{greencert}\left[\frac{SEK}{MWh_{heat}}\right]=\frac{price_{greencert}\left[\frac{SEK}{MWh}\right]\cdot P_{ST}[MW]\cdot\left(\frac{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]+\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}\right)}{\dot{Q}_{cond}[MW_{heat}]\cdot\left(\frac{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]+\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}\right)+\dot{Q}_{eco}[MW_{heat}]}$$

6.2.4 Other posts

The maintenance cost for heat production is estimated to be 8 SEK per megawatt hour of produced heat and for power production 8 times alpha per megawatt hour of produced heat.

$$K_{maintenance}\left[\frac{SEK}{MWh_{heat}}\right]=8\left[\frac{SEK}{MWh_{heat}}\right]+8\left[\frac{SEK}{MWh_{SEK}}\right]\cdot\alpha$$

The alpha value is calculated as follows:

$$\alpha=\frac{P_{ST}[MW]\cdot\left(\frac{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]+\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}\right)}{\dot{Q}_{cond}[MW_{heat}]\cdot\left(\frac{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]}{\dot{m}_{S,Boiler}\left[\frac{kg}{s}\right]+\dot{m}_{S,HRSG}\left[\frac{kg}{s}\right]}\right)+\dot{Q}_{eco}[MW_{heat}]}$$

7 The online graphical user interface (GUI)

The ANN models are integrated on a power generation information manager (PGIM) server and continuously use the latest operational plant data to generate predictions, which are also stored on the server. Both operational data and predictions, historical or current, are accessible through the graphical user interface (GUI), which in return is accessible on all workstations connected to the PGIM server.

The GUI is developed in Excel to be foreseeable and easy to use. It is divided into five sheets where the first one (seen in Figure 19) displays an overview of the entire hybrid plant showing the main parameters for each component together with the production cost for the gas turbine and the solid fuel boiler. Different inputs to the system are also shown, both thermodynamic and economic. The ANN predictions are displayed below their equivalent measured values, which enables evaluation of plant performance. The user is also alerted about any observed difference. The remaining 4 sheets contain detailed information about the specific components of the hybrid plant, i.e. gas turbine, steam turbine, solid fuel boiler and HRSG.

Figure 19. GUI, Main View

The GUI update frequency is adjustable to fit the user needs and at every update the latest values are fetched from the PGIM server. The GUI includes a function for warning and alarm for possible deviations from normal operation together with a tool for parameter analysis. These features are described in detail later in this chapter.

Economical inputs are typed in by the user, except price of electricity which is updated automatically with data from Nordpool.

7.1 Gas turbine

The representation of the gas turbine in the GUI is used to exemplify the detailed component information sheets. Previously described ANN input and output parameters are seen in this view together with calculated values of efficiency and alpha value. Measurements and predictions are always shown together.

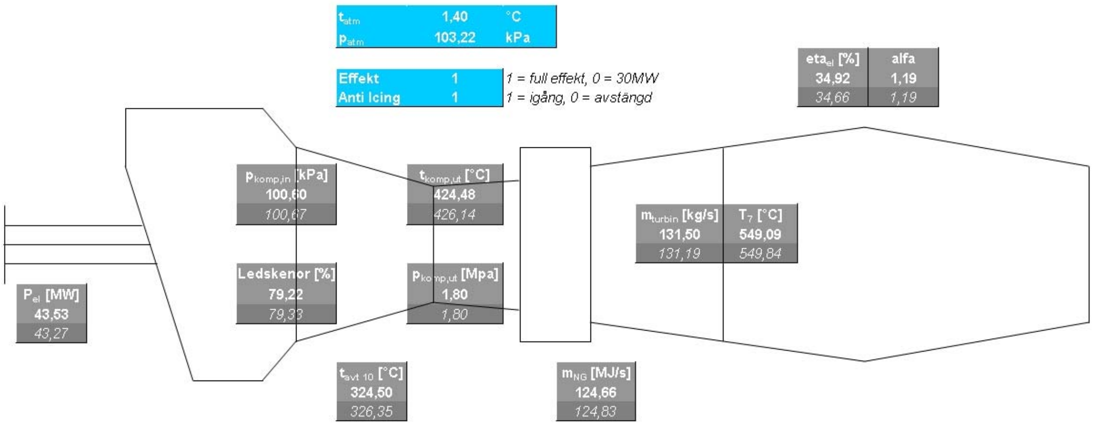

Figure 20. GUI, Gas turbine

7.2 Warning and Alarms

To alert the user on deviations between measurements and predictions a warning/alarm indicator is located on the main view of the GUI. Limits for warnings and alarms are individually specified for each parameter depending on e.g. measurement and prediction accuracy. In Figure 21 two warnings have been generated through lowering the warning limits to 0.5 %. When shifting to the gas turbine view the deviating parameters are indicated with a yellow color, demonstrated in Figure 22. In Figure 23 two warnings and one alarm has occurred.

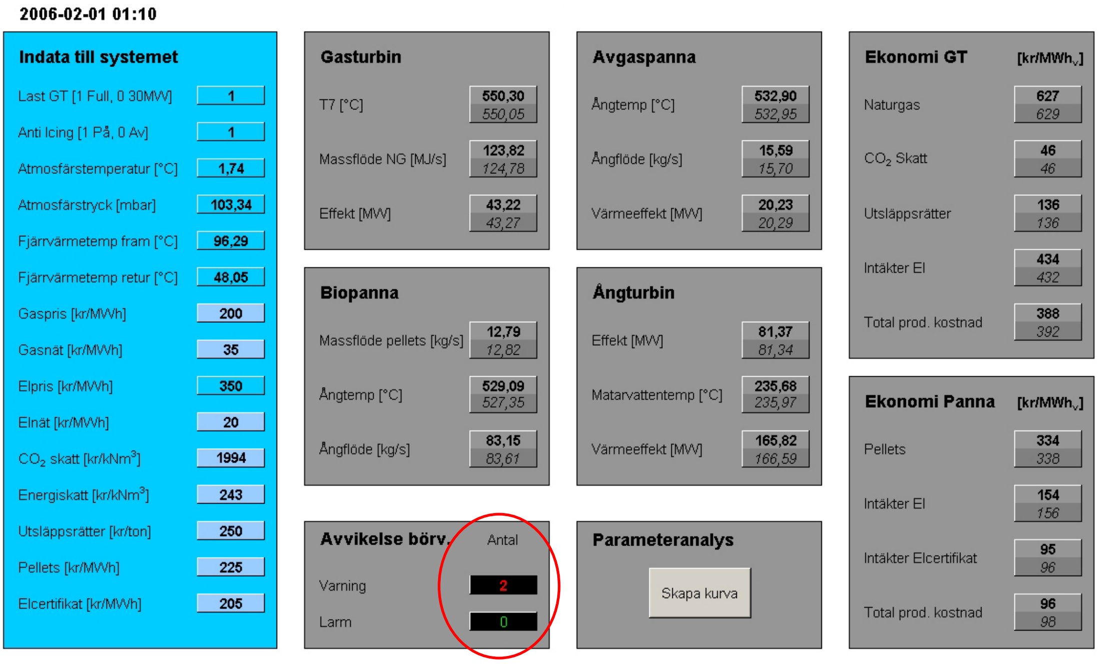

Figure 21. GUI, Main view with two warnings

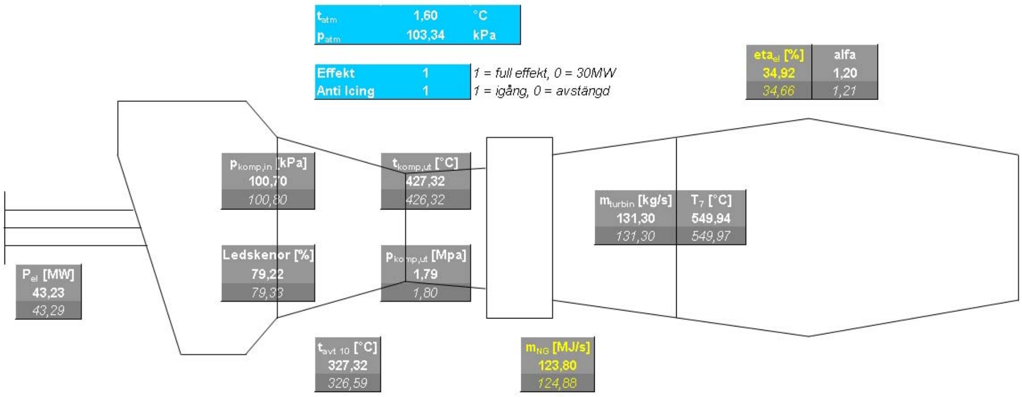

Figure 22. GUI, gas turbine with two warnings

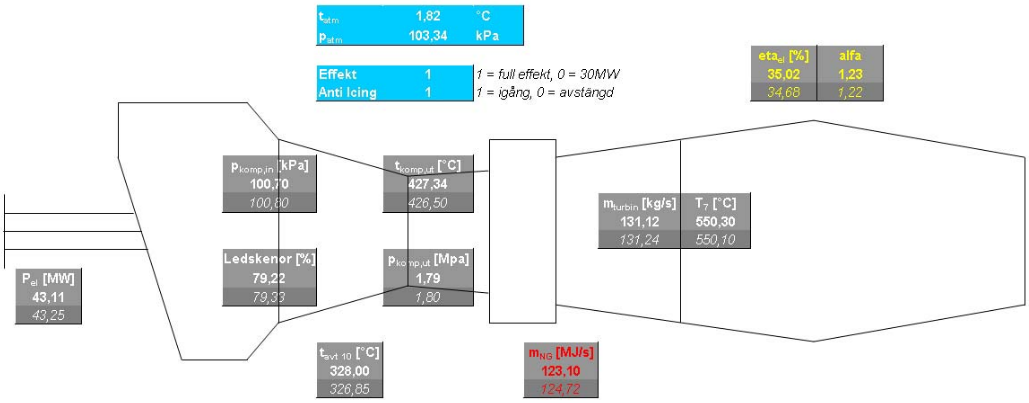

Figure 23. GUI, gas turbine with one alarm and two warnings

7.3 Parameter analysis

With the developed tool for parameter analysis the user is able to, with a few clicks, analyze any chosen parameter for any chosen time interval, demonstrated in Figure 24. After a parameter and interval is chosen a plot, with measurements and predictions, is generated, demonstrated in Figure 25.

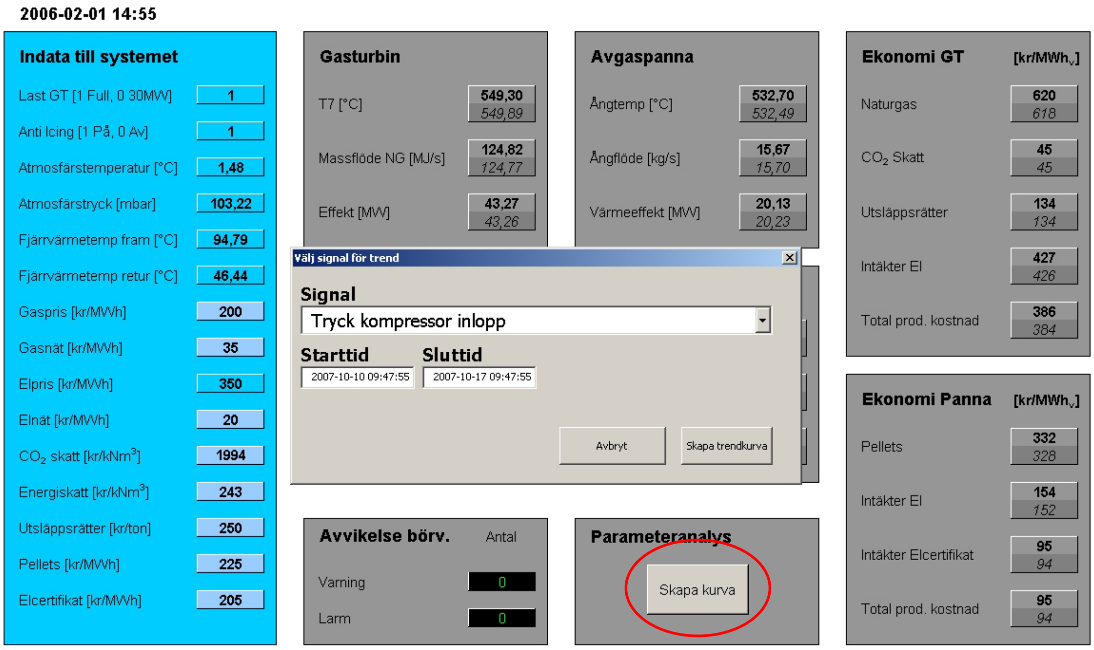

Figure 24. GUI, Parameter analysis

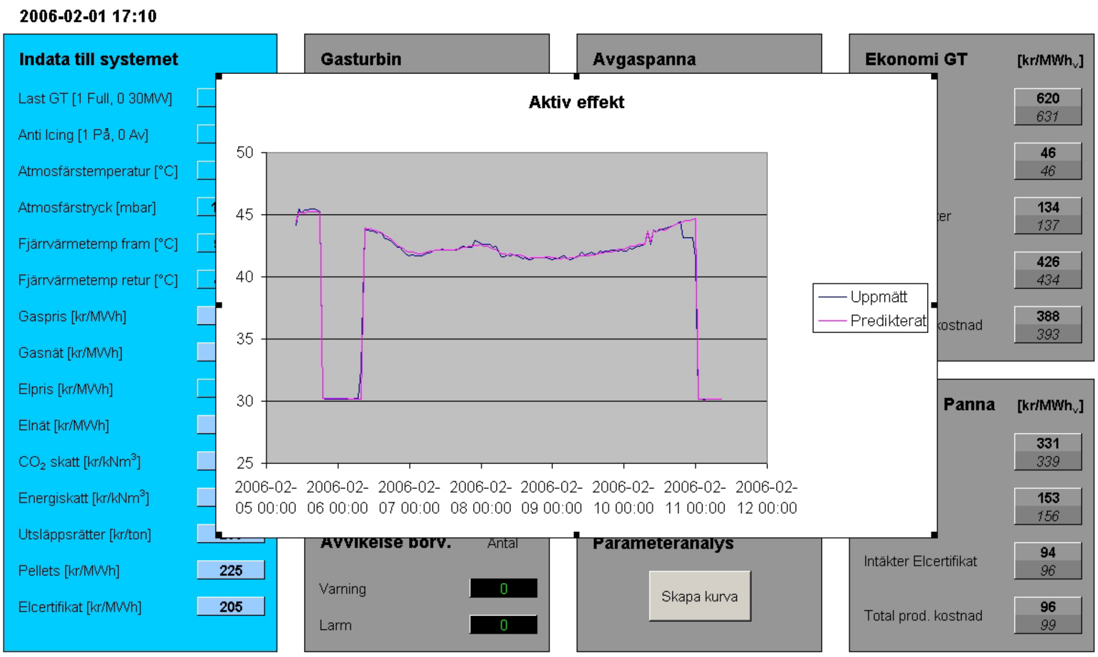

Figure 25. GUI, Plot with measured and predicted values

8 Results

The accuracy of the ANN models is summarized in the tables below.

Table 13. Gas turbine ANN prediction error distribution

Parameter	<1%	1-2%	2-4%	>4%
Power output	7179	58	1	1
Compressor inlet pressure	7239	0	0	0
Inlet guide vanes angle	6489	558	183	9
Bleed temperature	7142	90	6	1
Compressor outlet pressure	7234	3	2	0
Compressor outlet temperature	7223	16	0	0
Mass flow rate of fuel	6649	579	8	3
Mass flow rate through turbine	7229	8	2	0
Exhaust gas temperature	7239	0	0	0

Table 14. HRSG ANN prediction error distribution

Parameter	<1%	1-2%	2-4%	>4%
Volume flow rate of district heating water	3387	2225	1188	165
Mass flow rate of steam	5757	1019	165	24
Superheater 1 steam exit temperature	6949	16	0	0
Superheater 2 steam exit temperature	6965	0	0	0
Stack exit temperature	6481	464	17	3
District heating economizer heat	4729	1711	453	72

Table 15. Boiler ANN prediction error distribution

Parameter	<1%	1-2%	2-4%	>4%
Mass flow rate of steam	2628	229	25	18
Steam temperature	2332	517	51	0
Mass flow rate of pellets	2462	400	30	8
Economizer heat	157	168	389	2186

Table 16. Steam turbine ANN prediction error distribution

Parameter	<1%	1-2%	2-4%	>4%
Power output	2795	94	10	1
Feedwater temperature	2900	0	0	0
Condenser heat	1655	736	354	155

Other results are:

- The comparison between the gas turbine ANN models show good congruence.
- ANN where models successfully installed on PGIM server in Västhamnsverkets computer system.
- A GUI in Excel was developed, integrated and tested at site
- Economical parameters where connected to the ANN models for thermoeconomic analysis.
- An indicator for warnings and alarms was integrated in the GUI
- A tool for parameter analysis was integrated in the GUI.

9 Conclusions

The results show:

- ANN modelling of the hybrid plant can be done with high accuracy.
- ANN models can be integrated in the computer system of a power plant for online prediction of plant performance.
- Predictions from the ANN models are available through all workstations connected to the PGIM server.
- The GUI can be used for condition monitoring and thermoeconomic analysis

The ANN models are specifically developed for the hybrid plant at Västhamnsverket and can therefore not be used directly on other heat- and power plants. However, the method of developing the models, GUI etc. is general.

10 Recommendations and applications

The developed tool for condition monitoring and thermoeconomic analysis can be used by the power plant owner to make maintenance more efficient through a transition towards condition based maintenance.

11 Literature references

[1] Fast M., Assadi M., ”Modellering av hybridanläggning samt utveckling av övervakningssystem för Västhamnsverket baserat på Artificiella Neurala Nätverk”, Värmeforsk rapport, 2006

[2] Fast M., Assadi M., ”Tillståndsövervakning och termoekonomisk driftoptimering av en hybridanläggning med artificiella neurala nätverk”, Värmeforsk rapport, 2007

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