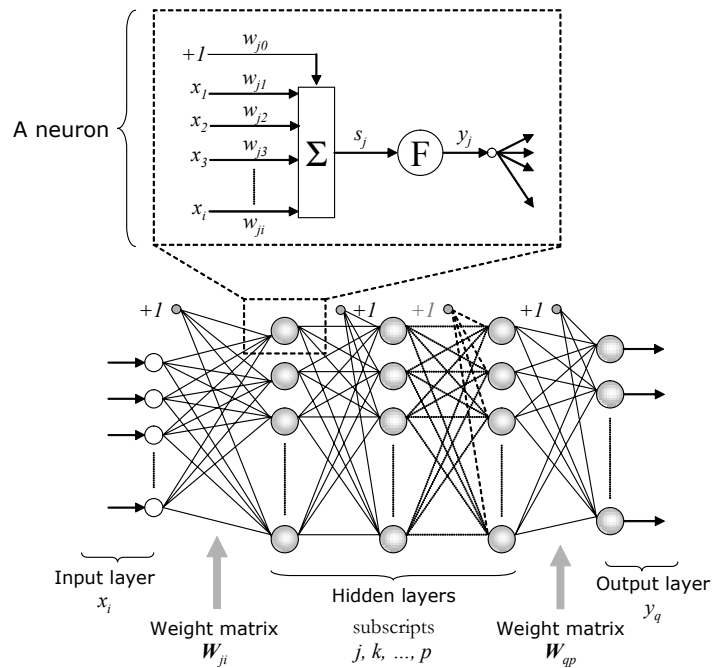*Rapport SGC 146*

# Statistical modeling and diagnosis of Turbec T100 CHP units

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Pernilla Olausson & Mohsen Assadi
Institutionen för värme- och kraftteknik
LUNDS TEKNISKA HÖGSKOLA

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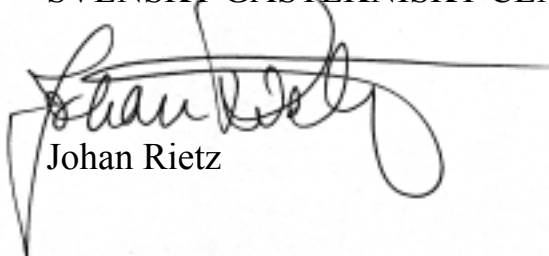
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Johan Rietz

# Executive summary

During the last decade the deregulated electricity market has been evolving in the western countries. This has changed the market considerably for the electricity producers as well as the consumers, resulting in an interest for distributed small-scale electricity generation. One of these small-scale electricity production units is the microturbine, which today is manufactured in the size between 30 to approximately 500 kWe. These units are excellent for self-support in electricity and heat for small businesses, as well as usage of earlier considered waste, which is reformed to fuel for combustion in these units. However these small-scale units have to be very cost effective and they do not have the possibility to carry personnel costs or a high rate of maintenance.

The need of a well functioning Condition Monitoring System (CMS) is therefore of great importance to make these units profitable in the long run. One tool that has been proven to be both fast and does not require large computational memory is Artificial Neural Networks (ANNs). In this report a type of ANN denominated Feed-Forward Neural Network (FFNN) has been tested for modeling of the Turbec microturbine Combined Heat and Power (CHP) unit, T100. This modeling is to be looked upon as a first stage in a three stage rocket, leading to a CMS including both sensor validation and fault diagnosis. This type of ANN utilizes the black-box approach, matching inputs with the desired outputs. By using available measurements for the T100 units, the ANN can be trained to learn the characteristics and behavior of the microturbine statistically, i.e. no physical relationships are involved in this model.

The general idea here was to look at the possibility of formulating a general ANN model for the whole fleet of microturbines, which could be delivered with every new engine. The CHP units, which data was used for this modeling were two units situated at Kastrup in Denmark. This choice was made since the engines have been operating the same amount of time, the conditions that they experience are similar, and there have been no major overhauls to any of the engines. First the modeling approach that was used was to train an FFNN with data from only one of these units, to establish a certainty that it is possible to use the available data for this task. The result of this study was that a maximum modeling error of 4.7% was reached, with an average error of 1.2%. This result was considered to be satisfactory, so the test was carried further, introducing the data from the other engine to the network. The result in this second attempt, however, increased the maximum modeling error to above 15% and there were a number of points above 10%. Since this result was not considered to be adequate, the third strategy was to train the FFNN with data from both engines simultaneously. Some improvement was obtained by this measure, but still it could not be comparable to the result that the individual model entailed. A conclusion that was drawn here was that the ANN models are preferably developed for each engine individually, i.e. it was not possible to formulate a general ANN model. However, it could be worth the effort trying to train a general ANN with the use of data from the performance tests, carried out for each engine before delivery. This general model would then be sent with the engines and then be updated continuously on-line during for instance the first operation year, making the model more individual and accurate.

A question that comes to mind when modeling is considered is of course, what is satisfactory modeling results? This is often a question for the user of the model, but the quality of the measurements is always an issue that has to be considered. In this case the error distributions of the measurement probes were given by Turbec for a number of parameters used in the ANN model. How do these propagate through the model? When using physical relationships and equations during modeling it is possible to calculate the error distribution of the outputs. However, when ANNs are considered it is not as simple. A test was carried out, manipulating the data within the margin of errors of the measurements to investigate the propagation through the network. Interesting results that were obtained here was that the ANN is that the rate of measurement error propagation is somehow proportional to the modeling error. This means that a badly trained network is influenced vastly by the measurement errors of the inputs of the network. This is however an issue that has to be further investigated to be statistically stipulated.

To conclude the study and to show on potential future work the following could be said. It is possible to use ANN for modeling of the Turbec T100 CHP unit, even though the choce of sensors and the measurements carried out were not intended for this type of modeling. Once the model is trained and fixed it is very fast since no iterations are necessary and hereby computational memory of only a few kB is used of the model. The model could, however, never be better than the data it is trained with. For the future there are some questions that. The model has potential of being much more accurate and a close collaboration with the manufacturer would introduce the possibility of identifying and refining the measurement setup, and hereby also the network. A goal of modeling error of less than one percent is desirable, since this would introduce the opportunity of including the ANN model with the control system. It is also the authors' opinion that to obtain an ANN model with lower error, probably additional parameter measurements have to be included. Measurements of mass flows of air and gas, and inlet temperature of the district heating water, and gas composition could be useful for a refinement of the ANN model.

To be able to formulate an all-inclusive CMS, formulation of the faults and degradation together with modeling or measuring of the same has to be carried out. This is considered as possible if a better model of the system is prepared, either by utilizing the existing physical model from Turbec or by additional measurement logs from the existing CHP units. This would lead to an effective CMS system which is both cheap and fast, and within the scope of small-scale energy production.

# Table of Contents

# 1  Introduction

During the last decade the deregulated electricity market has been evolving in the western countries. This has changed the market considerably for the electricity producers as well as the consumers, resulting in an interest for distributed small-scale electricity generation. These small-scale units have also become interesting due to environmental taxes and fees, and political incentives.

One of these small-scale electricity production units is the microturbine, which today is manufactured in the size between 30 to approximately 500 kWe. These units are excellent for self-support in electricity and heat for small businesses, as well as usage of earlier considered waste, which is reformed to fuel for combustion in these units.

The work carried out in this report has been made possible by data from the EU-project Optimised Microturbine Energy Systems (OMES).

## 1.1  Background of the OMES project

The participants in the OMES project are Dansk Olie og Naturgas A/S (DK), GASUM OY (SF), Svenskt Gastekniskt Center AB (S), Den Norske Stats Oljeselskap a.s (N), Vattenfall AB (S), and Turbec AB (S). As sub-contractors to these contractors are among others, the universities NTNU (N), LTH (S), and AAU (DK).

The project contains development and demonstration work concerning design, installation and operation of 18 micro gas turbine based CHP units in different applications including development of necessary control and peripheral equipment. The same core engine/CHP unit of 100 kWe (Manufacturer Turbec, Sweden) will be used as basis for all installations.

Data on energy efficiency, availability, emission, O/M costs etc. will be recorded and reported over the 1-2 year's operation period. The data obtained will form a basis for possible energy savings and reduced emission through the use of efficient microturbines in CHP applications.

## 1.2  Objective

The objective with this report is to summarize the measurements made available to LTH (9 CHP microturbine units) and to investigate their usefulness when trying to model the CHP units with Artificial Neural Networks (ANNs). Modeling of the CHP unit with ANN could seem as an exaggerated measure, since the physical modeling of this engine is often possible. However this modeling should be looked upon as a first necessary stage in a future three-stage rocket, where process identification, sensor validation, and fault diagnosis all are to be carried out by ANNs.

## 1.3 Report outline

This report has as its main target to show on the possibilities of using ANNs as modeling tools for process identification. Since ANN cannot be considered as a common knowledge a short survey of this tool is presented in section 2. In section 3 the available measurements are investigated and commented further, as well as overhauls made for some of the microturbine units. This section is then followed by the description of the developed ANN models used for identification of the microturbine units in section 4. Finally concluding remarks regarding the results are elucidated in section 0, followed by some words about the future work in section 0.

# 2  Artificial neural networks

The technology of Artificial Neural Networks originates from the structure of the biological nervous system and the function of the human brain. This biological system is very complex with non-linear, parallel information processing, which has the capability of representing, interacting with, and adapting to the surroundings. To be able to translate this behavior into a model, simulating a power process for example, would be very useful.

Some basic tasks where ANNs have been shown to be useful are:

- ✓ function approximation – process identification
- ✓ fault diagnostics – pattern recognition
- ✓ estimation of degradation
- ✓ sensor validation
- ✓ control
- ✓ time-series prediction
- ✓ dynamic system modeling

The first task, function approximation, can be used as an engineering tool to model components and/or entire processes. In all the work carried out at LTH regarding process modeling/identification using ANN [1, 3, 5, 6, 12], the network architecture called multi-layer, Feed-Forward Neural Network (FFNN) has been utilized successfully with backpropagation as the learning algorithm. This type of network architecture has also been used at LTH for sensor validation [9] and fault diagnosis [4]. Due to this, an explanation of what FFNN is and how it mathematically works are given below in section 2.2.

## 2.1  Characteristics of ANN

As mentioned, artificial neural networks are able to solve non-linear, multivariable tasks, which is a great advantage for this tool compared to physical modeling, where this could be a difficulty. ANNs, which are modeled with a trail-and-error technique, are very fast models once they are trained and do not require much computational memory. This is due to the fact that no iterations are required within the fixed model. ANN is also a tool that is useful for a wide range of applications and for different system configurations.

However, the disadvantage with ANNs is that measured data is needed for the training of the model, which means that neural networks are not used for pre-design of heat and power systems. Once the model is trained it is also only valid for the specific configuration of the system. This means that if additional components are added or if the system is altered in any way, the model is no longer valid. The ANN model is also not better than the data it has been trained with.

## 2.2 Feed-forward neural networks

A feed-forward neural network contains a number of neurons, i.e. computational units, which are connected to each other, see Figure 1. The information or input from the surroundings is passed forward from the input layer of the network through the connections and summarized in the next layer of neurons. In this second layer, the total summarized input, also called effective input, $s_j$, is propagated through an activation function, which produces an output, $y_j$. This output is then either one of the outputs of the network or it is propagated further as an input to the next layer. This feed-forward process is shown in Figure 1, where the close-up of a single neuron showing the mathematical procedure carried out in a hidden neuron (summation of the inputs and calculation of the output value, $y$).

When building/programming a neural network it has to be trained with input-output patterns for the network to recognize the process at hand. This means that a selection of inputs and outputs has to be carried out. The selection of outputs is up to the user of the network, but the choice of inputs is more difficult and of most importance. The inputs have to include all parameters that affect the outputs that are to be predicted. When a vast amount of measured parameters are available, the best way of choosing the inputs is to use a-priory knowledge together with something called pruning. The parameters often used as inputs are the parameters that cannot be controlled by the operator, such as ambient conditions, but also the parameters that are directly controlled by the operator, such as load or a temperature.
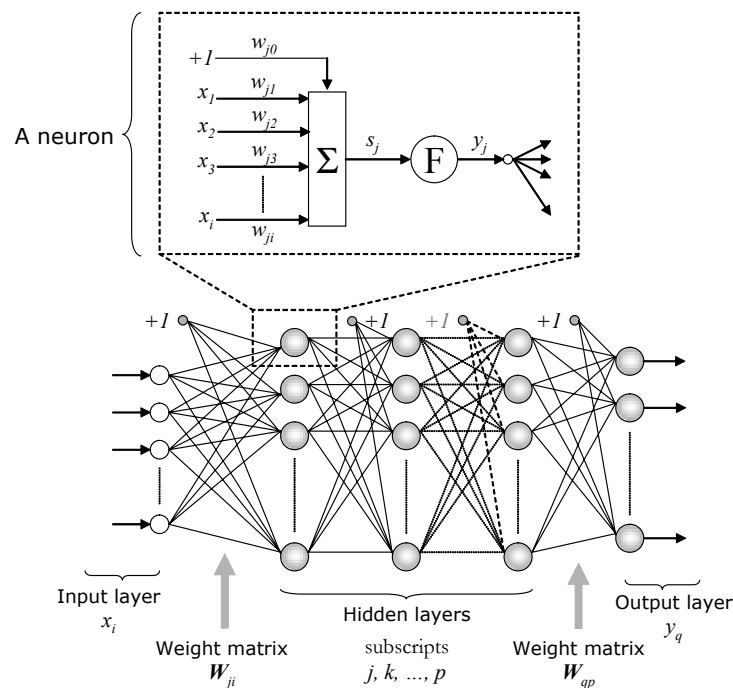


Figure 1, Multi-layer feed-forward neural network.

Pruning is a trial-and-error procedure where the inputs are included or excluded one by one through training of different neural networks. One example of how this pruning is carried out is to introduce all parameters that are not outputs as inputs. By excluding one of these input parameters and train the network without it, the output result of this new network is compared with the result of the network that included all the input parameters. If the prediction result is unchanged or better when a parameter is excluded, this input parameter can be considered as unimportant for the model and be excluded, i.e. pruned.

### 2.2.1 Training of the network

The term training has been unexplained until now and here follows a short description of what training involves and why this is necessary to make the network model useful. As mentioned earlier, input-output-patterns are introduced to the network for it to learn the underlying physical relationship within the pattern. As an energy related example, consider Figure 2, where the ANN is shown as a black box to the left with gas turbine related parameters as inputs and outputs. To find the relationship between the inputs and the outputs, a hidden layer of neurons as well as weights between the input and hidden layer, and between the hidden and output layer has to be present. Before the training can start the values of the inputs and outputs have to be normalized. This due to that the magnitude of the different parameters otherwise would reflect on the values in the weight matrices, which could cause computational problems.

When building the ANN-model, the values in the weight matrices are randomly initiated, which leads to the fact that when the inputs are passed through the network for the first time, the prediction of the outputs will be incorrect, i.e. errors between the calculated and the target output values are present. To find the right values of the weight matrices, a training procedure has to be carried out. When using the multi-layer, feed-forward neural network architecture, often the backpropagation learning algorithm is used. To be able to use this algorithm a cost- or error function has to be used. This error function could be the least mean square error function, which then has to be minimized during training for the best neural network performance. The backpropagation algorithm can then simply be said to update the weights by a backward pass of the gradient decent of the error function in respective to the weights. For more reading about the backpropagation learning algorithm, the text books by Haykin [8] and Bishop [7] is recommended as well as the theses by Olausson [11] and Arriagada [1].
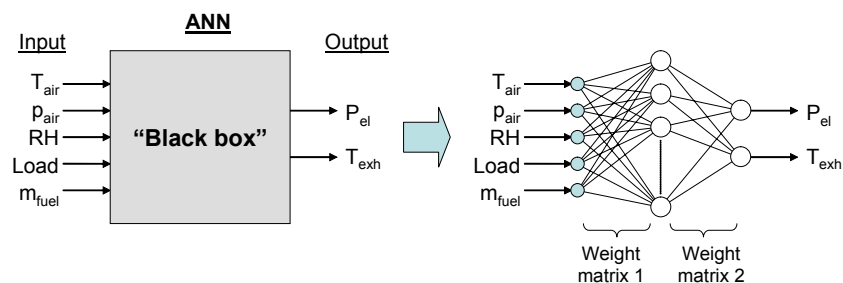


Figure 2, Example of a fully connected multi-layer, feed-forward neural network model
(T: temperature, p: pressure, RH: relative humidity, m: mass flow, P: power,
el: electricity and exh: exhaust fumes).

During the training, the number of neurons in the hidden layer is altered in a trial-and-error manner. Another parameter that is possible to vary during the training phase is the number of epochs that the input-output-patterns are presented to the network. The data that is available is often split into three sections; training data, cross validation data, and test data. The training data and the cross validation data is used to train and optimize the network, while the test data is unseen data that is used for final validation of the possibility of generalization of the neural network. By introducing all the input-output-patterns of the training data to the network, one epoch has been realized. The training patterns are then shuffled and introduced again, and so on through the whole training. If too many epochs are used during training, the network can become overtrained, which means that the generalization ability of the network is lost although the training error is small. By utilizing the cross validation data set to compare the training error with the generalization error, obtained with the cross validation data set, the network can be prevented from being overtrained.

### 2.2.2 The final choice of network

Once the network has been trained and the network has reached the acceptable error-limit, the weight matrices are fixed. The allowed magnitude of errors is up to the user to set, and are of course enormously dependent on the data that has been available during the training of the network. If the data are measurements from a real process, the network could never produce better results than the measurement error levels. This also goes for the width of the data that the training data withhold. If for instance measurements are available for ambient temperatures between $0 - 20$ °C, the interpolation of network patterns between these limits are applicable. However extrapolation with the neural network has to be handled with care. Often some extrapolation is possible depending on the normalization of the data in the network, but it is preferable to have as broad range of data available already during the training.

A fixed neural network contains the weight matrices, the normalization and de-normalization vectors together with the transfer/activation functions, so the memory size needed for this fixed model is only a few kilobytes. This would make this type of model suitable for inclusion with the control- and/or log-system. The calculations that are carried out with neural networks are also very fast, since the calculations do not involve iterations of any kind [12]. The data is solely sent forward through the vectors, matrices and functions, producing the outputs.

# 3   Survey of Available Measurements

In this section available measurements are investigated, as well as, a description of the Turbec T100 microturbine. This for the reader to understand the design of the CHP unit and what measurements that are available for ANN-modeling.

## 3.1  Description of the Turbec T100

The Turbec T100 microturbine is a combined heat and power (CHP) unit with a power production of 100 kWe. The complete physical setup of the CHP unit is shown in Figure 3.



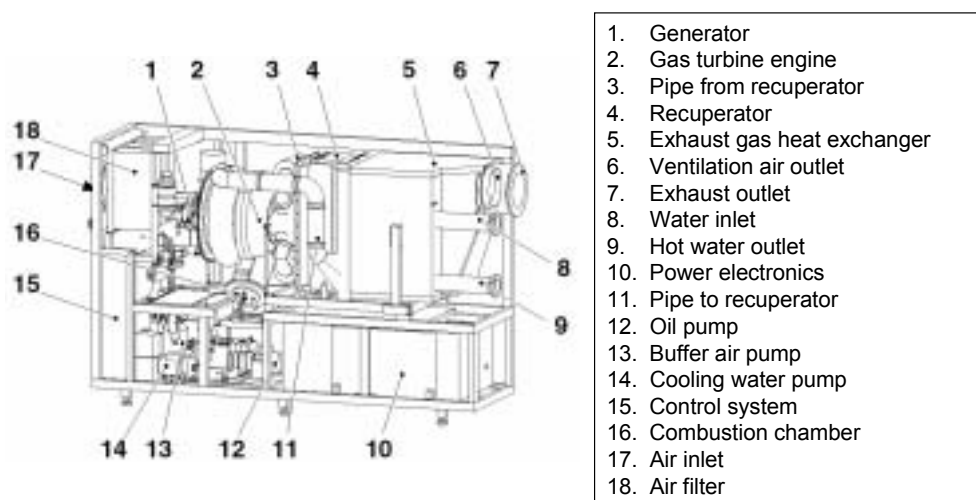| | |
|---|---|
| 1. | Generator |
| 2. | Gas turbine engine |
| 3. | Pipe from recuperator |
| 4. | Recuperator |
| 5. | Exhaust gas heat exchanger |
| 6. | Ventilation air outlet |
| 7. | Exhaust outlet |
| 8. | Water inlet |
| 9. | Hot water outlet |
| 10. | Power electronics |
| 11. | Pipe to recuperator |
| 12. | Oil pump |
| 13. | Buffer air pump |
| 14. | Cooling water pump |
| 15. | Control system |
| 16. | Combustion chamber |
| 17. | Air inlet |
| 18. | Air filter |

Figure 3, Product description of the T100 microturbine [13].

This small-scale CHP unit measures 840 x 1920 x 2900 mm in volume and has the weight of 2 000 kg. Broadly this system consists of a gas turbine engine for power production (centrifugal compressor and a radial turbine), a heat exchanger network for heat production (recuperator and exhaust gas heat exchanger) together with piping and filters as well as power electronics, which all is fitted into the given volume.

These types of small-scale CHP units do not have the possibility of carrying personnel costs, so today a control system is delivered with the unit, operating the system at full load (site level: 0 m above sea level, 15 °C, 60 % relative humidity and natural gas as fuel). The performance data for this unit at full load are as stated in Table 1. All engines considered in this report are utilizing Danish natural gas as fuel, but there is also a possibility of utilizing digester gas (> 18 MJ/Nm3) in these units. The bearings in these units are oil bearings, which mean that lubrication oil has to be cooled and pumped in the system.

Now that the T100 CHP microturbine unit has been comprehensively described, regarding the measured parameters that will be discussed in section 3.2.

Table 1, Performance data for T100 [13].

| | |
|---|---|
| Fuel gas pressure, bar(g) | >6 |
| Electrical output[*], kW | 105 (±3) |
| Electrical efficiency, % | 30 (±1) |
| Total efficiency, % | 78 (±1) |
| Thermal output (hot water), kW | 167 (±5) |
| Fuel consumption, kW | 350 |
| Exhaust gas flow, kg/s | 0.80 |
| Exhaust gas temperature, °C | 85 |
| Shaft speed, rpm | 70 000 |
| Noise level, dBA (at 1 meter) | 70 |
| $NO_x$-level, ppmv | <15 |
| CO-level, ppmv | <15 |

Below in Figure 4, a schematic thermodynamic process scheme is shown with selected pressures and temperatures.
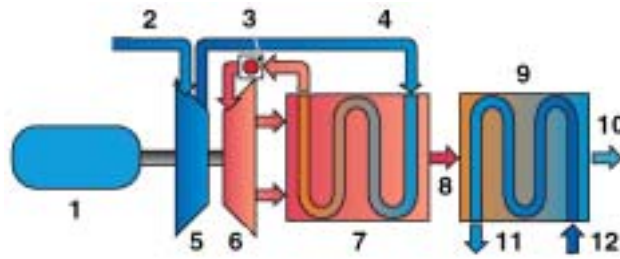


1. Generator ➔ rotating permanent magnet, water-cooled, 2 oil-bearings
2. Inlet air
3. Combustor chamber ➔ lean pre-mix, electrical igniter for start
4. Air to recuperator
5. Compressor ➔ radial centrifugal design, $\pi \approx 4.5{:}1$
6. Turbine ➔ radial design, $T_{in} \approx 950$°C, $p_{in} \approx 4.5$ bar
7. Recuperator ➔ close to atmospheric pressure, $T_{exh,in} \approx 650$ °C
8. Exhaust gases ➔ $T \approx 270$ °C
9. Exhaust gas heat exchanger ➔ gas-water, counter-current
10. Exhaust gas outlet ➔ $T \approx 85$ °C
11. Hot water outlet
12. Water inlet

Figure 4, Schematic process scheme of the T100 power and heat production
(*T*: temperature, *p*: pressure, $\pi$: pressure ratio) [13].

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[*] Performance with a high pressure gas source. With a low pressure gas source a fuel gas compressor is needed, which changes the performance; net electrical power output of 100 (±3)kW, net electrical efficiency of 28.5 (±1)%, and net total efficiency of 76.5 (±1)% [13].

## 3.2 Operational 'everyday' measurements

The measurements that have been received are for totally nine microturbines. Below these CHP units are named together with the number of operating hours and at which hour the log of the engine was started according to the measurement-files. All these CHP units are identical regarding the withholding components. However, the 'Dong-unit' has been altered along the way and has some difference in the location of the components in the CHP unit casing.

|  | Starting log-hour | Total number of operating hours |
|---|---|---|
| T10018 Dong (DK) | 1 400 | 20 283 |
| T10026 Kävlinge (S) | 37 | 12 625 |
| T10095 Kastrup (DK) | 262 | 5 264 |
| T10096 Kastrup (DK) | 300 | 5 260 |
| T10107 Torpgården (S) | 178 | 4 644 |
| T10108 Torpgården (S) | 153 | 4 694 |
| T10109 Hastrup Venge (DK) | 939 | 7 539 |
| T10110 Tigervej (DK) | 4 | 3 140 |
| T10113 Stenlökke (DK) | 4 | 975 |

For each of these engines a log-file has been received, where the log-time approximately equals every 24 hours or everyday data. The parameters that are included in the daily log are:

| | | |
|---|---|---|
| ENG_RUN_HOURS | ➜ | Operating hours of the microturbine [h] |
| TUR_OUT_TEMP | ➜ | Turbine outlet temperature [°C] |
| OIL_INL_TEMP | ➜ | Lubrication oil inlet temperature to the bearings [°C] |
| ENG_SPE | ➜ | Shaft speed [%] (nominal speed 70 000 rpm) |
| AIR_INL_TEMP | ➜ | Air inlet temperature [°C] |
| HOT_WAT_TEMP | ➜ | Hot water temperature [°C] |
| AIR_FIL_PRE_DROP | ➜ | Air filter pressure drop [mbar] |
| GAS_PRE | ➜ | Gas pressure of the fuel [mbar] |
| ELE_POW_OUT_DEM | ➜ | Electric power – set point [kW] |
| WAT_TEMP_DEM | ➜ | Hot water temperature – set point [°C] |
| WARNING | ➜ | Warning signal (true/false) |
| SnapshotDateTime | ➜ | Date of log (i.e. 07-jan-04) |
| MachineName | ➜ | Engine name (i.e. T10018 Dong) |
| ELE_POW_OUT | ➜ | Net electric output [kW] |
| PROD_ELE_POW_MWH | ➜ | Total electricity production – the MWh value[**] |
| PROD_ELE_POW_KWH | ➜ | Total electricity production – the kWh value[**] |
| NUM_OF_ENG_STARTS | ➜ | Number of engine starts |
| FAULT_STOP | ➜ | Engine stop due to engine fault (false/true) |

The locations of these measurement points have been drawn in Figure 5, where *T* equals temperature, *p* pressure and *N* shaft speed. This means that no flows are measured regarding mass or composition, and also no pressures around the compressor and turbine are available.

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[**] These parameters are added to get the total electricity production for the whole lifetime of the microturbine.

To be able to use these measurements for building an ANN-model, the data have to be investigated further to exclude outliers, as well as snap shot measurements logged during startup and shutdown.
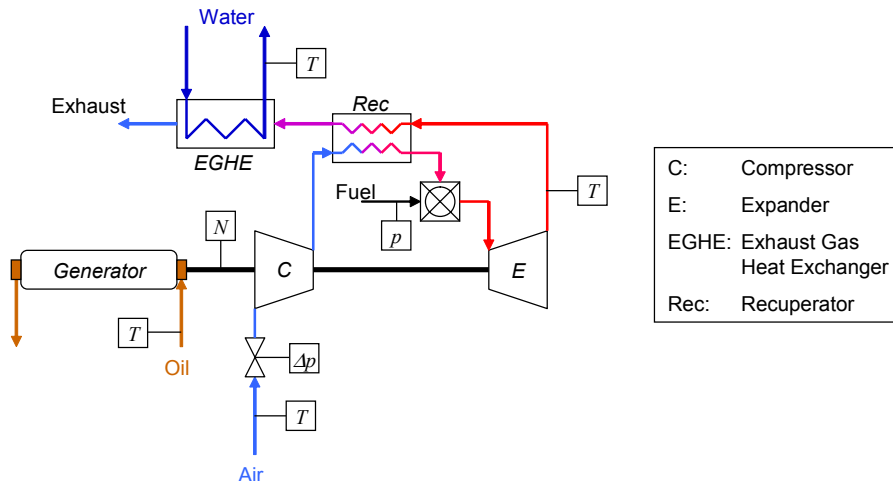


Figure 5, Location of the measurement points that are
potentially useful for ANN-modeling.

## 3.3 Everyday data for the DONG T10018

Since the microturbine located at DONG is the microturbine that has been in operation for the longest time, this data was handled first. Showing the difficulty of handling data logged on a daily basis, the data was plotted against the log date. In Figure 6 – Figure 9 the obtained raw data is plotted for the air inlet temperature, the electric power production, and the turbine outlet temperature. From an ANN modeling approach the wide distribution of air inlet temperature is promising. However, when observing the power production and the turbine outlet temperature graphs it is obvious that some of the log points have to be excluded. The reason for these unlikely values is that the log of the machine is carried out at the same time each day, whether the machine is operating, starting, shutting down or at idle condition.

The CHP unit is supposed to operate on full load and the engine is often operated over a number of days without any stop. To ensure that the measurements used during the training of the ANNs, the first and last measurement of each start are excluded. This would ensure that any startup and shutdown measurements are disregarded. Other exclusion limits that have been used further on in the modeling, as a measure of full load, are that at least the following additional criteria have to be fulfilled:

- ✓ The shaft speed has to be ≥ 80 % (100% equals 70 000 rpm)
- ✓ The gas pressure has to be ≥ 5 000 mbar
- ✓ The turbine outlet temperature has to follow the pattern given by the setup values, see Figure 10. These setup values have been chosen by Turbec since the torque is higher the lower the ambient temperature is, which the generator has problem to handle.

By performing this pruning of data, the outliers are considered as disregarded, as well as, are the startup or shutdown sequences.
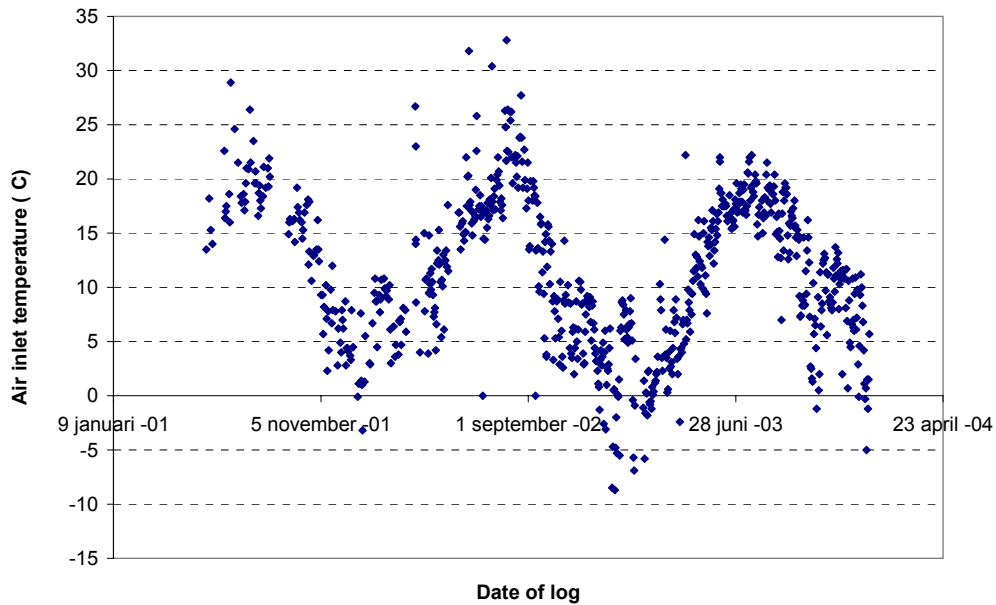


Figure 6, Air inlet temperature distribution of the total log time for DONG T10018.
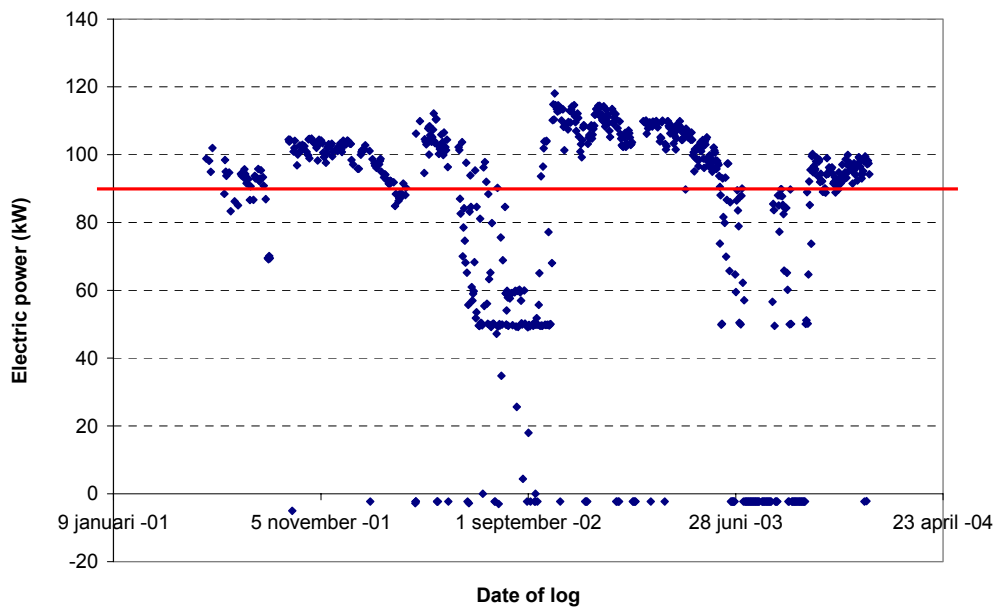


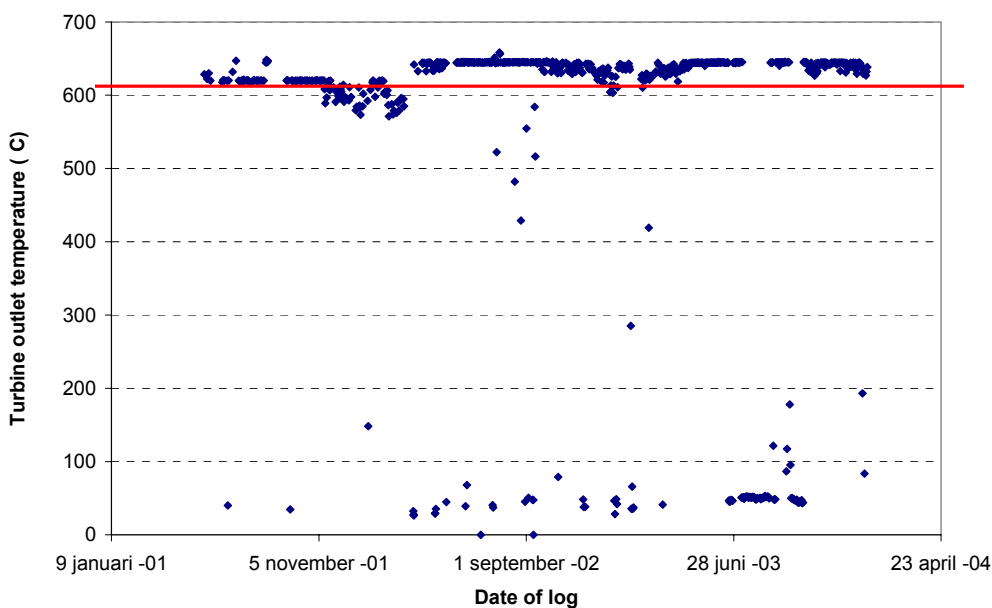Figure 7, Electric power production distribution of the total log time for DONG T10018.

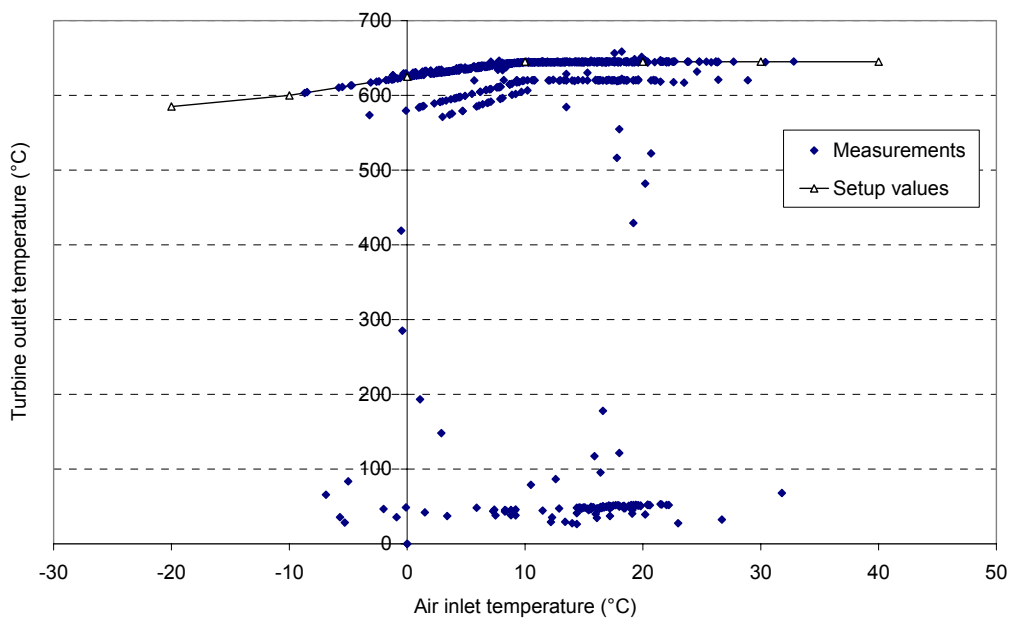Figure 8, Turbine outlet temperature distribution of the total log time for DONG T10018.



Figure 9, Turbine outlet temperature as a function of the air inlet temperature
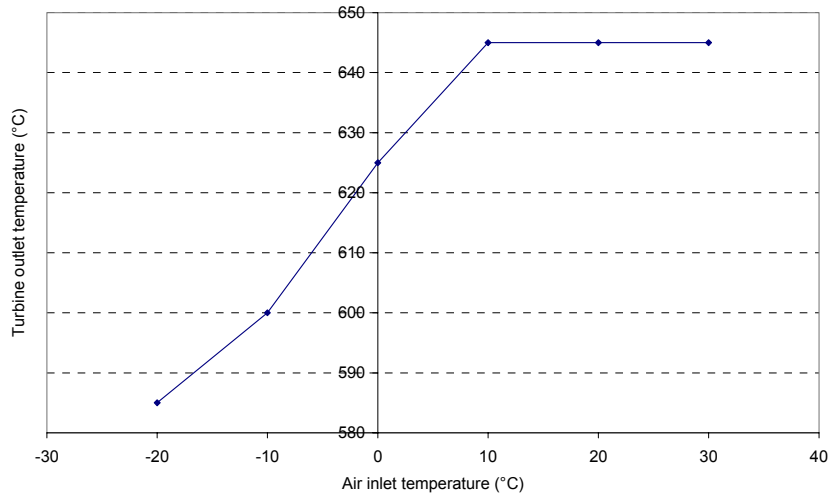for DONG T10018.

Figure 10, Setup values for the turbine outlet temperature
as a function of the air inlet temperature.

The DONG T10018 unit has also been going through some major overhauls and modifications over the time, which is visible in close-ups of the data-graphs. In Figure 11 – Figure 13 the revised data are shown for the electric power, the turbine outlet temperature, and the air filter pressure drop. The major overhauls and modifications (a – h) have also been included in these figures.
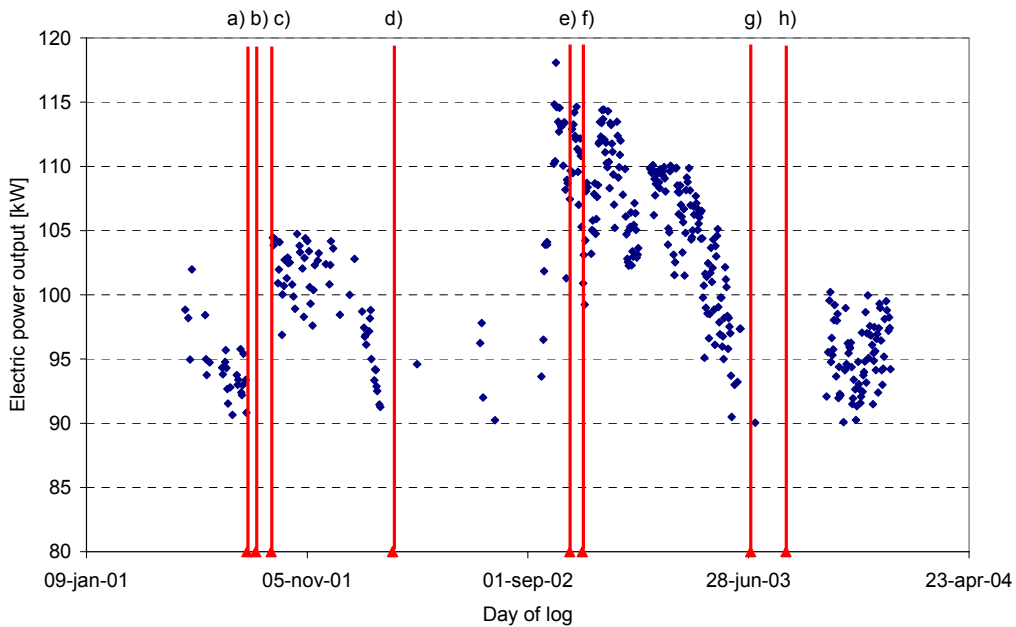


Figure 11, Revised electric power data for DONG T10018
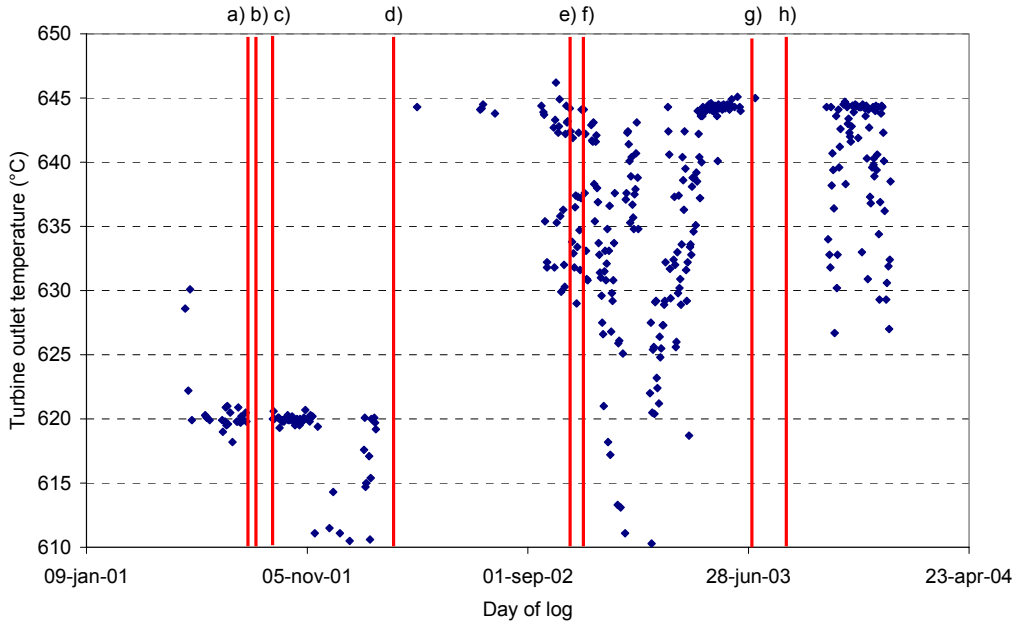with marked overhauls and modification.

Figure 12, Revised turbine outlet temperature data for DONG T10018
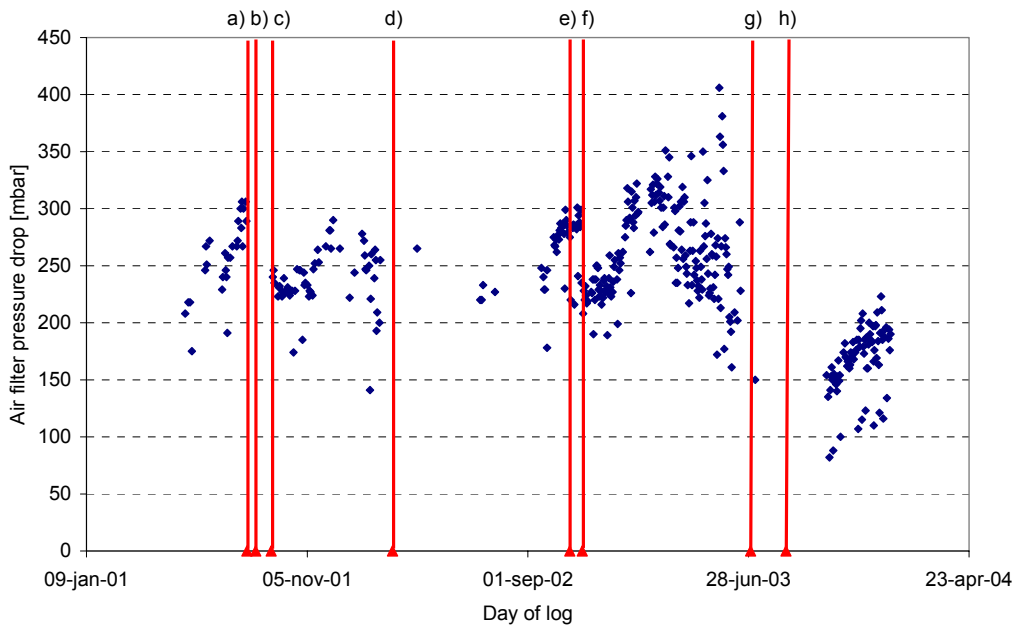with marked overhauls and modification.



Figure 13, Revised air filter pressure drop data for DONG T10018
with marked overhauls and modification.

The list of events, provided by Turbec AB, regarding the major overhauls and modifications are as follows:

| | |
|---|---|
| *a) 15 August, 2001*: | the combustion chamber is damaged, which lead to an inspection. The inspection showed damaged insulation inside the power module. A new combustion chamber was fitted. |
| *b) 27 August, 2001*: | low output power, which lead to replacement of insulation in the gas turbine as well as in the CBP. A replacement of the recuperator is at sight. |
| *c) 17 September, 2001*: | low output power, which lead to an inspection at Turbec AB. The thermo couplings were replaced and the lower thermo coupling was moved further into the engine. The air intake pre-filter was also changed. |
| *d) 1 March, 2002*: | turbine backplate springs changed. Change of the Turbine outlet temperature thermocouple position. |
| *e) 28 October, 2002*: | revision – the exhaust diffuser dimensions were changed |
| *f) 14 November, 2002*: | scheduled maintenance. Both a new combustion chamber and a new fine air filter were fitted, and the course air filter was inspected. |
| *g) 1 July, 2003*: | revision – the exhaust diffuser dimensions were changed |
| *h) 18 August, 2003*: | 18 000 hours service |

As can be seen in this list, there have been exchanging of components as well as service done on this engine. To be able to use this data straight ahead for process identification with ANN of the microturbine would be impossible. However, there are sections between the major events that are interesting (c→d, f→g, and h→) for degradation confirmation as well as for a future fault diagnosis situation. This data will hereby not be used as general basic data for the ANN-modeling of the microturbines.

The next interesting set of data available as general basic data is the data for the two microturbines located at Kastrup (T10095 and T10096).

## 3.4  Everyday data for Kastrup T10095 and T10096

The data available for the two Kastrup units are considered to be more stable with fewer interruptions over time. However, the time series available is of approximately 6 500 hours, and hereby covers whole year. The range of the air inlet temperature measurements are in this case not as wide as was the case for the DONG unit, but still all the seasons are covered.

The data for the Kastrup engines was revised according to the same limits as was the DONG-data, regarding shaft speed, power output and turbine outlet temperature. It was then decided that this data will be tested for ANN-modeling of the engines one by one, together and as general model of all microturbines (except the DONG unit and the unit in Kävlinge, where the latter also has experienced major changes over time).

The other everyday data-files of the remaining five, newer units have been browsed but are not further discussed here.

## 3.5 Measurement probes and errors

The measurement probes used in the Turbec T100 CHP units are low budget probes, since these units are supposed to be as cost-effective as possible. They are only calibrated before installation in the CHP unit, except the thermo couples measuring the turbine outlet temperature. These thermo couples are exchanged every other year (after 12 000 hours). This leads to the fact that the operation point could be changed, if a degraded element is changed.

The estimated measurement errors that the available probes have, according to Turbec, is as follows:

- ✓ Electric power $\pm$ 1%
- ✓ Turbine outlet temperature $\pm$ 2 °C (Totally two thermo couples where the average value is used if the difference is not to large.)
- ✓ Air filter pressure drop $\pm$ 1%

The measurement errors of the ambient temperature, gas pressure and shaft speed are considered to be very small.

# 4    Description of the Neural Network Models

The ANN modeling has been carried out in the software NeuroSolutions. This choice was made since good experience has been obtained with this software for other applications. In this software it is possible to vary the number of hidden neurons as well as epochs as a parameter variation, and the best solution is saved automatically.

## 4.1 Process identification models

The ANN-model built up for the process identification of the T100 unit is as follows in Figure 14.
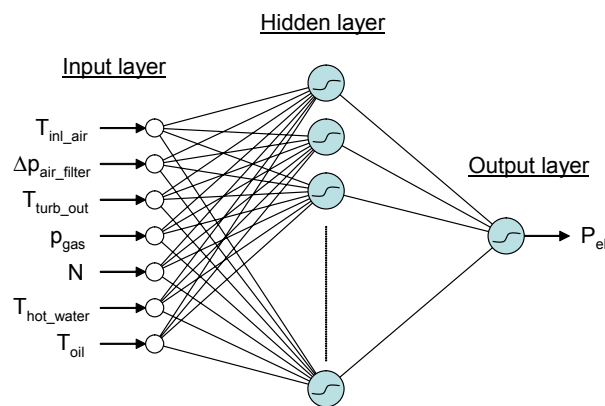


Figure 14, Starting model for the ANN for process identification of the T100 unit.

This means that the only output predicted here is the power output and the rest of the available data is used as inputs. This choice was made since these parameters are considered to be controlled or otherwise influencing the power output. As mentioned earlier the first test carried out towards a generalized ANN-model is to train the network with the data for the Kastrup engines.

The ANN training parameters[**] chosen are as follows:

- ✓ *tanh* (hyperbolic tangent) is chosen as transfer function in both the hidden and the output layer
- ✓ Normalization and de-normalization of data between -0.8 – 0.8
- ✓ The number of hidden neurons are varied between the number of inputs and 20
- ✓ On-line training is used (not batch)
- ✓ The number of epochs is varied between 0 and 5 000
- ✓ The learning rate is 0.5 for the hidden layer and 0.05 for the output layer
- ✓ Momentum ($\alpha$) of 0.7 is introduced to stabilize the training

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[**] For further explanations to these parameters, see references [1, 7, 8, 11].

These training parameters will be used for all the following ANN-models if nothing else is declared.

## 4.2 ANN-model for T10095

Since the Kastrup engines are considered as individuals, the training was started with the revised data from only the T10095 engine. The model shown in Figure 14 was used in the first training session.

Tests were also carried out, where the oil temperature and the hot water temperature were excluded as inputs. Also alteration of the transfer function in the output layer to a purelin was examined. The whole set of data for the T10095 was divided into three section; a training set, a cross validation set and a test set. This is done to be able to find the best generalization of the network. It is possible to train the network with tremendously low training error, but these networks are often overtrained. To check the cross validation error continuously, that is how good the trained network predicts unseen data, promise a more generalized network when the cross validation error is low. To choose the network architecture with the lowest cross validation error is called early stopping. However the final test is to pass the test data through the fixed network and find the true error of the network.

The best results with these revised data was obtained for 13 hidden neurons, *tanh* transfer function in both execution layers, and when the inputs $T_{oil}$ and $T_{hot,water}$ were excluded. The number of epochs used during the training was 2466. The total maximum error for this network was 4.71 % and the average error was 1.26 %. This maximum error was found during the pass of the test data through the network. The average error for the test data was 1.56 %, with 1 point above 4 % error, 2 points above 3 % error and 7 points above 2 % error. The total number of points used as test data here was 28.

## 4.3 ANN-model for both T10095 and T10096

The second step towards a generalized model for the T100 microturbine was to test ANN-model created with the T10095 revised data, with the revised data for the second Kastrup engine (T10096). This test was carried out without success. The maximum error increased to approximately 18 % and there were a number of points over 10%.

The new strategy was now to train a new network, utilizing both the data from the T10095 and the T10096. The same ANN architecture given in section 4.1 was used but the parameters $T_{oil}$ and $T_{hot,water}$ was excluded also in this model. In this test the total maximum error became 13.36 % and the total average error was 2.18 %. The maximum error was once again found for the test data and the distribution of the errors became; 11 points above 5 % error, 13 points above 4 % error, 19 points above 3 % error and 31 points above 2 % error. The total number of test points in this case was 72.

## 4.4 Measurement error propagation in an FFNN

As mentioned in section 3.5 the measurement probes of the turbine inlet temperature, $T_{turb,out}$, the pressure drop over the air filter, $\Delta p_{air}$, and the electric power output, $P_{out}$ have unavoidable uncertainties. These unavoidable uncertainties are often declared as a margin of error. So if measurement errors are present for the input parameters a model, these will propagate through the model. This propagation will influence the modeled power output, which already has an error margin. Is it then possible to find this influence, mapping the input-output relationship between the parameters.

If the model is of physical nature there are measures to handle the error propagation. For instance if two measured parameters are multiplied with each other, the margin of error of the output will be a sum of the former two margin of errors. However, in the case of neural networks, which is a fully connected network, all input parameters influence the outputs and the input values are weighted. This brings forward an interesting situation of how this is to be solved.

### *4.4.1 Error propagation in the Kastrup T10095 network*

To estimate the error propagation in an FFNN, the best network for the Kastrup T10095 engine was used, i.e. five inputs ($T_{air,inlet}$, $\Delta p_{air,filter}$, $T_{turb,out}$, $N$, and $p_{gas}$), one output ($P_{out}$), and 13 hidden neurons. The fixed network was tested by introduction of the margin of error to the test set used to validate the network. This means that the turbine outlet temperature and the pressure drop over the air filter are modified with $\pm 2°C$ and $\pm 1\%$, respectively, see Table 2 and equations (1) and (2).

Table 2, Setup of the manipulation of the test set

| Test set number | $\Delta\{T_{turb,out}\ (°C)\}$ | $\Delta\{\Delta p_{air,filter}\ (\%)\}$ |
|---|---|---|
| Reference (original test set) | 0 | 0 |
| 1 | +2 | 0 |
| 2 | -2 | 0 |
| 3 | 0 | +1 |
| 4 | 0 | -1 |
| 5 | +2 | +1 |
| 6 | +2 | -1 |
| 7 | -2 | +1 |
| 8 | -2 | -1 |

$$T_{turb,out,test} = T_{turb,out,original} + \Delta\{T_{turb,out}\} \qquad (1)$$

$$\Delta p_{air,filter,test} = \Delta p_{air,filter,original} + \Delta\{\Delta p_{air,filter}\} \qquad (2)$$

The first test carried out was for a network that was not as good as the best network presented for the T10095. Both the maximum and the average error of this network was higher than for the best network, presented in section 4.2. The results of this test are depicted in Figure 15 and Figure 16, showing the absolute error and the percentage error respectively. The error bars for the measurements of the power ($\pm 1\%$) are also shown in Figure 15.
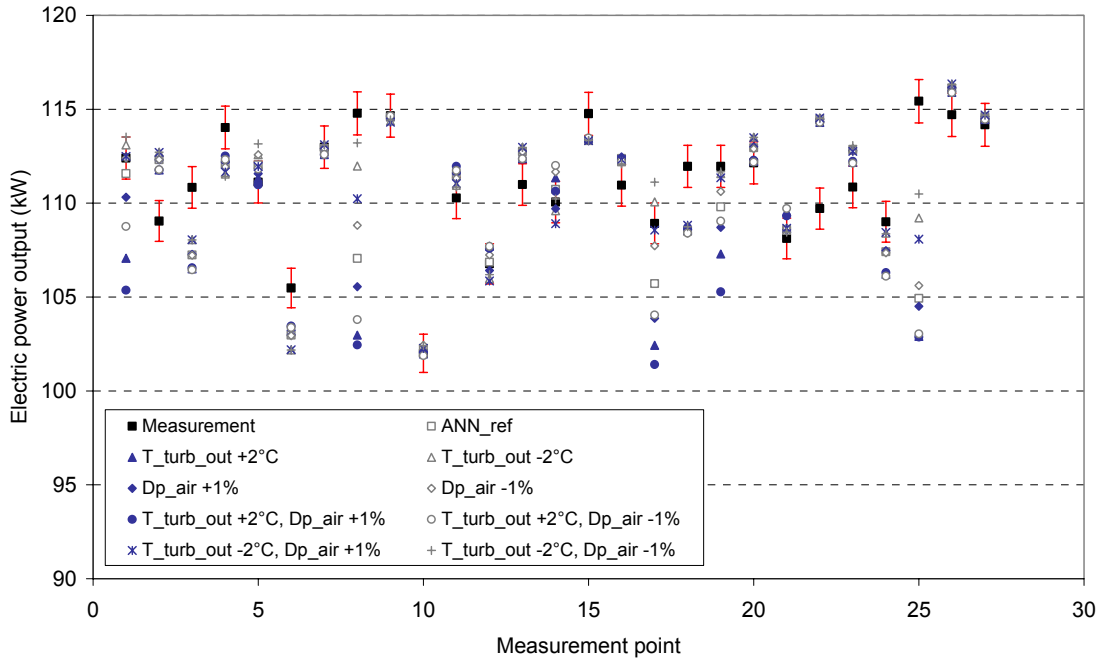
Figure 15, Influence of the modeled electric power output with an arbitrary FFNN for the T10095 engine. The turbine outlet temperature and the pressure drop of the air filter are manipulated within the margin of measurement error.
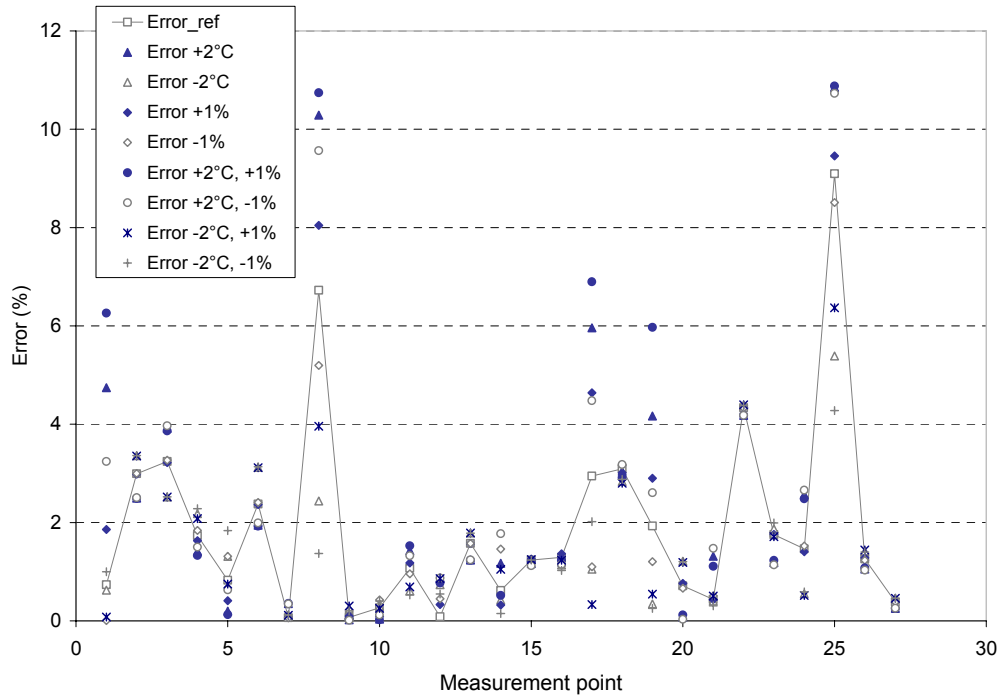


Figure 16, Distribution of the percentage error for the arbitrary FFNN, when the turbine outlet temperature and the pressure drop of the air filter are manipulated within the margin of measurement error.

As can be seen in Figure 15 and Figure 16, the distribution of the estimated modeled results of the measurement points is rather scattered. Even with the error bars, the ANN estimation is often out of range. This is of course due to the non-optimized network. However, to be able to draw any conclusions of the individual contributions to the error of the separate modifications of the temperature or the pressure drop is almost impossible. One observation that can be made is that the change in temperature contributes more to the deviation from the reference value than the pressure drop. It is also obvious that the combinations of measurement errors in most cases add up and move the modeled power output further away from the reference value. This means that if the measurement error of both the temperature and the pressure drop is positive, they will deviate more together from the reference ANN value than stand alone. This is also valid in an opposite way for negative measurement error deviations. However, this does not say anything about the relative deviation from the actual measurements, since the ANN reference value could be both higher and lower than the calculated ANN reference value.

Looking at the percentage errors in Figure 16, it can be seen that large reference errors of the neural network often widens the influence of the measurement errors of the inputs. So it seems that if the neural network is optimized, the scattering of the distribution will decrease and thereby also the influence of measurement errors.

The same manipulation of the test set was made when testing the more optimized fixed network for the T10095 engine. The results of this test are shown in Figure 17 and Figure 18.
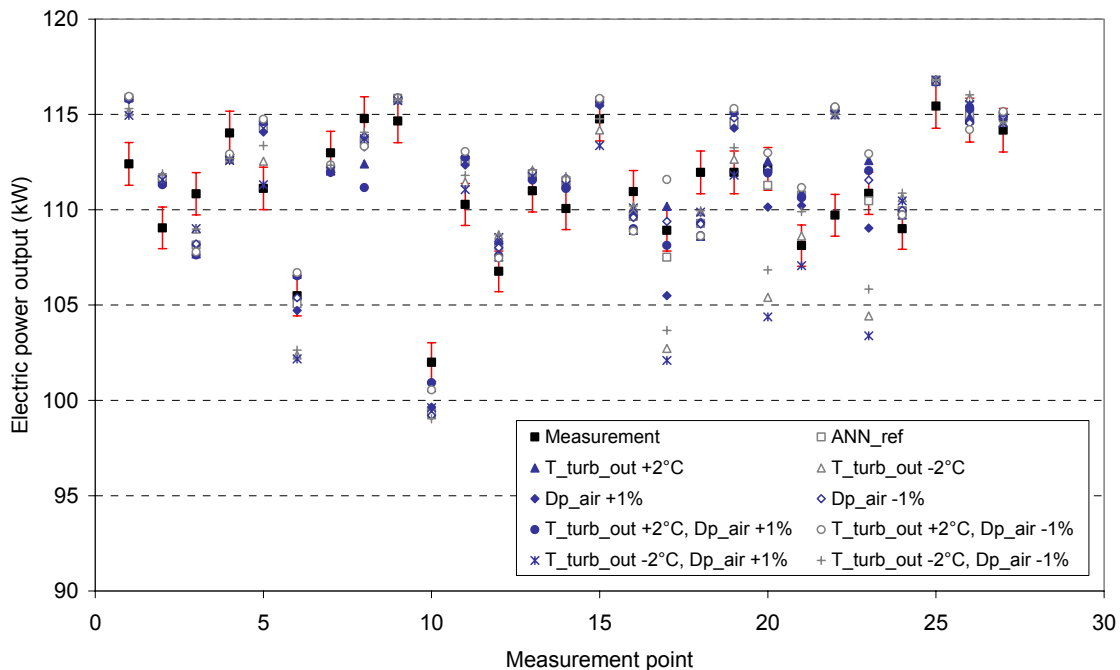


Figure 17, Influence of the modeled electric power output with the semi-optimized FFNN for the T10095 engine. The turbine outlet temperature and the pressure drop of the air filter are manipulated within the margin of measurement error.
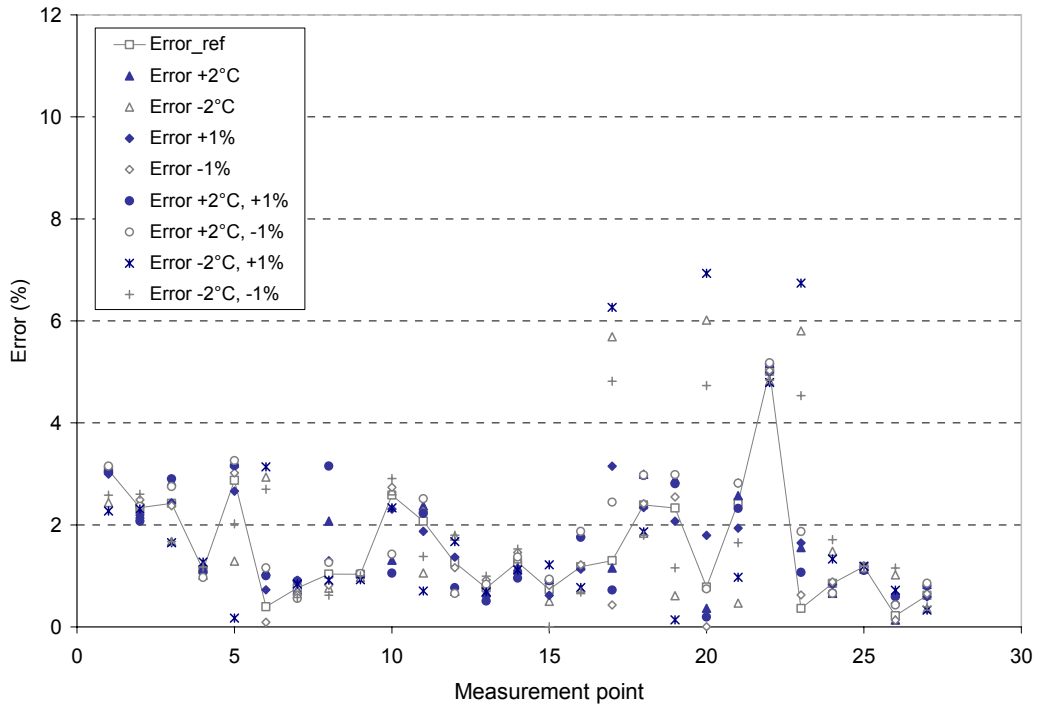
Figure 18, Distribution of the percentage error for the semi-optimized FFNN, when the turbine outlet temperature and the pressure drop of the air filter are manipulated within the margin of measurement error.

As can be seen in Figure 17 and Figure 18 the scattering has now decreased significantly, suggesting that a better trained network also is less influenced by measurement errors in the input parameters. However, to be able to set up an empirical equation of the measurement error propagation at this time is not possible. This could of course be considered as an interesting work for the future that could be very useful in a future sensor and fault diagnosis system. Perhaps an improvement would be obtained if the error margins were introduced already during the training of the network to see if there are any off-sets of the sensors, measuring the turbine outlet temperature and the pressure drop over the air filter.

## 4.5 Conclusions

The conclusion that can be drawn from the process identification of the T100 unit is that the data received for the microturbines are to poor to be able to train a general network, or it could also be that the individual engines are to different to ever get a general model of all T100 microturbines. It seems like all engines have to be trained individually in order to use the ANN model for condition monitoring. One result that was obtained during this study was that ANN could predict the system with a total average error of 1.26 % which is close to the measurement error of 1% for the electric power production. However, since the predicted errors in average are over 1% it might be impossible to combine the ANN model with the existing control system. This is at least a conclusion that other gas turbine manufacturing companies have drawn for their gas turbines and some of them are presently using this error limit for their engines.

To formulate a general model that could handle the total fleet of microturbines was not possible in this study; the engines have to be trained individually. By using only data for one engine during training and then testing this model for other engines did not have an encouraging result at all. By using a mix of engine data, i.e. data from different engines lumped together, improved the model slightly, but not enough for the model to be used as a general model.

An investigation of the measurement error propagation was also made in order to se how this influences the ANN model. A general conclusion that can be drawn from this investigation is that the more accurate the ANN model is the less sensitive it is for unavoidable measurement errors.

# 5  Concluding Remarks

The objective with this report was to summarize the measurements made accessible to LTH (9 CHP microturbine units) and to investigate their applicability for modeling with Artificial Neural Networks (ANNs). This modeling should be looked upon as a first necessary stage in a future three-stage rocket, where process identification, sensor validation, and fault diagnosis all are to be carried out by ANNs.

The data that was more thoroughly investigated was the data for the DONG-engine, since this unit had the longest operational time, and the data for both the Kastrup-engines, since these units seemed to be the most stable and unchanged ones. During the investigation of the raw data it was obvious that major changes had been done to the DONG-engine. This data was hereby excluded as considerable data for training of a general ANN model. However, since a number of overhauls have been made this data is regarded as potentially useful for degradation studies and for a future fault diagnosis system. For further comments on this, see section 0.

The two CHP units located at Kastrup airport, have until the date of today been operating for fully 6 500 hours, i.e. a bit longer than a year. These microturbines as well as the other engines in the report are constantly operated in full load. The accessible data for these two engines was used to try to formulate a general ANN model of the Turbec CHP unit, T100. This choice was made since no major overhauls have been made up till now and they have been operating relatively smoothly the whole lifetime. The result obtained during the ANN modeling of these two engines was that no general ANN model could be built for the two units. Each engine has to be modeled individually to obtain an acceptable average error of fully 1%. The final ANN architecture used to model the CHP unit used five inputs ($T_{air,inlet}$, $\Delta p_{air,filter}$, $T_{turb,out}$, $N$, and $p_{gas}$) and one output ($P_{out}$). This means that the hot water temperature and the oil temperature was excluded, or pruned, in the model, since they did not contribute with additional information to the model. This however does not mean that these measurement probes could be excluded from the system. They have the task to guarantee the hot water temperature to the district heating system and to keep the oil temperature at an acceptable level, regarding viscosity among other things.

It is the authors' opinion that to obtain an ANN model with lower error, probably additional parameter measurements have to be included. Perhaps measurements of mass flows of air and gas, and inlet temperature of the district heating water, and gas composition could be useful. This might even lead the way to the possibility of a general ANN model for the entire fleet of microturbines. By obtaining a modeling error less than 1%, the ANN model could be directly connected with the existing control system. As shown in the report, the influence of the measurement errors of the input parameters to the ANN have less effect the better the ANN model is trained. Having an ANN model with calculated errors less than 1% would considerably decrease the influence of these measurement errors.

# 6  Future Work

The ANN modeling carried out in this report could be considered exaggerated, but it has a purpose in the long run. Since this model could be considered as the first step in a three-stage rocket, it will be very useful for a future condition monitoring system (CMS), including fault diagnosis.

Since microturbine CHP systems, such as T100 from Turbec, do not have the possibility to carry personnel costs, and since the maintenance is to be kept to a minimum, a well functioning CMS with possibility of fault diagnosis must be considered a high priority. ANN is one possible tool that could be used to combine process identification, sensor validation, and fault diagnosis, all included. Regarding the ANN-model that would be included in the engine once it is delivered, this could be pre-built with data obtained from the performance tests. To be able to co-operate with the manufacturer of the microturbines and to utilize the data base of performance tests of new-and-clean engines, perhaps a general ANN can be built and sent with the delivered engine. Then to use on-line training continuously after a number of operation hours (> a month of operation at a time) the ANN-model can be improved for each engine, taking the individual and local condition into account. It could also be a possibility to 'optimize' the sensors that are to be mounted with the delivered engine, by using ANN and pruning. To be able to train the ANN with a large number of measurement parameters and exclude them one by one, would establish the optimal sensor setup for ANN modeling, in the same time as redundant measurement probes are excluded and hereby reducing costs as well as unnecessary measurement errors.

To be able to formulate an all-inclusive CMS, fault formulation together with modeling or measuring of the same have to be carried out. This is considered as possible if a better model of the system is prepared, either by utilizing the existing physical model from Turbec or by additional measurement logs from the existing CHP units.

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