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NEW ALSTOM MONITORING TOOLS LEVERAGING ARTIFICIAL NEURAL NETWORK TECHNOLOGIES

[1]Thomas Palmé, [1]Peter Breuhaus, [1]Mohsen Assadi, [2]Albert Klein, [2]Minkyo Kim

[1]Department of Mechanical- and Structural Engineering and Materials Science
University of Stavanger
N-4036 Stavanger, Norway

[2]Alstom Power
Baden, Switzerland

ABSTRACT
This study presents a methodology to improve monitoring of gas turbines (GTs) while not having the specific engine characteristics available by applying a nonparametric statistical modeling based on operational data. The goal is to quantify the relationship between the operational conditions and the GT performance parameters during normal operation. In this study, the Multi-Layer Perceptron (MLP) Neural Network (NN) model is used to develop so called baseline models of the GTs. To verify the generic applicability, two different GTs and several units for each GT type are evaluated. A methodology to both, selecting the appropriate models with regard to input and output parameters as well as validating the selection of the parameters is reported. The key result can be summarized as: MLPs can be used for statistical modeling of GTs with very high accuracy, which permits an accurate prediction of the performance parameters during different operational conditions. It is also shown that under certain conditions, a developed NN model can be transferred to a similar GT. In summary, this study shows that NN can be used to improve on-line monitoring of a GT, making it possible to detect trends in the measured data indicating a change in the health status of the engine, requiring operational data only for model development.

Keywords: artificial neural networks, reheat gas turbine, non-reheat, condition monitoring, on-line monitoring

1 INTRODUCTION
Performance monitoring of power plants has attained increased attention during recent years due to the increased competition in the electricity market. In this more competitive market, power plant owners can lose a quarter's profit from an unexpected power plant trip [1]. Thus, knowing the plant's overall health status is of great importance for the overall economics of a plant. In addition, more stringent emission requirements in combination with endeavor to reach higher efficiencies have forced the manufacturers to operate closer to the operational limits. This has led to an emphasis on power plant reliability and availability, which in recent years has driven extensive investment in additional sensors and instrumentation. The result is that massively rich process data is generated. Tools to analyze the data are also required to extract the full value of the generated data. Most of the monitored parameters vary due to different operational conditions and the problem is to differentiate variation that is due to failure or degradation from variation that depends on different operational conditions. To overcome this problem, a model is required which can relate the operational conditions to the performance of the GT. With such a model, trending of the performance parameters can be improved and developing failures and degradation can be estimated. This would in turn provide the opportunity to shift to condition -based maintenance, which in the end results in optimized maintenance scheduling based on equipment health status.

Any monitoring methodology applied should be easy to use and interpret. It should also not require expert knowledge to be executed. In addition, it should be implemented on-line, thereby providing real-time surveillance of the plant in order to detect changes directly when they occur.

Selection of a monitoring methodology depends on a Return on Investment (ROI) analysis wherein the investment should be compared to the actual gain in economical terms. The selection of which monitoring technology to use depends on several factors. One main factor is the availability of actual information. Development of a physical model of the system is most often privileged information retained by the manufacturers, since they are the only that possess the information required for an accurate physical model of the GT.

With a physical model of the GT, measured data from the plant performance parameters can be used to compare the results from the physical model predictions and deviation in the performance can be identified. These models require very accurate measurement values for each input parameter as well as detailed information on the characteristic of the GT and its components. Any bias in the measured input is translated and affects the accurate predictions of the performance parameters [1]. In the real case, each unit may be unique in terms of its performance characteristics and local installation. This is not taken into account, at least not without any detailed configuration of the standard physical model. Some functional relationships is difficult to model, such as the exhaust gas temperature profile, which shows a radial and/or circumferential temperature spread and would usually require a detailed CFD model. A typical physical model provides an average value while the real profile most often is dependent on the GT / combustor type and to some extent also individual units. A data driven model, independent form this detailed information, learn the correct pattern based on historical data, which would provide a much faster detection of deviation in the measurements.

The Gas Path Analysis (GPA) [2-3] is a differential method to relate changes in measured parameters to derived health parameters and is especially suited for cases where limited parameters are available, such as for aero derivatives where limited space is available for instrumentation. This tool is normally used in conjunction with a normalization procedure where the performance parameters are recalculated back to ISO condition. One major advantage with this tool is that it evaluates differences in measurements instead of the absolute values, and is therefore less sensitive to constant bias in the measurement. Doel [4] has combined the least square algorithm with GPA to make it more robust against sensor faults. Several authors have combined the GPA with the Kalman filter [5] and the latest models incorporate nonlinear GPA applying the extended Kalman filter. The normalization procedure is explained in depth in [6] and also explained in ISO-standard 2314 in [7]. It might be said that in the case when the GT compressor and turbine operates at a constant physical speed there is no unique operation line on the compressor map during off-design operation [8]. The normalization procedure then needs to include the compressor map to recalculate the measured values back to ISO condition. This is, in cases when such detailed information is not available, usually performed by so-called correction curve. The basic concept is to assemble a set of performance or correction curves that plot the variation in a specific equipment performance parameter when one of the operating conditions changes. The total equipment performance fractional change is then computed by multiplying together the fractional changes for each operating condition, where each multiplying factor is generated using a separate correction curve. This approach is most accurate for small changes around the reference point.

Data driven methods for monitoring have received increased attention during recent years, due to their flexibility in parameter selection and the fact that only operational data are required. Flexibility of parameter selection means that parameters that might be necessary for a physical model to converge, can be omitted in data driven model with a small or indistinguishable increase in the error due to information redundancy in the other input parameters. The main idea in a data driven modeling approach is to use operational data collected from normal plant operation and then embed the relationships between the parameters in a model. This model then represents a so-called baseline model against which new data are compared. There are several different methods reported in the literature, such as Kohonen Networks, Kernel Based Similarity Modeling [9-10] as well as neural networks [11].

In this study the MLP based NN model is used for baseline development of two different GT types and for several different units of each type. The focus is on GTs that are applied in CCPP (Combined Cycle Power Plant) operation. Even though the methodology presented here could be applied to the whole CCPP, including steam turbine and HRSG, we cover the GT in this study. In addition, the result is focused on the main performance parameters for clarity of the results. By applying the same methodology on two different GT types, the generic applicability of the modeling approach is confirmed.

2 NONLINEAR, NONPARAMETRIC REGRESSIONS WITH MLPs

Feed forward MLPs are nonparametric hetereo-associative models for function approximation as shown in (1):

$$\boldsymbol{y} = f(\boldsymbol{x}) + \varepsilon_i \qquad (1)$$

Where f is estimated from representative data of $\boldsymbol{x}$ and $\boldsymbol{y}$ in (1) and ε_i is a stochastic component normally attributed to measurement uncertainty. The main point to be made here is that no assumption of f is implemented a priori, instead this is determined directly from the data, hence the name nonparametric modeling. This is performed in a so-called training procedure where the NN is iteratively adjusting its weights to fit the target data. MLPs have certain characteristic features compared to other existing methodologies such as polynomials and Radial Basis Functions (RBF). They can be used for nonlinear high dimensional function approximation. One of the main features focuses on linear scaling with the dimension [17]. This is compared to polynomial models and radial basis functions that scale exponentially with the dimension. The implication of this is that models with many input parameters can be constructed in an efficient manner. Neural networks also have the possibility to approximate any functional relationship, see e.g. [12], given that the number of neurons in the hidden layers is sufficient. Thus, the number of neurons in the so-called hidden layer determines the functional complexity that can be approximated by the network. However, in contrast to polynomials and RBF, there is no closed form solution to the network weights values; instead, it becomes a nonlinear optimization problem. This is solved by an iterative procedure, applying the back propagation procedure in conjunction with some optimization algorithm, such as the Scaled Conjugate Gradient Algorithm [13] or the Levenberg-Marquadt Algorithm. For a given input-output model, the question to solve is to select a sufficient number of neurons in the hidden layer to represent the functional complexity between the input and output parameters. There are no analytical methods for this selection, and usually this is performed with a trial and error process, where the selection of neurons in based on “best performance”. In section 5 we will elaborate this discussion and show that when the models are constructed with dependent input parameters, selection of neurons should also be based on the model sensitivity to small perturbations in the input parameters.

The drawbacks with MLPs are related to the nonlinear optimization problem, i.e., the training procedure. The training algorithm can be stuck in local minima, which means that the training converges to an error level that is higher than the optimal one given the neurons in the hidden layer. The second point is that the training procedure becomes time consuming in comparison to the cases where a closed form solution for the model parameters exists. However, previous studies have shown that the problem of getting stuck in local minima is rather limited for practical cases and the training time is not a big issue with modern computers. In addition, the network prediction accuracy is rather robust to the network configuration, i.e. number of neurons. This means that the prediction accuracy is not dependent on an exact selection of number of neurons.

3 MODEL SELECTION

A prediction model configured in a hetereo-associative modeling is based on selected input and output parameters. For this application, the network should produce a reliable prediction based on the input parameters. The values predicted by the network are then compared to the actual values and any differences are interpreted as a system change, due to some unexpected event. The main issue becomes to select appropriate input parameters for the specific GT type. To do this, it is necessary to take into account the parameters that affect the GT performance such as ambient condition, operational mode and specific installation issues. Input parameters should be selected so, that the variation caused in the output parameter are removed. Hence parameters that affect the GT performance should be selected.

The control of an industrial GT is normally performed by combining inlet guide vanes (IGV) control and GT inlet temperature control. The TIT is usually calculated, based on measurements of compressor outlet condition, as well as the turbine outlet temperature; however the actual measurement used depends on GT type. In load control, a specific load is determined for the GT. In 100% load, power is dependent on the ambient conditions, given a constant TIT, where the main influencing parameter is the ambient temperature. Frequency control is an operational mode where the GT is operated to sustain the grid frequency. It basically means that the GT operation load is related to the actual frequency change on the grid. This operation is highly dynamic, as the VIGV angles are constantly varying. In this operating mode the GT usually has to operate below the maximum power output (PO) level to be able to increase the load when needed to support grid frequency.

Ambient conditions refer to the ambient temperature, pressure and humidity, where the ambient temperature is the main dominating value influencing the mass flow through the GT. The ambient pressure changes the density of the air and thereby the mass flow, while a change in the humidity changes the properties of the working media. The specific effect of these parameters depends on the operational changes in their values on site. This might differ greatly between different geographical locations. The effect of changes in ambient conditions depends on the actual control strategy adopted, which varies depending on GT type. For example, a change in the ambient temperature has a different affect in the GT performance when a constant temperature after turbine (TAT) is used instead of constant TIT.

The effect of specific installations refers to filter pressure drop, inlet air humidification, and bleeds flow for cooling, etc., which all affect the GT performance and operational characteristics.

For each plant and GT type, the operation needs to be evaluated and parameters that influence the GT performance need to be identified. This can be performed on a component basis as well as on an overall plant consideration. In any case, it is desirable to keep the number of inputs as low as possible for several reasons. The first one is for the interpretation of the model. Most desirable, the input parameters should be independent of the GT performance. This means that a change in the GT performance caused by e.g. an efficiency drop in the compressor, should not affect any of the input parameters. This might not be possible for all types, due to high interaction between the systems. This issue will be further discussed in section 5. The second is the sensitivity to failure in input parameters. With fewer input parameters, the model is less likely to be invalid due to input parameter failure such as sensor problems. Any nonparametric model that is developed with operational data is a statistical model, defining the statistical relationship between input and output parameters. It is therefore not a physical model of the engine.

4 MODEL DEVELOPMENT – NETWORK STRUCTURE AND TRAINING

When an initial selection of input and output parameters has been done, operational data covering the operational conditions are selected. No data driven model, especially not a nonlinear model, should be used outside the boundaries in which it is developed. The next step is to develop a NN model based on the parameter selection and the data collected. The level of complexity between an input and output dimension is determined by the number of neurons in the hidden layer. To establish the required number of neurons a parameter variation is performed. The most common procedure starts with a low number of neurons and continues until additional neurons do not improve the accuracy of the network prediction. Selection of neurons should be based on accuracy as well as model complexity. From a practical modeling perspective, as simple a model as possible should be selected.

In this study the models are trained with Scaled Conjugate Gradient Optimization Algorithm [13], which is implemented in the standard Matlab toolbox. This training algorithm is suitable for large data sets. In contrast to the standard Gradient Descent algorithm it requires no user defined training parameters, such as optimization step size or similar. This greatly simplifies the training process, since the modeler just has to start the modeling and perform a variation with regards to number of neurons in the network. When the network is trained, the MSE for each network for a specific configuration is evaluated.

Once the model is trained and the number of neurons is determined, the accuracy of the model is evaluated for each parameter. This means evaluating the individual error as well as performing a statistical analysis of the prediction error. One example is to perform a linear regression between the target and network prediction for each parameter. Any bias error in the predictions can be easily detected, which indicates a poor training or the fact that a specific of the selected parameters cannot be accurately predicted. To verify the need for each input parameter, a sensitivity analysis can be carried out, which basically means that an input parameter is removed at a time and the NN prediction accuracy is evaluated. Redundant parameters can be removed if they do not contribute to the network prediction accuracy. However, before the input parameters are removed, sensitivity quantification as discussed in next section should be performed.

5 MODEL QUANTIFICATION AND SENSITIVITY EVALUATION

Model quantification means the correct network structure for a given input and output selection. The first step is to train the network and to evaluate the accuracy in the output predictions. However, it must also be assured that the network is robust which is related to the issue of ill-posed problems. Hadamard [14] defined a well-posed problem that has a solution which is unique and that the solutions are stable or smooth under small perturbations of the data. Therefore small perturbations in the input data should produce small perturbations in the output data. The issue of a smooth solution is related to the problem of collinear input parameters, meaning that there is a relationship, either linear or non-linear, between the input parameters. If this is not the case they are said to be orthogonal. However, in most applications, the input parameters are not orthogonal and the problem of multicollinearity to exists. As a result it causes large variances and covariance for the least-squares estimators of the regression coefficient, see [15] for a detailed description for parametric regression models. To ensure that co- linearity between any inputs has not caused any ill-posed problems, the network response to small perturbations in the inputs need to be quantified.

To perform sensitivity analysis to perturbations in the inputs we consider the Taylor series expansion of $f_i(x)$ about the point x, and include only the first order:

$$f(x + \Delta x) = f(x) + J(x)\Delta x \qquad (2)$$

Where the Jacobian J is:

$$J = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \cdots & \frac{\partial y_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_m}{\partial x_1} & \cdots & \frac{\partial y_m}{\partial x_n} \end{bmatrix} \qquad (3)$$

The Jacobian provides information about the sensitivity in the output parameter with respect to each input parameter. The size of the Jacobian is therefore number of input parameters times' number of output parameters.

For the neural network model, we adopt the concept by evaluating:

$$(\Delta y_1, \Delta y_2, \dots, \Delta y_n) = f(x_1 + \Delta, x_2, \dots, x_n) \qquad (4)$$

where Δy is expressed in error percentage and Δ is the perturbation in the input values. In (4) Δ is adopted to parameter x_1, but this is performed for each input parameter, one at a time. To establish the sensitivity, Δ is varied in a certain interval and the effect on each output parameter is evaluated. If the variation of Δ is performed for each input parameter, a sensitivity for each output parameter can be determined by plotting the error in each output parameter versus each input parameter, perturbed with Δ. Since the model is developed for different operational conditions, this is evaluated for each specific data pattern, in the test set, and an average value in each output for each value of Δ can be calculated. With this methodology, the average effect in each parameter can be established. In addition, an input parameter that does not cause change in the output parameters can be assumed to be unnecessary, since its effect on the network prediction is low.

If the input parameters are uncorrelated and thereby orthogonal, the sensitivity of each input parameters defines the effect of that specific input variable on the performance parameter. However, if the parameters are correlated, this does not mean a physical effect of each parameter. Instead it should be interpreted as a statistical relationship between a specific input and a specific output.

6 ALSTOM GT24/GT26 AND GT13E2

The Alstom GT24 is a GT with sequential combustion and was introduced to the market in the mid 1990s. The GT24 is geared for the 60 Hz market and GT26 for the 50 Hz market. The main characteristic feature, the sequential combustion principle, or reheat principle, provides higher efficiency at lower turbine inlet temperature compared to a single-combustor GT. The sequential combustion is based on first the EnVironmental (EV) burner in an annular combustor, followed by the Sequential EnVironmental (SEV) burner in the second annular combustion stage. From an operational point of view, the sequential combustion provides very low emission and high exhaust gas temperature form baseload to 25% load [16]. This has been more important in the deregulated electricity market, which demands a higher operational flexibility together with high efficiency of power plants.

The Alstom GT13E2 is a well-proven industrial GT and the first unit was commissioned in 1987. Its configuration consists of a multiple stage compressor and turbine on a common rotor, and the first model was equipped with a single silo combustor. The need for higher thermal efficiency and dry-low NO_x technology with low NO_x emissions led to the development of the GT13E2 in 1991. This engine retains the main aerodynamic and mechanical design features of GT13E but replaces the silo combustor with the Alstom EV based annular combustor. The GT13E2 is rated at 180 MW and provides mature technology, superior performance and the highest efficiency in its class.

7 CASE STUDIES

Two different power plants were evaluated in this study. The main point is that they differ in plant configuration, GT type as well as ambient conditions. Plant-1 consists of several units of Alstom reheat GTs while Plant-2 consists of several Alstom non-reheat GTs. The data sets collected are extensive and in each model at least 10 000 data observations, which correspond to approximately one month of operation, is used in the training data set. For each model, the cross validation set as well as the test set are equally which in total means that at least three months of continuous operation is used for evaluation. In the figures, test data means data collected after the training period, which simulates a real case where new data are validated by the NN model.

7.1 PLANT-1

Plant-1 consists of several Alstom reheat GTs, where each GT is configured with an HRSG, steam turbine and generator. All units are single shaft units, and the PO from the generator includes the steam turbine contribution as well. Thus, independent power measurement from the GT is not part of the instrumentation and therefore not available. The inlet air is cooled by passing it via a wet evaporative cooler medium, which reduces the air temperature by evaporation. The airflow though the GT is controlled by three variable guide vane rows, which are part of the three first compressor stages. For cooling and sealing purposes, air is extracted from the compressor main flow at different pressure levels. This airflow is partly cooled by two once-through coolers, which are fed with HP feed water from the HRSG system. The steam system is of two casing design, with a single flow low-pressure exhaust. The high-pressure section is a geared turbine, connected with a clutch of self-synchronizing design. The IP/LP turbine section operates at generator speed. The HRSG is of a once-through design and produces steam at two pressure levels, HP and LP. For cooling of the steam cycle, a common forced draught wet cooling system is employed.

7.2 PLANT-1, OPERATIONAL CONDITIONS

The selection of appropriate input parameters depends on the operation conditions defined by ambient conditions and operational mode. In figure 1-5 the operational condition for Plant-1 is shown.

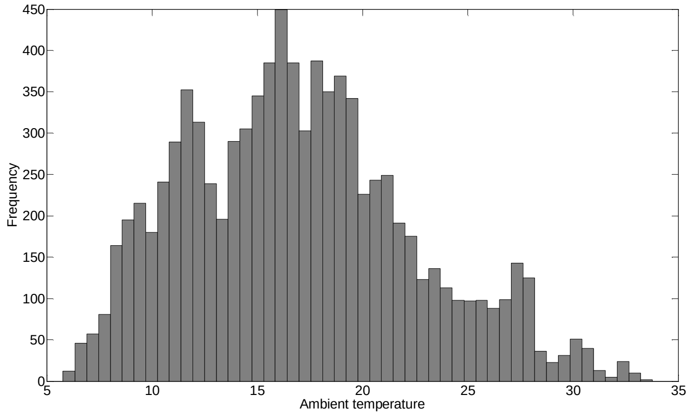

Figure 1 Histogram of ambient temperature, Plant-1

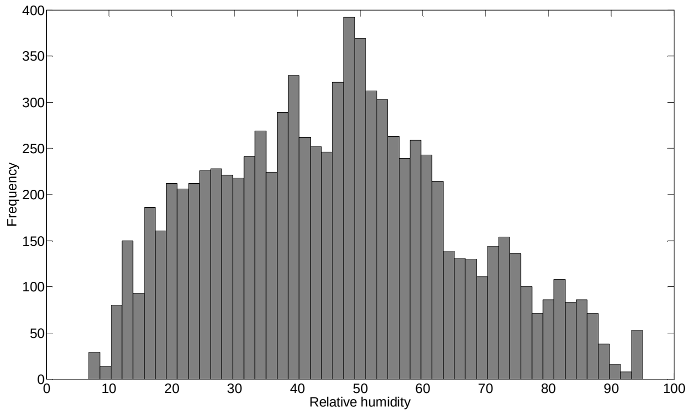

Figure 2 Histogram of ambient humidity, Plant-1

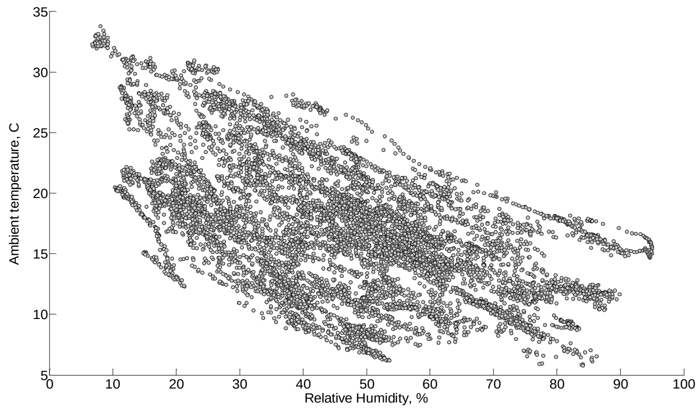

Figure 3 Scatter plot between humidity and ambient temperature, Plant-1

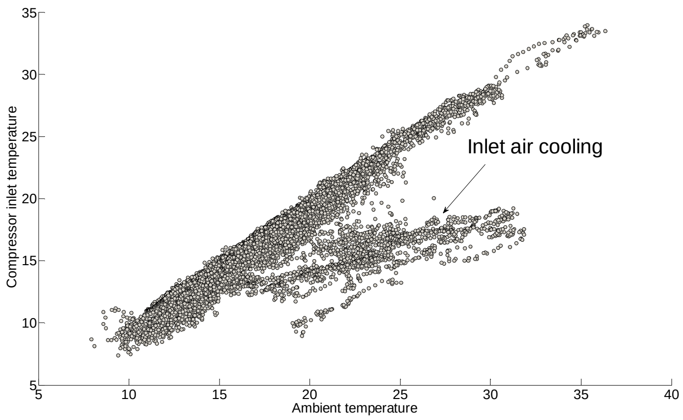

Figure 4 Scatter plot, ambient temperature and compressor inlet temperature, P1-U4

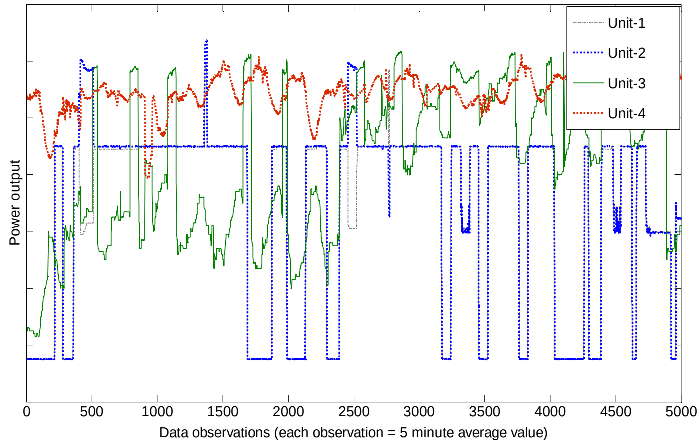

Figure 5 PO from Plant-1, Unit 1-4

Plant-1 operates in rather different ambient conditions whereas ambient temperature varies from 6 to 33 °C and ambient humidity from 8 to 95 %. A scatter plot between ambient temperature and humidity does not indicate a strong correlation between the two parameters. Since the inlet air is cooled prior to compressor entry, a scatter plot between the ambient temperature and the compressor inlet temperature is plotted for one unit and the effect of inlet air cooling is clearly seen. Figure 5 shows the power profile of each unit and three different operational modes can be identified, base load operation for U-4, a mix of base load and frequency control for U-3 and a similar load control profile for U-1 and U-2.

7.3 PLANT-2

The second power plant investigated in this study is a CCPP consisting of several non-reheat GTs. The two investigated units will be named P2-U1 and P2-U2. These two units are operated in a multi-shaft configuration which means that the GT and ST are connected to independent generators. Hence, in contrast to Plant-1, the PO from the GT can be independently measured from the generator. Also in contrast to Plant-1, there is no cooling of the inlet air; hence the inlet temperature is similar to ambient temperature.

7.4 PLANT-2, OPERATIONAL CONDITIONS

Figure 6 to 10 show the main operational conditions for Plant-2.

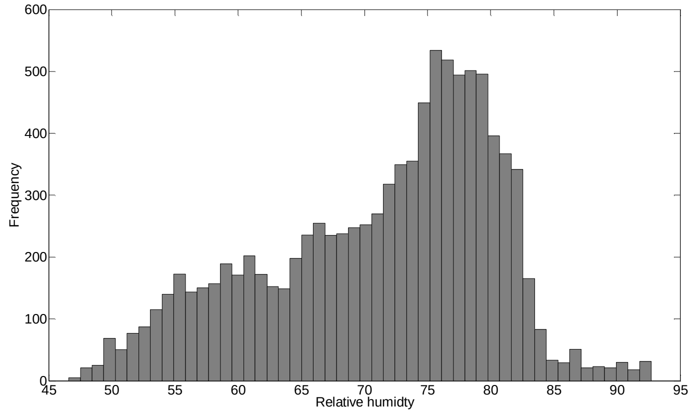

Figure 6 Histogram of relative humidity, Plant-2

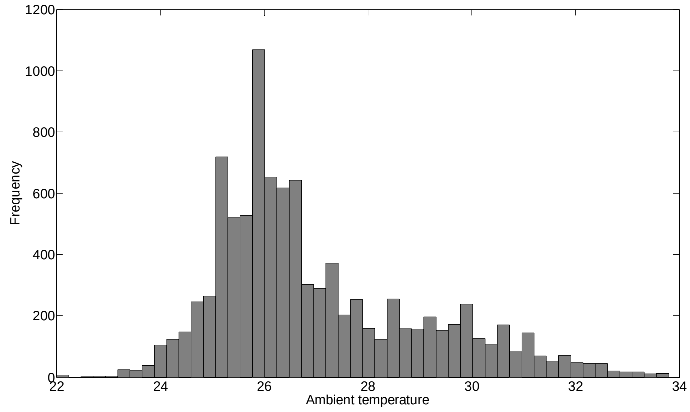

Figure 7 Histogram of ambient temperature, Plant-2

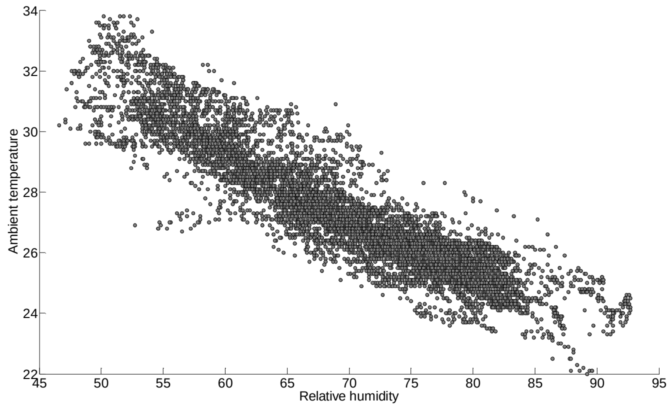

Figure 8 Scatter plot relative humidity and ambient temperature, Plant-2

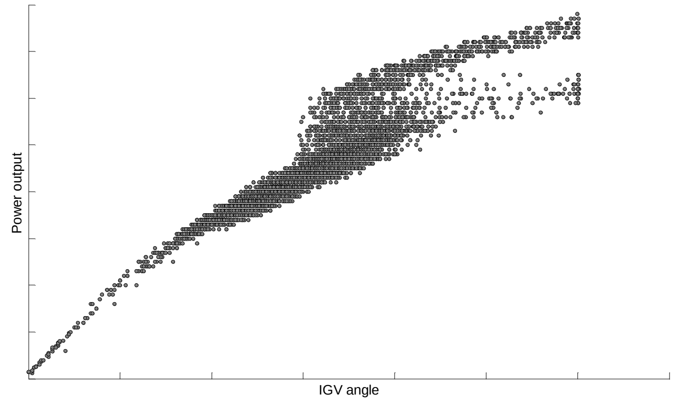

Figure 9 Scatter plot IGV angle and PO, Plant-2

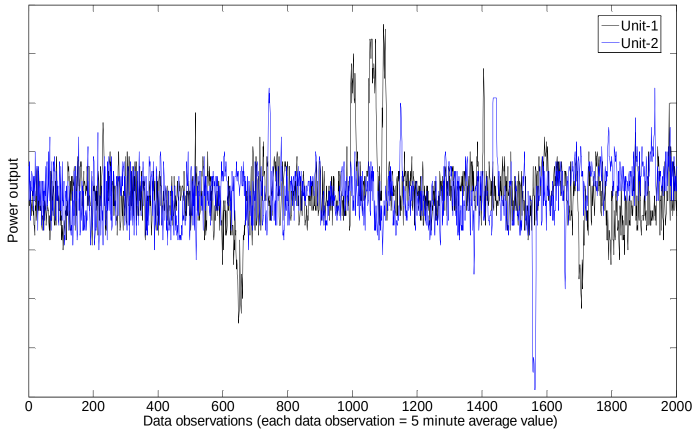

Figure 10 PO, Plant-2

In contrast to Plant-1, Plant-2 operates in more consistent environment, where the ambient temperature ranges from 22 to 34 °C with a mean value of 26°C. Humidity range from 50 to 90% and the scatter plot between ambient temperature and humidity reveal a rather strong correlation between the two parameters. A scatter plot between the IGV and PO shows that for low IGV angles, the PO is directly correlated to the IGV angle. Figure 10 show the power profile for both units in Plant-2, and both units operated almost constantly in frequency control.

8 ANN MODELING RESULTS

In this section, the model result will be shown for both power plants highlighting the difference in parameter selection between the power plants. In addition, the difference between the units and the possibility to transfer a unit to a similar unit will be shown.

8.1 Reheat GT, PLANT-1

For Plant-1, an initial input parameter selection was performed based on the operational conditions. Table 1 shows the first selection and the final selection after sensitivity analysis, meaning that each parameter was validated by removal and retraining. If the prediction accuracy remains when a parameter is removed, the parameter is regarded as unnecessary. In this case, the ambient humidity could be removed, because the inlet air is cooled by humidification for several data points as shown in figure 4. The result was the same for all units, even though they differ in operation model. Each network was trained with regard to a variation in number of neurons, and the best selection is based on two factors, accuracy as well robustness which will be discussed later on.

Table 1 Input parameters for Plant-1

Input parameters	First selection	Final model
PED	X	X
VIGV-1a	X	X
VIGV-1b	X	X
VIGV-2a	X	X
VIGV-2b	X	X
VIGV-3a	X	X
VIGV-3b	X	X
Ambient humidity	X	
Ambient pressure	X	X
Ambient temperature	X	X
Intake filter drop	X	X
Temperature, compressor inlet	X	X

Figure 11 shows the NN model result for the main performance parameters for all four units in the test data set. It should be mentioned here that the result is indistinguishable from the training and cross validation sets, which is a requirement for acceptable network performance. Even though the different units operate in different mode, the prediction accuracy is very similar. Note that the PO can be predicted with an accuracy of 0.2% and less, which in this plant also includes the HRSG and ST operation. This is not a surprise, since the ST performance is directly dependent on the GT performance.

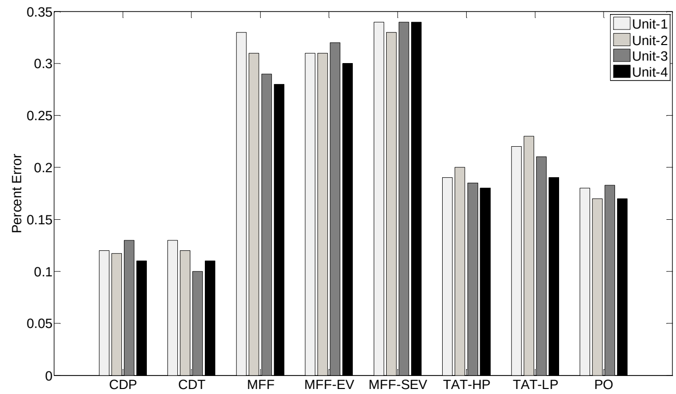

Figure 11 Average errors in test data set, Unit 1-4, Plant-1

To verify the model generalization, the models are tested with test data, which means data collected after the data used in model development. This is done within 3 months after training to minimize the effect of degradation in power plant components. Figure 12 shows the training capability of the network on a part of the test data for Unit-1 and the NN model closely follows the measured PO from the specific unit. Figure 13 show the same result for Unit-4, which operates in base load. Thus, the generalization capabilities of the NN models are verified.

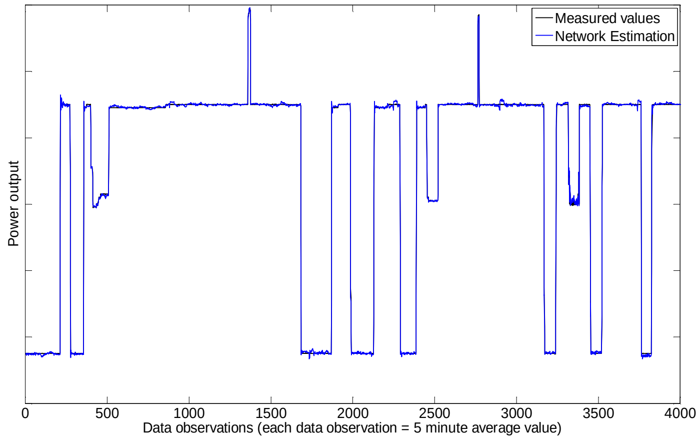

Figure 12 Measured and predicted values, PO, Unit-1

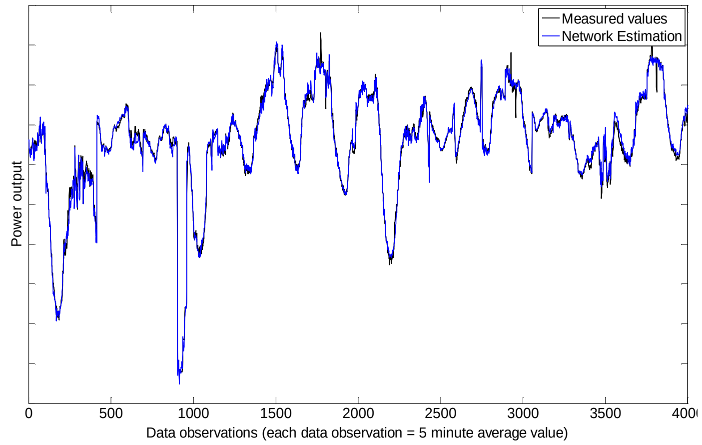

Figure 13 Measured and predicted values, PO, Unit-4

Event though the network performance in terms of prediction accuracy is satisfactory, a methodology to verify the sensitivity of each input is needed. First, how sensitive is the model selection to a specific selection of number neurons? Figure 14 shows a comparison between a model with 30 hidden neurons and 40 hidden neurons, applying data from Unit-4. As seen, the network prediction accuracy is rather robust against the selection of neurons even though it can be seen that 30 neurons increase the error slightly compared to the model with 40 neurons.

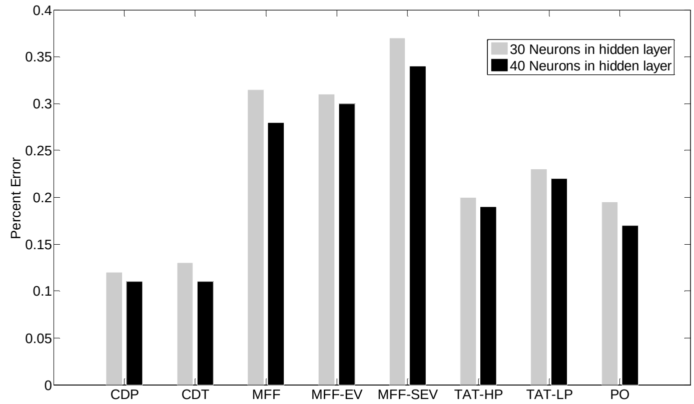

Figure 14 Prediction accuracy comparison, 30 and 40 neurons in hidden layer, P1-U4

To verify the model, sensitivity quantification is carried out for each input parameter. Figure 15 and 16 shows the effect in PO when compressor inlet air temperature is perturbed for the network with 30 and 40 neurons respectively. Two interesting point can be made, first both model as rather insensitive to small perturbations in compressor inlet temperature. Secondly, higher number of neurons provides a slightly higher error and thus a more sensitive network. This illustrates the fact that a network should be selected in both accuracy as well as robustness. The effect is the same in all parameters, and the more number of hidden units that are used, the higher the sensitivity. Thus, the selection of number of neurons should be as low as possible.

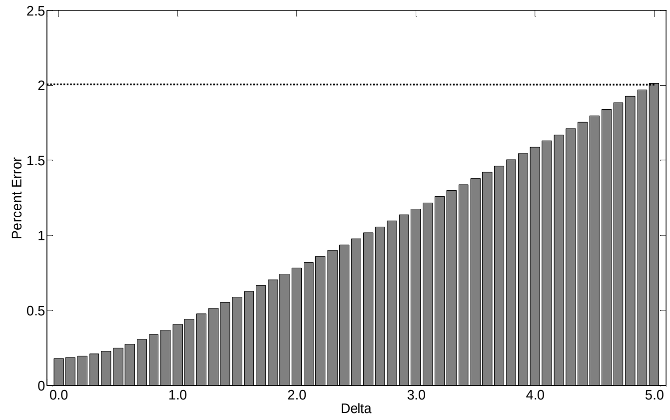

Figure 15 Sensitivity quantification, effect in PO when inlet air temperature is perturbed, 30 neurons, P1-U4

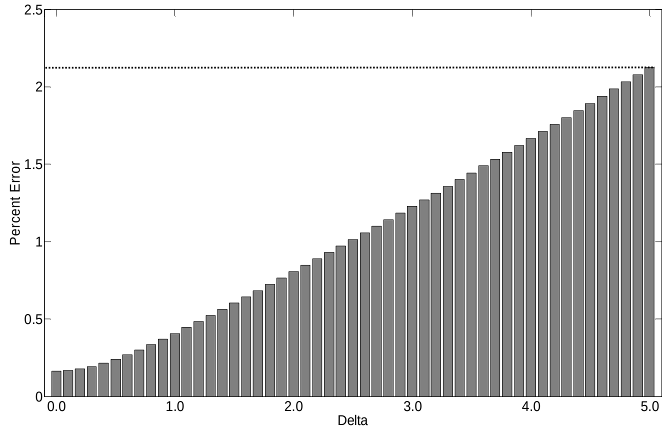

Figure 16 Sensitivity quantification, effect in PO when inlet air temperature is perturbed, 40 neurons, P1-U4

Two units, U-1 and U-2, operate in almost the same operational conditions following the same load profile. This provides a case where a model trained on one unit can be validated on similar unit, operating in the same conditions. This was performed on the test data set, where the input parameter from U-2 was applied to the NN model trained on U-1. Figure 17 show the result, and an increase in prediction error can be seen. Figure 18-19 show the predicted values with the NN model trained on U-1 and measured values from U-2 for PO and CDP. This shows that it in certain bases may be possible to transfer a NN model directly to a similar unit. The difference seen reflects the difference between units, which the NN model cannot compensate. Furthermore, this difference can be both measurement differences as well internal unit specific differences.

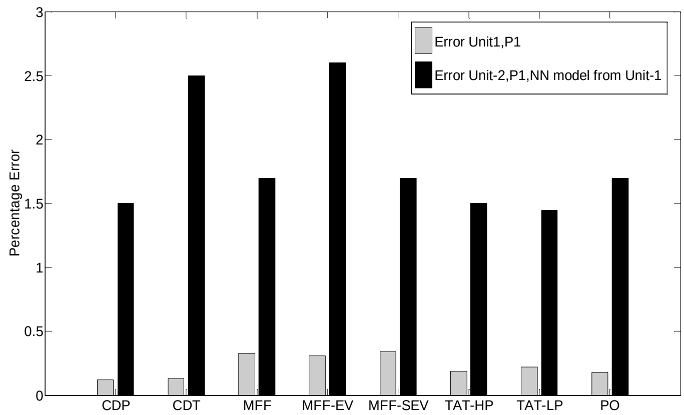

Figure 17 Test of NN model trained on U-1 and applied to U-2

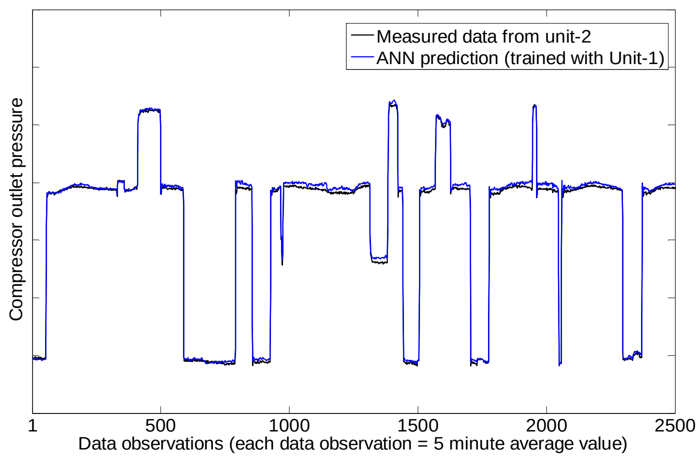

Figure 18 Compressor outlet pressure, predicted with NN model trained on U-1, applied on U-2

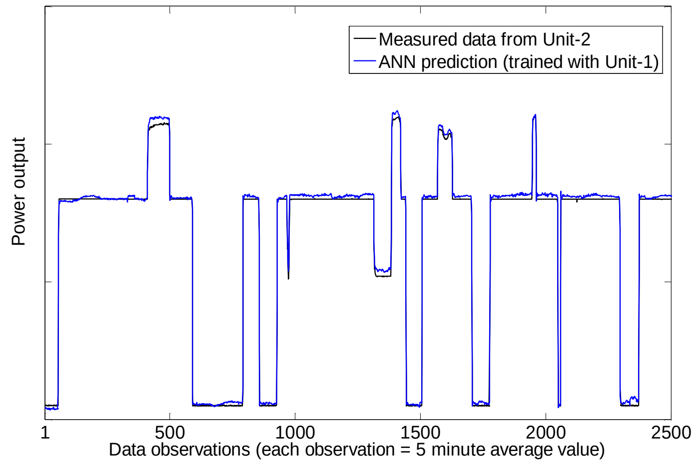

Figure 19 PO, predicted with NN model trained on U-1, applied on U-2

8.2 Non-reheat GT, PLANT-2

For Plant-2, an initial parameter selection was performed based on the operational conditions, see table 2. Basically, pressure in exhaust diffuser, inlet filter pressure drop, VIGV angles and ambient conditions were selected. However, a sensitivity analysis revealed that ambient humidity and pressure could be removed. Ambient pressure has a comparably low impact on the GT performance, and since both these plants operate in a frequency control mode, the effect might not be noticeable. However, ambient humidity affects the GT performance. But, in this case a rather high correlation between ambient temperature and humidity was seen, which means that the ambient temperature also provide information about humidity. The NN model just imbeds the relationship between the input and output not caring about the physics behind. In this case, this does not mean that humidity does not affect the performance.

Table 2 Used input parameters, Plant-2

Input parameter	First selection	Final model
PED	X	X
VIGV-1a	X	X
VIGV-1b	X	X
Ambient pressure	X	
Ambient temperature	X	X
DP-filter	X	X
Ambient humidity	X	

Table 2 shows the initial selected parameters and the final parameters applied in the model. The output parameters in this model were 38, but we limit the presentation of the result to the main performance parameters. Many of the output parameters are temperature measurements from the exhaust profile measurements. Figure 20 shows the training error between the two units. Furthermore, it can be recognized that the two units are modeled with similar accuracy.

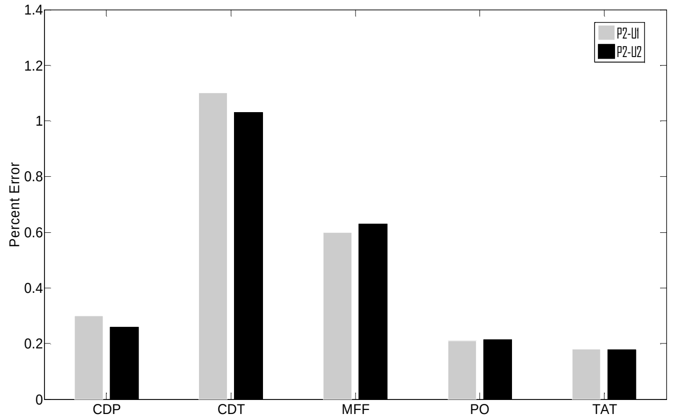

Figure 20 Percent error in main performance parameter in test-set, Plant-2

Since both units operate in frequency control the operation is highly dynamic. Figure 21 shows the prediction accuracy for PO, U-1, and figure 22 for fuel mass flow (MFF) also on U-1.

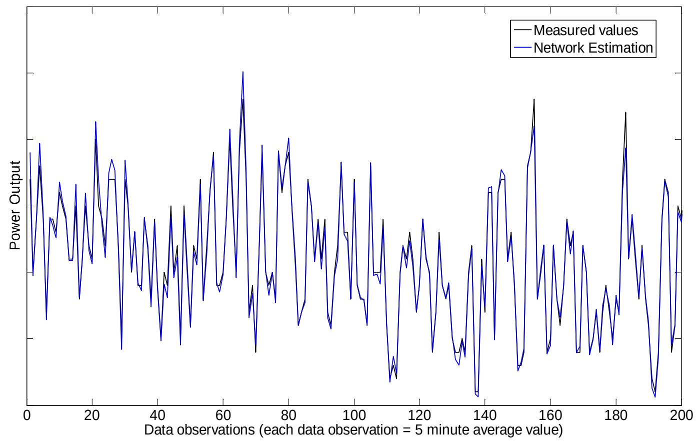

Figure 21 Trending PO, test data, P2-U1

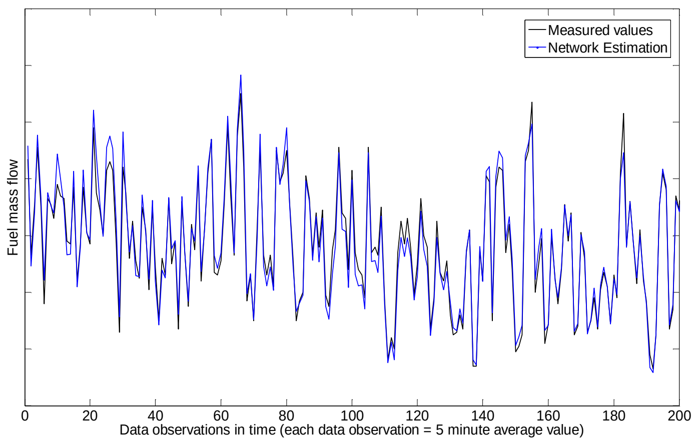

Figure 22 Trending fuel mass flow, test data P2-U1

Both figure 21 and 22 confirms the NN model has captured the GT performance allowing close tracking of the performance of the unit.

Similar to P-1, the two units in P-2 operate in the same operational mode. A similar test was performed to verify the possibility to transfer a NN model trained on one unit to a similar unit in the same operation conditions. Figure 23 show the error in main performance parameters when the ANN model trained with U2 is applied to U1, and a drastic error increase is seen. This confirms that in this case, each unit needs to be trained with a unit specific ANN to maintain the prediction accuracy.

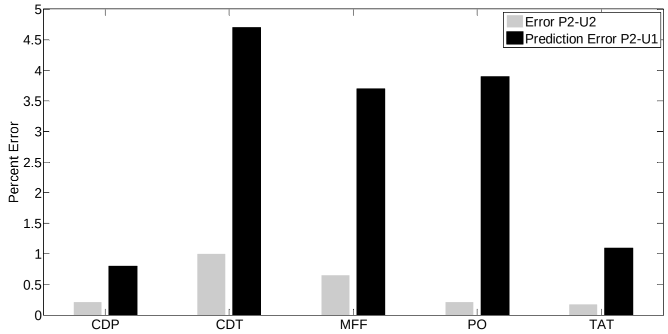

Figure 23 Prediction errors when applying ANN model trained with Unit-2 applied to Unit-1

Compared to P-1, where U-1 and U-2 was evaluated, the error is substantially higher in this case. Figure 24 shows a time interval for the measured PO from U1 and the NN predicted PO when applied to input data from U2.

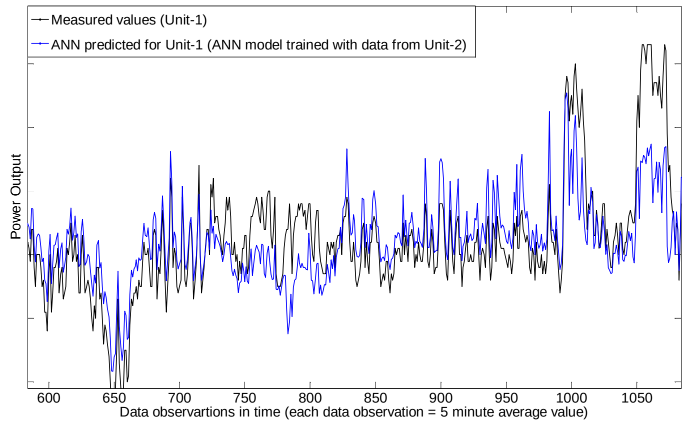

Figure 24 Test of ANN model trained with data from P2-U2 on P2-U1, PO

As recognized in figure 24, the NN model trained with data from Unit-2 does not produce any reliable PO predictions for Unit-1 and confirms that each unit, in this case, needs to be modelled with a unit specific NN model.

10 DISCUSSIONS AND CONCLUSION

In this study the MLPs successfully establish the statistical relationship between the performance parameters and the operational conditions. Since the NN models are trained with data representing the GTs in healthy conditions, these NN models become baseline models that can be used to validate new data from the engine. A detailed discussion was given on the selection of input and output parameters as well as the network structure. The result shows that the methodology is generic and not limited to certain GT types. Developing an NN model for a GT requires that the operational conditions be identified, and based on this, the needed input parameters can be identified. Once the initial model is established, a sensitivity parameter variation is performed to validate each input parameter. The final model is validated against ill-posed problems by establishing the model sensitivity to perturbation in each input parameter and thereby secure that the trained model is robust and not over trained. Quantification of the input parameter sensitivity also provides the knowledge to which extent each parameter affects the network prediction. Before performing a full sensitivity analysis, which includes removal in input parameters and retraining, input parameter sensitivity quantification can reveal parameters that can be omitted since their effect on network prediction accuracy is low when perturbed, however in this case this should be to sensible range in each input parameters. Selection of network structure, i.e. number of neurons, should be based on accuracy as well robustness. Selecting a higher number of neurons than necessary to perform the functional mapping between input and output results in a less robust model, hence selection of a simple model is preferable.

In this study we see that if two GTs are of similar type and operate in the same operating conditions, an NN model of one unit could be transferred to another unit to some extent, however, this results in a higher prediction error. This was actually expected, and the difference between the prediction accuracy is most probably due to unit specific differences. Since each GT installation is unique when considering all different operational boundaries, it might be more suitable to develop an NN model for each engine. The main advantages of unit specific NN models are that models directly reflecting an individual “behavior” are more accurate. No matter which approach that is taken, physical or data driven model, the difference between the units needs to be taken into account.

The pros of applying a NN monitoring approach can be summarized:

- No detailed physical information about the GT is needed.
- Only operational data is required.
- NN-calculation is fast and can be used for online use
- The interpretation is easy to understand.
- It can establish relationships between performance parameters and operational conditions that are difficult to model (such as the exhaust temperature profile)

The drawbacks with ANN can be summarized as:

- As in all statistical models, data covering the entire operation range is needed for training.
- Any new operational condition requires a retraining.

Even though the ANN itself does not perform diagnostics, interpretation of the differences in one or several output parameters can be helpful for the diagnostic engineer. Furthermore, the ANN supports the operator or expert to, in case of deviations, efficiently identify the problem area, allowing moving very soon to an in-depth analysis and corrective actions Hence, ANN is a cost efficient method for early warning diagnosis, which can lead to significant savings in terms of downtime, thus improving the overall plant economics.

11 FUTURE WORK

The methodology of applying NN for nonparametric modeling development for industrial GT has been investigated and the technology seems to be mature enough to be applied for real applications test. Remaining tasks relate to data processing tasks, such as an efficient methodology to clean training data, since this is the most time consuming part during model development. Another main issue is to quantify model prediction accuracy with regard to training data, which can be used to establish the needed data sampling frequency but also the level of outliers that can be accepted in the training data.

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NOMENCLATURE

ANN	Artificial Neural Networks
EV	EnVironmental
SEV	Sequential EnVironmental
CDP	Compressor discharge pressure
CDT	Compressor discharge temperature
CFD	Computational Fluid Dynamics
CV	Cross Validation
CCPP	Combined Cycle Power Plant
EV	EnVironmental
GPA	Gas Path Analysis
HRSG	Heat Recovery Steam Generator
IP	Intermediate Pressure
LP	Low Pressure
J	Jacobian
MFF	Mass flow fuel
MFF-EV	Mass flow fuel, EV combustor
MFF-SEV	Mass flow fuel, SEV combustor
MLP	Multi Layer Perceptron
P1-U1	Plant-1, Unit-1
P1-U2	Plant-1, Unit-2
P1-U3	Plant-1, Unit-3
P1-U4	Plant-1, Unit-4
P2-U1	Plant-2, Unit-1
P2-U2	Plant-2, Unit-2
PED	Pressure Exhaust Diffuser
PO	Power Output
SCG	Scaled Conjugate Gradient Algorithm
SEV	Sequential EnVironmental
TAT	Temperature after turbine
TAT-HP	Temperature after high-pressure turbine
TAT-LP	Temperature after low-pressure turbine
TIT	Turbine Inlet Temperature
RBF	Radial Basis Functions
ROI	Return on Investment
VIGV	Variable Inlet Guide Vanes

REFERENCES

[1] Therkorn, D., "Remote Monitoring & Diagnostic for Combined-Cycle Power Plants" Proceedings of GT2005, ASME Turbo 2005

[2] Urban, L.A., *Gas Path Analysis – A tool for engine condition monitoring*. Safe & Efficient Management Energy Proceeding at the 33rd Annual International Air Safety Seminar, 1980

[3] Urban LA. GT engine parameter interrelationships: Standard Division of United Aircraft Windsor Locks; 1969

[4] Doel DL. TEMPER – a gas-path analysis tool for commercial jet engines. Journal of Engineering for GTs and Power. 1994; 116:82

[5] Volponi AJ. Gas Path analysis: an approach to engine diagnostics. Time-Dependent Failure Mechanisms and Assesment Methodologies. 1983

[6] Volponi A. J.; GT Parameter Corrections, ASME, 98-GT-947, Stockholm, 1998

[7] International Standard ISO-2314, GT – Acceptance tests, Second edition, 1989

[8] Genrup, M., Assadi, M., Torisson, T., "A review of GT flow path analysis – From paper calculation to Artificial Neural Networks", GT-2002-30027, ASME Turbo Expo 2002, June 3-6, Amsterdam, The Netherlands

[9] Herzog, J. P., Hanlin, J., Wegerich S.W., Wilks, A. D., "High Performance Condition Monitoring of Aircraft engines", ASME Turbo Expo 2005, GT2005-68845

[10] Singer, I. R. M., Gross, K. C., King, R. W., Wegerich, S., "A pattern-Recognition-Based, Fault-Tolerant Monitoring and Diagnostic System", Proceedings of 7th Symposium on Nuclear Reactor Surveillance and Diagnostics, Vol.2, Avignon, France 18-23 June 1995

[11] Fast, M., Palmé, T.,"Application of artificial neural networks to the condition monitoring and diagnosis of a combiend heat and power plant, Energy (2009)

[12] Cybenko G., 1989, Approximation by Superimposition of a Sigmoidal Function, Mathematics of Control, Signals and Systems, 2, pp. 303-314

[13] Møller, M. F., 1993, "A scaled conjugate gradient algorithm for fast supervised learning". Neural Networks, Vol.6, pp.525-533

[14] Hadamard, Jacques (1923) Lectures on Cauchy's Problem in Linear Parial Differential Equations, Dover Publications, ISBN: 0486495493

[15] Montgomery, D. C., Peck, E. A., Vining, G. G, "Introduction to Linear Regression Analysis"

[16] Hiddeman, M., Marx, P. "Operating Experience with the Latest Upgrade of Alstom's Sequential Combustion GT26 GT", Proceedings of ASME Turbo Expo 2010: Power for Land, Sean and Air GT2010, June 14-18, 2010, Glasgow, UK

[17] Bishop, C. M., Pattern Recognition and Machine Learning ISBN-10:0-387-31073-8

