Proceedings of ASME Turbo Expo 2011
GT2011
June 6-10, 2011, Vancouver, British Columbia, Canada

GT2011-46340

APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR THE HEAT TRANSFER INVESTIGATION AROUND A HIGH-PRESSURE GAS TURBINE ROTOR BLADE

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ABSTRACT

This paper presents the preliminary results of using artificial neural networks in the prediction of gas side convective heat transfer coefficients on a high pressure turbine blade. The artificial neural network approach which has three hidden layers was developed and trained by nine inputs and it generates one output. Input and output data were taken from an experimental research program performed at the von Karman Institute for Fluid Dynamics by Camci and Arts [5,6] and Camci [7]. Inlet total pressure, inlet total temperature, inlet turbulence intensity, inlet and exit Mach numbers, blade wall temperature, incidence angle, specific location of measurement and suction/pressure side specification of the blade were used as input parameters and calculated heat transfer coefficient around a rotor blade used as output. After the network is trained with experimental data, heat transfer coefficients are interpolated for similar experimental conditions and compared with both experimental measurements and CFD solutions. CFD analysis was carried out to validate the algorithm and to determine heat transfer coefficients for a closely related test case. Good agreement was obtained between CFD results and neural network predictions.

NOMENCLATURE

i,j	- Neuron Number
n,k	- Number of Neurons at a Layer
l	- Intermediate Layer
L	- Last Layer
t	- Iteration Number
f'( )	- Derivative of a Function
a_i	- i^{th} Input to a Neuron
x_j	- Sum Function of j^{th} Neuron
$w_{i,j}$	- Weight from i^{th} Neuron to j^{th} Neuron
$E^L_i(t)$	- Error of i^{th} Neuron at Iteration t at Layer L
$d^L_i(t)$	- Desired Output of i^{th} Neuron at Iteration t at Layer L
y_j	- Output of j^{th} Neuron
μ	- Learning Rate
s	- Curve Length [mm]
c	- Chord Length [mm]
Tu_∞	- Free Stream Turbulence Intensity [%]
$M_{a,i}$	- Inlet Mach Number
$M_{a,e}$	- Exit Mach Number
i	- Incidence Angle [deg.]
T_{wall}	- Blade Wall Temperature [K]
$P_{o,\infty}$	- Inlet Total Pressure [kPa]
$T_{o,\infty}$	- Inlet Total Temperature [K]
h	- Heat Transfer Coefficient [W/m^{2}K]

INTRODUCTION

Modern high-pressure turbines are increasingly challenged by high inlet temperatures and stage pressure ratios in order to improve the engine efficiency. Since temperature in high-pressure turbines exceeds the melting point of blade material, efficient turbine cooling is most often required to ensure acceptable lifetimes. Turbine cooling designs depend on accurate determination of gas path boundary conditions such as pressures, temperatures, heat transfer coefficients, and film effectiveness [1].

Computational Fluid Dynamics (CFD) is increasingly being relied upon in the design and analysis of gas turbine components. The need to predict heat transfer along with aerodynamics during the design of turbine blades greatly complicates these analyses. Thus, the heat transfer predictive capability of CFD currently lags that of aerodynamics [2]. CFD techniques based on Reynolds-averaged Navier-Stokes (RANS) equations are routinely used to predict the pressure loadings and flow distributions of multi-stage blade rows. Although applications of CFD to predicting turbine heat transfer have achieved only limited success, Medic et al. [3] showed that physical and mathematical modifications on solution techniques made the CFD results more reliable. Typically the external heat transfer coefficients on turbine vanes and blades are obtained from the empirical correlations or boundary layer codes rather than directly from RANS analyses. This is especially true when there is laminar-to-turbulent boundary layer transition [4]. Heat transfer data is therefore needed both to assess the effects of various flow parameters and to improve CFD analyses so that these effects can be accurately predicted.

In this study, heat transfer coefficients around a turbine rotor blade are predicted using artificial neural network (ANN) from nine input variables. The ANN is trained using the experimental data of Camci and Arts [5,6].

ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial Neural Network, which is an emulation of biological neural system, is a collection of simple processors connected together. Artificial Neural Network is also called as Neural Network or simply ANN. ANNs are applied in many fields as a function approximation tool including time series prediction, regression analysis, interpolation, and extrapolation; as a classification tool including fault detection, pattern recognition; as a data processing tool including filtering and clustering.

ANNs can handle noisy data and can be implemented to any application. Once a network is trained, parameters are fixed and any case can be executed within a seconds without need for reprogramming and remodeling. Although there are advantages of ANNs, large nets require high processing time and need more information from real life applications. Since ANNs are not based upon conventional computing, they tell or predict what they are trained for [8].

Structure of a network consists of three layers. An input layer including input neuron(s). Hidden layer(s) including hidden layer neuron(s) where the calculations are implemented. An output layer including output neuron(s). Neurons of a network are interconnected to each other with weights which can be considered as synapses of a biological neural network. While teaching a network training examples (inputs) are presented to the network first. Then how closely the actual output of the network matches to the desired output is determined. Finally weight of each connection is changed so the network produces a better approximation of the desired output at the next iteration.

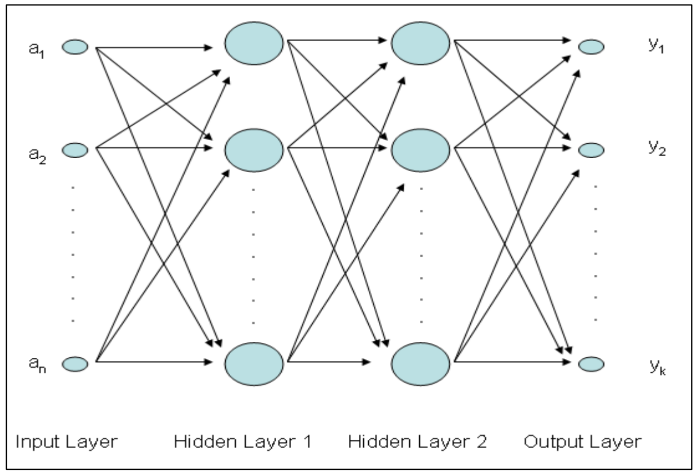

Figure 1: Structure of a Network with Two Hidden Layers

In this study a Feed Forward Network, where signals travel in one direction from input layer to output layer, with Back Propagation Algorithm is used. Back Propagation Algorithm propagates the error backwards in order to adjust weights to decrease error. In the Feed Forward Network output of a single neuron is calculated with S-type non-linear activation function Sigmoid [9].

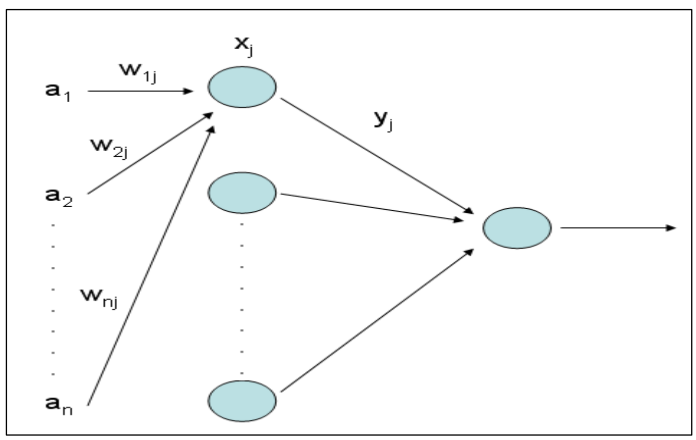

Figure 2: Calculation of Output for a Single Neuron

$$x_j = \sum_{i=1}^{n} w_{i,j} * a_i \qquad [1]$$

$$y_j = f(x_j) = \frac{1}{1+e^{-x_j}} \qquad [2]$$

Derivative of sigmoid activation function is given as:

$$f^{'}(y_j) = \frac{\partial y_j}{\partial x_j} = \frac{1}{1+e^{-x_j}} * (1 - \frac{1}{1+e^{-x_j}}) \qquad [3]$$

Error of i^{th} neuron of last layer (L) at iteration t is calculated as:

$$E_i^L(t) = d_i^L(t) - y_i^L(t) \qquad [4]$$

Error of i^{th} neuron of intermediate layer(s) (l) at iteration t is calculated as:

$$E_i^l(t) = f^{'}(y_i^l) * \sum_{j=1}^{n} (E_j^{l+1}(t) * w_{i,j}(t)) \qquad [5]$$

Where $f^{'}(y)$ is the derivative of sigmoid activation. Weights are adjusted according to the formula:

$$w_{i,j}(t+1) = w_{i,j}(t) + \mu * y_i^l * E_j^{l+1}(t) \qquad [6]$$

μ is learning rate which varies between 0 and 1 is used to speed up or slow down the learning process. For stable learning and better generalization it is found that lower learning values such as 0.1 are more suitable [10].

Stopping criteria based on total error. Absolute value of the error for each neuron is added and if the total error is smaller than the target error, learning is stopped. Last calculated weights are the final weights of the network [11].

PREDICTION OF HEAT TRANSFER COEFFICIENTS BY ANN

ANNs are non-conventional statistical tools. In this work ANN can be considered as a multiple non-linear regression model. Heat transfer coefficient along a high pressure turbine blade surface is aimed to fit to an equation with multiple inputs. In contrast to other function approximation techniques like curve fitting and regression ANN do not give a simple equation between input and output variables. It works as a black box but eliminates the restriction of user to specify an equation to fit a model between input and output variables where specifying an equation is a must in conventional statistical tools.

Heat transfer coefficients of an uncooled turbine blade were obtained from short duration heat transfer experiments that were performed during 1980's. Heat transfer coefficients under well simulated gas turbine conditions were obtained for many turbulence intensities and incidence angles. A 9-8-12-8-1 type network was trained to fit 108 data points to an equation. Nine input variables of the network are inlet total pressure, inlet total temperature, blade wall temperature, inlet Mach number, exit Mach number, turbulence intensity, incidence angle, specific location of measurement and the measurement location is suction side or pressure side of the turbine blade. Output parameter of the network is the predicted heat transfer coefficient.

Table 1: Notation for the Algorithm and Equations

Notation	Meaning
i,j	Neuron Number
n,k	Number of Neurons at a Layer
l	Intermediate Layer
L	Last Layer
t	Iteration Number
f'( )	Derivative of a Function
a_i	i^{th} Input to a Neuron
x_j	Sum Function of j^{th} Neuron
$w_{i,j}$	Weight from i^{th} Neuron to j^{th} Neuron
$E^L_i(t)$	Error of i^{th} Neuron at Iteration t at Layer L
$d^L_i(t)$	Desired Output of i^{th} Neuron at Iteration t at Layer L
y_j	Output of j^{th} Neuron
μ	Learning Rate

Table 2: Structure of the Network

Inputs 9	Network 8-12-8	Output 1
- Inlet Total Pressure - Inlet Total Temperature - Blade Wall Temperature - Inlet Mach Number - Exit Mach Number - Turbulence Intensity - Incidence Angle - s/c - Suction Side or Pressure Side	Three Hidden Layers	Heat Transfer Coefficient

Here *s* denotes the curve length of the portion up to the measurement point and *c* denotes the chord length of the blade. Six different experimental conditions are given below.

Table 3: Six Different Experimental Conditions

Case	Po,∞ [kPa]	To,∞ [K]	Twall [K]	Ma,i	Ma,e	Tu [%]	i [Deg.]
1	291.5	410	301.7	0.24	0.901	5.2	0
2	305	417.9	295	0.263	0.945	0.8	-10
3	305	417.2	292	0.271	0.952	0.8	0
4	304	417.8	297.8	0.31	0.948	0.8	10
5	304.5	417.6	299	0.316	0.951	0.8	15
6	333	409.2	294.2	0.251	0.923	5.2	0

In training process all data except the experiment number 4 are used. The network model fitted to the data and experiment number 4 is used for testing. In the below figures fitted data are given.

Test data and ANN interpolation for case 4 are generally close to each other (Figure 5). Differences may be caused from limited data for other cases.

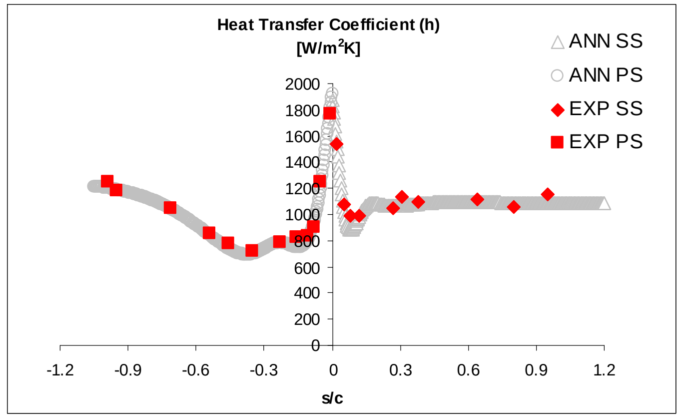

Figure 3: Fitted Data for Case 1

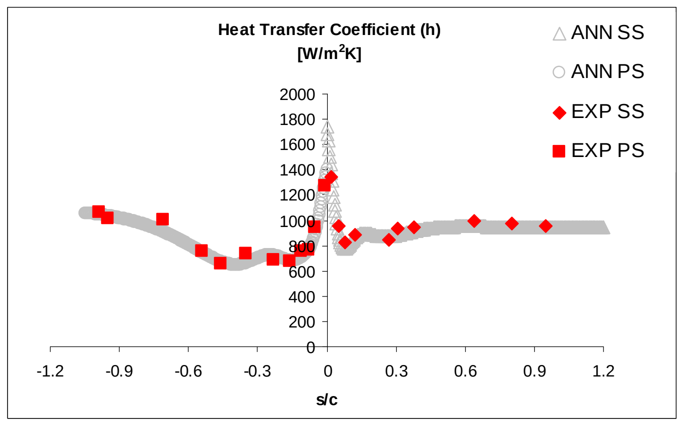

Figure 4: Fitted Data for Case 3

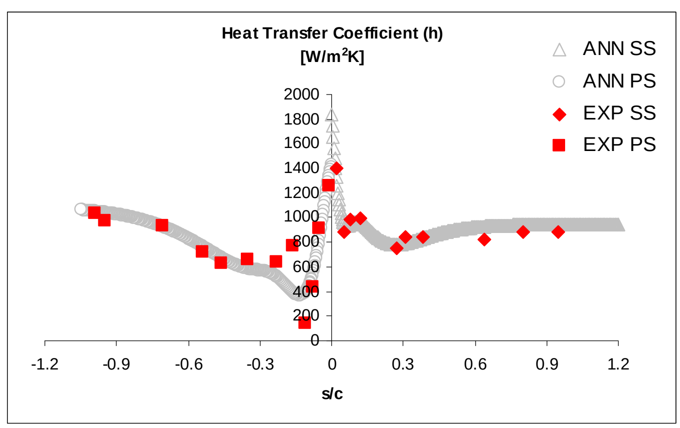

Figure 5: Predicted Data for Case 4 by ANN

In this study ANN is trained from one experimental data set. Input parameters are chosen to include especially flow parameters. If a network is thought to be trained with data from other sources like Arts et al. [12], input variables must be extended to include geometrical parameters such as chord length, profile thickness distribution, stagger angle, flow turning etc.

NUMERICAL METHOD

One of the objectives of this study is to compare the experimental data with predictions from a CFD analysis in order to validate ANN predictions. An experimental dataset is selected for this purpose based on the work of Camci and Arts [5,6].

The blade chord length of the VKI rotor equals 80 mm, with pitch-to-chord ratio equal to 0.67. The inflow angle is 30°. The specific dimensions of the VKI rotor and more detailed description of the geometry can be found in Camci and Arts [5,6]. Short duration experiments were conducted in a linear cascade consisting of five blades. The uncertainty for the heat transfer coefficient was estimated between +/- 5%. Camci [7] also examined incidence effects on the test blade.

Steady state simulations were obtained with FLUENT and all simulations were conducted with the Spalart-Allmaras turbulence model. Turbulent flows are significantly affected by the presence of walls. Obviously, the mean velocity field is affected through the no-slip condition that has to be satisfied at the wall.

The near-wall modeling significantly impacts the fidelity of numerical solutions, since walls are the main source of mean vorticity and turbulence. After all, it is in the near-wall region that the solution variables have large gradients, and the momentum and other scalar transports occur most vigorously. Therefore, accurate representation of the flow in the near-wall region determines successful predictions of wall-bounded turbulent flows.

As a result, the 2D simulation was performed with an unstructured quadrilateral mesh. y+ values are taken into account for the mesh in the near-wall region. The total grid size is 66349 cells. The near solid surface region of the blade was meshed such that y+ ~ 10 along the surfaces.

Table 4 summarizes the geometrical and boundary conditions used for the numerical analysis.

Table 4: Geometrical and Boundary Conditions

Pitch to Chord Ratio	0.67
Chord Length	80 mm
Inlet Mach Number	0.316
Inlet Re Number	$8.5x10^5$
Inlet Temperature	417.6 K
Inlet Flow Angle	30°
Stagger Angle	38.5°
Inlet Turbulence Intensity	0.8%
Exit Mach Number	0.951
Blade Surface Temperature	299 K

Figure 6 shows the comparison of experimental data with CFD result for Tu_{∞} = 0.8%, i=15°. It can be seen from the figure that CFD result represents the experimental trend.

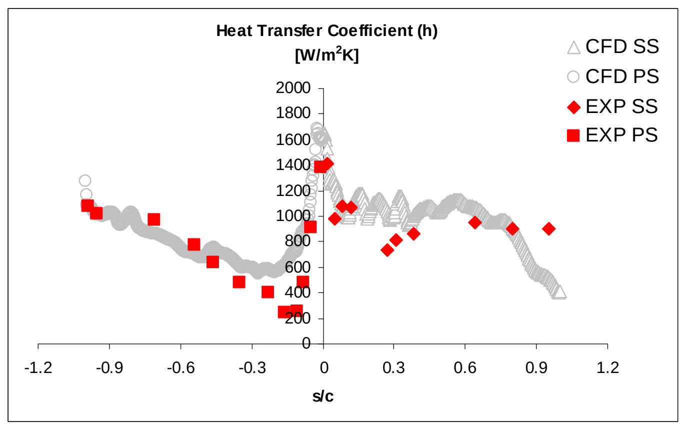

Figure 6: Comparison of Experimental Data (Case 5) with CFD Result for Tu_{∞} = 0.8%, i=15°

Additionally a CFD analysis is carried out for a different case bounded by the experimental conditions in order to compare ANN predictions with CFD results. The test case 7 which is test case 2 with incidence angle i = 5° is executed by ANN and CFD. The gathered results show that ANN can generalize successfully the trends in the range of trained data. It should be reminded that since ANN does not concern with the physics of flow, extrapolation for the out of training region may not be as successful as predictions for the learning boundary.

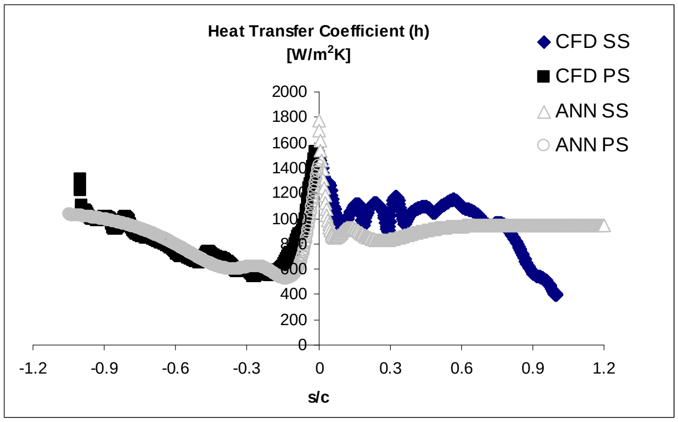

Figure 7: Comparison of ANN Prediction with CFD Result for Case 7

CONCLUSION

An artificial neural network code was developed to predict the convective heat transfer coefficient around a high pressure turbine blade. The code was trained by experimental input and output data of Arts and Camci [5,6]. The results of the code for heat transfer coefficient were in good agreement with experimental results. For test case 2 with an incidence angle of 5 degree CFD analysis was carried out to find the heat transfer coefficients. Results obtained from CFD analysis were compared to neural network code results for the same case and it was seen that the neural network code has a capability for generalization to estimate heat transfer coefficient around the blade, especially for pressure side of the blade. Since the network is trained with data from one experiment and include flow parameters as inputs, this work should be considered as an introductory approach for application of artificial neural networks to gas turbine heat transfer studies. More robust networks can be generated from distinct sources and different geometries including both flow and geometrical parameters as inputs.

For suction side, investigation of the turbulence models which best suit for the case and required modifications of the model can be assessed as a future work on this study. Also it is aimed to train the neural network for different experiment conditions and different geometries with more input variables and extend the approach for film cooling cases as a future work.

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