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# The Use of ANN for Turbo Engine Applications

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**Abstract.** To reduce environmental pollution and increase efficiency of commercially available turbo engines it is essential to optimize. The suggestion made in this paper, is the use of evolution strategies and artificial neuronal networks (ANN) for turbo engine applications. Optimizations of the impeller and the combustion process are only two applications in the wide range of improvements.

## 1 Simulation of turbulent flow with combustion

The chemical reactions and the coupling with turbulent flow have to be performed at the same time during the simulation process. Therefore it is necessary to describe the interaction between the turbulent flow and chemical reaction with probability density functions (pdf) to conform to the stochastic nature of highly turbulent combustion processes.

$$\tilde{\mathbf{S}}(\boldsymbol{\varphi}) = \int \tilde{\mathbf{f}}_{\varphi}(\boldsymbol{\psi})\,\mathbf{S}(\boldsymbol{\psi})\,\mathbf{d}\boldsymbol{\psi}$$

Herein $\boldsymbol{\psi}$ is the random vector corresponding to the vector of the $\boldsymbol{\varphi}$=(T, $Y_i$) with Temperature T and Mass Fraction of Species i, $\tilde{\mathbf{f}}(\boldsymbol{\psi})$ denotes the density weight (Favre) averaged scalar pdf and S($\boldsymbol{\psi}$) the chemical source term. **The** expression f($\boldsymbol{\psi}$)d$\boldsymbol{\psi}$ is defined as the probability that $\boldsymbol{\varphi}$(T(x,t),$Y_i$(x,t)) is between $\boldsymbol{\psi}$-d$\boldsymbol{\psi}$/2 and $\boldsymbol{\psi}$+d$\boldsymbol{\psi}$/2 at time t and the location **x** in the flow field. A transport equation for the scalar pdf can be derived from the transport equation for $\boldsymbol{\varphi}$ and an expression for the pdf as a delta function and consists of the temporal change of **f**, mean convection and velocity fluctuation in physical space and molecular mixing and chemical reaction in scalar space.A stochastically equivalent system in a Lagrangian framework is used for the solution procedure. A so called stochastic particle ensemble which has the same initial distribution like the physical scalar values is used to solve the equation [4].

### 1.1 Complex Chemistry

Prediction of emissions, like NOx- and CO-formation, depends on the chemical reaction mechanism used. Complex chemistry has more than 1000 reaction steps with over 200 species. The finite rate chemistry requires integration of ordinary differential equations (ODEs) of the form:

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$$\frac{dY_i}{dt} = \dot{r}_i(\bar{y}, T, p) .$$

Where $\dot{r}_i$ is the chemical reaction rate of species i, $\bar{y}$ is the mass fraction vector of all species, T is the temperature and p is the pressure. It is in general not possible to solve the equations for all particles of the stochastic particle ensemble, which is the solution of the pdf, because of CPU-time limitations. The use of databases for storing chemical reactions is also limited. The exponentially growing requirements of storage capacities limit the so-called look-up tables [8]. Therefore the complex chemical reaction mechanism like the GRIMech3.0 [5] that consists of 325 reactions with 53 species is trained in ANNs. So the evaluation of the complex chemistry with marginal CPU-time and memory resources is introduced.

For given boundary conditions it is possible to calculate the reaction progress till the chemical equilibrium is reached. That means to calculate the progress in composition space of species in discretely time steps. For example with methane air combustion the brutto reaction is:

$$CH_4 + 2(O_2 + 3{,}76N_2) \rightarrow CO_2 + 2H_2O + 7{,}52N_2 .$$

## 1.2 Approximation of Complex Chemistry with the use of ANN

The calculations of complex chemistry with ODEs were replaced by ANNs which configuration is given in table 1.

| Regarded Element | Values |
|---|---|
| momentum-term | 0.2 |
| learning-rate | 0.001-0,01 |
| structure (number of layers) | (in-hidden-out) 15-2x20-1(a) 15-2x20-14(b) |
| learning steps | (a) 600000 (b) 700000 |
| activation function include output layer | tanh |

**Table 1:** *Configuration of ANN, temperature (a), species (b)*

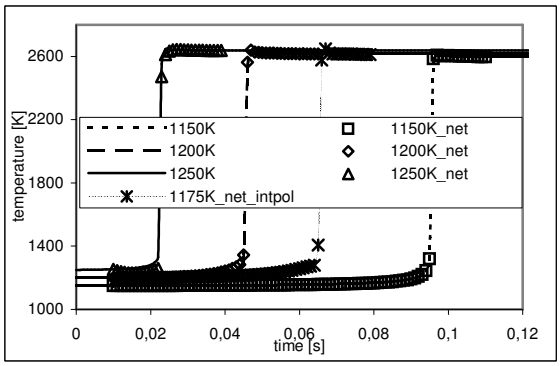


**Fig. 1:** *Temperature of equilibrium methane/air reaction, ANN prediction of temperature, variable starting temperature in the range of 1150 to 1250[K]*

Tests show that the structure of the ANNs and the number of neurons (>20) in hidden layers (>2) have no major impact on the results. The training data of the ANNs are the chemical stats for a given time step. The back-propagation learning algorithm with weight decay and momentum term was used. For the test case one ANN is

trained for prediction of the temperature and one further net for the concentration of the species. The input neurons are the temperature and the species concentrations. The ANNs predict the changes of the input values for the next time step. The so trained ANN calculates the output for temperature and mole fractions of the species with dt=0,001[s]. The output is taken as the input for the next calculation step. The test is finished, when there is no change in temperature and concentrations. The net out to given input of trained data series with starting temperature of 1150 to 1250[K] results in the net reproduction seen in Fig. 1. The net has learned the data and is able to reproduce the dataset with dynamic processing by getting the initial configuration at one time.

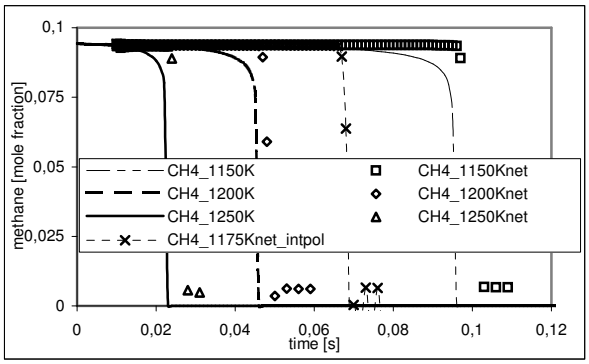


**Fig. 2:** *Methane concentration of equilibrium methane/air reaction, ANN prediction of methane concentration, variable starting temperature in the range of 1150 to 1250[K]*

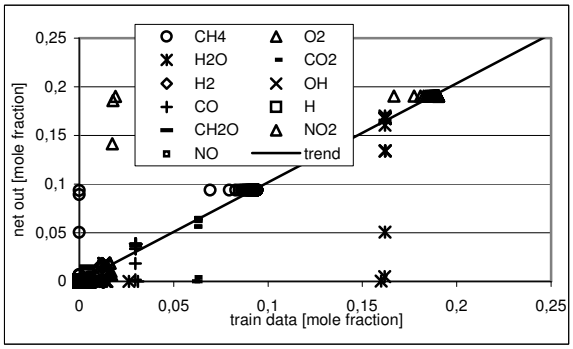


**Fig. 3:** *Species of methane/air combustion, starting temperature 1150[K], comparison of training data and net prediction*

Further the net is showing good results for the concentrations of methane with interpolated starting temperature of 1175[K]. By comparison the ANN shows a good prediction with a small time shift of about 0,003[s]. The concentrations of major species in Fig. 3 for 1150[K] starting temperature are showing the same time shift, but in summary good results in comparison training data and net prediction. As an example for species concentration the net prediction of methane is shown in Fig. 2. In the range of 1150 to 1250[K] the ANN is able to give good predictions.

### 1.3 Conclusion

The computation of temperatures and concentrations in separate ANNs show better results than in former studies [6]. Maybe further optimisations can be achieved with separate ANN for major species and ANN for different time steps.

## 2 Optimization of a Centrifugal Impeller using Evolution Strategies and Artificial Neural Networks

Evolution Strategies (ES) are used to optimize the geometry of an existing impeller to increase it's isentropic efficiency. Starting from an existing impeller several geometries are created using mutation and recombination procedures. To evaluate the performance of new designed impeller geometries a compressible three-dimensional Reynolds-averaged Navier-Stokes Solver (RANS) is used. The implemented grid generator uses B-Spline-Curves which describe the camber lines at hub and shroud. Since many solutions are produced during the optimization process, the performance evaluations are very time expensive. Therefore the implemented optimization system is parallelized using MPI. Furthermore an ANN is discussed to use the knowledge of recent performance evaluations for performance predictions with the goal to speed up the optimization process.

### 2.1 Centrifugal Impeller

In Fig. 4(a) the centrifugal impeller is shown with the flow channel between two adjacent blades. The impeller blades can be described by their camber surfaces because they are considered as infinitesimal thin blades. One channel is sufficient because the optimization is done at a steady state working point and so periodic boundary conditions can be set [2].

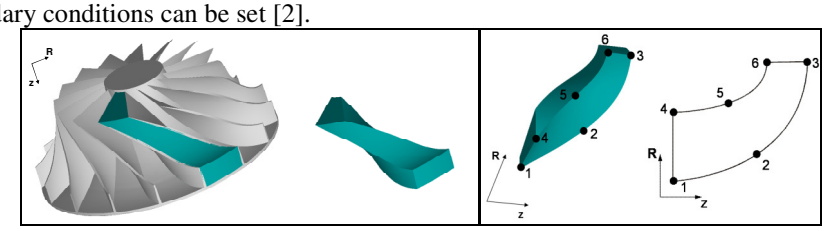


**Fig. 4.** *Centrifugal impeller and simulated flow channel (a), Variegated points on camber surfaces of the impeller(b)*

During the optimization process with ES several geometries will be generated. In Fig. 4(b) the variable geometry of the flow channel is shown. The two camber lines along the points 1-2-3 and 4-5-6 can be described by the two cylindrical coordinates $(\vartheta, z)^T$. The z coordinate represents the rotational axis and $R$ stands for the radial coordinate.

Each point on the camber line can be variegated by changing the $z$ - coordinate and by adding $\Delta\vartheta$ which describes the angle deviation to the reference impeller. The $z$ - coordinate at impeller inlet and outlet is kept constant. Because the impeller is to be fit in an existing housing, the radial distributions are also kept constant. In this case

$\Delta\vartheta_1$, $\Delta\vartheta_2$, $\Delta\vartheta_4$, $\Delta\vartheta_5$ as well as $z_2$ and $z_5$ are to be variable to generate different geometries for the optimization process using evolution strategies.

## 2.2 Optimization using Evolution Strategies

For the optimization of the centrifugal impeller one individual is described by a vector of six geometrical parameters. In the initialization process a number of $N$ individuals by uniformly distributed stochastic variation of the geometrical parameters are produced [9]. In the recombination process information between the individuals will be exchanged. The mutation process is needed for exploration in the search space which is important for getting new knowledge as well as overcoming some local maxima of the objective function. After this the individuals has to be evaluated by the fully three-dimensional Navier-Stokes solver using the k-$\varepsilon$-turbulence model. In the selection process the best individuals of the formerly generated $2N$ individuals which consists of $N$ parents and $N$ children, $N$ individuals with the highest efficiency are selected. This described procedure is passed through until a stopping criterion is fulfilled.

## 2.3 Performance Prediction using Artificial Neural Networks

A feed forward ANN is used with the view to use it as an approximation tool. Six input units, two hidden layers and one output unit were selected for the present approximation problem. The training pattern set consists of a six dimensional input vector $\mathbf{u}$ and the one dimensional output vector $\mathbf{t}$. The Resilient Backpropagation algorithm is used as a local adaptive learning scheme [11].

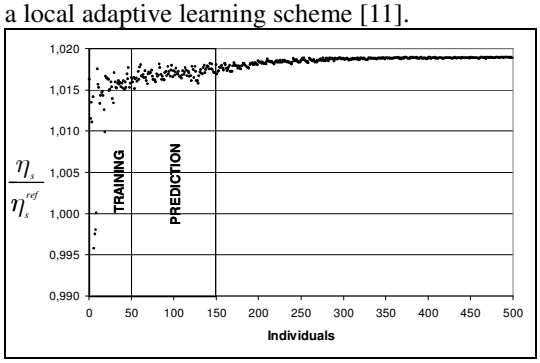


**Fig. 5:** *Convergence history of the optimization. The first 50 individuals were used as training data set to predict the next 100 individuals*

In Fig. 5 the convergence history of the performed optimization with evolutionary strategies is shown. To train and test the networks the first 50 individuals which were created during the optimization process were used as a training data set to test the network. 15 units in two hidden layers are a good choice for the given approximation problem. After training procedure the next 100 individuals are to be used to get information about prediction quality of the network [7].

Concerning the 50 individuals which were presented to the network during the training phase the correlations of predicted and simulated efficiencies as shown in

Fig. 6 are very exact. The individuals which were not presented to the network (the following 100 individuals) are characterized by the rhombi in Fig. 6. 65% of the predictions have a deviation of less than 0.05% to the correct ones.

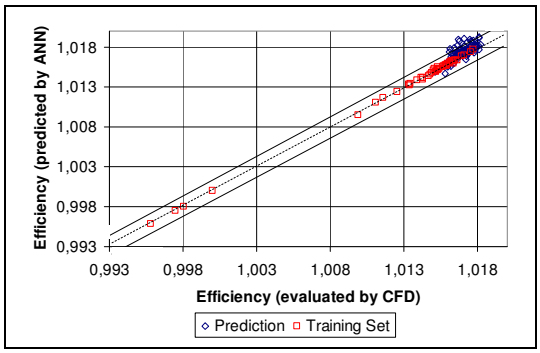


**Fig. 6.** *Correlations of predictions and simulations*

## 2.4 Conclusion

It could be shown, that evolution strategies are appropriated to optimize the geometry of a three dimensional centrifugal impeller. Furthermore an ANN was trained and tested to predict the isentropic efficiency. It has to be discussed how to integrate the network and its database into the optimization process to use the knowledge of performed simulations to speed up the optimization process.

## References

[1] Aungier, R. H. (2000). Centrifugal Compressors - A Strategy for Aerodynamic Design and Analysis. The American Society of Mechanical Engineers, New York

[2] Bartold A., Joos F. Optimization of a Centrifugal Impeller Using Evolutionary Algorithms. ASME Turbo Expo 2008, GT2008-50805, Berlin, Germany

[3] Chen J.-Y., Blasco J. A., Fueyo N., Dopazo C (2000) An economical strategy for storage of chemical kinetics: Fitting in situ adaptive tabulation with artificial neural networks, Proceedings of the Combustion Institute 28:115-121

[4] Harder, S., Joos, F.: Modelling a Non-Premixed Industrial 18 MW Gas Turbine Combustor, GTI/ASME Turbo Expo 2007, GT2007-27370 Montreal Canada

[5] GRI-Mech 3.0: Gregory P. Smith, David M. Golden, Michael Frenklach, NigelW. Moriarty, Boris Eiteneer, Mikhail Goldenberg, C. Thomas Bowman, Ronald K. Hanson, Soonho Song, William C. Gardiner, Jr., Vitali V. Lissianski, and Zhiwei [online]: http://www.me.berkeley.edu/gri_mech/.

[6] Große, L., Joos, F.: Usage of Artificial Neural Networks for Data Handling, GfKL 2008 German Classification Society, Hamburg Germany

[7] Meier, R., Joos, F.: Optimization Methods with Evolutionary Algorithms and Artificial Neural Networks. GfKL 2008 German Classification Society, Hamburg Germany

[8] Pope, S.B.: Computationally efficient implementation of combustion chemistry using in situ adaptive tabulation. In: Combust. Theory Modelling, Vol. 1 (1997), pp. 41-63

[9] Rechenberg, I., Evolutionsstrategie, Friedrich Frommann Verlag (1994)

[10] Zell, A., 1997, Simulation Neuronaler Netze, Oldenbourg, München