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OBTAINING FLUID FLOW PATTERN FOR TURBINE STAGE WITH NEURAL MODEL

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Abstract

In the paper possibility of applying neural model to obtaining patterns of proper operation for fluid flow in turbine stage for fluid-flow diagnostics is discussed. Main differences between Computational Fluid Dynamics (CFD) solvers and neural model is given, also limitations and advantages of both are considered. Time of calculations of both methods was given, also possibilities of shortening that time with preserving the accuracy of the calculations are discussed. Gathering training data set and neural networks architecture is presented in detail. Range of work of neural model was given. Required input data for neural model and reason why it is different than in computational fluid dynamics solvers is explained. Results obtained with neural model in 21 tests are discussed. Arithmetic mean and median of relative errors of recreating distribution of pressure and temperature are shown. Achieved results are analysed.

Keywords*: turbine, diagnostics, neural model, pattern, fluid flow*

Introduction

With development of diagnostics of technical objects many operations were automatized (e.g. valve handling). Still most of complex operations are handled by operators. These activities include detecting irregularities in the systems, learning their causes and then supervising processes or procedures to restore the correct operation of the system – often called in literature Abnormal Even Management (AEM) [1]. Technical object operator to decide which procedures should be undertaken have to take into consideration many conditions. The more complex technical object is the more factors there is and operators perception has its limits. Statistics shows [1] that about 70% of accidents in industry is caused by human error. Systems supporting operators work significantly facilitate decision making process. These systems analyse informational noise to obtain information e.g. in the form of single variable, supporting the operator. It also should be remembered that often measurements in technical object may be insufficient, incomplete due to multitude of reasons such as errors or defects.

The next stage in the development of diagnostic systems is AEM automation using intelligent control systems. The first step to do this is automatization of damage detection and diagnostic forms. Over the years, many different methods have been created, such as error trees, graphs based, based on analytical methods or neural networks.

Venkatasubramanian et al. divided modelling methodology for damage detection and diagnostics into three parts [1], [2], [3] based on quantitative models, qualitative models and process history based methods. These publications provide a good overview of the methods used, taking into account the specific needs of diagnostics and damage detection. In [4] history and further development perspective for diagnostics and detection is presented.

Kim and Joo [5] presented profits from application of model based on-line diagnostic systems for combined cycles in power plants Soeincheon and Sinincheon. Object's condition was estimated based on measurement of heat and power. On the other hand, Głuch and Żołna [6] based steam power plant diagnostics on patterns of proper operation and formulation of the pattern based on analysis of data from power plant that enabled detection.

Neural models are already present in technical objects diagnostics. Specific needs of models for diagnostics and detection on example of heat exchanger in tyre factory was shown in [7]. Mathematical model development based on measurements form the object was presented, based on the model simplified algorithm of fault detection was applied. Review of applications of neural models for thermal analyse of heat exchangers is provided by [8] where it was divided into 4 parts: modelling of heat exchangers, estimation of heat exchangers parameters, phase change and control of heat exchangers.

In this paper the author presents example of application of neural model for obtaining pattern of proper operation of turbine stage for further use in diagnostic system.

Difference between with Computational Fluid Dynamics solvers and Neural Model

To calculate flow in a turbine with Computational Fluid Dynamics solvers like ANSYS Fluent or CFX it is needed to solve equation system that consist of continuity equation, energy and momentum conservation equations, state and fluid equation. Due to complexity of the equation system it takes a lot of time to make the calculations – it is main reason why computional fluid dynamics calculations are unusable in diagnostic process especialy in the on-line one. Small change of any parameters implies the need to recalculate and again wait hours for calculation to complete.

This resulted in investigating new methods of calculating fluid flow like artificial neural networks. On a contrary to CFD, neural model does not contain equations describing physics of the flow. It is just a "black box" trained to provide distribution of thermodynamic parameter in certain conditions. Described neural model will never replace CFD simulations but author believes it can complement it, enabling new applications.

In Fig. 1 basic differences between CFD and neural model were presented. In order to calculate flow with CFD we need to prepare geometry file, mesh, define boundary and initial conditions and then solve the task. Solving is a matter of hours or days dependent on size of meshed model. For turbine stage presented in this article it is about 2h15min. If there is a need to re-calculate on the same geometry it will also take about 2h15m.

It is worth to emphasise that mentioned calculation time concern a case of only one from all possible operation points. Each turbine operates in wide range of parameters describing its load conditions. Thus number of calculation needed for diagnostic purposes is enormous. Properly trained neural model (ANN model) of turbine stage may significantly shorten time of calculation for a fluid-flow diagnostic procedure for a large range of turbine stage load.

On the other hand to prepare neural model it is needed to gather training data set and train the model – these are time consuming due to mentioned large range of possible load conditions. For training purposes sufficient number of operating points should be used. But, once the model is prepared the only data needed are inlet pressure and temperature and points coordinates (that part can be managed by graphical tool for selecting volume on visualisation) and then time of calculations reduces to 7 minutes. And there are still possibilities of lowering the time for example by decreasing point set (eg. selecting every second point) if it will be sufficient for the application. What is interesting lowering number of points will not affect accuracy of results in selected points. While if doing the same in CFD, it would significantly lower the quality of the results.

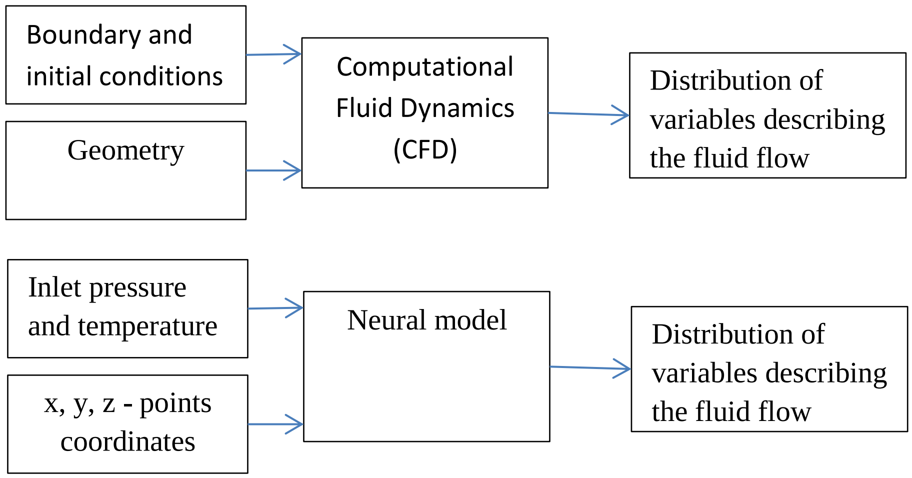

Fig. 1 Difference between CFD and Neural Model

Training procedure for turbine stages

In order to train neural model it is essential to gather reliable training data set. The most desired situation is large data set of measurements provided by the technical object. Such a situation is almost impossible. First of all, measurements are made in certain points like turbine inlet, outlet or extraction, but not inside of turbine blading. The aim of this work is to recreate fluid flow through turbine blading to obtain pattern of proper work of the turbine so it could be further applied in diagnostic system. It would be possible to compare results from neural model with measurements only in certain points. That is why computational fluid dynamics (CFD) simulations were taken into consideration as a provider of training data set.

Over 70 CFD simulations of fluid flow in investigated turbine stage were made. Half of them was used to train neural models, the rest was used for tests. Design working parameters of this stage is initial pressure $p_0 = 7{,}93\ MPa$ and initial temperature $T_0 = 745\ K$. Simulations were made in pressure range from 7,93 MPa to 6,74 MPa and three temperature levels 745, 725, 705 K. What is essential simulations used for training were excluded from testing.

Both pressure and temperature networks were trained Bayesian regularization backpropagation algorithm. By assumption artificial neural network was meant to be as simple as possible. Both neural networks were feed forward networks with two hidden layers. Details (like number of neurons) of architecture of each neural network was adjusted individually.

Results

In this article only results for pressure and temperature are presented, but it is possible to train artificial neural models for other parameters. In Table 1 results form 21 test are presented. It was listed for what area or volume the test was preformed, and both arithmetic mean and median of relative errors of recreating distribution of pressure and temperature were shown. What seems like 21 tests in reality is $4{,}37 \cdot 10^{6}$ tests because neural network is trained to preform calculations of 1 point at the time and that is number of points that were examined.

Table 1. Results of the tests.

Test no.	p0	t0	No. of points	Test area	pressure error		temperature error	
	[MPa]	[K]			Mean [-]	Median[-]	Mean [-]	Median [-]
1	7,89	745	1729	entire flow channel	0,0024	0,0024	0,0543	0,0268
2	7,81	725	716820	entire flow channel	0,0013	0,0013	0,0537	0,0264
3	7,81	725	382	volume in stator trailing area	0,0007	0,0007	0,0541	0,0242
4	7,81	725	8515	volume in rotor trailing area	0,0014	0,0014	0,0528	0,0257
5	7,65	725	716820	entire flow channel	0,0014	0,0014	0,0535	0,0262
6	7,65	725	382	volume in stator trailing area	0,0014	0,0014	0,0538	0,0243
7	7,65	725	8515	volume in rotor trailing area	0,0016	0,0016	0,0525	0,0255
8	7,18	725	716820	entire flow channel	0,0014	0,0014	0,0537	0,0262
9	7,18	725	382	volume in stator trailing area	0,0006	0,0006	0,0540	0,0248
10	7,18	725	8515	volume in rotor trailing area	0,0014	0,0014	0,0527	0,0255
11	7,51	705	716820	entire flow channel	0,0013	0,0013	0,1080	0,0535
12	7,51	705	382	volume in stator trailing area	0,0012	0,0012	0,1084	0,0535
13	7,51	705	8515	volume in rotor trailing area	0,0015	0,0015	0,1079	0,0538
14	6,86	705	716820	entire flow channel	0,0014	0,0014	0,1080	0,0532
15	6,86	705	382	volume in stator trailing area	0,0013	0,0013	0,1084	0,0532
16	6,86	705	8515	volume in rotor trailing area	0,0015	0,0015	0,1080	0,0535
17	6,95	730	716820	entire flow channel	0,0013	0,0013	0,0031	0,0016
18	6,95	730	382	volume in stator trailing area	0,0007	0,0007	0,0026	0,0026
19	6,95	730	8515	volume in rotor trailing area	0,0015	0,0015	0,0039	0,0022
20	6,95	730	16175	plane through entire flow channel	0,0010	0,0010	0,0031	0,0016
21	6,95	730	1873	entire flow channel	0,0010	0,0010	0,0027	0,0017

Arithmetic mean of relative error is more than satisfactory because it is below 0,25% in all the tests. Distribution of pressure generated with neural model is presented in left side of Fig. 2 while on the right side the distribution of relative error is given.

When it comes to temperature results are slightly worse but in some cases acceptable. In training data there were simulations only on 745, 725, 705 K and nothing between, most probably adding more training data with different temperatures will improve the situation. It will be the subject of further investigation. Distribution of temperature generated with neural model is presented in left side of Fig. 3 while on the right side the distribution of relative error is given. On the temperature error distribution there is a visible triangle area of higher error level that also will be a matter of future work.

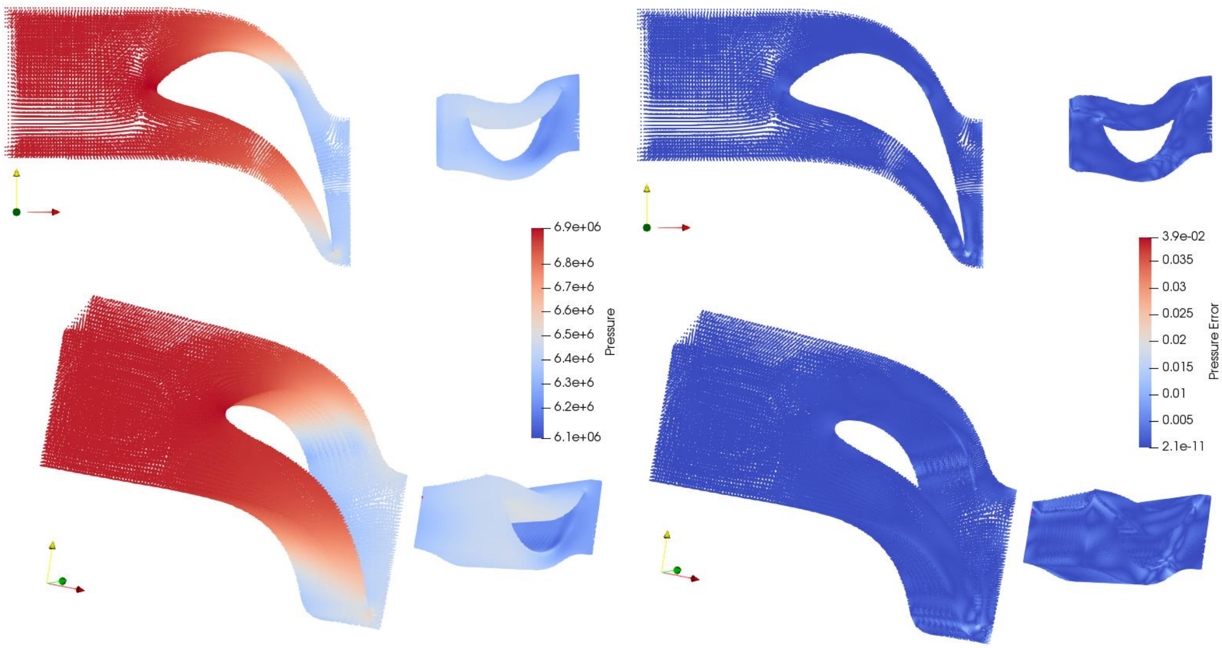

Fig. 2. Left: Distribution of pressure generated with neural model, Right: Relative error of the results

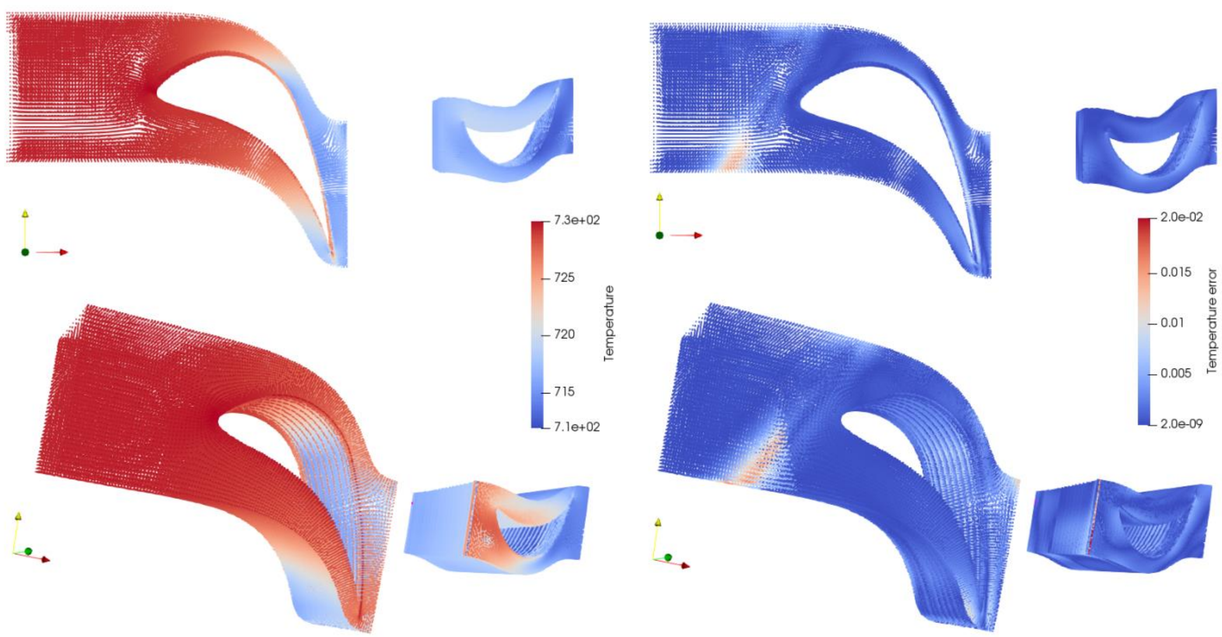

Fig. 3. Left: Distribution of temperature generated with neural model, Right: Relative error of the results

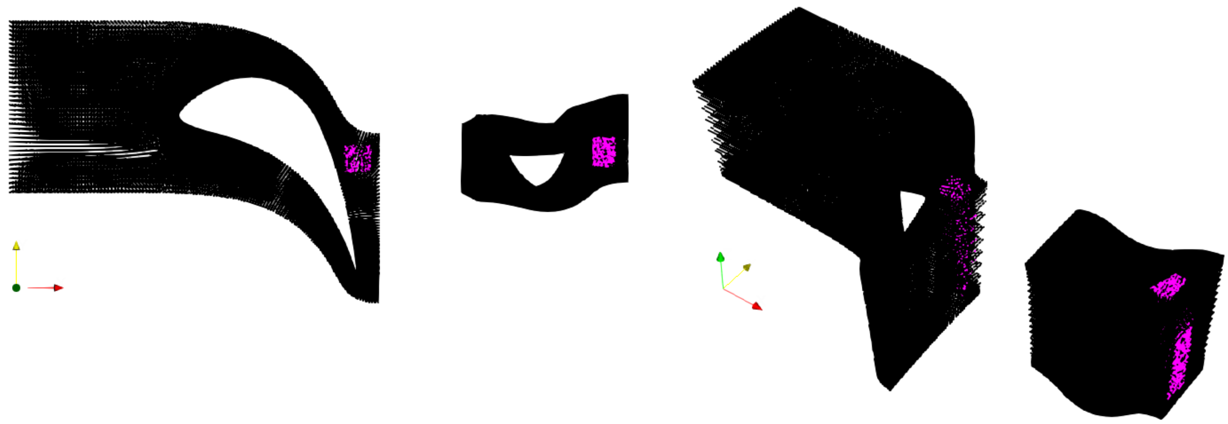

Fig. 4. Visualisation of selection feature that can be used by neural model

Summary

Neural model provides the possibility of calculating thermodynamical properties, it was trained for, in any point of flow channel without calculating all of the flow in the channel. That is why it is possible to select only problematic in diagnostic process area or volume in flow channel and calculating it within significantly shorter time. For example obtaining results for 382 points (marked in Fig. 4) in stator area (marked in Fig. 4) took 0,14 second, and in area of rotor for 8515 points it took 1,68 seconds. That kind of time span is acceptable for diagnostics purposes.

References

[1] Venkatasubramanian V., Rengaswamy R., Yin K. , Surya K. N., A review of process fault detection and diagnosis Part I: Quantitative model-based methods, Computers and Chemical Engineering 27 (2003) 293-311.

[2] Venkatasubramanian V., Rengaswamy R., Surya K. N., A review of process fault detection and diagnosis Part II: Qualitative models and search strategies, Computers and Chemical Engineering 27 (2003) 313-326.

[3] Venkatasubramanian V., Rengaswamy R., Surya K. N., Yin K., A review of process fault detection and diagnosis Part III:Processs history based methods, Computers and Chemical Engineering 27 (2003) 327-346.

[4] Venkatasubramanian V., Process fault detection and diagnosis: past, present and future, 2001, IFAC On-line Fault detection and supervision in the chemical process industries, Jejudo Island, Korea.

[5] Kim SM, Joo YJ. Implementation of on-line performance monitoring system at Seoincheon and Sinincheon combined cycle power plant. Energy, 2005;30: 2383–401.

[6] Głuch J., Ślężak – Żołna Justyna, Solving problems with patterns or heat flow diagnostics dedicated for turbine power plants,Proceedings of ASME TURBO EXPO, 2012, 969-979.

[7] Dragan D., Fault Detection of an Industrial Heat-Exchanger: A Model-Based Approach, 2011, STROJNISKI VESTNIK-JOURNAL OF MECHANICAL ENGINEERING, vol. 57.6, 477-484.

[8] Mohanraj M., Jayaraj S., Muraleedharan C., Applications of artificial neural networks for thermal analysis of heat exchangers - A review, 2015, INTERNATIONAL JOURNAL OF THERMAL SCIENCES, vol. 90, 150-172.