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Neural network approach to compressor modelling with surge margin consideration

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Abstract Artificial neural networks are gaining popularity thank to their fast and accurate response paired with low computing power requirements. They have been proven as a method for compressor performance prediction with satisfactory results. In this paper a new approach of artificial neural networks modelling is evaluated. The auxiliary parameter of 'relative stability margin Z' was introduced and used in learning process. This approach connects two methods of compressor modelling such as neural-networks and auxiliary parameter utilization. Two models were created, one with utilization of the 'relative stability margin Z' as a direct indication of surge margin of any estimated condition, and other with standard compressor parameters. The results were compared by determination of fitting, interpolation and extrapolation capabilities of both approaches. The artificial neural networks used during the process was a two-layer feed-forward neural-network with Levenberg–Marquardt algorithm with Bayesian regularization. The experimental data was interpolated to increase the amount of learning data for the neural network. With the two models created, capabilities of this relatively simple type of neural-network to approximate compressor map was also assessed.

Keywords: Modelling; Compressor map; Neural-network

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Nomenclature

ANN	–	artificial neural networks
MPE	–	the mean percentage error
MLP	–	multilayer perceptron
Z	–	surge stability coefficient

1 Introduction

Thanks to their versatility, gas turbines found their way to multiple industries. Numerous advantages, i.e. good response for load variations, had paved the way to their applications in aviation, marine, industrial or as auxiliary power units. Such a wide range of possibilities to utilize gas turbines put them in requirement of being capable to work in various and often harsh conditions, with every unscheduled interruption of their work time followed with significant costs. The necessity to monitor, diagnose and foresee incoming maintenance has arisen.

For aviation, the pre-pandemic estimations said that its traffic will double every 15 years [1]. On the other hand, the Flightpath 2050 Europe's Vision for Aviation challenges the aviation industry with achievements to be accomplished by 2050 [2]. The constant growth of air traffic must be paired with a constant drop in greenhouse emissions. That obviously puts the propulsion system on the main stage.

Modelling and simulation are a step towards meeting the above-mentioned goals. It allows not only to predict the performance of an engine at given conditions but also to simulate certain conditions for identification purposes. Modelling and simulation already play a vital role in the design and development process of the gas turbine. It can be used to predict the unit's characteristics without time and money consuming tests. Every time the unit's test can be replaced by simulation, the industry save not only money but reduce greenhouse and noise emissions to the environment.

To build a successful system model it is necessary to understand the behavior of its main components. Many problems in creating a meaningful gas turbine model are caused by inaccurate components' performance prediction [3]. The quality of the components' map is of particular significance for the purpose of simulation of off-design or transient states [4], because it provides better insight for representing the behaviour of the full gas-turbine system. The decisive component is the compressor and its characteristic, which usually defines the quality of the whole model, especially considering that turbines operate mostly in choked conditions [5]. Compressor's maps are derived from extensive test campaigns and are not published by the manufacturers.

The scientific society has developed many methods of compressor's map modelling. One of the most popular and easiest ways to model the compressor is the utilization of a look-up table. It uses a linear interpolation algorithm. For the best fit, the data should be well prepared – sorted, dense and regular. This is really rare, hence alternative methods have to be developed.

The auxiliary parameter method is based on the introduction of an additional parameter that helps present the compressor map in a more modelling-alike form. Predominantly this parameter is called a β [4–7], which has no physical meaning. Each β is basically a line crossing with each corrected speed line. That said the β equal to 1 should be the close or at the surge line, while the β equal to 0 indicates the choked region. Presenting the map in such a way helps not only in interpretation but also in the subsequent implementation of the raw data into the simulation model. The introduction of the β parameter eliminates the problem of complicated shape and non-uniqueness of the map in low and high-speed regions. Moreover, every operating point can be described as a function of the β paired with the corrected rotational speed. Kurzke developed an alternative way of deriving the β as parabolic lines, which are more suitable for later interpolation [8]. Miste and Benini investigated the possibility of an analytical representation of the β in order to increase the precision of compressor map modeling [9]. Two functions of the β were introduced. The first one, linear, assuming that β is a simple plane crossing x and y planes. The second function is more complicated and composed of two parts – radial and tangential. Through the modification of four parameters (density n, translation p, curvature c, and slope a), the user can easily change the distribution of β lines, leaving more degrees of freedom than the linear method. A mean relative error of this method is less than 0.2%, much less than that of Kurzke's parabolic β method, which has around 1%.

Orkisz and Stawarz proposed to present a compressor map in an auxiliary coordinate system – in function of the corrected rotational speed and Z parameter [3]. The analytical function Z has physical meaning denoted as a surge stability coefficient and is given by the equation

$$Z = \left(\frac{\pi_{S\mathrm{surge}}}{\dot{m}_{\mathrm{corr\ surge}}} \frac{\dot{m}_{\mathrm{corr}}}{\pi_S} \right) - 1, \tag{1}$$

where π_S, $\pi_{S\text{surge}}$, $\dot{m}_{\text{corr}}$, and $\dot{m}_{\text{corr surge}}$ denote the pressure ratio, surge line pressure ratio, corrected mass flow rate and surge line corrected mass flow, respectively. Building a complete compressor model requires additional determination of a relationship between $\pi_{S\text{surge}}$, $\dot{m}_{\text{corr surge}}$ and corrected rotational speed (n_{corr}). In [10], two-variable second-degree and third-degree polynomials were used to determine the relationship between parameters. The maximum error between the real data and the data calculated from the model did not exceed 1.4%. However, in [11, 12] it was demonstrated that this method is prone to error when used for extrapolation.

Jensen and Kristensen developed a model in which the compressor characteristics are expressed by dimensionless parameters [13]. The compressor work is represented as a head parameter ψ, and mass flow rate as flow rate parameter φ. Then, the head parameter and compressor efficiency are expressed by the relationship of dimensionless flow rate and inlet Mach number (Ma), which is dependable on inlet conditions and compressor tip speed. Subsequently, using the compressor manufacturers data, the fitting equation was determined in the form of $\psi(\varphi, \text{Ma})$. Tsoutsanis, Meskin, Benammar, Khorasani also used the equation fitting methodology, with an equation of ellipse [5, 14, 15]. They showed that it is convenient to assume that every speed line is an elliptic curve. The relationship between the pressure ratio and mass flow rate can be described with the equation of ellipse. Presuming that the ellipse can be rotated, three approaches of modelling were proposed with different levels of complexity; the ellipse is fixed at: (i) centre point at (0, 0) and no rotation, (ii) centre point at (0, 0) with rotation by angle θ, and (iii) centre point at (x_0, y_0) with rotation by angle θ, which represents the center coordinates of the ellipse. Similar approach was presented in [16], with addition of consideration of bleed air extraction and variable inlet guide vanes impact.

NASA and General Electric developed a method of compressor map representation suitable for the simulation model [7, 17]. The main goal of this work was to minimalize the computing power needed for calculations. The method puts more focus on the pressure losses, which are presented in function of enthalpy and rotational speed. Then, from the minima of each curve, a backbone is created which can be used for interpolation and extrapolation. The last step is the linearization of differences between pressure losses related to work output.

Kong proposed generating maps of individual engine components on the basis of having partitive manufacturers data, e.g. test or exploitation data or from engine deck [18–20]. In [18], scaling was performed by determining the scaling coefficients between the calculated parameters and the actual data, then the relationship between pressure ratio, mass flow rate and efficiency is approximated as a function of engine rotational speed. In subsequent publications [19, 20] a genetic algorithm was used to determine these relationships. It offers better accuracy. It should be mentioned that this method may be less accurate when calculating parameters in operational areas distant from those previously available to which the model was fitted.

Zagórowska and Thornhill proposed the utilization of Chebyshev polynomials in order to approximate the compressor characteristics [21]. The compressor mass flow rate and rotational speed were used as input to determine the pressure ratio. The method was compared with the traditional third order polynomial approximation. It was concluded that Chebyshev polynomials allow the map to be reconstructed accurately from fewer points compared to the third order polynomial and are less computationally demanding. On the other hand, they require initial data preparation. Li presented the results of using the statistical method of partial least squares regression [22]. The authors used two basic functions of partial least squares regression method, that is a traditional polynomial and a trigonometric function. For comparison purposes, they did similar with popular look-up tables and neural networks of back-propagation type. The results proved that partial least squares regression method requires less computing power to produce similar or even better results.

Ghorbanian and Gholamrezaei in their works analysed the use of four types of neural networks: general regression neural network, rotated general regression neural network, radial basis function network, and multilayer perceptron (MLP) [4, 23, 24]. They took two approaches to modeling; one based on the pressure ratio as an output and the second based on the corrected mass flow. The obtained results show that multilayer perceptron provides the best output accuracy. The rest of the evaluated neural networks were displaying good precision in regions of known experimental data, but performing poorly when used to interpolate or extrapolate. Yu, Chen, Sun, and Wu used back-propagation neural network. They utilized the method of double-learning resulting in good accuracy [25].

This paper proposes a new approach to compressor modelling, which links the standard, well-known introduction of an auxiliary parameter with the neural-network tool for interpolation. The neural network utilized in this work is a shallow network, consisting of only one hidden layer and an output layer. The ability of such network configuration to cover compressor map is investigated since it is already proven that more sophisticated networks are able to give reasonable outputs. The evaluation of performance of this simple artificial neural networks (ANNs) is of particular importance because it is easier and more intuitive to use, hence having low entry-level difficulty. Thanks to that it may become a new tool for modelling and analysis for gas turbine engineers, which are not specialists in the field of artificial intelligence, or may be a first step for them to become one. Furthermore, the relative stability margin Z was introduced as an auxiliary parameter. The knowledge of the compressor's working line is crucial during simulation and analysis of its performance. Due to its clear and physical meaning and surge margin indication, it was deemed to be highly beneficial as an additional output of the model. Moreover, as aforementioned, the auxiliary parameters were generally introduced to make a compressor map representation more modelling-friendly. By comparison of two ANNs – one with standard compressor parameters and the second with Z utilization, the impact of different map representations was evaluated.

2 Methodology

2.1 Basic methodology of compressor map representation

The typical compressor's map is depicted in Fig. 1. Usually, it is presented in the form of:

$$\pi_s = f\left(n_{\mathrm{corr}}, \dot{m}_{\mathrm{corr}}\right), \tag{2}$$

$$\eta_s = f\left(n_{\mathrm{corr}}, \dot{m}_{\mathrm{corr}}\right). \tag{3}$$

The above variables can be described with the following relationships:

- pressure ratio

$$\pi_s = \frac{p_{\mathrm{out}}}{p_{\mathrm{in}}}, \tag{4}$$

- isentropic compressor efficiency

$$\eta_s = \frac{\Delta h_{\mathrm{is}}}{\Delta h_{\mathrm{real}}}, \tag{5}$$

- corrected rotor speed

$$n_{\mathrm{corr}} = \frac{n}{\sqrt{\dfrac{T}{T_{\mathrm{ref}}}}}, \tag{6}$$

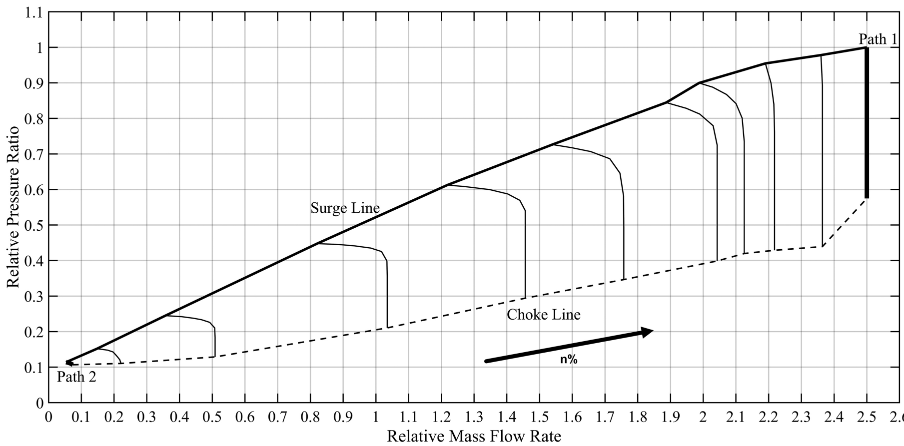

Figure 1: Exemplary compressor map representation.

- corrected mass flow rate

$$\dot{m}_{\text{corr}} = \frac{\dot{m}\sqrt{\dfrac{T}{T_{\text{ref}}}}}{\dfrac{p}{p_{\text{ref}}}}\,, \tag{7}$$

where: p_{in}, p_{out} – compressor total inlet and outlet pressure, respectively, Δh_{is}, Δh_{real} – isentropic and actual enthalpy change, respectively, p, T – pressure and temperature at chosen reference station, $p_{\text{ref}} = 1013.25$ kPa, $T_{\text{ref}} = 288.15$ K.

For the constant corrected rotor speed line, two particular points can be identified. The upper limit is a *surge line*. The surge is a violent aerodynamic phenomenon, which due to excessive pressure rise downstream of the compressor causes the flow oscillations in the axial direction of a compressor. It usually leads to severe instability of the whole engine system, which can be fatal in consequences. On the opposite end of a speed line, a choke occurs. The choke is a state during which the flow speed through the compressor is close to sonic velocity and further increase of mass flow rate is not possible.

Generally, the compressor map is presented in the form of experimental data collected in a discrete form of single test points taken at the constant corrected rotational speed. This is a major problem of compressor modelling. In order to simulate the off-design or transient cases, the whole compressor map has to be known. The most popular approach is to utilize two-dimensional (2D) linear interpolation. It is easy to use and offers fast results without overwhelming memory usage. Unfortunately, the accuracy is usually low. Potential modelling problems come from the following facts [3]:

1) non-uniqueness – it is necessary that each pair of variables is unique and do not repeat itself;

2) bad conditioning, when a low change in one parameter causes a big change in another;

3) high variability of the parameters, when the whole envelope is of interest;

4) usually unknown compressor low-speed performance.

Especially very high and very low corrected speed regions of compressor map are problematic. The high-speed lines (*Path 1* in Fig. 1) are nearly vertical in contradiction to low-speed lines (*Path 2* in Fig. 1) which are almost horizontal. Due to a highly non-linear character of the compressor's performance, the interpolation method may lead to increased error.

2.2 The neural network

Artificial neural networks are gaining popularity thanks to their fast and accurate response paired with low computing power requirements. Their ability to process non-linearity and usage of an enormous amount of data is exceptional in modelling. ANN can build a model creating non-linear relationships without real physical meaning between inputs and outputs. It can produce meaningful responses to inputs not used during the training process. The above-mentioned features allow neural networks to solve very complex problems. Hornik *et al.* [26] have shown that a two-layer network can be a universal approximator. Pinkus did further research on the multilayer feed-forward perceptron and its approximation capabilities [27]. Hagan, Demuth and de Jesus [28] have described how the MLP can be used in control systems, Fig. 2.

The two-layer feed-forward neural network is utilized in this paper. It is available *via* neural fitting tool in Matlab [29]. The simplicity of the network architecture makes it easier and more intuitive to use while offering fast and reliable output. It consists of one hidden layer and one output layer. The

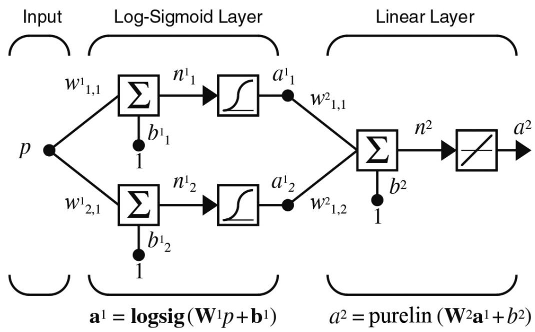

Figure 2: Exemplary schematic of a two-layer feed-forward neural network with just one input and two neurons in the hidden layer [28], where: a – transfer function output, b – biases, n – weighted sum value, p – input, w – weights.

hidden layer uses a log-sigmoid transfer function, while the output layer is fitted with a linear transfer function. The two inputs of the corrected rotational speed and pressure ratio are fed to ten neurons in the hidden layer, with one output acquired from the output layer – relative stability margin, mass flow rate or isentropic efficiency for this particular case, Fig. 3.

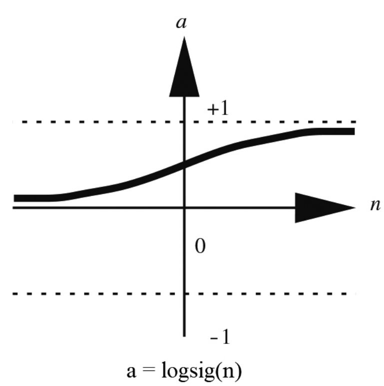

Figure 3: Log-sigmoid transfer function [28].

The Levenberg–Marquardt back propagation algorithm with Bayesian regularization was used for learning [30]. Bayesian regularization requires more memory but tends to be more robust and can eliminate the need for lengthy cross-validation. Moreover, this approach mitigates the risk of overtraining because of the objective criterion for stopping the training, and overfit thanks to its ability to work only on effective network parameters [31].

2.3 Compressor map data preparation

A modelled compressor is a single-stage centrifugal compressor from an auxiliary power unit gas turbine. Its performance map is illustrated in Figs. 4 and 5. It is expressed in conventional approach, understood as the pressure ratio and isentropic efficiency as a function of the corrected mass flow rate.

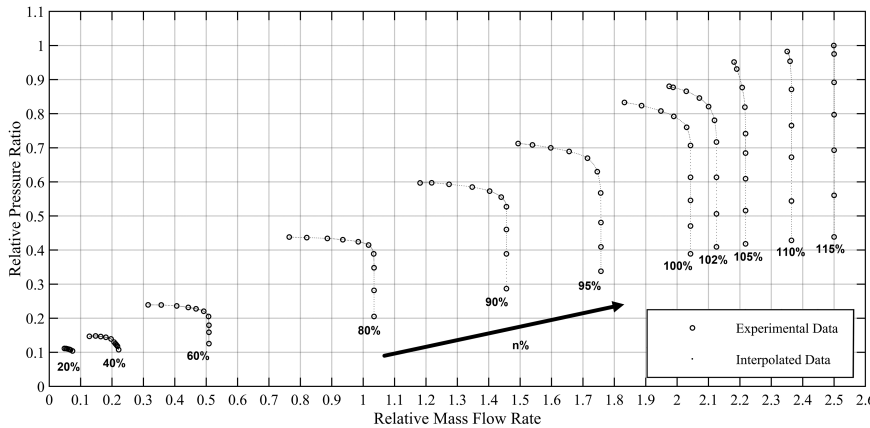

Figure 4: Compressor map under evaluation – pressure ratio.

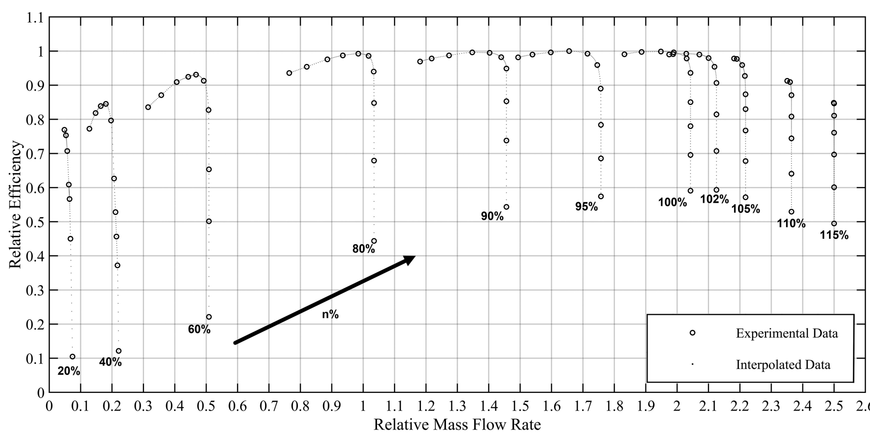

Figure 5: Compressor map under evaluation – efficiency.

The experimental data of each speed line was purposely interpolated due to two main reasons. The first was to reproduce compressor operation with higher resolution. The utilization of cubic interpolation was successful in accurate representation of compressor operation at each evaluated corrected speed. That results in learning more focused on the compressors performance instead of just interpolation between the possessed test data. The second benefit of test data interpolation is an increased amount of input data used for learning, which results in better efficiency of the network. Interpolated data points can be seen in Fig. 5. Having 76 experimental test points results of compressor performance, each speed line was interpolated by 100 test points. Additionally, in order to enhance the efficiency of learning, the maps were rescaled to relative parameters in the range of [0, 1].

Obviously, the relative stability margin coefficient was calculated for both experimental and interpolated data to feed one of the models. It was defined as in Eq. (1).

The approach taken in the compressor map generation was based on the corrected rotational speed N_c and pressure ratio π_c as an input. Considering that assumption, two models were created:

I Model A – based on three neural networks fitting the following data:

- relative stability margin, $Z = f(n_{\mathrm{corr}}, \pi_s)$;
- relative mass flow rate, $m_c = f(n_{\mathrm{corr}}, Z)$;
- relative isentropic efficiency, $\eta_c = f(n_{\mathrm{corr}}, Z)$;

II Model B – based on two neural networks fitting the following data:

- relative mass flow rate, $m_c = f(n_{\mathrm{corr}}, \pi_s)$;
- relative isentropic efficiency, $\eta_c = f(n_{\mathrm{corr}}, \pi_s)$.

Moreover, to evaluate the interpolation and extrapolation capabilities of the network, three constant speed lines were excluded from the input data. For interpolation purposes, the data from 95% of the corrected speed were chosen ($n\,95\%$), as the simulated engine operates mostly around 100% of the corrected speed ($n\,100\%$). Hence the interpolation accuracy between $n\,90\%$ and $n\,100\%$ is of major importance. Also, the experimental data above $n\,100\%$ is denser having $n\,102\%$ and $n\,105\%$ speed lines determined. Additionally, the $n\,20\%$ and $n\,115\%$ speed lines were not used. These were extrapolated to come up with capabilities to simulate transient states like start-up or over-speed of the engine.

3 Results and discussion

The analysis of neural networks learning regression charts (Figs. 6 and 7) shows that the learning quality stands high regardless of the model used. The $Y = T$ dotted curve represents the perfect fit. It can be observed that the "fit" curve is overlapping the $Y = T$ curve for both cases. Nevertheless, it is visible that the quality is improved with the utilization of an auxiliary parameter in the form of a relative stability margin (Model A). Figures 6 and 7 show that in terms of individual performance points prediction, the amount of points outlying from $Y = T$ and *fit* curves is significantly reduced. It can be concluded that the introduction of the relative stability margin to the learning and modelling process results in a better accuracy. The actual performance of the models can be estimated by the analysis of Figs. 8 and 9.

a) b)

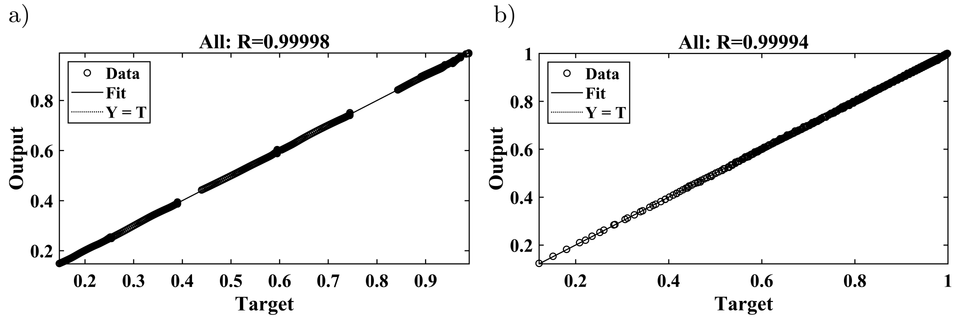

Figure 6: Regression plots learning and testing data for Model A: a) relative mass flow rate, b) efficiency.

a) b)

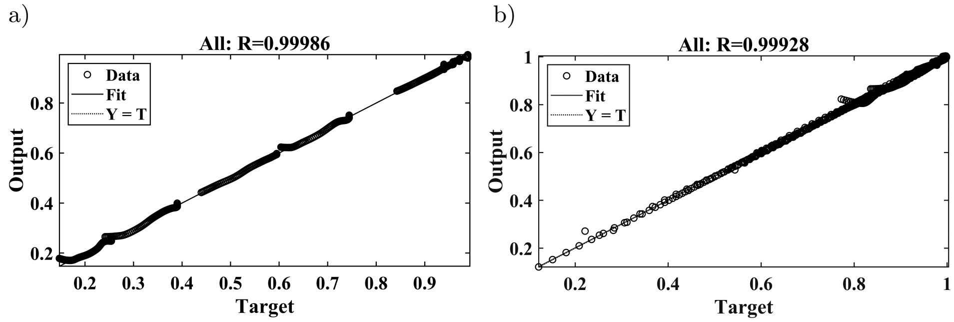

Figure 7: Regression plots learning and testing data for Model B: a) relative mass flow rate, b) efficiency.

a) b)

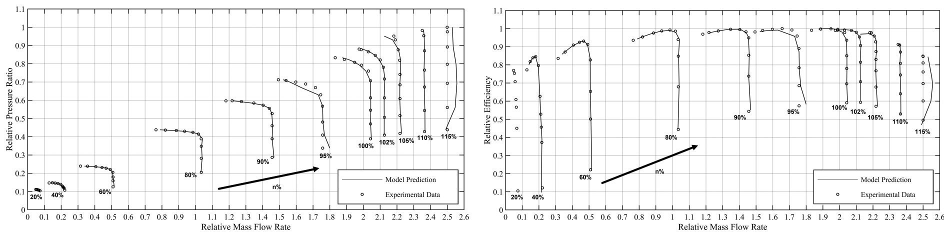

Figure 8: Compressor map prediction of Model A.

a) b)

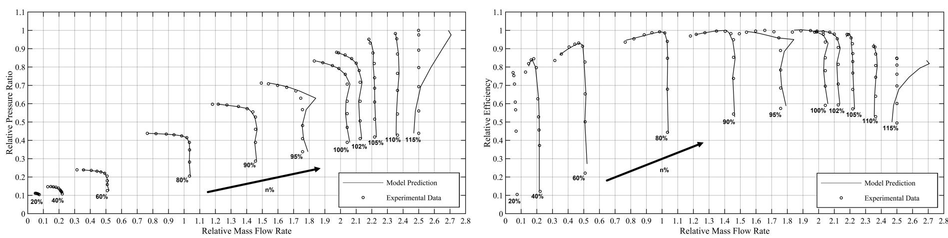

Figure 9: Compressor map prediction of Model B.

Furthermore, as an additional measure of the models' capabilities, the mean percentage error (MPE) was calculated between the experimental data and predicted data for a given corrected rotational speed and pressure ratio. The mean percentage error is defined as follows:

$$\mathrm{MPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|f\left(\mathrm{Exp}_i\right) - f_p\left(\mathrm{Pred}_i\right)\right|}{f\left(\mathrm{Exp}_i\right)} \times 100, \tag{8}$$

where $f\left(\mathrm{Exp}_i\right)$ and $f_p\left(\mathrm{Pred}_i\right)$ are the experimental data and predicted data, respectively. The MPE results for each constant speed line and overall one are presented with the interpolated and extrapolated speed lines included.

In the next step, the actual prediction from the considered models was compared. The comparison takes into account the fitting, interpolation and extrapolation accuracy. The fitting accuracy was assessed based on analysis of the models' prediction for each constant speed line, which was fitted into the learning process. Additionally, the MPE was calculated between the prediction and test data, and was presented in Figs. 10 and 11. It is visible that in terms of fitting, the shallow neural network is capable of providing robust results with MPE below 1% for the high-speed region of compressor operation ($> n\,80\%$). The MPE significantly increases for lower speed regions ($< n\,80\%$), where it can even reach values of 3%. That is an important error, which may cause unacceptable discrepancies during gas turbine start-up and/or sub-idle operation simulation. Further research is necessary to mitigate that issue.

The interpolation capability was evaluated based on the prediction of $n\,95\%$ of the compressor corrected speed. The performance test data for this

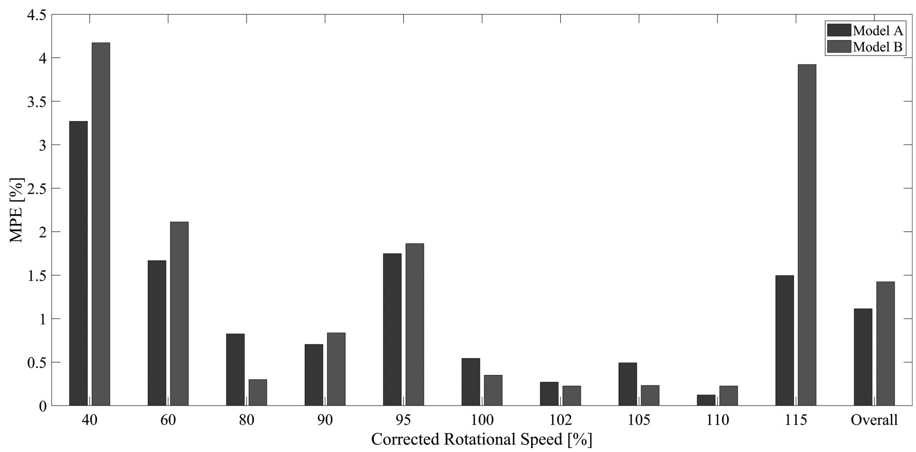

Figure 10: Compressor mass flow rate mean percentage error for given corrected rotational speed.

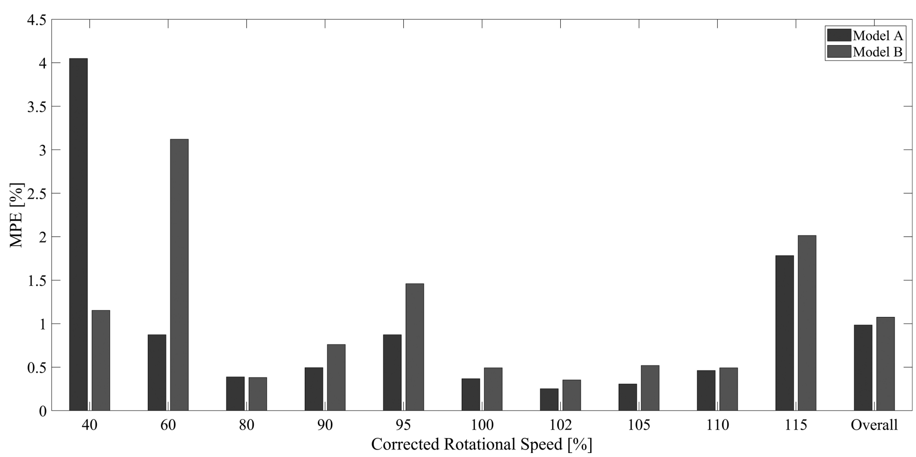

Figure 11: Compressor efficiency mean percentage error for given corrected rotational speed.

constant speed line was excluded from the learning data provided to the neural network, hence the ANN has to predict the compressor performance based on residual data. The prediction was then compared to the actual experimental data to assess the interpolation effectiveness. The accuracy of $n\,95\%$ prediction can be visually examined in Figs. 8 and 9, while the MPE is presented in Figs. 10 and 11. It can be concluded that the interpolation capabilities are also satisfactory for the shallow neural network. The MPE for the mass flow rate and efficiency prediction is below 2% and 1.5%, respectively. It should be emphasized that the interpolation capacity is increased with the utilization of the relative stability margin in the learning process (Model A). It is especially visible for efficiency modelling, where the MPE is reduced thoroughly, reaching values below 1%.

The extrapolation capability was evaluated in a similar manner as the interpolation one. The $n\,20\%$ and $n\,115\%$ of the compressor corrected speeds were excluded from the learning data. Then, the trained networks were predicting the compressor's performance at these speeds. Unfortunately, both models A and B were unable to predict the performance at $n\,20\%$, which makes the subsequent simulation of gas turbine start-up impossible. On the other hand, the $n\,115\%$ speed could be predicted. The MPE for this particular extrapolated speed was visibly higher compared to fitting. Worth highlighting is the fact that the $n\,115\%$ extrapolation ability of the network was increased by the utilization of the auxiliary parameter, especially for the mass flow rate prediction at which the MPE was below 1.5% (compared to almost 4% of Model B).

3.1 Surge margin evaluation

The utilization of Z parameter brings a unique opportunity to track the surge margin *live* during analysis and simulation. It is of high importance during the analysis of various transient states like sequential loads application or Bodie maneuvers of the gas turbine system. The accuracy of prediction of surge margin was evaluated for the high-speed region ($> 80\%$) of the compressor map. The six constant relative stability margin lines were determined. These are considered as indicators of the surge margin at which the compressor is expected to operate during steady-state and transient-state operation. The model prediction of the constant relative stability margin for each compressor's speed was depicted in Fig. 12.

The results were presented on top of experimental data, based on which the experimental relative stability margin was evaluated. It is visible that

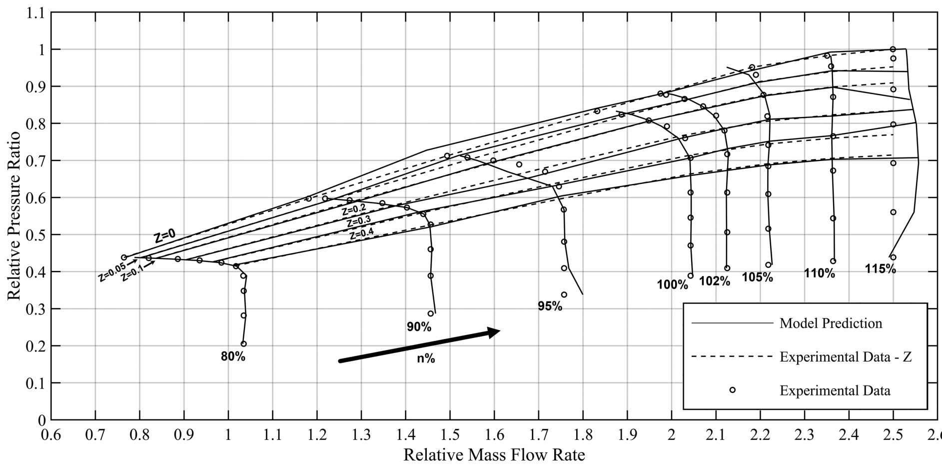

Figure 12: Compressor map high-speed region with constant relative surge margin lines.

the precision is satisfactory and similar to the previously obtained results. The only exceptions are speeds of $n\,95\%$ and $n\,115\%$, which are interpolated and extrapolated speeds, respectively, at which the estimated Z values are prone to bigger error. It can be concluded that the model is able to determine the surge margin correctly, similar to the compressor's performance.

3.2 Validation of numerical results

In the research of [21,22] it was deemed that the MLP network is the most versatile one, being able to fit, interpolate and extrapolate. The results presented in this paper bring similar conclusions. With the utilization of ANN of a less developed architecture (fewer hidden layers), the obtained mean percentage error values of fitting and interpolation are at a similar level to the one presented in [3]. However, it should be emphasized that the accuracy of this tool is deteriorating at attempts of predicting the low-speed regimes. It may be caused by various reasons. The research done in [3] shows that the accuracy depends on the neural network input and output data vector chosen for learning – either the mass flow rate or pressure ratio accompanied with the rotational speed. By visual inspection of the presented results, a similar conclusion can be drawn from [23], where the low-speed regime prediction seems to be less accurate. Another suspected reason is the structure of the test data fed to the network. The high-speed data (at and above $n\,80\%$) was substantially denser than the low-speed data. There were 8 speed lines data used as learning data to the network, from which 6 (75%) were above n 80%. This fact can explain the inferior accuracy at lower operating speeds.

To mitigate the above-mentioned issues and furthermore decrease the overall MPE of modelling with the shallow neural network, several new ways need to be evaluated:

- Different approach to learning data organization – i.e. initial interpolation of experimental data to generate a variable amount of test points per each speed line. Having more data at low speed, simultaneously with less data at high speeds may result in a better performance without compromising the high-speed accuracy.

- Double learning method – the neural network can be learned further after the first iteration. Some of the generated data, for example from interpolation, can be fed to the network as an additional learning portion [23]. It can lead to an overall improvement of prediction accuracy.

- Utilization of other methods – other compressor map modelling approaches, which show better precision in particular areas of performance prediction, can be used. The data generated from the chosen method can be used as additional learning data for the neural network, as it was proven to have a very high accuracy of data fitting.

- Modification of the neural network – the number of neurons or learning methodology can lead to different results.

4 Summary

Summarizing, it can be concluded that the shallow neural network is a powerful tool capable of compressor map modelling. The fitting accuracy is comparable to current state-of-the-art approaches discussed in Introduction, simultaneously being intuitive to use and providing fast and reliable response. It is valid for both Model A and Model B approach, indicating that the shallow neural network is capable of interpolation and extrapolation of compressor's performance, and subsequently can be used for transient simulation. Furthermore, the introduction of an auxiliary parameter of relative stability margin has a positive impact on the learning and output quality of the ANN, improving the analysis' capabilities at the same time.

On the other hand, the extremes of compressor's operating regimes (low and high rotational speeds) tend to output less accurate results depending on various factors.

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