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AXIAL COMPRESSOR MAP GENERATION LEVERAGING AUTONOMOUS SELF-TRAINING AI

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ABSTRACT

The paper describes the study performed by SoftInWay in the scope of the Phase I SBIR project funded by NASA.

The project was dedicated to a study of optimization of the variable geometry reset angle schedules with the use of innovative autonomous AI technology. In the scope of the project, an automated compressor performance data generation workflow was developed. Three highly loaded multistage axial compressors were designed. The developed workflow was used to generate the training, validation, and test data sets for all three compressors. Multiple different architectures of artificial neural networks were studied, and parametric models for the representation of performance speedlines were developed.

Utilizing the developed approaches, the artificial neural networks were trained for all three compressors to predict their performance with a relative error below 3 %. The trained neural networks were successfully used in the optimization of the variable inlet guide vanes and variable stator vanes reset angle schedules with a relative error of total-to-total pressure ratio prediction below 2 % for most of the points and relative error of total-to-total efficiency prediction below 1 % for all the points of the operational line.

The capability of the developed AI models to accurately predict the optimal combination of reset angles and efficiency of the axial compressor with multiple vanes controlled independently allowed doing quick evaluations of efficiency and stability margins. The availability of such information enables the opportunity to make technical-economical decisions about the reasonability of implementation of independent variable vanes and their number during engine system analysis.

Keywords: Axial Compressor, Performance Map, Machine Learning, Artificial Neural Network, Compressor Vanes' Angles, Optimization

NOMENCLATURE

NASA	The National Aeronautics and Space Administration
HPC	High-Pressure Compressor
SBIR	Small Business Innovation Research
AI	Artificial Intelligence
KPI	Key Performance Indicator
SOA	State Of the Art
ML	Machine Learning
1D	One-Dimensional
2D	Two-Dimensional
3D	Three-Dimensional
CFD	Computational Fluid Dynamics
NN	Neural Network
AutoML	Automated Machine Learning
EEE	Energy Efficient Engine
IGV	Inlet Guide Vane
VGV	Variable Guide Vane
RPM	Revolutions Per Minute
MSE	Mean Squared Error
MFR	Mass Flow Rate
ptr	Total-to-Total Pressure Ratio
psr	Total-to-Static Pressure Ratio
eff_tt	Total-to-Total Efficiency
eff_ts	Total-to-Static Efficiency
Deqx	Equivalent Diffusion Factor
Dhub	Compressor Hub Diameter
Dshroud	Compressor Shroud Diameter
ReLU	Rectified Linear Unit

1. INTRODUCTION

NASA is looking for improvement in aeropropulsive power density and efficiency in support of its Strategic Thrust in the area of Ultra-Efficient Subsonic Transports, focusing on small core turbofan engines for next-generation and future large commercial transport aircraft. The trend in the design of modern gas turbine engines is for ever-increasing cycle efficiency and reduced specific fuel consumption. To achieve these engine cycle efficiency goals, the low and high-pressure compressors (HPC) are pushed to ever-increasing levels of pressure ratio.

Increasing levels of compressor pressure ratio results in higher rotor tip relative Mach number in the HPC front stages, and consequently steeper performance characteristic maps. The compressors with steep characteristics typically require variable geometry inlet guide vanes as well as variable stators in the first few stages to provide the desired performance and stability in an engine system. The design and development time of a modern high-pressure compressor with variable geometry can take years of design-build-test iterations which includes testing a large number of possible reset angles of the variable vanes. Determining the optimal combination of vane angle resets that will provide the desired compressor performance in an engine system environment is a time-consuming and expensive part of the development of high-pressure compressors.

The axial compressor performance map generation task can be solved with currently available SOA approaches, which can be considered from two perspectives.

One perspective is that numerous codes allow generating performance maps of compressors without the involvement of any ML technologies. The fidelity of these tools varies from 1D to 3D CFD. 1D is typically very fast so the map generation duration can be comparable to the one required to create a map with AI technologies. The peculiarity of 1D codes is that they are typically based on some empirical correlations or analytical equations derived with certain assumptions valid in some ranges only. For example, the CMGEN code [1] developed by General Electric for NASA Glenn Research Center is capable to generate maps taking only design point pressure ratio, inlet corrected flow per unit area, and stall margin as input. However, the performance maps generated by CMGEN can serve only as preliminary ones for quick utilization in cycle simulations, due to low fidelity. The modern requirements for compressors require higher fidelity and better confidence in predictions. In turn, 3D CFD codes are more universal in this respect, but they are much more time-consuming compared to 1D. Employment of autonomous ML technologies allows obtaining the fidelity of performance prediction comparable to 3D CFD codes faster than 1D codes if 3D CFD would be used to generate training data set.

Another perspective is that there are numerous ML technologies successfully used in areas of visual recognition, natural language processing, evidence-based treatment plans, games, and many others. However, despite remarkable success in the mentioned above areas the application of AI for the prediction of compressor performance is limited [2, 3, 4]. Some approaches in this area require assumptions on the shape of the speedlines (second or third-order polynomials) [2]. These approaches work well in rare cases only, because the speedline for the compressor changes its character from low speeds to high ones and they can rarely be approximated by a polynomial with sufficient accuracy based on a limited number of performance points. The other approaches do not require any assumption on speedline shape, but they typically require a relatively high number of points to accurately represent the speedline [3, 4]. Moreover, both mentioned approaches require the manual definition of NN architecture, which means that a substantial amount of time shall be spent to find the architecture which provides sufficient accuracy of performance prediction and short training time. It should be noted that none of the mentioned works considered variable guide vanes. The generation of a map for a compressor with multiple variable guide vanes is a very complicated and time-consuming task employing mentioned ML approaches.

This work was focused on the advancement of the application of ML technologies for axial compressor performance map generation considering multiple variable guide vanes and comprised of three major steps:

1. Development of the capability to create an AI-based model for performance prediction of the axial compressor
2. Study of the versatility of the developed capability, i.e., investigate the applicability of the techniques found for the first compressor to other two compressors
3. Study of applicability of the trained AI model of axial compressor for optimization of reset angles strategies for different operational lines

2. APPROACHES AND METHODS

The following technical activities were performed:

- Compressor design
- Training data generation and pre-processing
- ML techniques, hyperparameters fine-tuning, and training
- Utilization of the trained models in optimization task

This section describes the approaches and methods used for every type of technical activity.

2.1 Compressor Design

In order to be able to train an artificial NN, it is required to have training data. In this work, the training data are performance maps generated at various combinations of reset angles for some multistage axial compressors. For the first step of the project, it was planned to use some specific compressor flow path design and for the second step, to verify the versatility of the developed capability, it was planned to consider another two compressors.

For the first step, it was decided to use the EEE compressor [5, 6] as a prototype, and for the second step to perform the flow path preliminary design of the other two axial compressors. The EEE compressor geometry reconstruction and preliminary designs of the other compressors were done using the AxSTREAM® [7], which will be referred to in the paper as AxS. In particular, AxS meanline/streamline code was used employing loss model correlations based on Lieblein’s test data [8] approximated by Aungier [9]. Inlet total pressure, inlet total temperature, outlet total pressure, and the mass flow rate were used as the input parameters for the preliminary design. Due to NASA SBIR solicitation requirements, the input parameters and design constraints were selected considering typical parameters for high-pressure (HP) compressors of the modern turbofan engine, such as GE9X [10]. The optimal rotational speed, number of the stages, mean diameters, blade heights, blade numbers, profiles geometrical parameters, etc. were found automatically by AxS taking into account design constraints.

2.2 Training Data Generation and Pre-processing

Once the preliminary design of the flow path was completed it was required to perform training data generation. However, training data generation for compressors with IGV and multiple VGV is not a trivial task, because it is not known apriori which combination of angles has valid speedlines or not, as well as the range of operation. For this purpose, a special workflow for compressor performance data generation was developed (FIGURE 1).

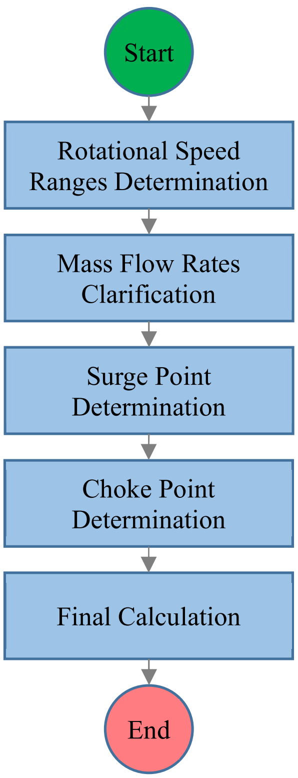

FIGURE 1: AUTOMATIC WORKFLOW FOR COMPRESSOR PERFORMANCE DATA GENERATION AND PRE-PROCESSING

In general, the purpose of the workflow in FIGURE 1 was automatic data engineering to prepare raw data coming from compressor performance code to a form suitable for successful training, i.e., remove outliers, smooth choke, and surge limit lines, determine the ranges of existences of stable compressor operation for a wide variety of IGV and VGV angle combinations and save the data set in a proper format. In particular, surge point determination is typically performed based on the criteria of static pressure maximum for the given speedline, which is sufficient for ideal cases (FIGURE 2a). However, due to complexity of surge phenomena the calculated speedlines might have multiple maximums (FIGURE 2b and FIGURE 2c). In turn, the process of performance points generation can start anywhere on the speedline (even beyond surge and choke points) so it was required to make the algorithm calculate speedline to all possible extends to the left and the right, and then automatically select the correct speedline section with surge and choke boundaries. The choke point was determined based on criteria of efficiency drop by 15 % relative to the maximal value on the speedline. The performance points beyond surge and choke points were considered as outliers.

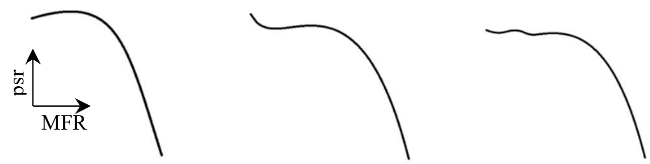

FIGURE 2: EXAMPLES OF SPEEDLINE SHAPES. a – IDEAL SPEEDLINE SHAPE; b – SPEEDLINE SHAPE WITH TWO MAXIMUMS; c - SPEEDLINE SHAPE WITH MULTIPLE MAXIMUMS

It should be noted that the workflow presented in FIGURE 1 is a schematic representation. Every block in the figure is a block scheme created in AxSTREAM ION™ (hereafter referred to as ION) where certain blocks and scripts were integrated into a specific algorithm that processes the data. For example, the workflow for the determination of ranges of rotational speed is shown in FIGURE 3.

The first loop in FIGURE 3 iterates through the IGV/VGVs combinations, and the second one iterates through the rotational speed of each IGV/VGV combination. The first loop is used as the main for all future actions, i.e., for the determination of compressor surge and choke limits for each IGV/VGVs combination. Block labeled “Initial data” in the figure defines the design shaft speed, pressure ratio, and mass flow data for the compressor. These data are used for shaft rotational speed and mass flow limits calculation for the internal Monte Carlo loop (RPM varying). “Script_1” is used for zeroing the vectors variables data accumulated at previous iteration before new loops calculation. AxS 1D/2D Streamline solver was used to find the compressor performance for specified input data. “Solution check” tracks the solver completion response and makes the current rotational speed equal to zero in the case if no solution was found. This step is required for convenience during future data processing and determination of maximal and minimal speed. “Accumulator” gathers all responses of AxS and transfers data for processing in the “MAP 1” block. It should be noted that in the developed automated workflows it is possible to use not only AxS for compressor performance calculation, but the other 1D, 2D, and 3D CFD codes as well.

The generation of IGV/VGV combinations and RPM values is performed according to the Sobol sequence [11], which allows covering the area of interest more evenly avoiding clustering, intrinsic to random number generators, and providing more useful information compared to regular grids with the same number of points.

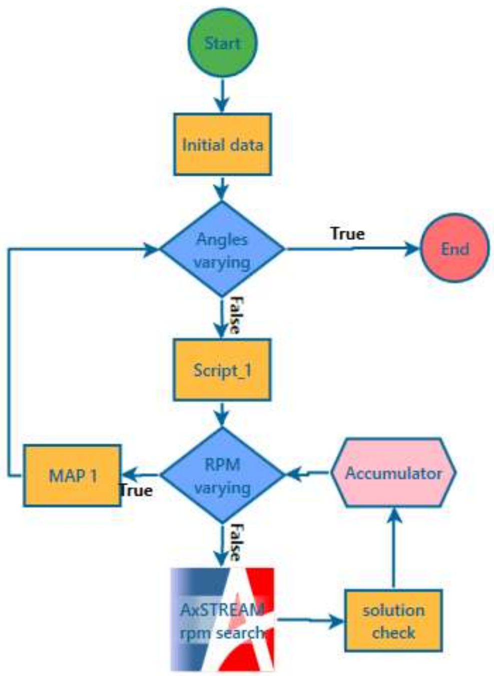

FIGURE 3: WORKFLOW FOR DETERMINATION OF RANGES FOR SHAFT ROTATIONAL SPEED

The ranges for IGV/VGV angles variation were assigned according to the following rules:

- IGV from 0 to 30 deg
- VGV2 from 0 to IGV/1.1
- VGV3 from 0 to VGV2/1.2
- VGV4 from 0 to VGV3/1.3
- VGV5 from 0 to VGV4 /1.4
- VGV6 from 0 to VGV5 /1.5

The presented workflow was successfully used to generate data sets for all considered compressors.

During the process of generation of the data sets for compressors, authors developed a new parametric models-based approach for the representation of the compressor maps to improve the quality of prediction of the speedline shapes, because preliminary predictions of speedlines in pressure ratio vs mass flow rate coordinates showed that sometimes the shape of speedlines was predicted incorrectly (unrealistic oscillations near the surge point).

The requirement for the parametric model was the flexibility sufficient to represent the wide variety of speedline shapes on one hand and inherited correspondence to the typical shape of speedline without unrealistic oscillations on the other hand. The flexibility of polynomials of the second order was not sufficient. In turn, the polynomials of the third or higher orders suffered from unphysical fluctuations. The solution was found by combining three Bezier curves [12]: two linear Bezier curves and one quadratic Bezier curve in the middle section. The developed parametric model is shown in FIGURE 4. The model was named parametric Model 1. The connections of the sections of the combined curve are tangent to each other at respective connection points P0 and P2 forming a composite Bezier curve.

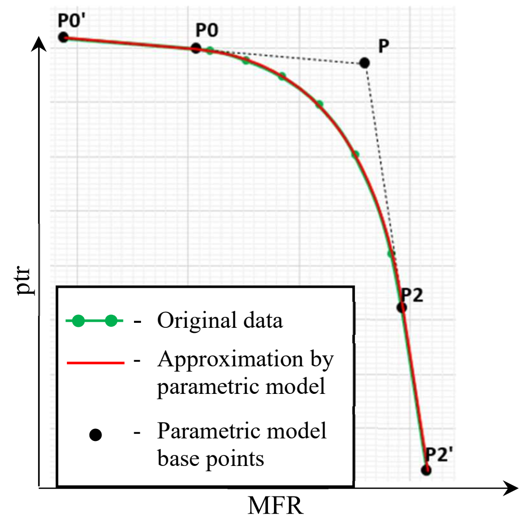

FIGURE 4: PARAMETRIC MODEL 1

The linear and quadratic Bezier curves are determined by equations (1) and (2) respectively, accounting for (3).

$$\boldsymbol{B}(t) = \boldsymbol{P}_0 + t(\boldsymbol{P}_1 - \boldsymbol{P}_0) \quad (1)$$

$$\boldsymbol{B}(t) = (1-t)[(1-t)\boldsymbol{P}_0 + t\boldsymbol{P}_1] + t[(1-t)\boldsymbol{P}_1 + t\boldsymbol{P}_2] \quad (2)$$

$$0 \le t \le 1 \quad (3)$$

where

t – is a parameter

$\boldsymbol{P}_0, \boldsymbol{P}_1, \boldsymbol{P}_2$ – are Bezier curve base points in the respective coordinate system

According to Model 1, the shape of the combined curve is fully determined by 8 parameters: two coordinates of surge point **P0'** plus two coordinates of choke point **P2'** plus four dimensionless factors determining the relative locations of the other three base points.

The described above parametric curve was suitable for the representation of speedlines in pressure ratio vs mass flow rate coordinates. However, it was not sufficient to accurately represent the speedlines in efficiency vs mass flow rate coordinates. Therefore, another parametric model was developed, by replacing the linear Bezier curve near the surge point with a quadratic Bezier curve (FIGURE 5). It was named parametric Model 2.

According to Model 2 the shape of the combined curve is fully determined by 10 parameters: two coordinates of surge point **P0'** plus two coordinates of choke point **P2'** plus six dimensionless factors determining the relative locations of the other four base points.

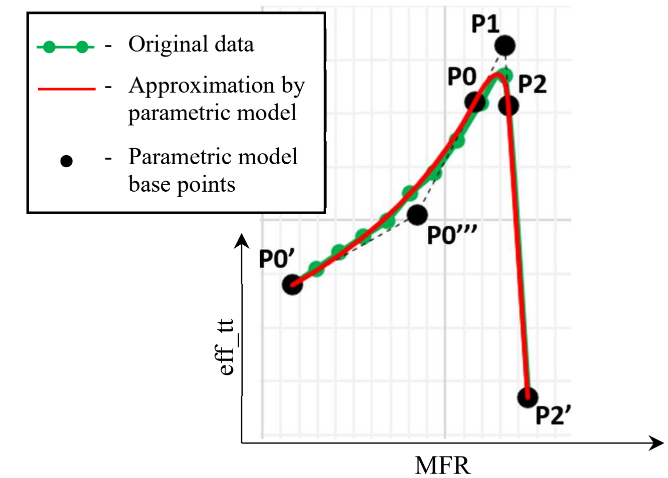

FIGURE 5: PARAMETRIC MODEL 2

It should be noted Model 2 can be applied to both pressure ratio and efficiency. However, utilization of this model for pressure ratio does not provide substantial benefits compared to Model 1 but adds one more degree of freedom, which complicates the curve fitting. Therefore, Model 1 was used for the representation of speedlines in pressure ratio vs mass flow rate coordinates, and Model 2 was used for the representation of speedlines in efficiency vs mass flow rate coordinates.

During the period of performance of the project on which the paper is based the authors were not able to find any sources in the public domain which considered the application of Bezier curves for approximation of turbomachinery performance isolines. Bezier curves are often utilized for approximation of geometrical features of turbomachinery, but not for performance isolines. The approach described above was proposed by the authors. However, it turns out that in 2021 the other authors were also studying the application of Bezier curves for the representation of compressor maps [13]. Their representation of speedline was based on a single Bezier curve of higher order. Their approach presumes a much wider variation of coordinates of base points, which makes it more difficult to train sufficiently accurate NN to predict base points coordinates for a variety of speedlines for a single combination of IGV/VGV reset angles and even more difficult for multiple combinations. This aspect was not considered in [13].

In order to train neural networks to predict parameters of parametric models and eventually entire speedlines, it was required to transform the training, validation, and test data sets, by doing automatic curve fitting for every speedline for every combination of IGV/VGV angles. The Levenberg-Marquardt algorithm [14] was used for automatic curve fitting.

2.3 ML Techniques, Hyperparameters Fine-tuning, and Training

The review of the previous works in this area showed that it is possible to utilize different machine learning approaches/techniques to predict compressor performance, such as the kriging model, feedforward neural networks with back-propagation, feedforward neural networks with back-propagation and Gaussian kernel function, and support vector machines [2, 3, and 4]. The other authors showed some advantages of one technique over the other, but their conclusions were somewhat relative because it was not clear if the used hyperparameters were optimal for every specific case. Thus, in this project, it was decided to use feedforward neural networks with back-propagation and focus on the search for optimal hyperparameters for them. For simplicity, hereafter, feedforward neural networks with back-propagation will be referred to as NN.

Prior to training, it was required to implement the capability to predict the IGV/VGV angle combinations where the compressor map exists (compressor can operate). It was important because if the user starts using the trained AI model without this capability it was possible to encounter the situation when the user enters an invalid IGV/VGV angles combination, and the model will extrapolate and predict the performance map where it does not exist. In order to implement this capability, the overall AI-based compressor map prediction method was organized into two levels: the first level is a classification model determining if IGV/VGV angles combination is valid (map exists) or not; the second level was a regression model predicting the performance map.

Multiple different combinations of hyperparameters were studied, including the number of hidden layers, number of neurons, activation functions, learning rates, application of different regularization techniques, such as L2 and dropout, and regularization rates. Sparce categorical cross-entropy was used as a loss function with accuracy as a metric for classification models. MSE was used as a loss function for regression models. “Adam” [15] optimizer was used for both classification and regression models. The data were normalized using z-scores [16].

A search for selected optimal hyperparameters was performed utilizing the AutoML algorithm. The determination of architecture is based on a competitive selection of architecture among the multiple ones during the training process. In FIGURE 6 one can see how the training process is performed conceptually. NN1, NN2, etc. stand for different architectural configurations of neural networks. The training process starts with some number of configurations (8 configurations in the example) and after a certain interval of timesteps T, the selection is being performed. The selection is based on a comparison of averaged accuracy levels for all configurations with the accuracy of each configuration. The configurations which have an accuracy level less than average (at the current selection instance) by a certain percentage are removed from further training process (NN2 and NN5 for the first selection instance in FIGURE 6). It should be noted that the number of the removed configurations per selection instance can be arbitrary. It is limited only by the number of total configurations considered minus 1. The selection process is being repeated after every interval T until the best configuration found (NN6 in FIGURE 4). The training process then continues with a single configuration until the accuracy target is met. It is important to notice that the AutoML algorithm automatically splits the data set into two subsets: training, validation, and test sets. By default, 90 % of the points are allocated for the training data set and 8 % go to the validation data set and the remaining 2 % go to the test set. The training is performed based on a training data set only. Validation is used at every selection instance during the selection process of different NNs to prevent overfitting. In turn, a test set was used to check the generalization capabilities of the best NN. In other words, blind test cases were used for the evaluation of the quality of compressor performance prediction.

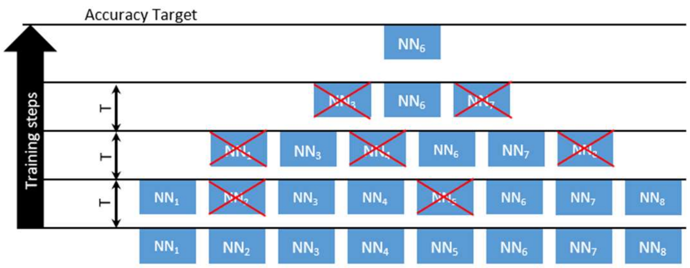

FIGURE 6: CONCEPTUAL EXAMPLE OF AUTOML PROCESS

It should be noted that the Key Performance Indicator (KPI) for the trained models was quantified not as MSE, but as a relative difference calculated using the equation (4) for every speedline from validation and test sets. The target value for the relative difference was < 3 % (equation (4)) in pressure ratio and efficiency for at least 10 points per speedline for at least 5 speedlines.

$$RD = \frac{2|AV - PV|}{AV + PV} 100\% \quad (4)$$

where,
RD – is a relative difference
AV – is an actual value
PV – is a predicted value

In the data sets transformed for the training of NNs to predict parametrized curves described in the previous section, the performance points belonging to a speedline are replaced with 8 parameters determining the shape of the parametric curve for pressure ratios and with 10 parameters for efficiencies respectively. It should be noted that coordinates of choke and surge points were taken directly from the original data sets and respective dimensionless factors were determined as a result of the auto fitting. After preliminary training sessions, it was determined that the coordinates of choke and surge points are playing a much more substantial role in the final level of error for speedlines compared to the dimensionless factors, and having a single NN for the prediction of all of them were leading to a reduction of accuracy of prediction of choke and surge points. Moreover, it turns out that the resultant speedline shape sensitivity to inaccuracies of prediction of dimensionless factors is rather small. Therefore, it was decided to train separate NNs for every coordinate of the choke point, separate NNs for every coordinate of the surge point, and separate NNs for dimensionless factors of parametric curves. The structure of all NNs is shown in FIGURE 7. As it can be seen such a split allowed having common models for the prediction of Choke MFR and Surge MFR and use them for ptr, psr, eff_tt and eff_ts. Moreover, it allowed consistency in MFR values across all models. All models were trained independently and then at the inference step the predictions of all the models were combined to recreate the entire speedlines for given IGV/VGV combinations and rpm values.

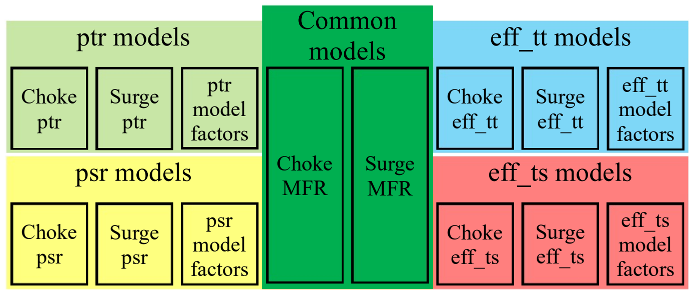

FIGURE 7: STRUCTURE OF ALL NN MODELS FOR PARAMETRIC CURVES

For clarity, the model without any parameterizations, hereafter, is being referred to as the “Direct” model.

Input parameters for all the models were IGV reset angles plus five VGV reset angles and rotational speed. The models were trained to eventually predict ptr, psr, eff_tt, and eff_ts taking a combination of reset angles and rpm as an input. It should be noted that the direct model was also taking MFR as an input to predict specific performance points. Parametric models were predicting entire speedlines, so MFR definition was not obligatory. Once the speedline was provided by the parametric model it was possible to determine the pressure ratios and efficiencies for any desired MFR value on the speedline.

The goal was to apply these techniques and find the best settings for the first compressor and then keep them for the training of the NNs for the other two compressors.

2.4 Utilization of The Trained Models in Optimization Task

The last step was to perform the study of the applicability of the trained AI model of axial compressor in the optimization of reset angles strategies for different operational lines.

The goal of the optimization was to maximize compressor total-to-total efficiency by varying IGV/VGV reset angles at every given point of the operational line (defined by three parameters: mass flow rate, total-to-total pressure ratio, and rotational speed) with minimal allowable surge margin of 12 % as a constraint.

For this purpose, the special workflow was developed in ION. The workflow was developed keeping in mind two scenarios of utilization: execution based on a trained AI model and based on an AxS solver. The created workflow is presented in FIGURE 8.

In FIGURE 8 the pink diamond “Parameters of the operational line” represents the cycle block that allows inputting the conditions of the operational line. The compressor operational line was specified by the vector variables that contain the mass flow, pressure ratio, and rotational speed for each operational point. The yellow rectangle "Files cleaning" cleans all results and variable combinations that are presented in the input and output files required for AI model execution. Once the files are cleaned the execution moves to blue diamond "Angles varying". This block generates the combinations of IGV/VGVs ratio for which the absolute values of IGV/VGVs will be calculated (yellow rectangle "IGV/VGVs recalculation"). Besides IGV/VGVs combination the rotational speed and mass flow for operational line points are transferred as well and each combination is written to the input data file. Once the input file for AI model execution is created the ION calls the AI models (blocks "PTR prediction" and "EFF prediction") and calculates the pressure ratio and efficiency for each combination of the input file. All results are written in the output file. The final stage of optimization is the post-processing of predicted results and determination of the optimal IGV/VGVs combination (block "Result typing to file").

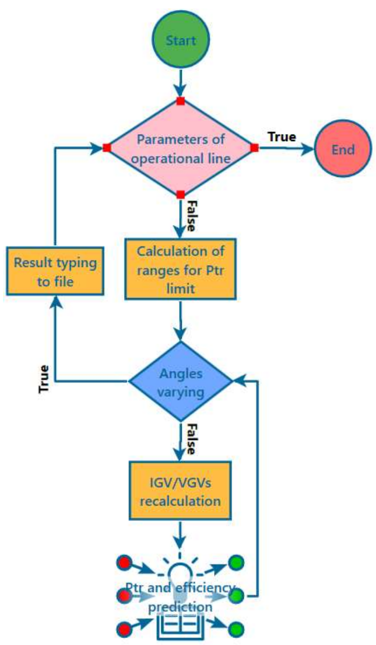

FIGURE 8: ION WORKFLOW FOR RESET ANGLES OPTIMIZATION

3. RESULTS AND DISCUSSION

Leveraging the approaches and methods described in the previous section respective technical activities were performed. Selected results are presented and discussed in this section. All results are given in the NASA SBIR Phase I technical report [18].

3.1 Compressor Design Results

The commentary on the selection of parameters for the considered compressors is given in Section 2.1. The first designed compressor was inspired by the EEE compressor [5, 6]. The analysis of the original EEE compressor showed that Deqx for all stators and some rotors is higher than 2. This leads to higher losses and a narrower range of the compressor operation. Therefore, to reduce Deqx some modifications to the design have been made. In particular, the outlet blade angles for the stators 1-6 have been reduced and the inlet blade angles for all stators and rotors have been redesigned to provide the incidence angles in the range -2 ...+ 2. These modifications, allowed to reduce the Deqx for all stages. The obtained design is shown in FIGURE 9.

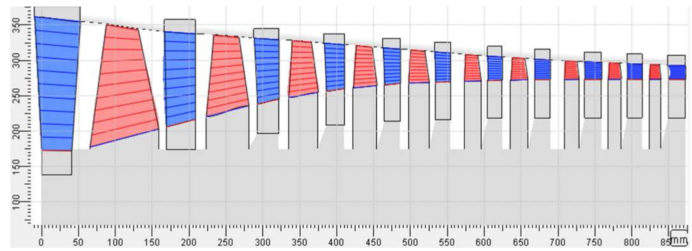

FIGURE 9: THE FLOW PATH OF COMPRESSOR 1. Y-AXIS IS RADIUS IN MM. THE X-AXIS IS THE LENGTH IN MM

The second designed compressor is presented in FIGURE 10. It is a 10-stages transonic high-loaded compressor with a total pressure ratio equal to 22.6, a mass flow rate equal to 39.95 kg/s, and a shaft speed is 12000 RPM at the design point. The compressor is designed for a constant mean diameter of 580 mm. The height of the blade at the compressor inlet is 120 mm, which provides an axial velocity of 170 m/s. The inlet hub relative diameter is Dhub/Dshroud = 0.65.

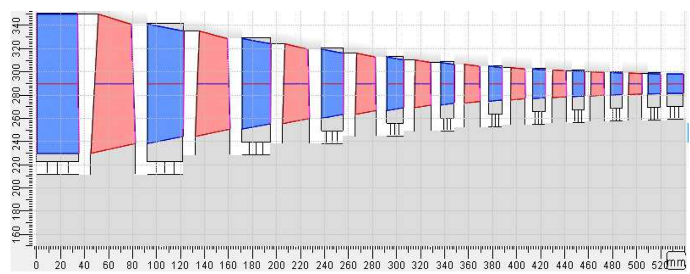

FIGURE 10: THE FLOW PATH OF COMPRESSOR 2. Y-AXIS IS RADIUS IN MM. THE X-AXIS IS THE LENGTH IN MM

Compressor 3 is a 10-stages transonic high-loaded compressor with a total pressure ratio of 20.03, a mass flow rate is 54 kg/s, and a shaft speed equal to 15000 RPM at the design point. The compressor is designed for a constant hub diameter of 440 mm. The height of the blade at the compressor inlet is 110 mm, which provides an axial velocity of 169 m/s. The inlet hub relative diameter is Dhub/Dshroud = 0.67. The compressor is shown in FIGURE 11.

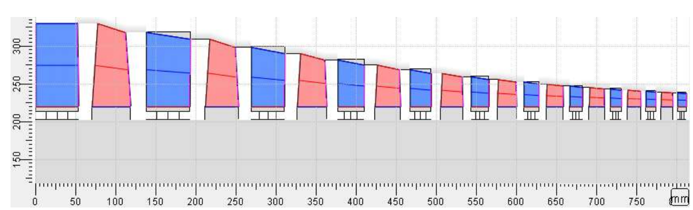

FIGURE 11: THE FLOW PATH OF COMPRESSOR 3. Y-AXIS IS RADIUS IN MM. THE X-AXIS IS THE LENGTH IN MM

The presented above compressors were used for the generation of the performance maps at different IGV/VGV combinations.

3.2 Training Data Generation and Pre-processing Results

Utilizing the workflow described in section 2.2 the performance data were generated for all three compressors. As it was described the data generation included data pre-processing and preparation, i.e., the generated data sets were clean and ready to be used for training in direct models.

The following data sets were generated:

- Compressor 1: 46978 performance points for the training data set, additionally 1344 data points were allocated for the validation data set (8 IGV/VGV reset angles combinations) and 495 data points for the test set (2 IGV/VGV reset angles combinations).
- Compressor 2: the training data set included 46157 points, additionally 1147 data points went to the validation set (8 IGV/VGV reset angles combinations) and 609 points were allocated for the test set (2 IGV/VGV reset angles combinations).
- Compressor 3: 61324 performance points went to the training data set, 1804 data points to the validation set (8 IGV/VGV reset angles combinations), and 576 data points to the test set (2 IGV/VGV reset angles combinations).

For parametric models, the data sets for all three compressors were transformed, by automatic curve fitting as described in Section 2.2.

Examples of the generated data with automatic curve fitting for total-to-total pressure ratio (ptr) and total-to-total efficiency (eff_tt) are presented in FIGURE 12 and FIGURE 13.

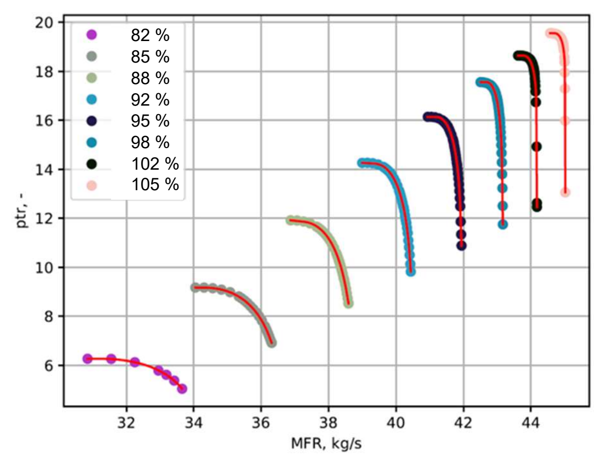

FIGURE 12: TOTAL-TO-TOTAL PRESSURE RATIO AUTOFITTING EXAMPLE WITH PARAMETRIC MODEL 1. THE MAP IS FOR COMPRESSOR 3 WITH THE RESET ANGLES: IGV = 16.9°, VGV1 = 7.4°, VGV2 = 1.4°, VGV3 = 1.1°, VGV4 = 0.8°, VGV5 = 0.0°

In FIGURE 12 and FIGURE 13 dots represent the performance points from the generated data sets, and red lines are fitted curves. Legend represents rotational speed in % to the design speed with respectively colored speedline points. As it can be seen both Model 1 and Model 2 have sufficient flexibility to approximate the wide variety of speedline shapes and do not have any unphysical oscillations. Remarkably, Model 2 was able to represent even very sharp spikes of efficiency curves for higher rpm values without losing the ability to represent smooth curves at lower rpm values.

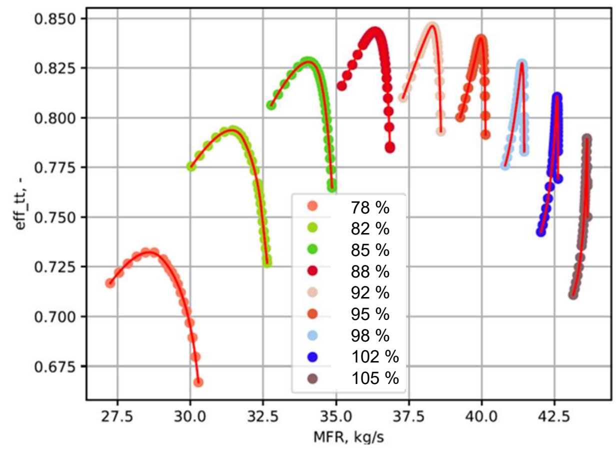

FIGURE 13: TOTAL-TO-TOTAL EFFICIENCY AUTO FITTING EXAMPLE WITH PARAMETRIC MODEL 2. THE MAP IS FOR COMPRESSOR 3 WITH THE RESET ANGLES: IGV = 17.3°, VGV1 = 12.7°, VGV2 = 9.7°, VGV3 = 4.7°, VGV4 = 2.3°, VGV5 = 1.1°

It should be noted that the process of data generation for compressor 3 was much faster compared to the ones of compressor 1 and compressor 2. This was because the raw performance maps data for compressor 3 were cleaner compared to the other two compressors, and fewer iterations were required in the loops of the data generation workflow (Section 2.2). Thus, data set generation for compressor 3 was completed earlier than for compressor 1 and compressor 2. Due to this fact, the compressor 3 data were used for the search for the best hyperparameters.

3.3 Hyperparameters Fine-tuning and Training Results

As a result of the utilization of the described in section 2.3 techniques and approaches for the classification model (validity of IGV/VGV reset angles combination), the accuracy value of 0.998 was achieved. The best classification model had two hidden layers with 50 neurons in each hidden layer, a ReLU activation function, and a learning rate of 0.001 without regularization. It turns out that most of the models were relatively simple and the average training time of one model was around 144 s.

FIGURE 14 and FIGURE 15 show the predictions of total-to-total pressure ratio (ptr) and total-to-total efficiency (eff_tt) by both a parametric model and by a direct NN for compressor 3. Direct NN had four hidden layers, 64 neurons in the first and second hidden layers and 128 neurons in the third and fourth ones. In turn, due to a split of the models in a parametric approach, it was sufficient to have only one hidden layer with

500 neurons to achieve desired validation accuracy for most of the models, and sometimes two hidden layers were required. It can be seen that both models were able to predict the performance map for unseen IGV/VGV angle combinations with good accuracy. However, direct NN sometimes had oscillations (at high rpm speedlines) not typical for compressor performance speedlines. The presented performance maps are representative of entire validation and test sets because the results were quite similar for the other IGV/VGV angle combinations.

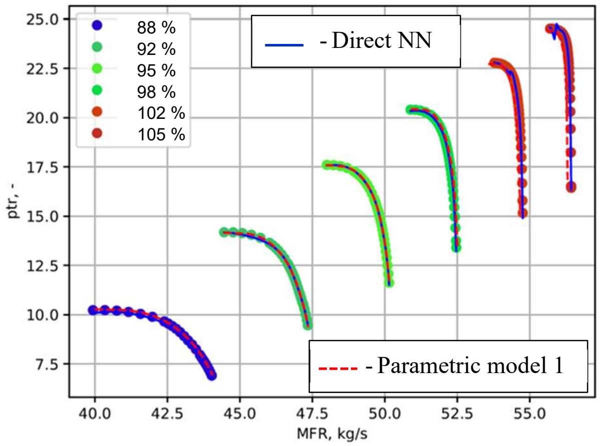

FIGURE 14: COMPRESSOR 3 TOTAL-TO-TOTAL PRESSURE RATIO PREDICTION RESULTS FOR IGV/VGV RESET ANGLES COMBINATION: IGV = 0.7°, VGV1 = 0.3°, VGV2 = 0.1°, VGV3 = 0.1°, VGV4 = 0.0°, VGV5 = 0.0°

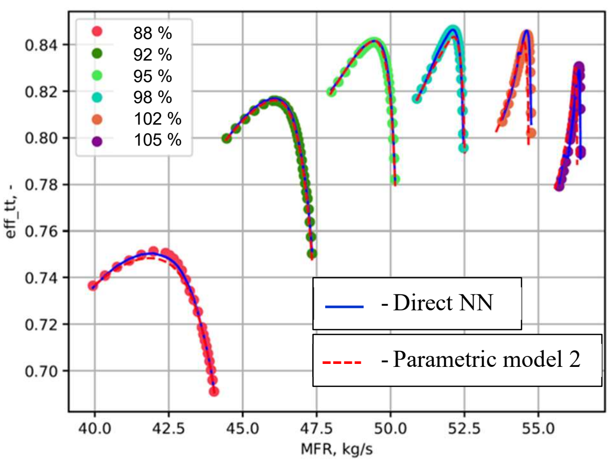

FIGURE 15: COMPRESSOR 3 TOTAL-TO-TOTAL EFFICIENCY PREDICTION RESULTS FOR IGV/VGV RESET ANGLES COMBINATION: IGV = 0.7°, VGV1 = 0.3°, VGV2 = 0.1°, VGV3 = 0.1°, VGV4 = 0.0°, VGV5 = 0.0°

It should be noted that AutoML tuned during training of parametric models to predict ptr and eff_tt was used to train models to predict total-to-static pressure ratio and total-to-static efficiency of compressor 3 (presented in FIGURE 16 and FIGURE 17 respectively) and all the models for compressor 1 and compressor 2 when the process of data generation was completed for them.

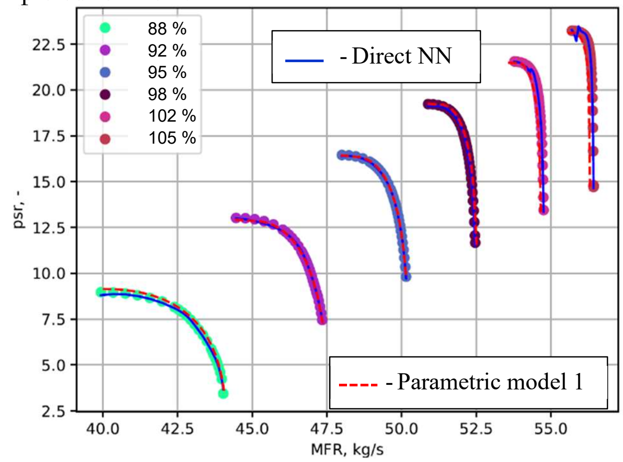

FIGURE 16: COMPRESSOR 3 TOTAL-TO-STATIC PRESSURE RATIO PREDICTION RESULTS FOR IGV/VGV RESET ANGLES COMBINATION: IGV = 0.7°, VGV1 = 0.3°, VGV2 = 0.1°, VGV3 = 0.1°, VGV4 = 0.0°, VGV5 = 0.0°

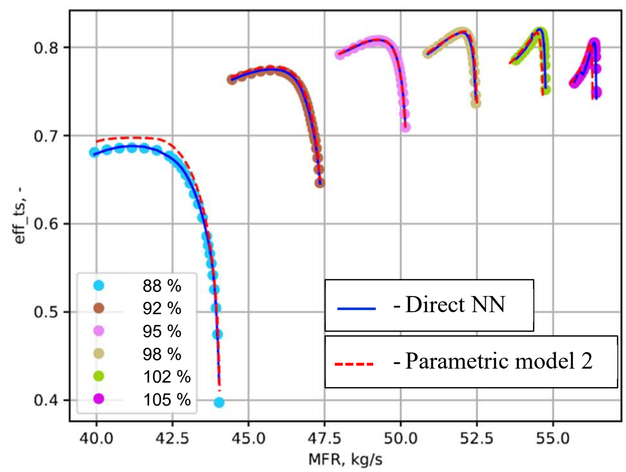

FIGURE 17: COMPRESSOR 3 TOTAL-TO-STATIC EFFICIENCY PREDICTION RESULTS FOR IGV/VGV RESET ANGLES COMBINATION: IGV = 0.7°, VGV1 = 0.3°, VGV2 = 0.1°, VGV3 = 0.1°, VGV4 = 0.0°, VGV5 = 0.0°

The accuracy of performance prediction by separately trained models for the other two compressors was quite similar to the one presented for compressor 3. Thus, due to a page limitation, the figures for them are not shown in this paper.

It should be noted that the method for determination of relative error was over strict and showed an error higher than 3 % even for the speedlines that were predicted with an accuracy, which would be more than acceptable when comparing 1D/2D/3D codes with experimental data (FIGURES 14, 15, 16 and 17). The relative error was exceeding the 3% level in the vicinity of the choke point where the speedline curve was very steep even though the predicted and original speedlines are very close (FIGURE 14 and FIGURE 18 (horizontal red solid line is 3 % threshold, solid blue lines are relative errors for Direct NN, and dashed colored lines are relative errors for parametric model)). Therefore, the overall accuracy of performance prediction for different IGV/VGV combinations of compressor 3 can be considered relatively high for the entire validation and test sets. The results of predictions for validation and test sets for all compressors are presented in TABLE 1.

TABLE 1: SUMMARY OF PREDICTION ACCURACY FOR VALIDATION AND TEST SETS FOR ALL COMPRESSORS. NUMBERS IN THE CELLS STAND FOR THE NUMBER OF THE PREDICTED SPEEDLINES WHERE THE RELATIVE ERROR DOES NOT EXCEED 3 %

Parameter	Compressor 1		Compressor 2		Compressor 3	
	Parametric	Direct NN	Parametric	Direct NN	Parametric	Direct NN
eff_tt	39	43	34	50	38	59
ptr	7	11	15	19	15	42
eff_ts	32	41	24	39	20	51
psr	6	6	15	18	9	32

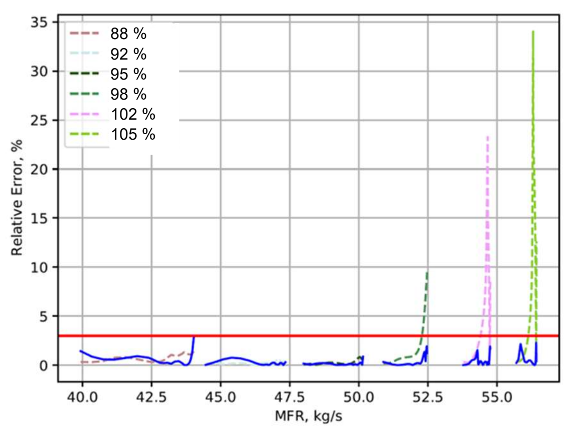

FIGURE 18: RELATIVE ERROR FOR COMPRESSOR 3 TOTAL-TO-TOTAL PRESSURE RATIO PREDICTION RESULTS FOR IGV/VGV RESET ANGLES COMBINATION: IGV = 0.7°, VGV1 = 0.3°, VGV2 = 0.1°, VGV3 = 0.1°, VGV4 = 0.0°, VGV5 = 0.0°

The accuracy target for the initial compressor was maximal relative difference < 3 % (equation (4)) in pressure ratio and efficiency for at least 10 points per speedline for at least 5 speedlines (TABLE 1). In turn for the other two compressors, it was required to achieve the same accuracy metrics, but utilizing the AutoML tuned during the training of the initial compressor (in our case compressor 3). Taking into account that number of the points on any speedline was always higher than 10 one can see that the accuracy target was met for all compressors and all models. Besides, one can notice that the parametric model typically had a smaller number of speedlines with an error of less than 3 %. However, the parametric model still looks preferable, because the shape of speedline curves is more consistent and closer to the typical shape of the speedlines in contrast with direct NN which had unphysical oscillations on some speedlines.

3.4 Reset Angles Optimization Results

Utilizing the workflow shown in FIGURE 8 the optimization of reset angles strategies for the given operational line was performed. The operational line was defined by specifying the values of mass flow rate, pressure ratio, and rotational speed for 10 points (FIGURE 19). It is important to notice that the operational line can be determined by system-level analysis and matching of the compressor with the driving device.

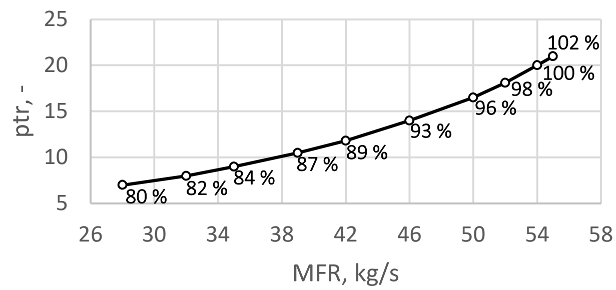

FIGURE 19: THE CONSIDERED OPERATIONAL LINE. PERCENTAGES STAND FOR ROTATIONAL SPEED RELATIVE TO THE DESIGN ONE

The optimization was performed for compressor 3 by generating 5,000 combinations of IGV/VGV angles utilizing the Sobol sequence [11]. During the optimization process, the evaluation of compressor performance was done by a trained AI model. It should be noted that the optimization task was performed twice. The first optimization was performed employing the trained parametric model and the second optimization was performed utilizing the trained direct NN model which enabled the opportunity to compare them (FIGURE 20 and FIGURE 21).

The obtained IGV/VGV combinations were inputted to the AxS solver to estimate the error between prediction by NNs and calculated by physical solver data. The error values are shown in FIGURE 22 and FIGURE 23.

The results obtained by both NN models are quite similar as well as estimated error values. The pressure ratio for most of the points on the operational line had a relative error below 2 % with several points exceeding 3 % with the parametric model. The efficiency was predicted very accurately with the relative error at any point below 1 %. The surge margin was kept above 12 % as anticipated.

It should be noted that the character of the variation of the optimal IGV/VGV reset angles does not allow to find an approximating curve to be able to predict the optimal combination for some arbitrary point on the operational line with reasonable accuracy. However, the developed AI models can be used to quickly predict the optimal combination of angles for any point on the operational line. Moreover, the developed AI models can predict not only the optimal combination of angles at the arbitrary point but also predict the efficiency of the compressor and evaluate stability margins.

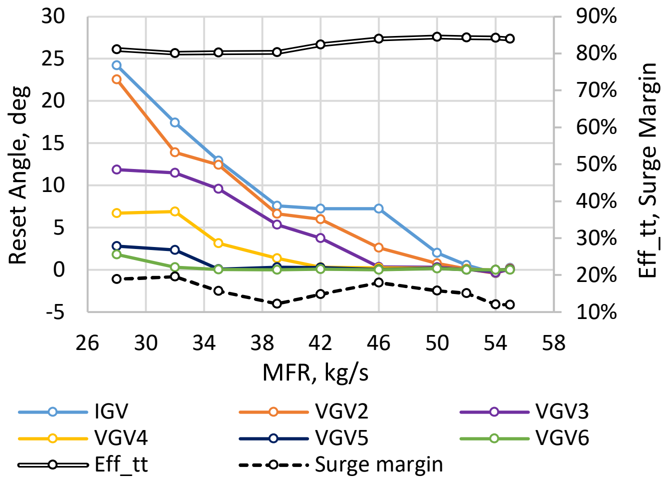

FIGURE 20: OPTIMIZATION RESULTS EMPLOYING PARAMETRIC MODEL-BASED NN

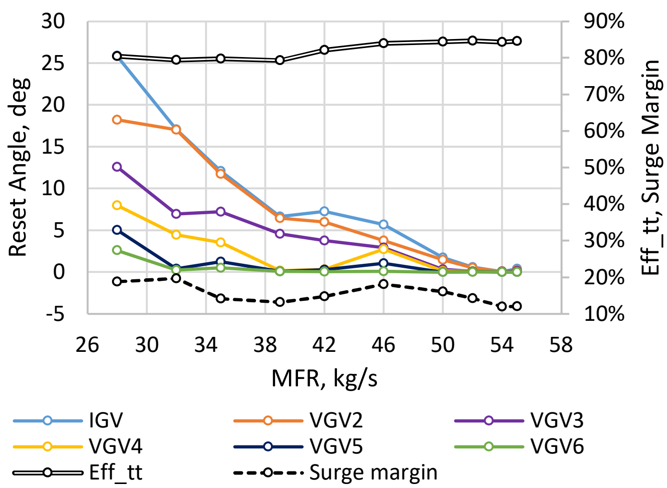

FIGURE 21: OPTIMIZATION RESULTS EMPLOYING DIRECT NN

The prediction of the optimal reset angles combination for one operational point in any of the trained AI models takes about 5 minutes. The same prediction based on 1D/2D solver typically takes about 4 hours on the same workstation. However, such a comparison is not representative, because it is required to spend a certain time for data generation and training in the case of AI models. In this study, the automatic data generation for a single compressor with the final workflows was taking around 120 hours, and training of AI models was taking around 24 hours per compressor. It is obvious that if 10 points at the operational line are considered, then optimization with a 1D solver would be faster in total, however, most likely it will be required to evaluate much more points due to the necessity of determining optimal reset angles, efficiency, and stability margin values for intermediate points as well. During the analysis of the entire engine, the system-level analysis software can call the IGV/VGV angles optimization procedure hundreds of times. The evaluation of time required to perform IGV/VGV reset angles optimizations using 1D Solver and AI models at different numbers of points at the operational line is shown in FIGURE 24. The green line (using the AI model) starts at 144 hours, to account for the time required to generate data and train models. As it can be seen the break-even is reached at around 37 points, i.e., at any number of points at the operational line higher than 37 the utilization of the AI model is more time-efficient. For example, at 100 points the time is 149 hours (AI model) vs 400 hours (1D solver) (performed at Windows 10 mobile workstation with Intel Core i7 6700HQ). It is important to point out that the more calls for optimization procedure during cycle analysis the higher the advantage of the utilization of the AI model.

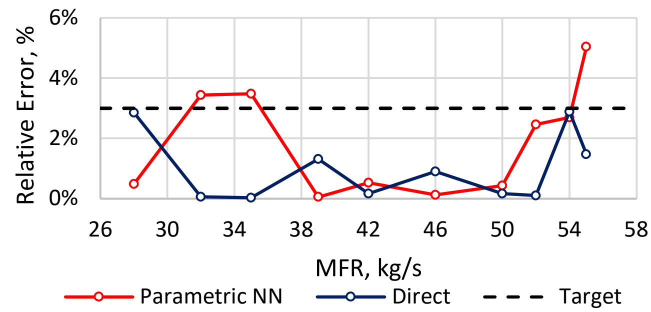

FIGURE 22: RELATIVE ERROR OF PRESSURE RATIO PREDICTION IN OPTIMIZATION TASK

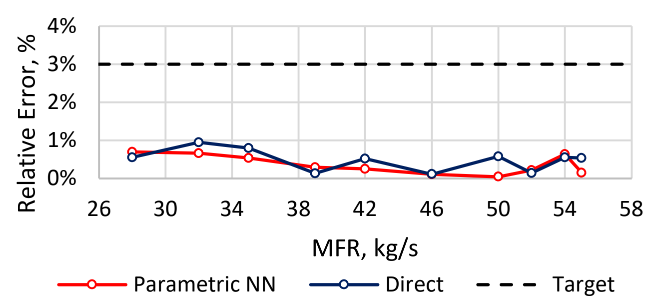

FIGURE 23: RELATIVE ERROR OF EFFICIENCY PREDICTION IN OPTIMIZATION TASK

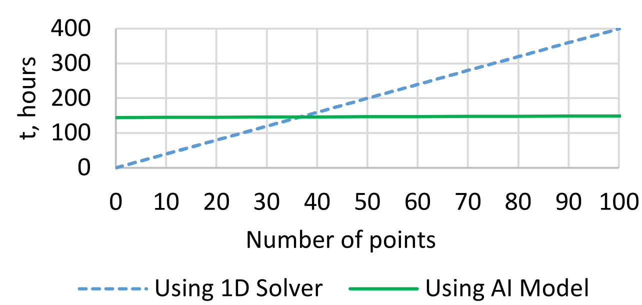

FIGURE 24: TIME REQUIRED TO OPTIMIZE IGV/VGV RESET ANGLES AT DIFFERENT NUMBERS OF POINTS AT THE OPERATIONAL LINE

4. CONCLUSION

The developed approaches allowed to automatically generate clean training data for multistage axial compressors with variable IGV/VGVs and train neural networks to predict their performance satisfying accuracy targets (3 %).

The trained neural networks were successfully used in the optimization of the variable IGV/VGVs reset angle schedules with a relative error of total-to-total pressure ratio prediction below 2 % for most of the points and relative error of total-to-total efficiency prediction below 1 % for all the points of the operational line.

The determination of the optimal reset angles combination for one operational point by AI model is faster compared to 1D code and the more calls of optimization procedure during cycle analysis the higher the benefit of utilization of AI model.

The capability of the developed AI models to accurately predict the optimal combination of reset angles and efficiency of the axial compressor with multiple vanes controlled independently allowed doing quick evaluations of efficiency and stability margins. The availability of such information enables the opportunity to make technical-economical decisions about the reasonability of implementation of independent variable vanes and their number during engine system analysis.

The developed system is automatic and flexible. It allows utilizing any codes to generate maps quickly without the need to have ML experience.

The successful completion of this project enabled the opportunity to apply for the NASA SBIR Phase II project. The Phase II application was awarded by NASA SBIR and is currently in progress.

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REFERENCES

[1] G.L. Converse and R.G. Giffin. “Extended Parametric Representation of Compressors Fans and Turbines.” Vol. I - CMGEN User's Manual. Technical Report No. NASA-CR-174645, General Electric Company, Cincinnati, Ohio. 1984

[2] Hongsheng, Jiang. Dong, Sujun. Zheng, Liu. Yue, He. and Fengming, Ai. “Performance Prediction of the Centrifugal Compressor Based on a Limited Number of Sample Data.” *Mathematical Problems in Engineering* Vol. 2019 (2019): Article ID 5954128, DOI 10.1155/2019/5954128

[3] Gholamrezaei, Mohammad. and Ghorbanian, Kaveh. “Compressor Map Generation Using a Feed-Forward Neural Network and Rig Data.” *Proceedings of the Institution of Mechanical Engineers Part A Journal of Power and Energy* 224(1): pp. 97-108. Tehran, Iran, February, 2010. DOI 10.1243/09576509JPE792

[4] Fei, Jingzhou. Zhao, Ningbo. Shi, Yong. Feng, Yongming. and Wang, Zhongwei. “Compressor Performance Prediction Using a Novel Feed-forward Neural Network Based on Gaussian Kernel.” *Advances in Mechanical Engineering* Vol. 8 (2016): DOI 10.1177/1687814016628396

[5] P. R. Holloway, G.L. Knight, C.C. Koch, and S.J. Shaffer. “Energy Efficient Engine - High-Pressure Compressor Detail Design Report.” Technical Report No. NASA-CR-165558, General Electric Company, Cincinnati, Ohio. 1982

[6] D. C. Howe and R. D. Marchant. “Energy Efficient Engine - High-Pressure Compressor Test Hardware Detailed Design Report.” Technical Report No. NASA-CR-180850, United Technologies Corporation, East Hartford, Connecticut. 1988

[7] Moroz, Leonid. Govoruschenko, Yuri. and Pagur, Petr. “A Uniform Approach to Conceptual Design of Axial Turbine / Compressor Flow Path” *Proceedings of the Future of Gas Turbine Technology 3rd International Conference* (2006): Brussels, Belgium, October, 2006

[8] Lieblein, Seymour. “Loss and Stall Analysis of Compressor Cascades.” *ASME Journal of Basic Engineering* Vol. 81 No. 3 (1959): pp. 387-397

[9] Aungier, Ronald. “Axial–Flow Compressors: A Strategy for Aerodynamic Design and Analysis.” ASME International, New York (2003): pp. 361. ISBN 0-7918-0192-6.

[10] Wikipedia.org. “General Electric GE9X.” Available: https://en.wikipedia.org/wiki/General_Electric_GE9X [Accessed: 18-Feb-2022]

[11] Sobol, Ilya. “On the distribution of points in a cube and approximate evaluation of integrals.” *U.S.S.R Computational Mathematics and Mathematical Physics* Vol. 7 No. 4 (1967): pp. 86–112. DOI 10.1016/0041-5553(67)90144-9

[12] Wikipedia.org. “Composite Bezier curve.” Available: https://en.wikipedia.org/wiki/Composite_B%C3%A9zier_curve#:~:text=In%20geometric%20modelling%20and%20in,point%20of%20the%20next%20curve. [Accessed: 18-Feb-2022]

[13] Shuang, Sun. Ze-Peng, Wang. Xiao-Peng, Sun. Hong-Li, Zhao. Zhi-Ping, Wang. “An adaptive compressor characteristic map method based on the Bezier curve.” *Case Studies in Thermal Engineering* Vol. 28 (2021): DOI 10.1016/j.csite.2021.101512

[14] Wikipedia.org. “Levenberg–Marquardt algorithm.” Available: https://en.wikipedia.org/wiki/Levenberg%E2%80%93Marquardt_algorithm [Accessed: 18-Feb-2022]

[15] Kingma, Diederik. and Lei Ba, Jimmy. “Adam: A Method For Stochastic Optimization.” *Proceedings of the 3rd International Conference for Learning Representations*, San Diego, 2015

[16] Wikipedia.org. “Standard score.” Available: https://en.wikipedia.org/wiki/Standard_score [Accessed: 18-Feb-2022]

[17] Burlaka, Maksym. and Moroz, Leonid. “Axial Compressor Map Generation Leveraging Autonomous Self-training AI.” Technical Report No. 1422-02-03. NASA Contract No. 80NSSC20C0447, SoftInWay Inc., Burlington, Massachusetts. 2021

