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Predicting Off-Design Performance of Axial Compressors Using Multilayer Neural Network Model for Surge Control

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Abstract
The incidence of surge within axial compressors profoundly influences the efficacy and reliability of aeroengines. Conventional methodologies in engine design have predominantly concentrated on the precise and efficient forecasting of critical characteristics during such occurrences. This paper presents a novel approach for predicting the surge phenomenon in axial compressors. Surge is a major issue in the operation of axial compressors, causing reduced performance, increased wear and tear, and in some cases, complete machine failure. The proposed approach utilizes a neural network model based on the compressor's design data to forecast the behavior of the compressor's working map under off-design conditions. The model is verified using real data collected over five years during compressor operation, including the opening angle of the Inlet Guided Van (IGV), an important parameter often ignored or assumed to be fixed in previous studies.

The results show that the neural network-based approach effectively predicts the compressor's behavior under different operating conditions, providing valuable insights into the onset of surge and offering a real-time surge prediction and control tool. The ability to predict the compressor's working map enables optimizing its performance and controlling instability. This model was validated by comparing its predictions with real operating conditions observed over five years across various compressor operating modes. As a result, this predictive model enables the safe operation of axial compressors by mitigating instability risks during operation. This study's findings highlight the model's effectiveness, as evidenced by the minimal error observed between the predicted and actual data collected across various compressor operating modes. The model exhibits a strong performance, characterized by a high regression factor of 0.92667 and a low mean squared error of 3.04465 x 10^-3. These numerical values underscore the reliability and precision of the proposed approach in predicting the operation of the axial compressor under diverse conditions, ultimately contributing to enhanced stability and safety during compressor operations.

Keywords: Axial Compressors, Surge, Neural Network, Inlet Guided Van and Prediction

Introduction
Axial compressor design and analysis take a lot of time and money because traditional methods call for numerous iterations between the cycle analysis phase and the final geometry. Modern cycles and components are frequently pushed to their breaking point to attain the maximum possible efficiency and the least amount of fuel consumption. In the pursuit

of superior efficiency and reduced consumption, particularly in contemporary gas turbine engines, there is a continuous escalation in the pressure ratio of high-pressure compressors (HPC). However, this leads to elevated rotor tip relative Mach numbers in the initial stages of the HPC, consequently generating a pronounced performance characteristicMap.

Axial compressors are widely used in various industrial and power generation applications and are crucial in ensuring stable and efficient performance. However, one of the major challenges in their operation is the phenomenon of the surge, which is characterized by a sudden and rapid increase in flow instability and can lead to decreased performance, increased wear and tear, and in extreme cases, complete machine failure Surge is a complex phenomenon that arises from the dynamic interaction between the compressor and its operating conditions, making it difficult to predict and control The traditional methods for predicting a surge in axial compressors have relied on approximate models and limited data, resulting in significant uncertainties in the predictions [5,8-10]. To address this issue, recent studies have explored the use of machine learning techniques, such as artificial neural networks, for modeling and predicting surges in axial compressors [11-14]. These approaches have shown promising results in improving the accuracy and reliability of surge predictions, especially under off-design conditions [15-17].

In this study, we propose a novel approach for predicting surges in axial compressors based on a neural network model trained using the compressor's design data. The proposed model is designed to forecast the behavior of the compressor's working map under various operating conditions and considers the opening angle of the Inlet Guided Van (IGV), which is an important parameter that is often ignored or assumed to be fixed in previous studies [1,4].

The performance of the proposed model is verified using real-time data collected during compressor operation over five years. This study's results contribute to axial compressor technology by providing a robust and effective tool for real-time surge prediction and control. The ability to predict the working map of the compressor enables the optimization of its performance and the control of instability, making it a significant contribution to the ongoing efforts to improve the stability and efficiency of axial compressors.

The Contributions of this Paper Include

- Predicts off-design conditions using IGV angle values for real compressor maps.
- Explains changes in compressor operation due to IGV angle changes.
- Develops a cost-effective neural network model for anti-surge control.
- Verifies model using five years of real-time compressor data.
- Improves compressor performance through adjustments based on real-time maps.

In this paper, we will first introduce the topic and context of the research. Then, in section we will review the related work in the field, including previous studies and their findings. Next, in section 3, we will present the mathematical model used to support the results of our research. In section 4, we will delve into the details of the neural network architecture and how it was implemented in our study. Section 4 also present the computer results and simulation data, along with a thorough analysis of the findings. Finally, in section 5, we will summarize our results and provide a conclusion to the research, discussing the implications of our findings and future work that can be done in this area.

Background and Related Work

The aerodynamic instability problem of the Axial compressor in an aero-engine significantly affects the engine's overall performance and reliability. When the flow through the compressor decreases, it operates outside of its design point, leading to disruptions in its internal steady flow. Once the compressor crosses the stability boundary, it enters an unstable state, such as a rotating stall or surge, which can have severe consequences. The decrease in flow rate and pressure rise significantly reduces efficiency, and recovery from a surge can be challenging due to the time that it occurs, and it is going in cycles. Furthermore, surge can cause forced vibration of the compressor rotor blade, damaging its structural integrity. To maintain surge margins, designers may sacrifice compressor performance during design. Therefore, controlling and studying surges is crucial in aero-engine compressor design, and numerous solutions have been investigated to suppress their occurrence and increase surge margin [18,19].

Over the years, various methods have been proposed to predict and control the surge in axial compressors. Some of the recent studies in this field include [20-22]. In the authors proposed using artificial neural networks (ANNs) to predict the surge boundary of axial compressors. The study showed that the ANN model could accurately predict the surge boundary with a high degree of accuracy [20]. However, the method was limited to a single compressor configuration, and its ability to generalize to other configurations was not evaluated. In the authors proposed a model-based approach to predict the surge of axial compressors [21]. The study showed that the model-based approach could predict the surge accurately, but the method required a detailed and accurate compressor model, which may not be available in practice [22,23]. In the authors proposed using data-driven methods to predict the surge of axial compressors. The study showed that the data-driven approach could predict the surge accurately, but the method required large amounts of data, which may not be available in practice. The neural network has been chosen due to its robustness and ease of learning when dealing with parameters that have nonlinear relationships.

Predicting compressor surge can be approached in three ways: ANN-based, model-based, and data-driven. The ANN-based approach offers accurate predictions of surge boundaries but is limited to a single compressor configuration [20]. The model-based approach provides accurate surge predictions but requires a detailed and exact compressor model. The data-driven approach is also capable of accurate surge prediction but requires a large amount of data to be effective [21,23].

While previous studies have made significant contributions to predicting and controlling the surge in axial compressors, there is still a need for a comprehensive and generalizable approach that considers both design conditions and real-time data [23]. This paper aims to fill this gap by proposing a neural network model based on compressor design data and real-time data to predict the compressor map and prevent surges in axial compressors.

Problem Formulation and Plan of Solution

Experimental studies of the post-stall phenomenon pose a certain degree of risk, as unstable operating conditions can lead to destructive effects, particularly surge, in multistage axial compressors with high speed and pressure ratios. To accurately predict the performance of the compression system during a surge, reliable numerical calculations are necessary, but this is a challenging aerodynamic problem due to the need to estimate steady-state performance, predict stability boundaries, and calculate flow field perturbation growth into surge cycles.

Simplified models have been developed to overcome this challenge, such as lumped parametric models and body-force models, which simulate the aerodynamic processes during surge transients. The key to such models is the simulation of blade forces and associated flow field parameters, which can be provided by correlations adapted for different flow conditions. In this paper, we use a complete operating design data to predict off-design operating conditions and a real operating parameter working of a high-speed multistage axial compressor at 14 stages each second for five years.

To create a neural network model that controls the compressor's operation parameters to provide stability of operation conditions and to avoid any instability problem.

Neural Network

Artificial Neural networks have made tremendous strides in recent years, propelling the field of artificial intelligence forward. Their ability to learn complex patterns and generalize from large datasets has resulted in breakthroughs across various domains. The recent advancements in neural network architecture, training algorithms, and applications, such as GANs, transfer learning, and explainable AI, have further expanded their capabilities. As research continues to progress, neural networks are expected to play an increasingly vital role in solving complex real-world problems.

Artificial Neural Networks (ANNs) have become a cornerstone in the realm of artificial intelligence due to their unparalleled ability to learn intricate patterns and generalize from expansive datasets. These networks, composed of interconnected nodes or "neurons" organized in layers, have seen significant advancements in architecture, training algorithms, and applications, such as Generative Adversarial Networks (GANs), transfer learning, and explainable AI [24,25]. Their rapid, reliable, and cost-effective responses have made them indispensable in various domains [26].

Neural networks learn from labeled data through a process called training. The weights and biases of the network are adjusted iteratively to minimize the difference between predicted outputs and ground truth labels. Gradient descent, backpropagation, and stochastic gradient descent are commonly used optimization algorithms in neural network training. Recent advancements in training algorithms, such as adaptive learning rate methods (e.g., Adam and RMSprop), have significantly improved the convergence speed and performance of neural networks.

Transfer learning enables the transfer of knowledge learned from one task or domain to another. Pre-trained neural network models, such as VGG, ResNet, and BERT, trained on large-scale datasets, can be fine-tuned on specific tasks with limited labeled data. This approach has proven effective in various applications, including image classification, object detection, and natural language processing.

In the authors indicate artificial neural network formation could be excellent to other curve fitting mechanism if the model is enough trained, but they reported insufficiency of artificial neural network informulation model of compressor Flow rate as a function of compressor pressure percentage and speed [27].

The authors used back propagation neural networks (BPNN) to paradigm map of centrifugal and screw compressors in the authors used BPNN to foretell compressor map thorough two-time training [28]. Experimental data as long as outcomes of first coaching are used to train the neural network [29].

A neural-network is a wide range Collimated distributed processor manufacturing of easy transformation units, that have a natural penchant for saving learning and using it for further workNeural networks are eligible to understand and thus to popularize refers to the neural network creating rational outputs for inputs not happen during learning process [30,31]. These data work ability to make it potential for neural-networks to fix nonlinear issues that are currently difficult. And to be used to foresee performance of a compressor map. Inthe authors ignore the effect of IGV in forecast of compressor map [32].

IGV open is highly concerned in his study as it shows the effects in the operating of the axial compressor The Back-Propagation method network was formed by propagate WindrowHoff educate rule to multi strata networks and non-linear set of transfer-functions. Input pattern and the congruent target patterns are used to train a network until convergent it to a function, support input pattern with specific output pattern, the nonlinearity relation Connection between input elements and output elements of the compressor, multistrata neural networks utilize Sigmoid transfer-function to create outputs.

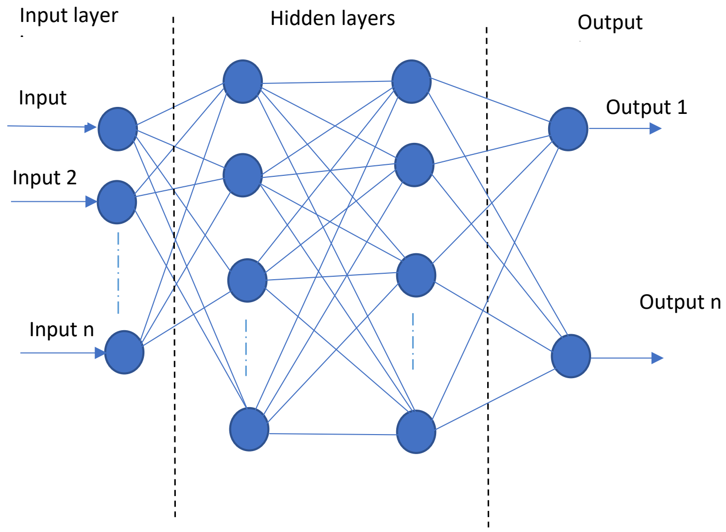

Figure 1: General Formation of Back Propagation Network

A trained back propagation neural networks fig.1 provide great answers when applied with inputs that they have never seen. Which is suitable to a nonlinear system prediction usually, a new pattern fulfills to an output similar to the right output pattern for input pattern used in learning procedure that are same to new input pattern existence presented. This popularization feature produces it likely to train a network on a set of input pattern sets and obtain perfect outcome without learning network on all probably input/output pattern sets.

A lot of difference of the backpropagation mechanism, the Levenberg–Marquardt mechanism is used here. Like the quasi-Newtonian method, the Levenberg–Marquardt mechanism was performed to process the second-order learning time period without having to calculate Hessian matrix. It is a methodology based on standard numerical Improvements technology. It is an adjustment between the speed of the Newtonian methodology and the convergence of the steepest descent methodology.

The Backpropagation neural network using the Levenberg-Marquardt training method offers significant advantages in terms of faster convergence, improved stability, robustness to initial conditions, and the ability to handle nonlinear optimization problems. Recent research has focused on enhancing the LM algorithm through adaptive damping, hybrid approaches, momentum, and dynamic adjustments. These advancements contribute to the continuous improvement of training deep neural networks, making them more efficient and reliable in various applications.

Backpropagation is a widely used algorithm for training neural networks. It is an efficient method for adjusting the weights and biases of the network based on the gradient of the error function. The Levenberg-Marquardt (LM) algorithm, a variation of the standard backpropagation algorithm, improves the convergence speed and stability of the network. This paper provides a comprehensive review of the Backpropagation neural network using the Levenberg-Marquardt training method, highlighting its advantages and recent research developments.

The backpropagation algorithm is a key component of training neural networks. It involves the iterative calculation of the gradient of the error function with respect to the weights and biases of the network, followed by the adjustment of these parameters to minimize the error. The algorithm propagates the error from the output layer back to the hidden layers, updating the weights using the chain rule of calculus. Backpropagation has been instrumental in training deep neural networks and has achieved significant success in various applications.

For this study, we employed a feedforward neural network, a prevalent architecture where information flows sequentially from the input layer, through hidden layers, to the output layer. Deep Neural Networks (DNNs), with their multiple hidden layers, were leveraged to capture the complex relationships inherent in the compressor data. The significance of the IGV opening angle, often overlooked in previous studies[32], was given paramount importance in our model.

Neural networks undergo a training process where their weights and biases are iteratively adjusted to minimize the difference between predicted outputs and actual labels. While gradient descent, backpropagation, and stochastic gradient descent are common optimization techniques, our study employed the Levenberg-Marquardt (LM) algorithm

[33,34]. This algorithm, an optimization method that amalgamates the merits of the Gauss-Newton method and gradient descent, offers:

Faster Convergence: Reducing the Overall Training Time Improved Stability
Ensuring consistent and reliable training.

Robustness to Initial Conditions: Offering consistent results regardless of the network's initial state. Proficiency in Handling Nonlinear Problems: Making it apt for intricate tasks.

The LM algorithm's damping factor ensures a balance between rapid convergence and stability, preventing potential pitfalls like oscillations or divergence.

The Levenberg-Marquardt algorithm is an optimization method that combines the benefits of the Gauss-Newton method and gradient descent. It adjusts the weights and biases of the neural network by minimizing a cost function, which measures the discrepancy between the predicted outputs and the desired outputs. The LM algorithm introduces a damping factor that balances between the speed of convergence and stability. It effectively handles ill-conditioned problems and avoids convergence to local minima [33,34].

Advantages of Levenberg-Marquardt Training

- Faster Convergence: The LM algorithm generally converges faster compared to traditional backpropagation methods, resulting in reduced training time for neural networks.
- Improved Stability: The damping factor in the LM algorithm ensures stability during training, preventing large weight updates that may cause oscillations or divergence.
- Robustness to Initial Conditions: The LM algorithm is less sensitive to the initial conditions of the network, allowing for more reliable and consistent training results.
- Handling Nonlinear Problems: The LM algorithm is particularly effective in handling nonlinear optimization problems, making it suitable for complex tasks where traditional backpropagation methods may struggle.
- Backpropagation with the Levenberg-Marquardt training method has been applied in robotics and control systems, including autonomous vehicles, robotic manipulation, and industrial process control. Neural networks trained using this method have demonstrated precise control and adaptation capabilities, allowing for efficient and accurate control of robotic systems in dynamic environments.
- Post-training, the model's efficacy was gauged using reserved test data. Metrics like the Regression Factor and Mean Squared Error (MSE) were employed. Our model exhibited a high regression factor of 0.92667 and a commendably low MSE of 3.04465 x 10^-3, underscoring its precision and reliability.

Mathematical Model

This study aims to predict an axial compressor's performance in off-design conditions using neural network techniques. The compressor map is generated using fixed parameters at a fixed point, and the aim is to predict the off-design readings using the design conditions through a neural network [35-37]. The compressor's performance is evaluated using a database collected for different operation modes over five years for each second reading.

$$\dot{m}_a(r_{IGV}, \omega, \beta) = \dot{m}_a(1, \omega, \beta) * r_{IGV} \quad (1)$$

A change in the inlet flow angle (IGV) modifies the dynamic flow characteristics of the compressor and, therefore, changes its characteristic curves. The variation of air mass flow produced by the IGV is estimated using a simple technique, which is highly relevant in this study. The mass flow rate can be described by equation (1), where rr_{IIIIII} is the percentage of the operative mass flow to total mass flow at the same speed and pressure ratio with fully open VIGVs (rr_{IIIIII}= 1), ω is the speed in rad/s, β is the pressure ratio, and $mṁ_{aa}$ is the mass flow rate in kg/s.

The selected neural network model, trained using the Levenberg-Marquardt backpropagation algorithm, is used to solve this issue. Using recent references and citations ensures the proposed model is up-to-date and relevant to the current state-of-the-art neural network applications in axial compressors [38,39].

Multilayer neural networks can utilize hyperbolic tan-Sigmoid transfer function

$$f = \frac{e^{nil} - e^{-nil}}{e^{nil} + e^{-nil}} \quad (2)$$

Secondly, the log-Sigmoid function creates a pattern between 0 and 1 as the neural network moves from negative value to positive infinity.

$$f = \frac{2}{(1+e^{-2nil})} - 1 \quad (3)$$

$$ni = Wp + bi \quad (4)$$

Equation (2), (3), and (4) represents the function of neural network where F is the i^{ts} element of the F vector containing the outputs from hidden neurons, and nil is the i^{th} element of in vector containing net inputs going into hidden neurons. p is input Patten, bi the vector of bias weighs on hidden neurons, W is the weight matrix between 0th (i.e., input) layer and 1th (i.e., hidden) layer. Each row of W contains the synaptic weights of the corresponding hidden neuron. W is the weight matrix between 0th (i.e., input) layer and 1th (i.e., hidden) layer. Each row of W contains the synaptic weights of the corresponding hidden neuron.

Where F is ith element of F vector container-inputs going into the hidden neurons. p is the input pattern, bi is the vector of bias weighs on hidden neurons, and W is the weight matrix between 0th (i.e. input) layer and 1th (i.e. hidden) layer. Each row of W contains the synaptic weights of the corresponding hidden neuron.

Compressor Control Surge System Methodology

The characteristic curves of the compressor are illustrated through the relationships of parameters, introducing a new analysis and prediction method for compressor operation based on neural networks. This method aims to operate the compressor away from instability condition parameters. Compressor performance capabilities are typically depicted through compressor maps or charts, which elucidate the relationships between the compressor's characteristic variables. These relationships are valid under steady-state conditions. Consequently, certain variables are required to define the fundamental characteristics of the compressor. These variables are selected by factors such as the viewer's perspective, producer preferences, and established traditions. These variables include compressor speed, Inlet Guide Vane (IGV) opening, mass flow rate, pressure rise, and energy efficiency.

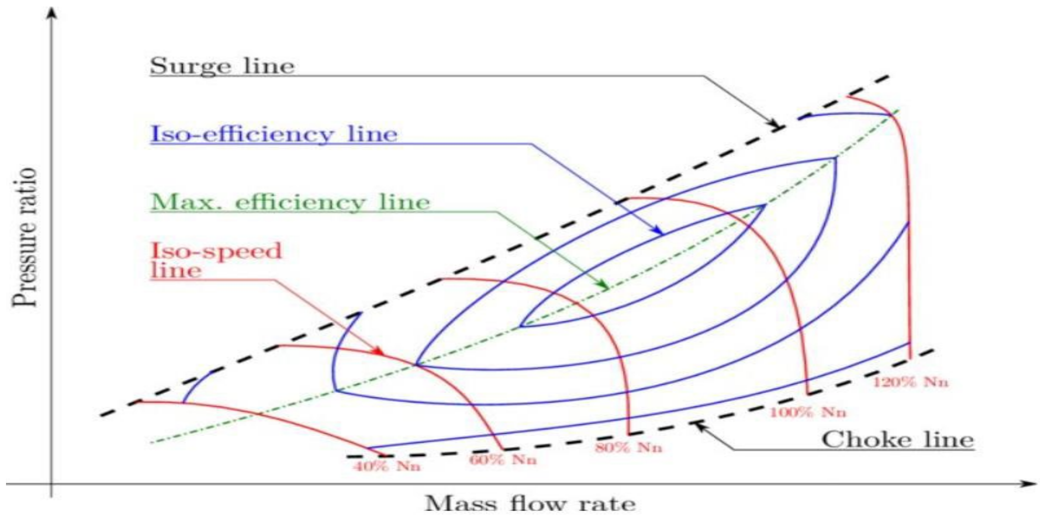

Figure 2: Typical Axial Compressor Map

Figure 2 illustrates the typical operating conditions of an axial compressor considered in our study. This axial compressor operates at a constant speed, with variable Inlet Guide Vane (IGV) opening angles, and demonstrates a relationship between the pressure ratio and mass flow rate.

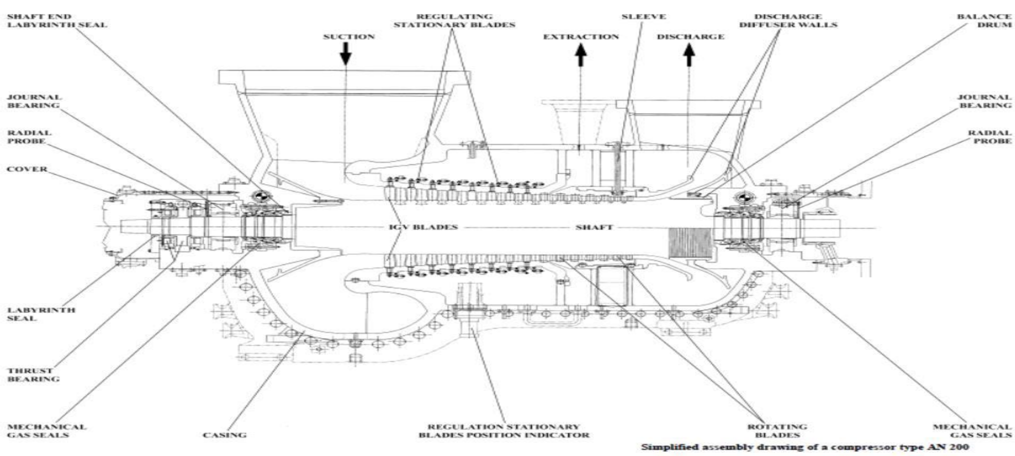

Figure 3: Axial Compressor Map in Our Study

In figure 3 a simplified diagram for the axial compressor (14 stages) in our study methodology to detect instability of compressor operation using the anti-surge application from CCC Company.

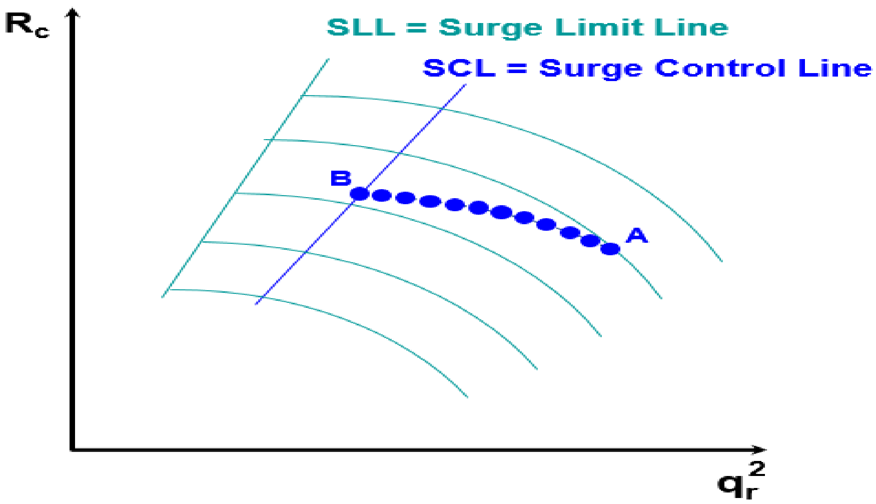

Figure 4: Surge Line Used in Surge Control Application

In figure 4, the application of surge by the Compressor Control Curve (CCC) philosophy is used to measure the distance on the curve. $RRcc$ (compression ratio) and $qq_{rr}{}^2$ (calculated reduced flow through the compressor). This measurement indicates "how far the operating point is to surge," where A and B represent the compressor's operating point parameters. The Surge Control Line (SCL) and Surge Limit Line (SLL) are also depicted. The operating point should not intersect with the SLL to maintain normal work operation.

Surge Measure Application Model

To calculate the distance to surge for the operating parameters, we begin with the compression ratio equation, as outlined in the following equations

$$Rc = \frac{Pd}{\mathrm{Ps}} \qquad (5)$$

Where PP_{PP},PP_{ss} are discharge and suction pressure

$$\mathrm{k} = \ln Rc \;/\; (\ln Rc - \eta\mathrm{p} * \ln(\frac{Td}{Ts})) \qquad (6)$$

In these equations, K represents the compressor design for our study, which equals 0.1 as it was calculated during the design phase. The symbol ηp denotes the polytrophic efficiency, while TT_{ss} and TT_{PP} refer to the suction and discharge temperatures, respectively

$$\sigma = \frac{\mathrm{k}-1}{\mathrm{k}*\eta\mathrm{p}} \qquad (7)$$

Where σ is the exponential factor

$$\mathrm{hp} = \frac{\mathrm{Rc}^{\ \sigma}-1}{\sigma} \qquad (8)$$

Where hp is the reduced polytrophic head

$$Zavg = \frac{Hp*MW}{(hp*\mathrm{Ro}*\mathrm{Ts})} \qquad (9)$$

In these equations, ZZ_{aaaaaa} represents the average compression ratio, HH_{HH} denotes the polytrophic head derived from the compressor map, and Ro stands for the universal gas constant of 8.31441.

$$Zd = 2 * Zavg - Zs \qquad (10)$$

Where ZZ_{PP} is discharge ratio

$$Qd = \frac{Qs*Ps*Td*Zd}{Pd*Ts*Zs} \qquad (11)$$

In these equations, ZZ_{SS} equals 0.994 and represents the suction gas compressibility, which is calculated during the design of the compressor. QQ_{PP} denotes the volumetric gas flow at discharge conditions

$$\rho d = \frac{Pd*MW}{Zd*Ro*Td} \quad (12)$$

In these equations, MW equals 24.836 kg/kmol and represents the gas molecular weight, while ρZZ denotes the gas density at discharge conditions.

$$\Delta Po = (\frac{Qd}{A})^2 * \rho d \quad (13)$$

In these equations, AA equals 149.924 and represents the constant for the flow-measuring device, while Δ$PPPP$ denotes the differential pressure across the flow-measuring device

$$Z = \frac{\alpha - \alpha lower}{\alpha span} \quad (14)$$

In these equations, α represents the Inlet Guide Vane (IGV) position under operating conditions, $\alpha_{llRRllllrr}$denotes the minimum position of the IGV, α span refers to the total range of the IGV angle, and ZZ is calculated from the IGV

$$F(Z) = 7.7396\, Z^5 - 13.8087Z^4 + 8.0402Z^3 - 1.0699Z^2 + 0.1003Z + 0.9991 \quad (15)$$

position Where F(Z) function of for IGV open characteristics with compressor map

$$F_6(hp) = 0.0152hp + 0.0121 \quad (16)$$

Where $FF_6(h_{pp})$ is linearization function for the antisurge control loop of h_{pp}

$$S_s = \frac{K*F(Z)*F_6(hp)*Ps}{\Delta Po} \quad (17)$$

Where SS_{ss} Surge function that is used to measure the distance to surge

$$DEV = 1 - S_s \quad (18)$$

In these equations, $DDDDDD$ represents the proximity to surge, as depicted in Figure 1B.
Then by using $DDDDDD$parameter for three condition statement
If
$DDDDDD < 0$

The compressor is at risk of entering the surge area
$DDDDDD = 0$

The point of maximum compressor efficiency is located on the Surge Control Line (SCL) as depicted in Figure 1B
$DDDDDD > 0$

The Compressor is Operating within a Safe Area, Albeit with Suboptimal Efficiency

Equations 5 to 18 illustrate how to measure the distance from the operating point to the surge limit line on the compressor map, as shown in Figure 1B. The DEV value should be approximately zero for the compressor to operate safely and with high efficiency.

In this study, data was collected under all operating conditions for the system under investigation to train the proposed neural network model. The initial design condition was used to predict offdesign scenarios, and this data was subsequently used to manage the surge issue, thereby ensuring the compressor operates within a safe zone. The model was trained to avoid conditions of instability.

The focus of this work is a 14-stage axial compressor with high flow characteristics, a subject not previously explored in existing research. Most studies have been limited to one or two stages, often relying on assumed operating parameters. In contrast, this study utilized actual operating parameters, collected over a span of five years, with readings taken every second under all modes of operation and across all encountered issues.

The tables below present the operating parameters on the compressor map at various points within the operating envelope.

Case	1	2	3	4	5	6
Point	"D"	'E	'D	'C	'B	"A"
GuideVanes Angle	-35	-30	-20	-10	0	10
Qs ACMH	145,000	159,500	176,000	194,750	219,000	253,000
Ps bara	4.30	4.30	4.30	4.30	4.30	4.30
Ps kPaa	430	430	430	430	430	430
ts °C	-34.20	-34.20	-34.20	-34.20	-34.20	-34.20
Ts K	238.95	238.95	238.95	238.95	238.95	238.95
Zs	0.994	0.994	0.994	0.994	0.994	0.994
Qd ACMH	46,084	44,564	44,003	45,022	47,699	54,641
Pd bara	17.20	20.10	22.90	25.40	27.20	27.80
Pd kPaa	1,720	2,010	2,290	2,540	2,720	2,780
td °C	45.50	54.25	62.50	70.50	75.25	77.75
Td K	318.65	327.40	335.65	343.65	348.40	350.90
Zd*	0.948	0.947	0.942	0.944	0.939	0.945
ρd kg/m^3	17.02	19.36	21.63	23.39	24.83	25.04
W kg/hr	784,140	862,554	951,784	1,053,182	1,184,322	1,368,190
Rc	4.00	4.67	5.33	5.91	6.33	6.47
Hp kJ/kg	124.75	140.75	154.25	166.00	173.25	176.50
Hp kgf*m/kg	12,721	14,352	15,729	16,927	17,666	17,998
ηp	0.850	0.867	0.865	0.863	0.863	0.858
k*	1.214	1.215	1.213	1.214	1.214	1.215
MW	24.836	24.836	24.836	24.836	24.836	24.836
Zavg	0.971	0.971	0.968	0.969	0.967	0.970
σ	0.208	0.204	0.203	0.205	0.204	0.206
ΔPo kPa	1.61	1.71	1.86	2.11	2.51	3.33
ΔPo mbar	16.1	17.1	18.6	21.1	25.1	33.3
ΔPo_calc kPa	4.82	5.83	7.06	8.66	10.90	14.65
X6	1.606	1.813	1.992	2.142	2.241	2.276
f6	0.112	0.136	0.164	0.201	0.253	0.341
X1	-35.0000	-30.0000	-20.0000	-10.0000	0.0000	10.0000
f1	1.0188	1.0308	1.0664	1.1582	1.3335	1.7381
DEV	0.018	0.001	-0.031	-0.045	-0.005	-0.151

Table 1: Calculation Results of Anti-Surge Controller for Maximum Suction Flow Within the OperatingEnvelope

Table 1 displays the calculated values of the Qs suction flow under maximum operating condition values on the compressor envelope. It indicates that point A represents the maximum working condition at the maximum opening of the IGV. Conversely, point D signifies the minimum working condition at the minimum opening of the IGV under the maximum allowable operating condition.

Case	'7	8	9	10	'11	'12
Point	"D"	'E	'D	'C	'B	"A"
GuideVanes Angle	-35	-30	-20	-10	0	10
Qs ACMH	136,000	150,500	165,750	184,000	206,000	239,000
Ps bara	4.30	4.30	4.30	4.30	4.30	4.30
Ps kPaa	430	430	430	430	430	430
ts °C	-34.21	-34.21	-34.21	-34.21	-34.21	-34.21
Ts K	238.94	238.94	238.94	238.94	238.94	238.94
Zs	0.961	0.961	0.961	0.961	0.961	0.961
Qd ACMH	46,930	45,578	45,291	46,839	50,145	56,315
Pd bara	16.80	19.50	22.15	24.50	26.00	26.80
Pd kPaa	1,680	1,950	2,215	2,450	2,600	2,680
td °C	51.25	60.00	69.50	77.75	83.50	86.00
Td K	324.40	333.15	342.65	350.90	356.65	359.15
Zd*	0.954	0.947	0.943	0.949	0.948	0.939
ρd kg/m^3	16.21	18.47	20.47	21.98	22.98	23.74
W kg/hr	760,879	842,003	927,322	1,029,425	1,152,508	1,337,134
Rc	3.91	4.53	5.15	5.70	6.05	6.23
Hp kJ/kg	122.09	136.80	150.29	162.06	168.92	171.62
Hp kgf*m/kg	12,450	13,950	15,325	16,525	17,225	17,500

ηp	0.860	0.873	0.875	0.873	0.867	0.860
k*	1.239	1.238	1.238	1.239	1.239	1.237
MW	24.840	24.840	24.840	24.840	24.840	24.840
Zavg	0.958	0.954	0.952	0.955	0.954	0.950
σ	0.224	0.220	0.220	0.221	0.223	0.223
ΔPo kPa	1.59	1.71	1.87	2.14	2.57	3.35
ΔPo mbar	15.9	17.1	18.7	21.4	25.7	33.5
ΔPo_calc kPa	4.57	5.55	6.71	8.32	10.41	13.89
X6	1.594	1.793	1.974	2.122	2.213	2.259
f6	0.106	0.129	0.156	0.193	0.242	0.323
X1	-35.0000	-30.0000	-20.0000	-10.0000	0.0000	10.0000
f1	0.9758	0.9982	1.0284	1.1299	1.3052	1.6729
DEV	-0.025	-0.032	-0.070	-0.071	-0.027	-0.196

Table 2: Computation Outcomes of Anti-Surge Controller for Lean Case Suction Flow in The OperationalEnvelope

The aforementioned Table 2 presents the calculated values of the Qs suction flow under minimum operating condition values on the compressor envelope. It indicates that point A corresponds to the maximum working condition at the maximum opening of the IGV. On the other hand, point D represents the minimum working condition at the minimum opening of the IGV during lean operation.

Case	**'N2**	**"Defrost L"**	**"Defrost R"**
Point	'surge	'surge	'surge
GuideVanes Angle	-35	-35	-35
Qs ACMH	105,800	106,900	106,700
Ps bara	0.99	1.02	1.02
Ps kPaa	99	102	102
ts °C	24.90	24.90	24.90
Ts K	298.05	298.05	298.05
Zs	1.000	0.998	0.998
Qd ACMH	49,236	70,528	63,567
Pd bara	3.14	1.84	2.08
Pd kPaa	314	184	208
td °C	168.96	81.55	87.77
Td K	442.11	354.70	360.92
Zd*	1.000	1.000	1.000
ρd kg/m^3	2.39	1.02	1.23
W kg/hr	117,792	71,776	78,111
Rc	3.19	1.81	2.04
Hp kJ/kg	125.72	98.31	109.34
Hp kgf*m/kg	12,820	10,025	11,150
ηp	0.840	0.785	0.813
k*	1.400	1.300	1.280
MW	28.010	16.280	17.750
Zavg	1.000	0.999	0.999
σ	0.340	0.294	0.269
ΔPo kPa	0.26	0.23	0.22
ΔPo mbar	2.6	2.3	2.2
ΔPo_calc kPa	0.55	0.34	0.37
X6	1.421	0.646	0.784
f6	0.056	0.034	0.036
X1	-35.0000	-35.0000	-35.0000
f1	0.6035	1.0011	0.8700
DEV	-0.657	0.001	-0.149

Table 3: Anti-Surge Controller Calculations for Nitrogen and Defrost Scenarios

Table 3 presents the outcomes of employing various media across the compressor to examine surge scenarios. This includes using pure Nitrogen, which differs in molecular weight, and the study of the efficacy of using the same gas mixture with different molecular weights and its impact on operational parameters. The objective is to observe the effects on the compressor's operating envelope.

Case	"Tested"	"Tested"	"Tested"	"Tested"
Point	"min surge"	'C	'B	"max surge"
GuideVanes Angle	-35	-10	3	8
Qs ACMH	143,509	188,512	218,397	243,356
Ps bara	4.30	4.30	4.30	4.30
Ps kPaa	430	430	430	430
ts °C	-34.20	-34.20	-34.20	-34.20
Ts K	238.95	238.95	238.95	238.95
Zs	0.994	0.994	0.994	0.994
Qd ACMH	45,181	45,663	48,145	55,927
Pd bara	17.30	23.82	26.52	25.46
Pd kPaa	1,730	2,382	2,652	2,546
td °C	44.41	64.52	70.69	68.88
Td K	317.56	337.67	343.84	342.03
Zd*	0.948	0.944	0.939	0.945
ρd kg/m^3	17.18	22.33	24.53	23.53
W kg/hr	776,077	1,019,447	1,181,061	1,316,036
Rc	4.02	5.54	6.17	5.92
Hp kJ/kg	125.06	158.52	169.69	165.91
Hp kgf*m/kg	12,753	16,164	17,303	16,918
ηp	0.864	0.874	0.882	0.876
k*	1.214	1.214	1.214	1.215
MW	24.836	24.836	24.836	24.836
Zavg	0.971	0.969	0.967	0.970
σ	0.204	0.202	0.200	0.202
ΔPo kPa	1.56	2.07	2.53	3.28
ΔPo mbar	15.6	20.7	25.3	32.8
ΔPo_calc kPa	4.72	8.12	10.84	13.55
X6	1.610	2.045	2.195	2.139
f6	0.110	0.189	0.252	0.315
X1	-35.0000	-10.0000	3.0000	8.0000
f1	0.9941	1.1720	1.3820	1.8155
DEV	-0.006	-0.032	-0.001	0.009

Table 4: Anti-Surge Controller Calculation Outcomes for Real-World Test Scenarios

In Table 4, different Inlet Guide Vane (IGV) angles are presented, which result in changes in the suction flow at certain points. These points serve as test verification points on the compressor operating envelope.

Proposed Method - Computer Results and Simulations

Neural Networks (NNs) are machine learning algorithms modeled after the structure and function of the human brain. They consist of interconnected nodes or neurons that process information through an activation function. NNs are commonly used for prediction, classification, and control tasks in various applications, including process control and modeling of physical systems. One of the advantages of using neural networks is their ability to learn from large amounts of data, which allows them to model complex relationships and patterns in data. Additionally, NNs can handle nonlinear and uncertain relationships between inputs and outputs, making them suitable for modeling complex physical systems.

Furthermore, NNs can generalize well to new data, even if the training data does not represent all possible inputs, making them robust in real-world applications. However, there are also some limitations of NNs. One of the main challenges is the need for large amounts of data to train the model and the difficulty of obtaining such data in some applications.

Furthermore, NNs can be sensitive to data quality, and small errors in the data can result in significant errors in the prediction. Additionally, NNs can be computationally expensive to train, especially for large models with many neurons.

Concerning applying NNs to the modeling and predicting surges in axial compressors, NNs effectively capture the complex relationships between the operating parameters and the likelihood of surge [38,39]. Additionally, NNs can handle the large amounts of data generated by the compressor and use this data to develop accurate models of surge behavior. However, it is important to validate the models using real-world data and ensure that they generalize well to new operating conditions. Overall, NNs offer a promising approach for modeling and predicting surges in axial compressors. Further research is needed to develop NNs models that are both accurate and robust in real-world applications.

The compressor is critical in various industrial technologies that directly impact our daily lives. It is a mechanical system used to increase the pressure of a compressible fluid, with suction pressure ranging from deep vacuum to high values and discharge pressure ranging from less than atmospheric to several hundred bars. The fluid can be any compressible gas, vapor, or mixture of gases, and the compressor configuration must match its intended application.

Compressors are widely used in power generation, gas production, gas transfer and transportation, and aircraft. It is imperative to study the operation of compressors and analyze any issues that may affect their operation, availability, performance, and lifespan. The key performance indicators are operability, availability, safety, and output specifications. One widely used compressor is the Axial compressor, used in electrical power generation, gas compression operations, and aircraft. Given the significance of the Axial compressor and the lack of data available about its operation, it is essential to study its off-design parameters by using design parameters to understand its operating envelope and performance in various scenarios.

Our research is grounded in an authentic dataset encompassing various compressor operating modes, ranging from no load to medium load and extending to high load. We have examined the impact of surge on the functioning of the compressor, based on five years of actual readings under diverse operating conditions, with a particular emphasis on surge-related actions. This extensive use of real-world data sets us apart from most researchers, who typically rely on theoretical framework datasets and researcher assumptions rather than actual data.

Our study focuses on an Axial compressor used to compress MR gas, a mixture of Methane, Ethane, Propane, and Nitrogen. The study used the design conditions of pressure ratio, inlet flow rate, and IGV opening at a constant speed. The compressor map in the design condition is shown in Fig. 5. The IGV opening readings range from -35 degrees to +10 degrees, with reference points A=10 degrees, B=0 degrees, C=-10 degrees, D=-20 degrees, E=-30 degrees, and F=-35 degrees. The corrected speed was set at 3636 RPM, and the molecular weight of MR gas was 24.836 kg/kmol.

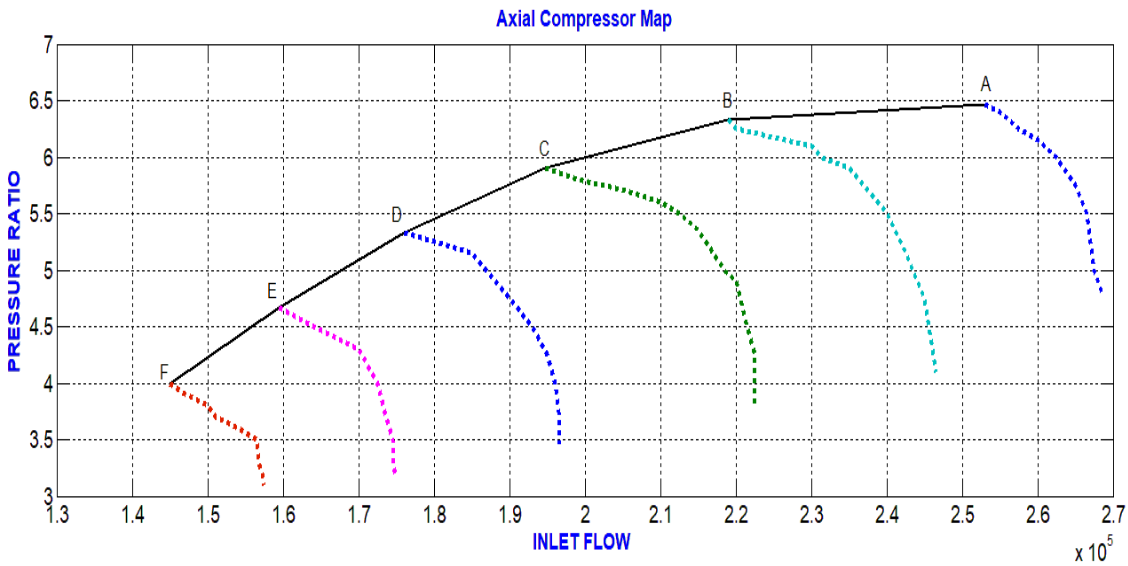

Figure 5: Compressor Map in Design Condition

The characteristic compressor map was predicted using a Back Propagation neural network, implemented using the Levenberg-Marquardt methodology in MATLAB's artificial neural network Toolbox. The network's inputs were the IGV angle opening and pressure ratio, with the output being the corrected mass flow. The network was trained using the design data of the compressor, and the results were used to predict the compressor map in off-design conditions. Fig. 6 Using these data through the learning of the Back Propagation neural network to predict the amount of the output corrected mass flow rate from the compressor in the area is different than the design conditions at a different opening IGV angle as following point H =5 deg., I= -5, J= 15 deg., K= -25 deg., L = -27.5 deg.

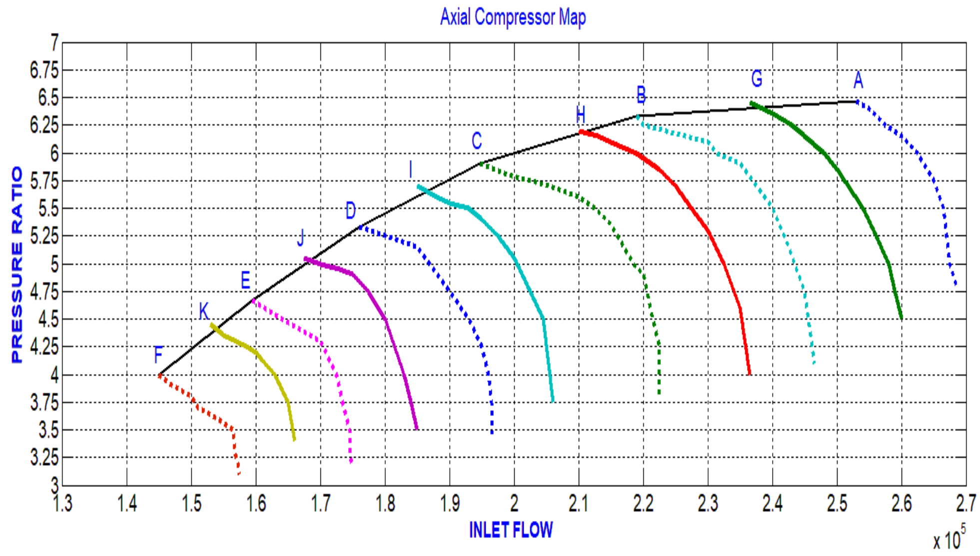

Figure 6: Predicted Data Using A Neural Network

The neural network outputs were compared to real working data to verify the accuracy of the results, as shown in Fig. 4. The network error was found to have a regression factor of 0.92667 and an MSE of 3.04465 x 10^-3.

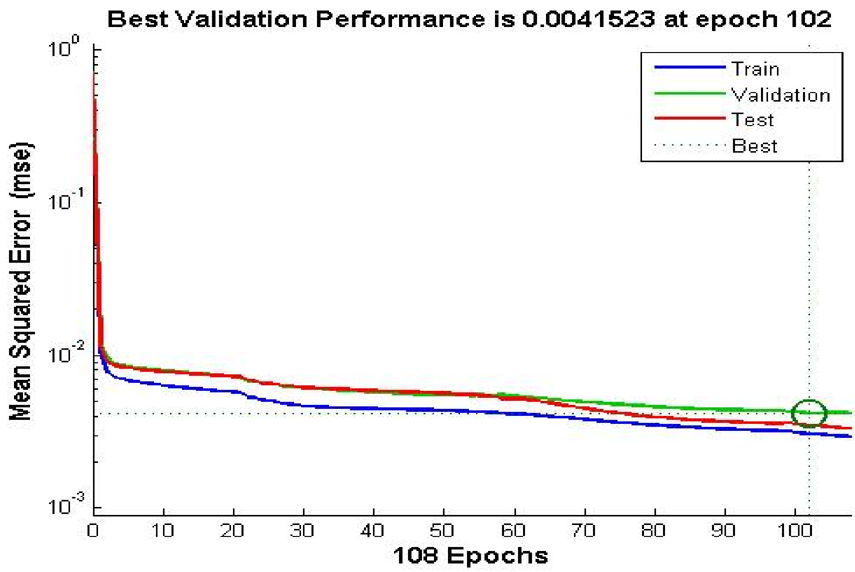

Figure 7: Network Error

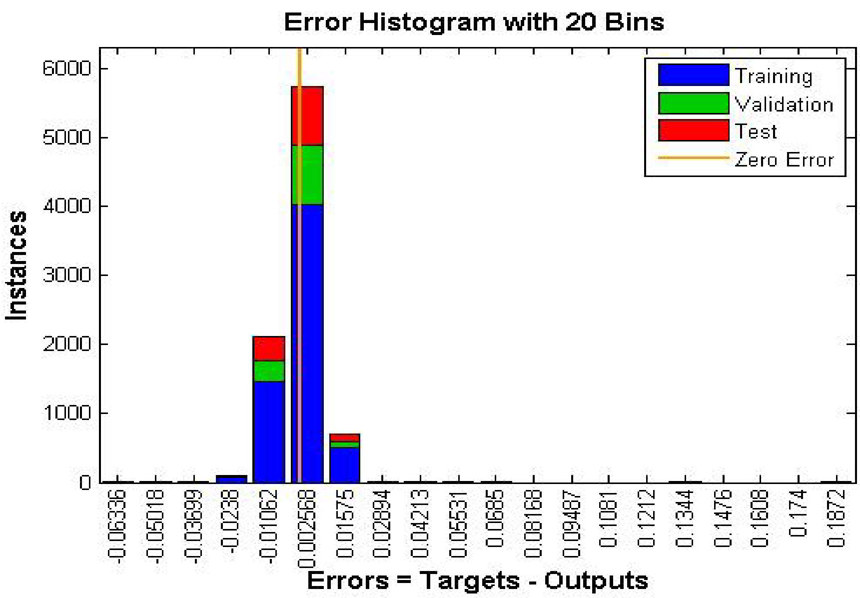

Figure 8: Error Shown Training Data Neural Network of Axial Compressor

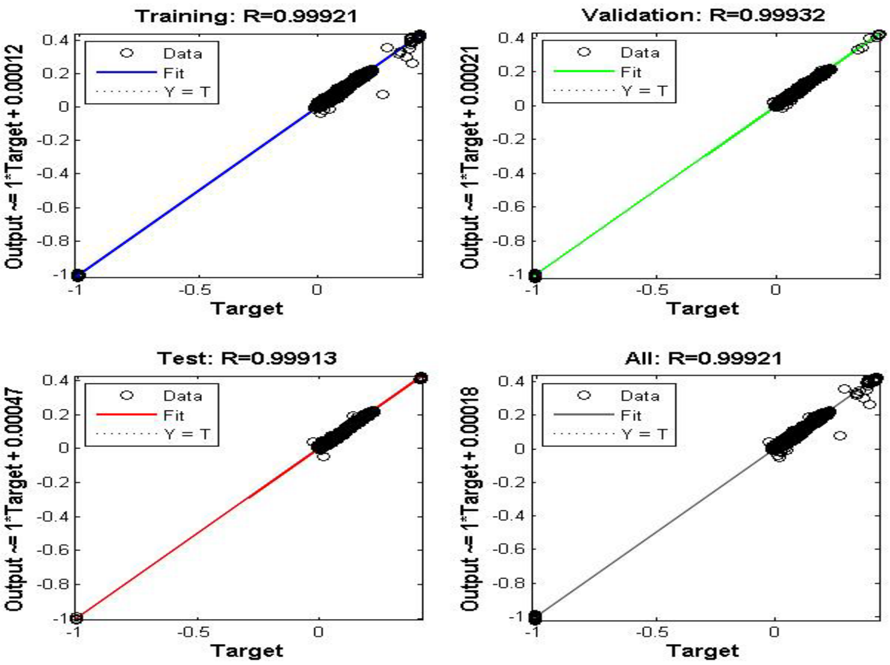

Figure 9: Axial Compressor Neural Network Model Regression Trend Between In/Out

Upon examining Figures 7,8 and 9, it becomes evident that the error range is situated between 0.0238 and 0.0157. This signifies that the surge occurrence within the axial compressor has been successfully managed and controlled with a remarkably small margin of error. The results presented in these figures provide strong evidence that our developed neural network model is highly accurate and efficient in controlling surge events during the operation of the axial compressor. This high level of precision is critical in maintaining the stability of the compressor and ensuring its safe operation under various conditions, thereby demonstrating the effectiveness and reliability of the neural network model in managing surge-related challenges.

Problem Limitation and Future Work

The research paper presents a novel approach for predicting the surge phenomenon in axial compressors using a neural network model based on the design data of the compressor. The proposed model is trained to forecast the behavior of the compressor's working map under different operating conditions, including the Inlet Guided Van (IGV) opening angle, which is often ignored or assumed to be fixed in previous studies. The model's performance is verified using real-time data collected during compressor operation over five years. The results show that the proposed approach effectively predicts the onset of surge and provides valuable insights into compressor behavior, enabling real-time surge prediction and control. The paper also highlights the research's contributions in improving compressor performance and stability through adjustments based on real-time maps. The related work in the field has proposed ANN-based, model-based, and datadriven methods for predicting surges, but these methods have limitations such as limited generalizability, detailed models, and large amounts of data requirement.

The limitation of the proposed approach for predicting a surge in axial compressors is that it is based on design data and real data collected over five years, representing all compressor configurations and operating conditions. The model may not generalize well to other compressor configurations and be accurate for predicting surges under extreme conditions. Additionally, the approach requires a significant amount of data for training, which may not always be available to other researchers.

The future work on the proposed data-driven neural network model for axial compressor surge prediction and control aims to improve its accuracy and robustness further. This can be achieved through additional testing and validation on other axial compressor configurations, incorporating operating conditions and environmental variables into the model, and integrating the model with control systems for real-time surge control. The model's ability to handle high-dimensional and complex datasets can also be improved by exploring deep-learning approaches. In terms of future direction, the model can be applied to other types of compressors and expand its application to other industrial domains. An online learning system can be developed to adapt to changes in the compressor's operating conditions andenvironment over time. The impact of uncertainties and perturbations on the model's predictions can also be investigated and addressed. Additionally, advanced machine learning techniques such as reinforcement learning can be explored to improve further the model's ability to control surge. Ultimately, this research can potentially benefit the industry significantly through improved compressor performance, stability, reduced downtime, and decreased maintenance costs.

Conclusion

In conclusion, this paper presents a new multistage axial-compressor characteristic maps analysis. A multilayer backpropagation artificial neural network was employed to establish a relationship between axial compressors' input and output patterns. The training data used for the neural network was the manufacturing data collected during the engineering phase. The analysis results demonstrate that the neural network model can accurately predict off-design parameters based on design data. The findings of this study showed that the error between the predicted and actual data collected during different compressor modes was small, with a regression factor of 0.92667 and a mean squared error of 3.04465 x 10^-3, as demonstrated by Figures 1,2, and 3. The results of this study indicate that the neural network can effectively control the operation of the axial compressor, reducing the likelihood of surge and instability issues.

Furthermore, using a neural network control system offers significant benefits, including improved performance and reduced power consumption compared to traditional control cards. Based on theseresults, future work is suggested to refine further and optimize the neural network control system for axial compressors. This could include exploring the use of other machine learning techniques, such as deep learning, to improve performance, as well as exploring the potential applications of this approach in other areas of fluid dynamics.

Additionally, further studies could be conducted to validate the neural network's performance under a wider range of operating conditions and assess its robustness in the face of unpredictable changes in working conditions [40-43].

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