Research on the lean and swept optimization of a single stage axial compressor

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ABSTRACT
Compressor design is always a prevalent research issue as nowadays the compressor demands higher performance. Designing a new compressor of higher aerodynamic performance will cost a tremendous amount of time and expense. Consequently, the wiser method of acquiring a higher performance compressor is to optimize a current compressor, discussed in this paper. First, a detailed numerical simulation of a compressor is done. A parametric rotor model is created and the variations of lean and swept parameters are limited. Then, an optimization calculation is carried out based on the combination of an artificial neural network and a genetic algorithm. The optimization iteration is started at three specified working points – a choke point, a design point and a near stall point – to acquire a comprehensive improved solution. A novel penalty function considering both pressure ratio and efficiency is constructed to find the optimal model. Finally, a detailed review is made of the original and the optimized compressor. The computational results show that the isentropic efficiency is successfully increased and the stall margin is remarkably improved. Ultimately, a detailed vortex structure analysis with increasing outlet pressure is discussed. This helps the performance increment mechanism to be understood further.

Penalty function
\[ = W_1 \cdot \left( \frac{\eta_{\text{imp}} - \eta_{\text{ref}}}{\eta_{\text{ref}}} \right)^2 + W_2 \cdot \left( \frac{\pi_{\text{imp}} - \pi_{\text{ref}}}{\pi_{\text{ref}}} \right)^2 \]

Corrected massflow
\[ \dot{m}/\dot{m}_{\text{choke,EXP}} \]

Pressure ratio
\[ P_{\text{total,outlet}}/P_{\text{total,inlet}} \]

Isentropic efficiency
\[ \left( P_{\text{total,outlet}}/P_{\text{total,inlet}} \right)^{(k-1)/k} - 1 \right) / \left( T_{\text{total,outlet}}/T_{\text{total,inlet}} - 1 \right) \]

Pressure coefficient
\[ 2(P - P_{\text{inlet}})/(P_{\text{inlet}} V_{\text{inlet}}^2) \]

Introduction
As one of the three major components of a gas turbine, the compressor has always been in a core position in investigations. Several decades of research has shown that the geometry of the compressor blades plays a key role in the overall performance of a compressor. With the development of computational fluid dynamics (CFD) and modern optimization techniques, blade optimization design has become one of the main ways of improving the aerodynamic performance of compressors (Y. Chen et al., 2019). Because most blades are constructed by a stacking...
law – a law of stacking 2D blade sections at different radial heights – so the lean and swept blade parameters are usually selected as modification factors. The terms ‘lean’ and ‘swept’ have been defined a little differently in some of the literature. Smith and Yeh (1963) defined ‘sweep’ with respect to the oncoming air direction. In this paper, ‘lean’ and ‘swept’ are defined related to the blade stacking law in the axial and tangential directions as shown in Figure 1.

Many researchers have done much work on the effects of lean and swept.

Song et al. (2004) focused on curved rotors that have a different curve type in the lean direction. Their simulation results showed that the passage shock in a negatively curved rotor moves downstream at the tip, which improves the stall margin of the compressor, while it moves upstream near the midspan, increasing the energy loss there. Consequently, the stage efficiency decreases. Conversely, a positively curved rotor improves the efficiency but decreases the stall margin. Yang et al. (2004) identified the fact that a curved stator in a steam turbine has weak control of secondary flow. In addition, due to the stator being curved, the flow angle is not adaptable to the next rotor in the radial direction, and a separation flow takes place on the rotor suction side. This provides a point where stage matching should be considered during the modification.

Wadia et al. (1998) reported on the experimental and analytical assessment of the pay-off derived from both aft and forward sweep technology with respect to aerodynamic performance and stability. A three-dimensional viscous analysis was used. The reduced shock and boundary layer interaction, resulting from reduced axial flow diffusion and less accumulation of centrifugal blade surface boundary layer at the tip, was identified as the prime contributor to the enhanced performance with forward sweep. Xie et al. (2006) simulated a leading edge skewed–swept blade on a meridian acceleration fan and found that the low energy liquid in the end wall region is involved in the main flow of the blade’s midspan, weakening the low energy liquid aggregation at the end wall and decreasing flow loss and blockage. In Halder and Samad (2016), an unswept and a backward-swept blade were compared. The simulation results showed that, at a higher flow coefficient, the backward-swept blade showed a higher pressure on the suction side, so delaying separation, which strongly affected the stall margin, while reducing peak efficiency. Jang et al. (2005) investigated the optimization of a swept rotor and utilized the response surface method (RSM) to redesign the swept rotor by means of two blade variables. The optimal geometry was a backward-swept rotor. The limiting streamline indicated that the increment of efficiency was caused by moving the separation line downstream on the blade suction surface. N.X. Chen et al. (2010) also did some research on swept rotors. They divided a swept rotors into those with a straight leading edge and those with an arbitrarily curved leading edge. Their results showed that a straight leading edge sweep has a small effect on the efficiency because the shock wave pattern is already well constructed and controlled in the reference blade. The method of tilting the whole blade changed the radius of the tip – the rotation speed decreased in the case of a backward sweep causing degradation of the performance, while a curved leading edge could improve the shock system near the tip.

The hydrodynamics of swept blades were simulated and tested in an article by Tao et al. (2013). Positive-sweep, negative-sweep and straight-blade pumps were studied in CFD simulations using large eddy simulation. They concluded that the main reason for instability was a vortex moving from hub to shroud driven by rotating centrifugal force and gathering in the tip region. An oppositely swept blade would give an extra force to maintain the vortex within the midspan, so improving the operating stability.

An original understanding of swept blades was obtained by Ji et al. (2005), i.e. that sweep is only a degree of freedom in compressor design. It affects a compressor’s stall margin by matching the aerodynamic loading of all elements along the span over the whole operational range. The different spans are regarded as tiny radial height compressors, each with its own performance map. The sweep improves the performance just by combining the adaptable tiny compressors at different radial heights.

Benini and Biollo (2007) made a detailed and large systematic investigation of the aerodynamic behavior of swept and lean blades in a transonic compressor. The rotor was been changed between leaned and swept, respectively. The results showed that a backward sweep has a slightly better performance compared with forward-swept rotors, and a forward lean can increase the efficiency substantially. The loss of shock decreases mainly due to the shock structure being delayed downstream both in backward-swept and forward-lean rotors.
All above papers mainly studied blade modifications in the lean or the swept directions separately. The results only show a single variable relation with aerodynamic performance. In the paper by Benini and Biollo (2007), further improvements in the overall efficiency could be expected from the simultaneous use of sweep and lean. The following articles focused on both the lean and swept modifications.

Seo et al. (2008) optimized a fan blade with respect to both lean and sweep. Four geometric variables concerning the spanwise distributions of the lean and sweep of the blade stacking line were chosen to find the maximum efficiency, adopting the response surface method. They found that the efficiency was remarkably improved by the lean blade smoothing out the massflow in the spanwise direction and suppressing the vortex leakage effectively. Similar work was done by Mao, Song, and Wang (2008), beyond which the 2D design in the mid-span was done to offset the performance decrease in the mid-span caused by lean and swept blades. Asgarshamisi et al. (2015) conducted a multi-point optimization of lean and swept angles for rotor and stator of an axial turbine. The optimization coupled a CFD simulation code and a genetic algorithm. Consequently, it successfully improves the turbine stage total-to-total efficiency 1.31 and 1.17% in its design and off-design speeds, respectively. Asgarshamisi concluded that leaned and swept blades have a lower pressure loading near the hub and tip, which produces a reduction in secondary flow. Razavi et al. (2014) investigated the swept and lean blade effect on the performance separately. With different forms of swept and leaned blade simulated, it was found that a both leaned and swept rotor67 can be improved in efficiency, pressure ratio and operating range. But the result showed that the sweep provides a major positive effect on the operating range and the lean improves the efficiency and pressure ratio much more. Neipp and Riedelbauch (2016) focused on the secondary flow of various leaned and swept blade in a hydraulic turbine. They concluded that the interactions of secondary flows are of decisive importance for turbine performance. By comparing the different blade designs it becomes clear that the positive compound lean of the optimized rotor blades leads to an efficiency increase owing to a change in shape and intensity of the horseshoe vortices at the leading edge.

Much work has been done, but most research only pays attention to one blade without considering rotor–stator matching, and the effect of lean and swept is optimized, respectively. In this article, a single stage axial compressor, Stage35, was simulated, and the rotor was fitted as a parametric model constructed by control points and curves. The rotor was optimized through a design system consisting of a combination of an artificial neural network and genetic algorithm optimization by changing the amounts of lean and sweep under three specified working conditions. The lean and sweep were changed together in every step. As a consequence, the optimization process is able to find the optimal design with compound lean and sweep. In addition, the parametrically redesigned rotor will be replaced in the stage. In that way, the stator’s response can transport back to the rotor simultaneously. It’s an effective method to avoid a mismatch in the optimization. A penalty function is constructed to find the most adaptable blade considering the pressure ratio and efficiency. A detailed analysis of the original and the optimized compressor is made in order to work out how the leaned and swept blade modification improves the compressor’s aerodynamic performance. The vortex structure is analysed in detail to find the mechanism of optimization. It turns out that the compressor flow field is improved in both peak efficiency massflow and near-stall massflow in different ways.

**Case description**

NASA Stage 35 is one of a series of single stages that were designed and tested to investigate the performance characteristics of low-aspect-ratio blading for the inlet stages of an advanced-core compressor. It was designed by the National Aeronautics and Space Administration Lewis Research Center in 1978 (Reid & Moore, 1980). The design parameters are shown in Table 1 and the full channel model is illustrated in Figure 2.

**Mesh and CFD verification**

The quality of mesh will affect the accuracy of numerical calculations and the quantity of the mesh will affect the optimization convergence time. Consequently, a balance
Table 1. Parameters of Stage35.

| Parameters                | Value     |
|---------------------------|-----------|
| Design rotation speed (r·min⁻¹) | 17,188    |
| Tip speed (m·s⁻¹)          | 454.456   |
| Rotor aspect ratio         | 1.19      |
| Stator aspect ratio        | 1.26      |
| Rotor number               | 36        |
| Stator number              | 46        |
| Hub-shroud ratio           | 0.70      |
| Tip clearance (mm)         | 0.408     |

The single periodic compressor channel is defined in O4H topology, the O-block runs around the blades and the H-block is used in the inlet, outlet and up and down the blade section. The butterfly mesh topology is selected in the blade tip. The $y^+$ distribution is a significant criterion for the grid, which is less than 2.5 for most of the blade surface. As regards Lan (2015), when cells number is specified as 1.45 million, it can predict the flow phenomenon inside the boundary layers precisely. Figure 3 shows the mesh distribution of the blade surface as well as the tip, and how the mesh is clustered near the leading and trailing edges. There are 25 nodes along the leading and trailing edges, and the control length of the edge is only 50% of blade’s maximum thickness.

CFD simulation is conducted with Numeca’s FINE™/Turbo commercial code, which is a state-of-the-art 3D multi-block flow solver able to simulate Navier–Stokes flows. From Zhang (2016), the results show that the Spalart–Allmaras turbulence model is good at calculating conditions from stall to choke as well as the non-reflecting 2D rotor–stator interface, guaranteeing the accuracy of prediction. The boundary conditions are specified as shown in Figure 4. A total pressure of 101,325 Pa, total temperature of 288.15 K and axial flow direction are specified at the inlet, while the average static pressure is given at the outlet. The blade and endwall surface are given a solid adiabatic non-slip. The simulation is carried out at the design rotation speed, as shown in Table 1. The convergence criteria are satisfied with a global residual drop off five orders of magnitude, and the import and export flow error can be less than 0.5%.

In order to investigate the accuracy of the simulation results, this study compares the overall performance of the compressor with the existing experimental value at 17,188 r/min. The experimental data are derived from the single-stage transonic compressor test rig of the Lewis Research Center. The test bed uses a pneumatic probe and laser gun on the transonic compressor for a detailed measurement. The massflow is non-dimensionalized as shown in Figure 5, the experimental values are compared with the results obtained by CFD, and the aerodynamic data calculated from CFD is averaged en-masse. This manifests that the CFD and experimental results have a good consistency. The massflow of the choke point obtained by simulation is less than the experimental value, while the stall point is basically the same. The variation tendency of the isentropic efficiency agrees well with the experiments, and the pressure ratio line is overlapped except near choke massflow. The most probable reason for the CFD not predicting the choke massflow correctly is the neglect of the cavity in the rotor hub; in addition, the turbulence model, the grid quality
Figure 4. Boundary condition setting.

Figure 5. Comparison of CFD and experimental results: efficiency and pressure ratio versus corrected massflow.

and the boundary conditions might affect the results as well (Ez Abadi et al., 2020). Nevertheless, from Li et al. (2017), the numerical calculation results are good enough to accomplish the prediction and optimization pre-step.

Methodology

Fitting process

The optimization system consists of three main modules, as shown in Figure 6. The fitting process aims at creating a parametric model that can change the original blade quantitatively. A database is generated of training samples for teaching an artificial neural network (ANN). The CFD and optimization loop are carried out to search for an optimum model.

In this article, the geometry is fitted through Numeca’s Autoblade software, which allows the designer to create a parametric blade model close to a given custom geometry defined by point coordinates. There are two types of classic curve, as shown in Figure 7, i.e. Bezier and B-spline, which are used to define the different curves in the geometry (NUMECA International, 2006). The B-spline curve has to pass through all prescribed points, but is less smooth than Bezier. All the constructions in the compressor are fitted to the two curves and Table 2 shows the details of parametric curves with different numbers of control points.

Figure 8 (left) shows that the rotor is divided into 12 blade sections in the radial direction. The center of gravity is computed as the geometrical center of the blade section, which is defined as the stacking point. The curve passing through 12 stacking points is defined as the stacking line. The swept and leaned are defined in the meridional plane and the tangential plane, respectively. The coordinates of the swept law are (Z, R) and of the lean

Table 2. Fitted curve parameters.

| Target geometry                        | Parametric curve | Number of control points |
|----------------------------------------|------------------|--------------------------|
| Hub                                    | B-spline         | 20                       |
| Shroud                                 | B-spline         | 20                       |
| Stacking line in tangential            | Bezier           | 6                        |
| Stacking line in axial                 | Bezier           | 6                        |
| Camber curve                           | B-spline         | 7                        |
| 2D blade profile                       | Bezier           | 15                       |
Figure 6. Workflow chart

Figure 7. Bezier and B-spline curves.

Figure 8. The distribution of the blade section (left), axial law (mid) and suction side definition (right).

The two independent stacking laws represent the position of the blade section in the axial and tangential directions. Figure 8 (mid) shows that the swept curve is better fitted as a Bezier curve with six control points, called \textit{Sweep}_H_j. In addition, this distribution is stretched along the span, where the geometric ratio is 1.05. The lean law is defined in the same way as the sweep law and the control points are called \textit{Lean}_H_j. Figure 8 (right) shows that the suction sides are defined by a Bezier curve with 15 control points and a geometric ratio of 1.05. The control points on suction side are based on the camber curve.

The fitting process utilizes a genetic algorithm to estimate the error between the current model and the target one. In order to obtain a better parametric model, a twice fitting process has been conducted. After fitting, the structure and the construction point of the blade are reset. Consequently, with a large number of parametric
control points, a parametric model can be obtained close enough to the target.

Figure 9 depicts the 2D blade profile of the target and fitted models at 10, 50 and 90% blade span. Next, the parametric model is calculated and compared with the original given the same static pressure outlet. Table 3 demonstrates that the aerodynamics between the fitted blade and the original model is very close. In general, the parametric model is similar enough to conduct the optimization calculation.

Table 3. Aerodynamic performance error between the original and the parametric.

|                         | Original | Parametric | Error (%) |
|-------------------------|----------|------------|-----------|
| Massflow (kg s⁻¹)       | 20.76    | 20.78      | 0.096     |
| Pressure ratio          | 1.8476   | 1.8484     | 0.043     |
| Isentropic efficiency   | 84.45%   | 84.57%     | 0.142     |

Artificial neural networks

In 1943, Warren presented a calculus model basing on a neural network that brings the neural network into the artificial intelligence field (McCulloch & Pitts, 1990). The artificial neural network model is based on the basic principles of neural networks in biology. An artificial neural network is similar to the human brain in the way that it processes information, which consists of learning, recognition, memory and so on (Cho et al., 2012). Artificial neural networks have been widely used in optimization design in recent years because of their strongly nonlinear model approximation ability. An artificial neural network topology is illustrated in Figure 10. A network usually contains several layers: an input layer, one or several hidden-layers and one output layer. Each output has its own artificial neural network to avoid interaction during training. The input vectors are linked to the nodes in layer 1 by a matrix weight. The summation of the weighted inputs will be a scalar output, and are converted by a sigmoidal function \( F_l \). The signal is propagated in the same way through the next layer until the signal reaches the output layer (Sha & Yue, 2014).

Pairs of input/output vectors are necessary in a training database so that the network will learn to predict. In addition, there is no need to train all the pairs of input/output. The ANN will try to predict the results even though it has never seen them, so representative samples are provided to save learning time.

In this article, an ANN model is used to find the approximate function, and then the function is optimized by a genetic algorithm. In this case, there are two layers in the ANN architecture, 13 nodes in layer-1 and 7 nodes in layer-2. The initial optimal solution is then re-calculated in CFD. Then the new results are added to the database.
in order to generate a more accurate approximation function. Repeating the intelligent search process, the optimal solution can be obtained. As shown in Figure 11, the ANN and the numerical optimization algorithm are combined to calculate the excellent solution. This procedure is effective in shortening the optimization period and improving the optimization efficiency.

**Optimize settings**

In this study, there are 12 free parameters SWEEP\_H\_1\_6, LEAN\_H\_1\_6 for controlling the blade stack law in the meridional and tangential directions. Therefore, the database samples are a set of 36, equaling three times the number of free parameters. The free parameters range is redefined from lower to upper bound considering industrial processing; consequently, the blade geometry won’t be changed irrationally. Table 4 shows each parameter bound. The value can only vary in a small range. During the database generation and optimization, the parameters can be changed automatically within limits. Moreover, in order to acquire a good performance of the compressor, each sample is calculated under three working condition: choke point, design point and near-stall point. In summary, 108 cases of CFD calculation are completed.

Next, the database samples are imported to an ANN learning system and the optimization objective function is specified as the isentropic efficiency and total pressure ratio under the three working conditions. The isentropic efficiency is expected to be 1.0 and the total pressure ratio is 2.0.

The optimization design iterations have 30 steps. The genetic algorithm drives the cases evolution in order to reach the best possible solution. As shown in Figure 12, the blue points assemble to be the Pareto front surface as the iteration proceeds.

**Analysis of the optimization results**

During the process of optimization, the stacking parameters of the blade geometry have been changed observably. There are 29 (one crashed at the stall condition) valid optimized results after 30 iteration steps. The penalty function is constructed as follows:

\[
\text{penalty function} = W_1 \cdot \left(\frac{\eta_{\text{imp}} - \eta_i}{\eta_{\text{ref}}}\right)^2 + W_2 \cdot \left(\frac{\pi_{\text{imp}} - \pi_i}{\pi_{\text{ref}}}\right)^2.
\]

**Table 4. Parameter bound settings.**

| Name         | Lower bound | Value | Upper bound |
|--------------|-------------|-------|-------------|
| SWEEP\_H\_1 | -0.0111     | 0.0000| 0.0109      |
| SWEEP\_H\_2 | -0.0107     | 0.0003| 0.0113      |
| SWEEP\_H\_3 | -0.0138     | -0.0022| 0.0088    |
| SWEEP\_H\_4 | -0.0033     | 0.0077| 0.0187      |
| SWEEP\_H\_5 | -0.0241     | -0.0131| -0.0021   |
| SWEEP\_H\_6 | -0.0004     | 0.0106| 0.0216      |
| LEAN\_H\_1  | -0.0161     | 0.0009| 0.0179      |
| LEAN\_H\_2  | -0.0151     | 0.0019| 0.0189      |
| LEAN\_H\_3  | -0.0178     | -0.0008| 0.0162    |
| LEAN\_H\_4  | -0.0081     | 0.0089| 0.0259      |
| LEAN\_H\_5  | -0.0228     | -0.0058| 0.0112    |
| LEAN\_H\_6  | -0.0072     | 0.0098| 0.0268      |

**Figure 11.** Approximate model philosophy.

**Figure 12.** Optimizer population distribution with different iterated steps.
Figure 13. Penalty function of optimized results.

(a) Lean and swept law

(b) Overlapped compare

Figure 14. Comparison of original and optimized rotor.
The penalty function measures both the efficiency and the pressure ratio, and the weights $W_1$ and $W_2$ are prescribed by the designers. In this case, $W_1 = W_2 = 1$. It’s easy to draw the conclusion that the lower are the penalties, the better is the performance. As shown in Figure 13, cases near the bottom left perform with lower penalties and the four cases circled by triangles are selected as the potential candidates. Although cases 3, 13 and 15 show a slightly better penalty function value, only in case 16 is the massflow not decreased. As a consequence, case 16 is selected as the final optimization result by comprehensive consideration.

Figure 14 shows the difference between the original and the optimized blade in the stacking laws, overlapped coordinates and blade section views. The optimized blade and original blade appear as distinguishable distorted

**Figure 15.** Comparison of original and optimized results: efficiency and pressure ratio versus corrected massflow.

**Figure 16.** Limit streamline in the suction side at the peak efficiency point.
shapes. According to Figure 14, the optimized blade is modified to be forward swept along the radial direction, especially from the midspan to the tip, and modifications of the forward sweep are also performed in the bottom half but to a lesser degree. The characteristic lean in the tangential direction is also changed differently in the two parts of blade sections. The optimized blade performs a negative lean from hub to midspan, and a positive lean from the midspan to the tip. A detailed numerical simulation with an optimized rotor is carried out to find the optimization mechanism of the leaned and swept modifications.

As Figure 15 depicts, the isentropic efficiency of the optimized compressor has been improved with respect to the overall corrected massflow, especially in the vicinity of the choke condition. The peak efficiency is raised from 84.45 to 85.01%, and in the vicinity of the stall condition the efficiency is raised from 73.56 to 73.85%. In addition, the working massflow range is enlarged remarkably. In the optimized performance curve, the choke point has moved toward the right and the stall point has moved towards to the left. The red line depicts the optimized flow range and the blue line represents the original range. It turns out that the massflow range augmentation occurs mainly near the stall conditions. The stall margin is defined as the distance between the stall line and the operating point on a vertical line for a constant corrected...
massflow value. In this case, the stall margin is improved from 16.11 to 20.07%. The efficiency and massflow range are improved at the cost of a small partial reduction in pressure ratio. In fact the pressure ratio is still keeping to almost the same level, while the stall margin is very much raised.

In order to understand the mechanism of the increase in the isentropic efficiency and the massflow range, the

**Figure 19.** Pressure coefficient at peak efficiency point from different blade spans: 0.75 (left) and 0.95 (right).

**Figure 20.** Mach contour at peak efficiency from 0.75 of the blade span.
flow field inside the compressor is analysed under different working conditions.

**Peak efficiency work condition**

The peak efficiency point is selected for analysing the mechanism of the increase of isentropic efficiency. From Figure 16, the limit streamline in each model is basically the same – there is a separation line caused by a shock wave on the suction side. The flow near the top is more influenced in the original blade because there is a tiny vortex at the top. A large version of the tip local vectors distribution is shown below. The low energy fluid gathers at the tip and mixes with the main flow. From Figure 17, the massflow distribution along the radial direction is improved a little from blade span 0.5 to 0.85 as well as the efficiency as shown in Figure 18. Moreover, the increase in efficiency from the stator outlet is more obvious and to a larger extent. This suggests that the modifications mainly change the flow structure in the upper half blade and this positive impact is able to transmit to the stator passage.

As shown in Figure 19, the pressure coefficient is improved on both sides. The abrupt pressure rise represents the position of a shock wave, and the shock wave is

![Figure 21. Entropy contour at peak efficiency point from the rotor outlet.](image1)

![Figure 22. Entropy distribution along the theta direction.](image2)

![Figure 23. Efficiency along the blade span of different outlet pressures: original (left) and optimized (right).](image3)
delayed toward the trailing edge in the optimized blade. This indicates that the separation zone along the suction side would be decreased. In the other hand, the less fluctuanted pressure along the pressure side in the optimized blade evidences that the intensity of the shock is weakened. There is a second fluctuate along the pressure side curve. It’s an over-expanded shock because the blade has more trailing edge camber than is required to produce the called-for exit static pressure under this operating condition, a similar phenomenon to that observed by Wadia and Copenhaver (1996). Likewise, it is improved in the optimized blade (Figure 20).

Figure 24. Entropy along the circumferential direction of different outlet pressures: 0.75 and 0.95 of the blade span.

Figure 25. Pressure coefficient at 0.95 of the blade span: original (left) and optimized (right). “Junlong et al., 2006”

Figure 26. Stream cut vortex structures.
Figure 26. Continued.
Figure 26. Continued.
The high entropy area from the rotor outlet clusters at the top and blade trailing edge. It manifests that the loss of flow is mainly caused by the wake mix and blade tip clearance interaction. In the optimized blade, the high entropy area is smoother and thinner. The entropy distribution at 0.25, 0.5, 0.75, 0.95 of the blade span in the theta direction is depicted in Figure 21. The optimized blade has the advantage at 0.75, 0.5, 0.25 of the blade span. Especially at 0.75 of the blade span, the entropy increases sharply on the modified suction side (Figure 22).
Stall work condition

First, four working conditions near stall are selected in each model. For the original blade, the outlet pressures are 151,000, 152,000, 153,000, and 153,800 Pa (the convergence case of the highest pressure), called ORI -$P_{out} - 1,2,3,4$. Similarly, for the optimized blade, the outlet pressure is 151,000, 152,000, 153,000, and 154,150 Pa, called OPT -$P_{out} - 1,2,3,4$.

As shown in Figure 23, the isentropic efficiency at the rotor outlet of both models keeps decreasing versus increasing outlet pressure. Additionally, the main isentropic reduction happens near the tip. In Figure 24, a detailed entropy distribution is illustrated. At 0.75 of the

![Figure 27. Limit streamline on the suction side at the stall point.](image)
blade span, versus rising pressure, the entropy remains stable. In addition, the optimized blade performs at a lower entropy than the original one. Conversely, at 0.95 of the blade span, the entropy fluctuates intensely as the pressure rises. Figure 25 shows that the shock position moves forwards and the shock intensity increases as the pressure goes up. Both the position and the intensity make the entropy increase sharply. It turns out that modifying the tip flow structure is an effective approach to enlarging the massflow range.

A detailed analysis of the secondary flow in the streamwise cut is shown in Figure 26. As shown in Figure 26(a), there are three main vortex structures at cut1, called vortices A, B and C. Vortex A is a passage vortex near the hub that is growing and attaching gradually to the suction side as the outlet pressure increases. Vortex B is generated by the shock and the endwall flow interacting. It’s stimulating vortex C further. Vortex C is mainly affected by the tip leakage flow and low energy fluid accumulating at the tip on the suction side. A low velocity region occupies most of the shroud area. It can be seen that, in the comparison of the two models, the supersonic and low velocity areas in the optimized case are smaller. This indicates a lower flow loss and vortex intensity in the optimized case. In the optimized blade, the sweep drives the shock position ahead, which reduces the intensity of vortex B, and then vortex C is improved a little. But vortex C in the optimized blade is improved mainly because of the lean effect, which makes the low energy fluid on the pressure side accumulate more in the mid-span. This effectively avoids low energy assembling at the tip and controls vortex C developing further.

As shown in Figure 26(b), vortices A and C remain, but vortex B goes off behind the shock wave surface. It’s worth noting that there is separated flow behind the shock on the suction side, and a vortex D is easily formed. As the massflow is going down, vortex D is expanding as well. But in the optimized blade, vortex D is limited by the effect of lean. The bottom half of the blade leaned backwards, causing the low energy fluid to be constrained in the root. Figure 26(c) indicates that the vortex structures are similar to the cut 2. But in the optimized

![Figure 28](image1.png)  
**Figure 28.** Pressure coefficient at 0.95 of the blade span.

![Figure 29](image2.png)  
**Figure 29.** Tip leakage flow.
blade, the secondary flow structure near the tip is smaller, and vortex C is almost dissipated with increasing outlet pressure.

Near the stall point, a corrected massflow of 0.874 is selected, and a flow field comparison between the original and the optimized blade is performed.

From Figure 27, the separation line in the optimized blade is a little curved because of the lean, and near the tip the flow is influenced more by tip leakage flow. As shown in the large version of the local vectors, for the optimized blade there is less tendency for the centrifuged boundary layer to collect at the casing. Additionally, the

![Figure 30. Mach contour at stall from 0.95 of the blade span.](image)

![Figure 31. Entropy contour inside the blade passage.](image)
pressure coefficient distribution proves the shock intensity is weakened by the lean and sweep (Figure 28).

As shown in Figures 29 and 30, the low momentum flow climbs over the tip clearance first, and turns down near the leading edge. The flow continues to mix with the main flow in the passage. The flow will spin to form a vortex and dissipate at the next blade suction side. Evidently, the endwall secondary flow is interacting all the time during the above process. In the optimized blade, the tip leakage vortex divergence angle is lower, and more vortex flow turns to the blade outlet. Conversely, the original blade has a large divergent angle of the leakage vortex, which leads to a more complex flow structure and a crash on the next blade. At the stall condition, the tip vortex encounters a strong adverse static pressure gradient. As a reaction to the adverse static pressure gradient, the vortex expands. In the original blade, the vortex has already burst, but in the optimized blade the vortex is still in a much better shape. At a blade span of 0.95, the low momentum area is very obvious after the shock wave, and a significant block in the passage ensues. It would exacerbate the compressor entering the unstable work state. But in the optimized blade, the tip leakage vortex and shock are modified remarkably. Though the low momentum area still exists, the extent has been reduced a lot.

As shown in Figure 31, in the original blade the entropy is much higher than the optimized one, and it would spread along the blade passage. In contrast, the entropy of the optimized blade is controlled to an acceptable level.

**Conclusion**

In this article, a numerical simulation of NASA Stage35 was carried out and verified by experiment. A parametric model is created in Autoblade with suitable fitting parameters. Based on the combination of an artificial neural network and a genetic algorithm optimization design system in Design3D, the rotor is optimized in a multi-point working condition and the conclusions are as follows.

By changing the control points and the stretching factor of the Bezier curve and the B-spline curve an accurate parametric blade can be obtained. With more parameters, the fitting results possess a better consistency. The optimal design system based on a neural network and a genetic algorithm has high efficiency. The lean and sweep laws have a significant effect in changing the shock wave system. By changing the position and intensity of the shock wave, the isentropic efficiency is improved in an obvious way. Through analysis of the stall condition flow field, the compressor usually enters an unstable state because of tip flow. And near the stall condition, the optimized blade can effectively reduce the intensity of the tip leakage vortex, and this is the main reason for stability enhancement. In each streamwise cut, the vortex structures are also improved.

The optimization in this article has mainly focused on the effect of the sweep and lean of the blade, and the simulation results indicate that the stability range is much improved. In further research, the blade should be reoptimized to trade back the gained aerodynamic stability for a further gain in its efficiency. More geometry factors including a 2D blade profile and a camber curve should be considered.

**Disclosure statement**

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