# Accepted Manuscript

Stochastic axial compressor variable geometry schedule optimisation

Luis Gallar, Manuel Arias, Vassilios Pachidis, Riti Singh

Please cite this article in press as: L. Gallar et al., Stochastic axial compressor variable geometry schedule optimisation, Aerospace Science and Technology (2010), doi:10.1016/j.ast.2010.08.010

ELSEVIER

# Stochastic axial compressor variable geometry schedule optimisation

Luis Gallar, Manuel Arias, Vassilios Pachidis, Riti Singh

*Department of Power and Propulsion, Cranfield University, Gas Turbine Engineering Group, Cranfield, Bedfordshire, MK430AL, England*

**Abstract**

The design of axial compressors is dictated by the maximisation of flow efficiency at on design conditions whereas at part speed the requirement for operation stability prevails. Among other stability aids, compressor variable geometry is employed to rise the surge line for the provision of an adequate surge margin. The schedule of the variable vanes is in turn typically obtained from expensive and time consuming rig tests that go through a vast combination of possible settings.

The present paper explores the suitability of stochastic approaches to derive the most flow efficient schedule of an axial compressor for a minimum variable user defined value of the surge margin. A genetic algorithm has been purposely developed and its satisfactory performance validated against four representative benchmark functions. The work carries on with the necessary thorough investigation of the impact of the different genetic operators employed on the ability of the algorithm to find the global extremities in an effective and efficient manner. This deems fundamental to guarantee that the algorithm is not trapped in local extremities.

The algorithm is then coupled with a compressor performance prediction tool that evaluates each individual's performance through a user defined fitness function. The most flow efficient schedule that conforms to a prescribed surge margin can be obtained thereby fast and inexpensively. Results are produced for a modern eight stage high bypass ratio compressor and compared with experimental data available to the research. The study concludes with the analysis of the existent relationship between surge margin and flow efficiency for the particular compressor under scrutiny. The study concludes with the analysis of the existent relationship between surge margin and flow efficiency for the particular compressor under scrutiny.

*Keywords:* Axial Compressor; Variable Geometry; Genetic Algorithm; Optimisation; Compressor Performance.

## 1. Compressor variable geometry operation

Surge occurs when the pumping capability of the compressor is exhausted and the flow breaks away from the blade in an irretrievable manner. This causes an abrupt reversal of the airflow through the compressor. To this regard, surge margin is a measure of how close an operating point is to surge. Safe operation of a jet engine at some conditions requires the value of surge margin to be greater than a minimum.

It is a known fact that at part speed the reduction in the axial velocity $V_a$ of the flow through an axial compressor overcomes the reduction in the spool speed, $U$, and so pushes the early stages towards surge. There is a number of methods available to the designer to alleviate this undesired part speed compressor behaviour, usually known as "part speed crutches", that include multi spooling, handling bleeds and variable geometry stator blade rows as the most

common. In particular, handling bleeds achieve an increased mass flow through the early stages of the compressor – for an increased $V_a$ and therefore a reduced incidence angle – by dumping overboard the excess of flow that would choke the rear stages otherwise. On the other hand, variable IGV's and VSV's redirect the air towards the respective downstream rotors so that the incidence angle to those rotors is kept well within an acceptable range away from the stalling incidence. The effect attained with both systems is however different (fig. 1); whereas the air bleed promotes a lower working line, by skewing the compressor variable blade rows the surge line is raised with a correspondent change in the compressor aerodynamic speed lines. It is generally accepted that a variable geometry stator row is required for each additional stage beyond 5[1]. To a first order, the working line position on the compressor map is regarded as unaffected by any re-stagger of the blade rows, although strictly speaking it is a function of the compressor efficiency that indeed varies with changes in the blade row stagger angle.
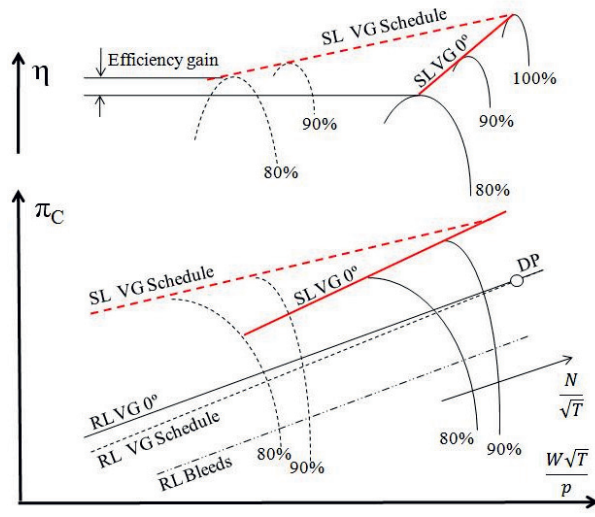
Figure 1: Effect on bleeds and variable geometry on the compressor map

At low speed the early stage variable geometry stators push the speed lines almost horizontally. At high spool speeds, however, their impact is subtler since stall is controlled by the rear stages and early stages migrate towards choke. At such speed, by further opening the variable vanes, the blade passage sectional area is increased and the compressor is able to swallow a larger mass flow – increased capacity - with a modest improvement in surge line. If the VSVs settings are rescheduled in such manner, the compressor is said to be upflowed.

In power generation applications the low pressure spool must run at a speed synchronised with the grid frequency, usually 50 or 60Hz. The variable vanes and the bleeds valves are operated jointly to accommodate changes in power demand; in other words, at the same firing temperature and spool speed the attainable pressure ratio and mass flow are modulated to meet the load requirements. In aero applications on the other hand, variable blade rows are optimised for flow efficiency at high speed, and for part-speed surge margin at low speeds. It is for this reason that the IGVs are generally devised as thin flat or little cambered profiles aligned with the flow – no swirl component is introduced in the oncoming flow- at nominal conditions for minimum pressure losses. To restrain the compressor from surge at off design conditions the flat plates are skewed in as much as the incidence to the first rotor is acceptable (fig. 2). The cost of doing this is a remarkable rise in pressure loss that emerges as the flow detaches from the plate.

## 2. IGV/VSV Schedule eduction

The IGV/VSVs and bleed valves settings are usually mapped into the engine control unit scheduled versus the aerodynamic speed of the compressor so that the
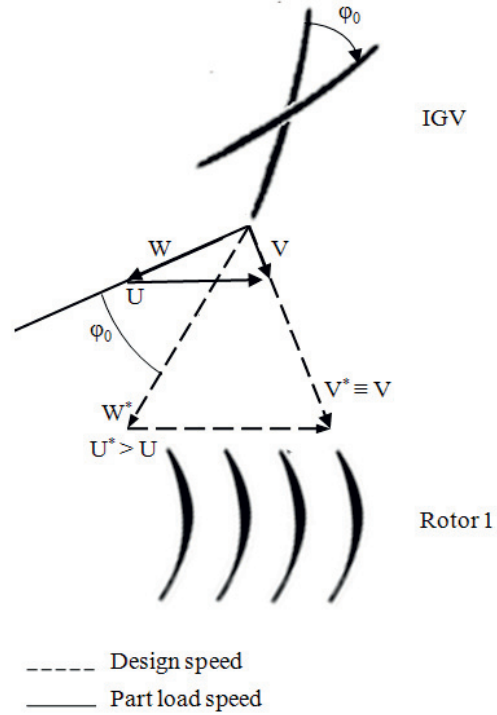


Figure 2: IGV operation fundamentals

compressor geometry and bleeds are univocally defined for a given spool speed. During the engine design process the VIGVs and VSVs are devised and optimised for design point operation following the usual rules and numerical procedures. Conversely at off design conditions, the settings that constitute the IGV/VSV schedule are usually obtained from rig tests in which a large number of possible combinations of the variable stator settings is tested and compared. This trial and error process is carried out for the whole operating envelope of the compressor and, although effective, it is also lengthy and expensive. The aim of this work is to engineer a computational tool able to deliver the most flow efficient IGV/VSV schedule that at the same time conforms to a prescribed minimum surge margin. In so doing, not only the required experimental trials could be shortened and made cost effective but the rig resources could be employed in other tasks.

During the tests the variable stator rows are moved independently from each other by means of separate mechanical actuators that permit the blades to be restaggered at the controller's will. Nevertheless, for simplicity, weight and cost reasons the engine is equipped with a single mechanical actuator that is connected with each variable row by a rod. Therefore, the movement of the VSVs rows obeys a fixed proportionality that depends on certain geometrical parameters of the gearing mechanism. The proportionality constant can be changed to fit a determined optimised schedule – in fact to obtain such constant is the object of the aforementioned rig trials- but once fixed it constrains the movement of the stator rows;

i.e. for a given turn of the $VSV_1$, $\varphi_1$, the $VSV_2$ is forced to rotate an angle $\varphi_2$, equal to $\lambda$ times $\varphi_1$. It is clear that a non linear response of the system is desirable from an aerodynamic point of view, but such benefits are offset by the mechanical simplicity of a single actuator system. As an example, figure 3 shows the datum schedule for the three variable rows of the eight stage axial compressor employed in the current study.

The optimisation of the variable geometry schedule of a compressor in isolation provides spurious solutions. A point on the working line – defined by a determined value of the non dimensional mass flow and a given pressure ratio - can be achieved with different settings of the variable geometry rows. However, it is unlikely that for those different configurations the speed at which the compressor runs would be the same. Any change in spool speed will have an impact on the efficiency of its correspondent downstream turbine and although the compressor efficiency may be raised the turbine efficiency can plummet and the overall performance of the engine can turn out to be impaired. It is for this reason that the variable geometry schedule of a compressor should be derived in conjuction with its associated turbine. However and to a first order, it is not unreasonable to assume that the characteristic is flat for most of the power range for modern turbines.

## 3. Variable geometry schedule optimiser

### 3.1. General arrangement

A genetic algorithm based optimiser has been chosen to obtain the most flow efficient variable geometry schedule with user specified surge margin criteria. The choice of such method is dictated by the properties of the problem to be optimised. Namely, the algorithm handles three degrees of freedom ($\varphi_0$, $\varphi_1$, $\varphi_2$), and this fact gives rise to multiple local optima for a myriad of angle combinations. Moreover, loss and stall models used to calculate compressor aerodynamics are generated from empirical data and are usually expressions that fit the mentioned data or in some cases losses are given in tabular form from which any operating point is found by interpolation. Furthermore, the prediction of the compressor performance is a highly constrained problem – e.g. De Haller number and Lieblein's equivalent diffusion factors, minimum acceptable surge margin, or the maximum acceptable spool speed variation are parameters that severely restrict the design space. It is for all these reasons that the problem is multimodal and highly constrained, and as such is suitably tackled with GAs and other heuristic techniques as demonstrated previously in the literature [2 to 15], in contrast with classical gradient based numerical approaches like those undertaken by Dennis and Schnabel [16], Fletcher [17] and Rao [18] that perform successfully for smooth functions where the shape of the objective function

is known beforehand. On top of all, the problem is characterised by
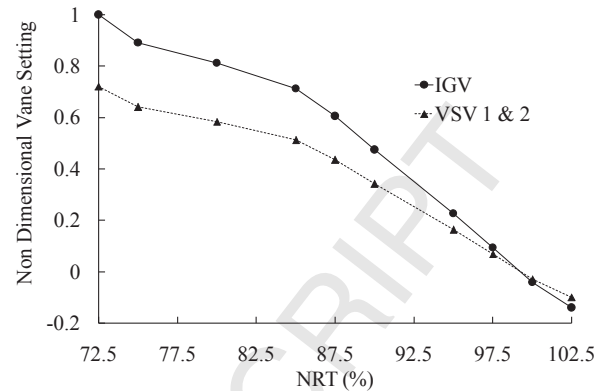


Figure 3: Datum compressor variable geometry schedule

conflicting design options that make impossible a trial and error approach. In particular, surge margin is commonly ameliorated by design decisions that impair the compressor efficiency. Genetic algorithms have been successfully applied to virtually every aspect of the design of gas turbines: from models ideated to design combustors following a nodal network approach [2,3], to engine inlet design [4] or axial compressors aerodynamic design [5], engine components map generation techniques [6] and blade aerofoil design based on a parameterization of Beziers curves [7,8]. This type of optimiser has also been coupled with computational fluid dynamics techniques to narrow the design space and alleviate the time required to complete CFD based designs [9]. Wider scopes of application include intercooled recuperated turbofan design [10] or even jet engine controller design [11].The fact that there is no requirement for the fitness function to be defined analytically makes these codes particularly attractive to the design of axial compressors where most of the correlations employed are attempts to fit empirical data.

In this work a genetic algorithm has been developed from scratch. The code has been programmed in Matlab and has been coupled with a Fortran 1D mean line analysis code to predict the performance of the compressor. The interface between both codes is accomplished by means of txt data files. The GA generates the txt data files that encode the compressor geometry and characteristics required by the Fortran code as an input. In turn, the prediction code assesses the fitness of the created chromosome and delivers a new txt data file that contains the predicted compressor performance to be read by the GA. The program structure is sketched in fig. 4.

One of the results provided by the mean line analysis code is the mass flow that the compressor is passing at a given aerodynamic speed. By skewing the variable geometry of the compressor the aerodynamic speed at which a determined mass flow passes through the compressor changes. To a first order, for the engine to operate at the same point that it does with the original variable geometry schedule it is the value of the non
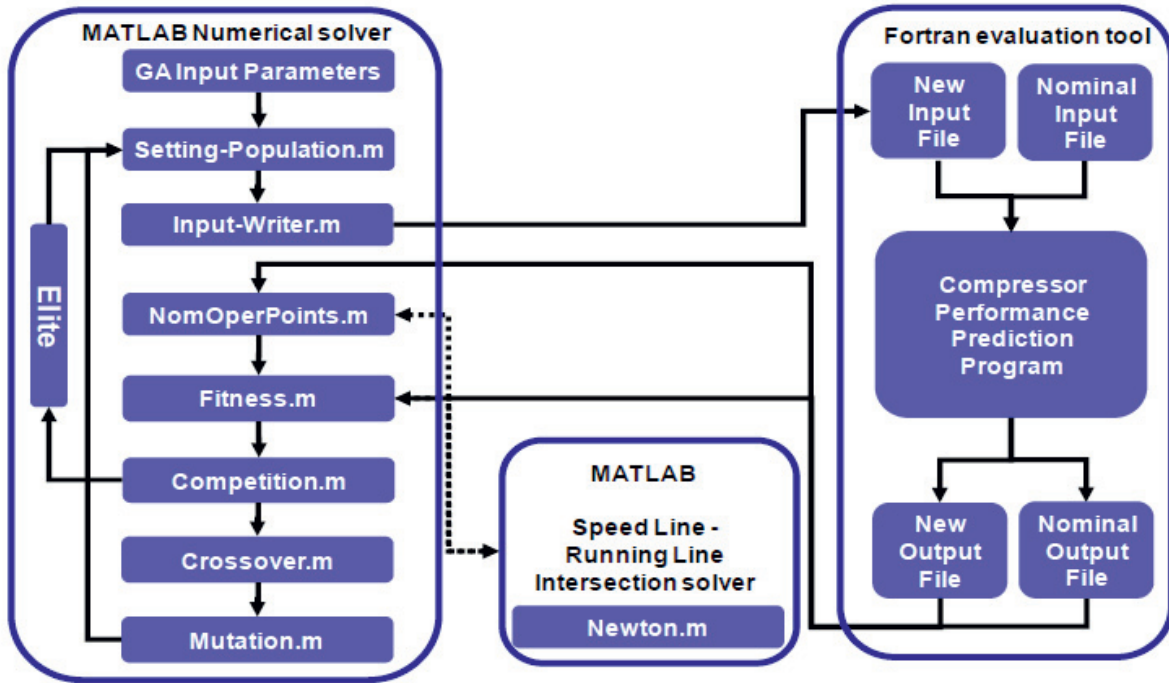
Figure 4: Genetic algorithm general arrangement

dimensional mass flow and pressure ratio that must be kept constant, rather than the aerodynamic speed of the compressor that varies when the variable geometry of the compressor is skewed. Prior to the application of any genetic operator, this effect is accounted for in the algorithm by means of a loop that finds the spool speed at which the mass flow and pressure ratio are within an error of $10^{-3}$ of their datum values.

### 3.2. Genetic algorithm structure

The genetic algorithm had its breakthrough with the work undertaken by Holland [19] and Goldberg [20] and belongs to a group of heuristic optimisation techniques like the simulated annealing [21], the particle swarm optimisation [22] or the Tabu search [23 to 25]. The premise onto which the genetic algorithm is founded is to mimic the natural selection in which only the strongest individuals make it to survival while less fit individuals die away. The main advantage of the GA is its robustness and its ability to avoid getting trapped in local maxima once the algorithms parameters are tuned by means of a sensitivity analysis. This is guaranteed by the algorithm's mechanisms that produce diversity in the population, particularly the number of chromosomes per generation and the rate of mutation.

The code operates by generating a random population of compressors where the IGV's / VSV's schedule is represented by a string of zeros and ones so that it can be easily handled mathematically. The program then translates such strings to input files that are read by the prediction program to evaluate the performance of each individual of

the population. The fitness subroutine assigns to every compressor a fitness value that corresponds to the adiabatic efficiency of such compressor. The proximity of the working line to the surge line can be accounted for in the calculations implicitly in the fitness function by penalising those solutions with a small surge margin or by rejecting any individuals that violate a given surge margin constraint. Once the fitness of every individual has been obtained they are subjected to the genetic operators. First the chromosomes are selected randomly in pairs and forced to compete so that the fittest of the two replaces the less fit in the original population in what it is known as a "tournament selection". The resultant individuals are randomly selected to mate and generate an offspring population. The children are generated in a so called multipoint crossover strategy in which each bit of the offspring is randomly chosen as the correspondent bit from either of the parents. Lastly, following natural genetics, the population is subjected to a degree of mutation that transmutes a prescribed percentage of bits in the population to its opposite value. In order to assure that the fittest individuals are not discarded from the population and hence accelerate the convergence of the code to the solution, after the competition the ensuing chromosomes with the highest fitness value are separated from the lot and set aside in an "elite" group that is exempted from undergoing any further transformation during that generation. To conclude the calculations the program runs mutation free for a number of generations in what is called a damping process to let the program converge to a solution. The algorithm stops when the average fitness of the population equals the fitness of

the fittest individual; that is, when all the individuals in the population have become the fittest.

### 3.2.1. Validation – Benchmark functions

To investigate the capabilities of the algorithm to accurately predict the location of global maxima and assess the sensitivity of the code to the different algorithm control parameters the program has been subjected to trial by several benchmark functions with multiple local maxima, given by the following expressions (functions A to D; all for $0 \leq x \leq 20$ and $0 \leq y \leq 10$):

$$z = 20 \left[ \frac{\sin\left(\sqrt{0.1 + (x-4)^2 + (y-4)^2}\right)}{\sqrt{0.1 + (x-4)^2 + (y-4)^2}} \right]$$

$$z = 1 - (x \sin(4x) + 1.1y \sin(2y))$$

$$z = 1 - (y \sin(4x) + 1.1x \sin(2y))$$

$$\begin{cases} z = \frac{(\cos^2(x) - \cos^2(y))^2}{\sqrt{x^2 + y^2}} \\ \\ subjected\ to\ the\ constraints \begin{cases} x \cdot y > 0.75 \\ x + y < 15 \end{cases} \end{cases}$$

The results provided by the code are grouped in table 1, and are found to agree closely with the maxima found analytically by the method of Lagrange multipliers. The runs are carried out for 100 chromosomes per generation, during 100 generations. The number of competitions per generation is 120 after which the resultant chromosomes are crossed 100 times. The mutation rate is 10%, 5 elements are kept within the elite and the algorithm ends with 30 damping generations. The calculations are completed in 10 seconds.

Figure 5 plots the evolution of the fitness value (for this simple case the fitness value is the value of the function z that needs to be maximised) of the best specimen and the average of the population for the function D as the calculations progress. The results show that within the first 40 generations the algorithm is able to capture at least one chromosome with a fitness value of 0.37 whilst for the remainder of the generations the program explores other regions of the design space. The average fitness of the population rises gently over 90 generations (continuous trend line) while the population is subjected to mutation. For the last generations the absence of mutation allows the code to rapidly converge to the final solution.

### 3.2.2. GA's input parameters sensitivity analysis

The performance of the GA is heavily dependent on the right choice of input parameters, and care must be put to assure that the program has not been trapped in any local maxima. On the other hand, an excessively conservative approach would eventually find the right solution to the

| Function | GA Result | Lagrange Multipliers result | Dev |
|---|---|---|---|
| A | f(3.9999, 4.0001)=19.6633 | f(4.0000,4.0000)=19.6633 | 0 |
| B | f(9.0400,8.6681)=19.5547 | f(9.0390,8.6681)=19,5547 | 0 |
| C | f(9.0390,8.6645)=19.5619 | f(9.0390,8.6681)=19,5547 | 0.0370 |
| D | f(1.5869,0.4727)=0.3755 | f(1.585,0.473)=0.3793 | -1.012 |

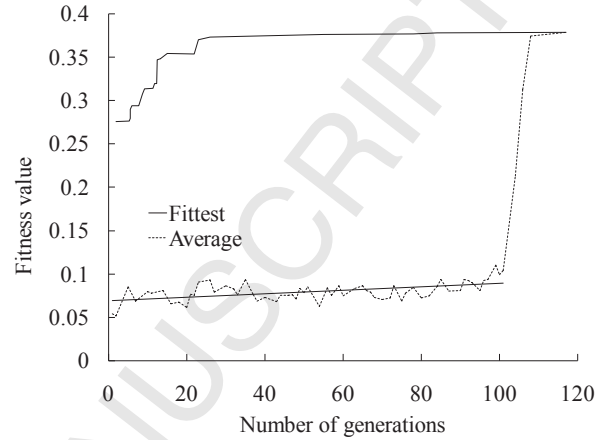Table 1: Benchmark functions optimiser results.



Figure 5: Maximum fitness value evolution – Function D

problem but at the cost of a dramatic increase in computational time. Therefore, it is of the utmost importance to carry out a sensitivity analysis to tune the algorithm. The effect of the input parameters on the algorithm's behaviour in outline is:

- A number of competitions greater than the numbers of chromosomes (around 20%) improves the convergence.
- A small percentage of mutation (1-5%) may hinder the algorithm from finding the solution and the code is trapped on local maxima. Conversely, if the mutation is excessive (20%) the program eventually finds the global maximum but it behaves as a random search technique.
- The number of elements in the elite group should not represent a large percentage of the population as this delays unnecessarily the convergence to the solution. There is a threshold of generations and chromosomes below which there is no guarantee that the global maximum is found. This is demonstrated by the erratic behaviour of the algorithm for runs with less than 100 chromosomes and a small number of generations. Figure 6 and 7 illustrate this behaviour, and are an indicator of the repetitiveness of the algorithm. Particularly figure 7 groups the results of the maximum deviation from an average of 5 identical runs for the same operating point. The 30% deviation that appears for 50 chromosomes shows that the algorithm fails to reach the global maximum unequivocally.
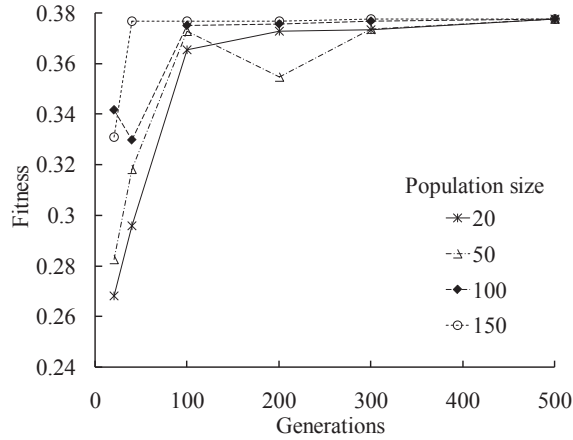
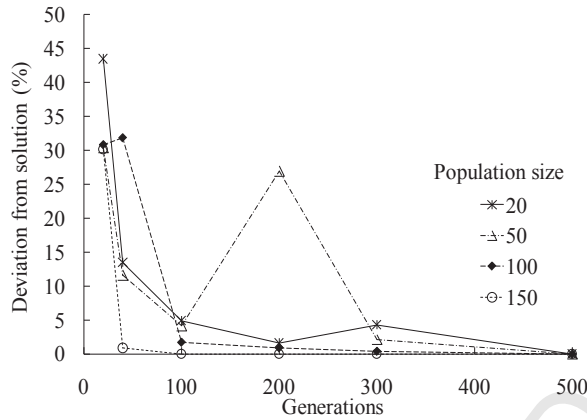Figure 6: Ave. fitness value evolution – Function D


Figure 7: Max. dev. from final average value – Function D

The sensitivity of the algorithm to the number of generations and the percentage of mutation is investigated by three different sets of runs. In the baseline case the number of competitions is increased 70% from the baseline case (300 generations, 120 competitions, 100 individuals, 10% mutation) whereas in cases B and C the percentage of mutation is modified to 20% and 2% respectively. Increasing the number of competitions results in a less effective coverage of the design space compared to the baseline as illustrated in figs. 8 and 9 where each chromosome is plotted as a dot. This is reasonable since the number of different individuals that make it through the competition operator and are allowed to mate is sternly reduced by increasing the competitions.

Other effects associated to the increase in the number of competitions are:

- The number of generations required to damp the solution (no mutation) and converge to the fittest individual is generally reduced.
- The number of generations required to find the location of the global maximum is normally greater. This is a consequence of the previous – greater number of generations without mutation results in a worse coverage of the design space.

- The average fitness value reached during the fluctuation period is also higher.
- Overall, the final solution value is slightly improved and the deviation minimised when compared to the same percentage reduction in mutation rate.

It is found that an increase in the mutation rate has the opposite effect to any increments in the number of competitions. As an example, figure 10 shows the evolution of the calculations for the baseline (10% mutation) and the high and low mutation scenarios (20% and 2% mutation). It can be observed that the average fitness of the population in the initial phase is slightly higher for moderate values of the mutation rate and increases sharply for the low mutation case. Thereafter the mutation operator is switched off and the algorithm is allowed to converge to the final solution, and it does so in a reasonably quick manner (less than 20 additional generations). On the other hand, for high
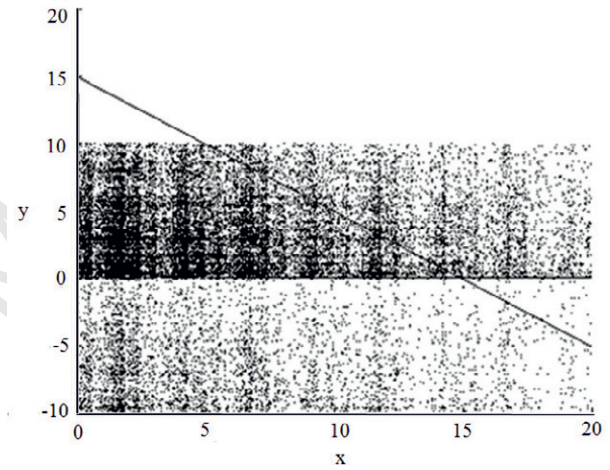

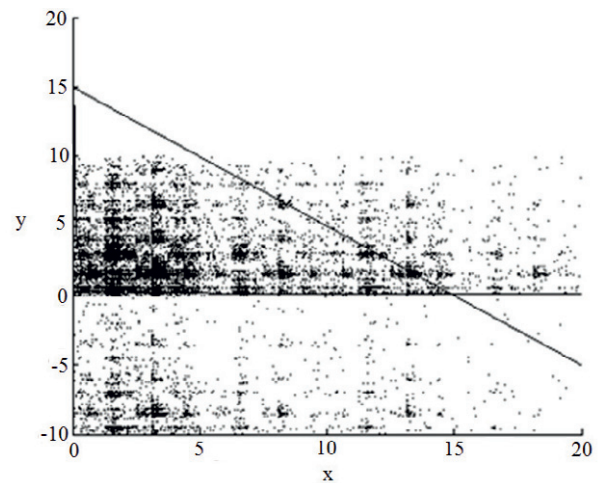Figure 8: Design space coverage – Baseline case
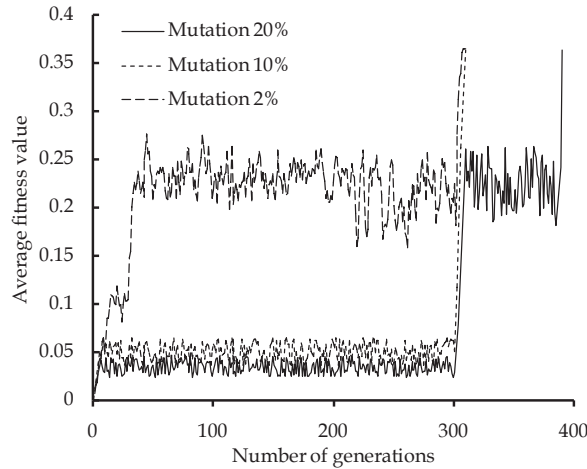

Figure 9: Design space coverage – case A

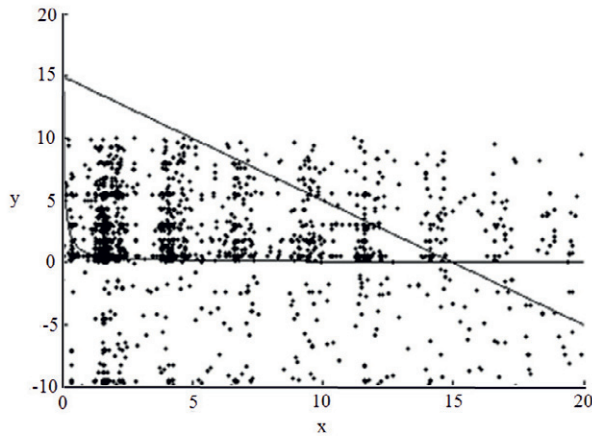Figure 10: Ave. fitness value – Baseline and B and C cases



Figure 11: Design space coverage – case C

values of mutation the algorithm performs poorly in that after a lower average initial phase, it behaves erratically for almost 100 generations until it is eventually able to pick and bring the fittest individual out of the crowd. On the other hand, although the reduction in mutation rate rises the average of the fitness of the population, the coverage of the search space is less efficient and the code is more likely to get trapped in local extremities (fig. 11).

### 3.3. Compressor performance prediction program

The code employed to evaluate the fitness function for each compressor is a Fortran computer program used to obtain the preliminary off design performance of axial flow compressors. It is an industry proprietary 1-D mean line multi stage analysis that uses the correlations published and validated by Wright and Miller [26] to calculate the loss, flow turning and annulus wall blockage growth across the blades. These correlations are based on the diffusion factor as ideated by Lieblein [27] and modified by Swan [28]. Besides, the stall incidence is calculated with the help of the expressions developed by Miller, and the interested

reader is encouraged to confer [26] and its associated references for further details. Due to the strong flow separation present across variable vane rows at off design conditions Lieblein's based approaches to predict blade losses are flawed and hence the loss models employed were upgraded by Gallar et al [29] .

The program requires some input data including number of stages, annulus geometry, blade geometry, variable geometry schedule and bleed data. It obtains the compressor performance via an iterative process. First of all, the mean line velocity triangles are obtained solving 1D Euler and mass flow continuity equations. The annulus wall blockage, rotor and stator loss coefficients can be derived applying blade loss and blockage empirical correlations. From those coefficients and the stage pressure ratio the stage temperature rise can be obtained and the velocity triangles are calculated again. The process is repeated iteratively until consistent values of mean-line velocity triangles, blade row losses and annulus wall blockage are found. Once the program has converged, the remainder blade angles are then derived from correlations of incidence and deviation. For validation purposes, the code has been applied to two different state-of-the-art eight stage axial compressors, A and B. Results are shown in figures 12 and 13 and it can be observed that the computational results follow closely the rig data.

## 4. Results

To illustrate its capabilities the program has been applied to a state of the art compressor of a modern high by pass ratio turbofan that features a VIGV row and two rows of VSVs, for a defined value of the minimum surge margin admissible (SM1). The population size of the algorithm is 100 individuals that run over 300 generations with a 10% mutation rate. The design parameters that can be changed in the program are three: IGV, VSV1 and VSV2 settings
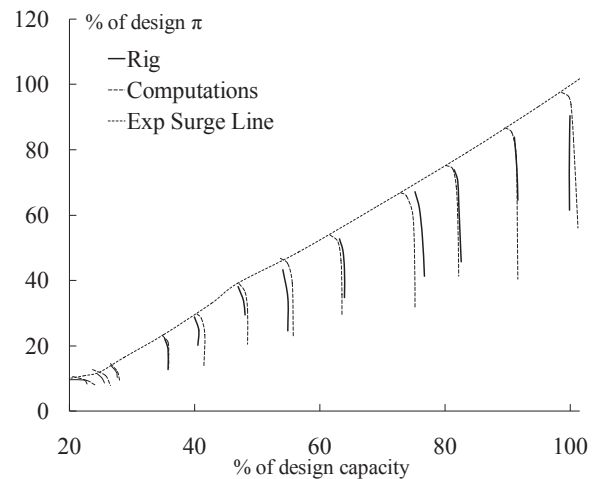


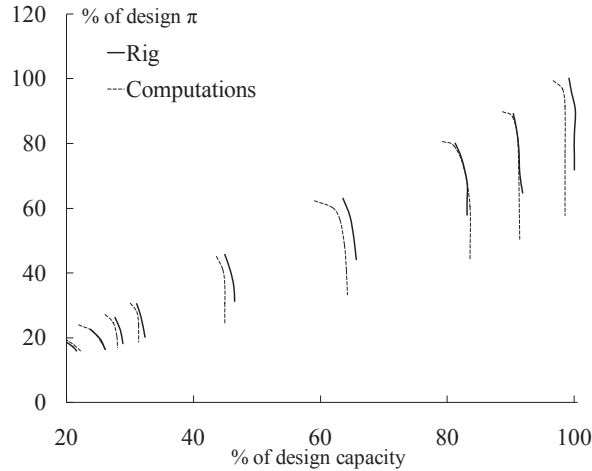Figure 12: Compr. A – Performance prediction validation

Figure 13: Compr. B – Performance prediction validation

are allowed to vary ±10 degrees around the datum. The fitness function is the flow efficiency of the compressor. Solutions with a surge margin smaller than a user defined value are assigned a fitness value of zero and die away in the subsequent generation.

The progression of the algorithm for this real-world optimisation problem is depicted in figure 14. The algorithm starts with a fittest individual with an efficiency of 0.45 and rises to an average of 0.65 after 5 generations. During 295 generations it explores the design space and as a result the efficiency of the fittest individual rises slowly up to 0.8243 after 95 generations. During the remaining 200 generations the algorithm does not find a fitter individual. After the mutation is switched off, it takes 4 generations for the GA to converge to the solution.

The resultant schedule is plotted in figures 15 and 16 for the IGV and VSV1 and 2 respectively. The optimised solution exhibits a clear trend towards a more opened position of the IGV row with respect to the datum. The first row of variable geometry is more opened at high speeds and gets progressively closer to the nominal down to 85%*NRT*; then it matches the original schedule until the solution departs again slightly from the nominal for the lower region of the speed range. The second row of variable vanes on the other hand, is more open at the top end of the speed range and more closed for the remaining of the speed range.

Figure 17 reflects the benefits of the proposed new methodology when applied to the compressor under study compared with experimental data obtained for the datum schedule on a compressor rig. As expected, at high speed the gain in compressor efficiency obtained is minimal as the compressor blading is optimised for flow efficiency at design conditions. Results show that a marked rise in compressor efficiency can be attained with respect to the nominal schedule utilising the new methodology, in particular at partial speed operation, for different values of the minimum surge margin required for engine operation. The line labelled SM1 refers to the maximum adiabatic that

can be attained with the same surge margin prescribed for the datum schedule throughout the operating speed range. The SM2 line shows the maximum flow efficiency that can be obtained for the nominal surge margin increased by 5%. It is noticeable that for both scenarios the compressor efficiency is still higher than the datum, despite the increase
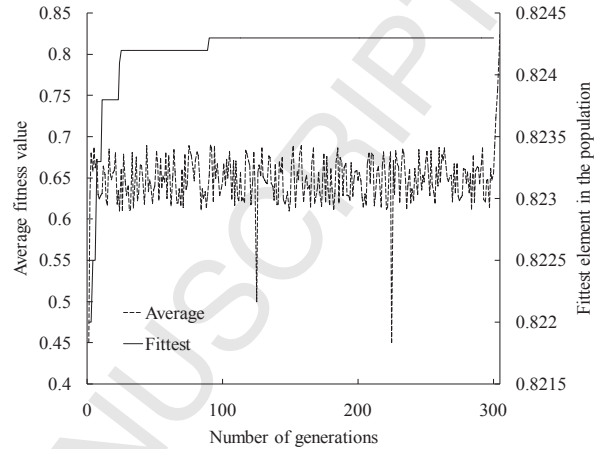


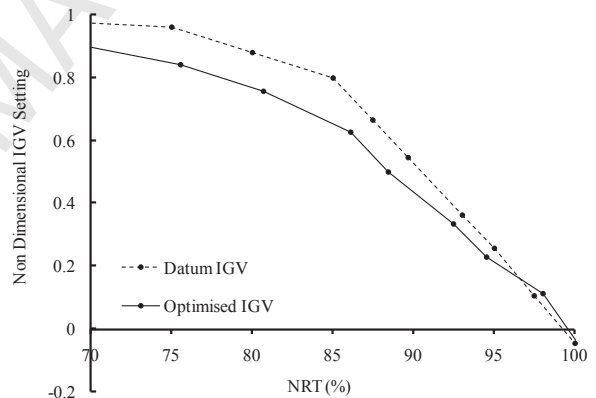Figure 14: VSV optimisation – GA progression
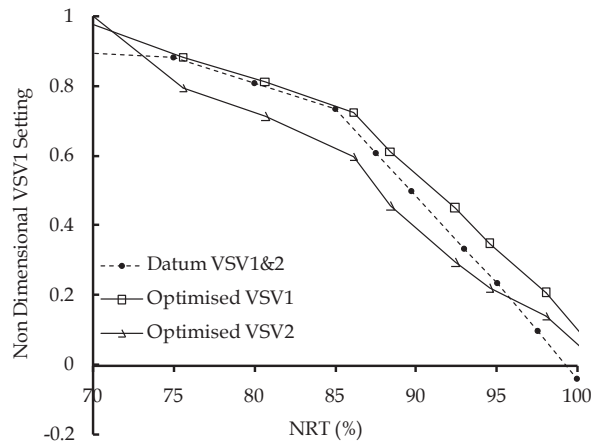


Figure 15: IGV optimised schedule



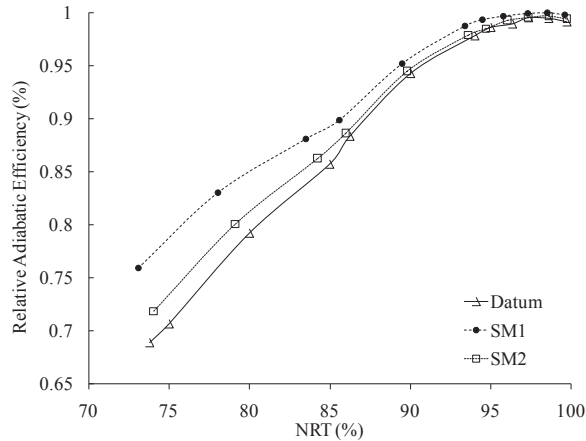Figure 16: VSV1 and VSV2 optimised schedule
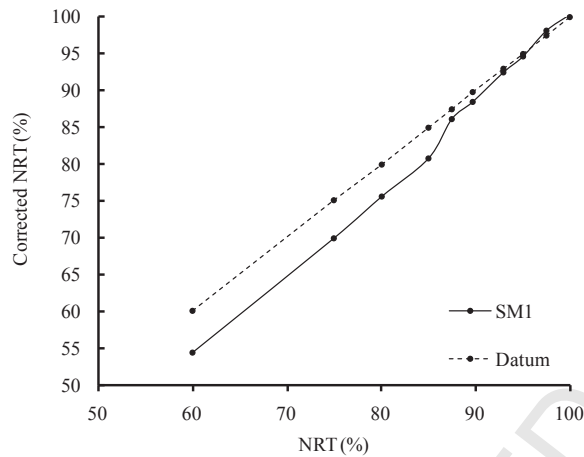
Figure 17: Optimised schedule efficiency



Figure 18: Optimised schedule aerodynamic speed

in surge margin required from the machine in the SM2 case.

Moreover, the subtle change in efficiency trend that is present at 85%NRT for all three scenarios is caused by the operation of the bleed valves at such speed. The opening of the valves allows the compressor to reach slightly higher efficiencies since the required surge margin for engine operation is provided by dumping the air overboard through the bleed valves rather than giving up adiabatic efficiency.

The mentioned efficiency gain is obtained with a considerably reduction in aerodynamic speed (around 5%) for the slower segment of the operating envelope with respect to the datum, for the same mass flow and pressure ratio (fig. 18). On the other hand, the careful scrutiny of the results suggests that the mass flow for this particular compressor is chiefly controlled by the stagger of the inlet guide vanes. Those results are then justified by the fact that the marked opening of the IGVs promotes a reduction in compressor losses by reducing the flow incidence onto the vanes. To assure that the compressor supplies the same mass flow and pressure ratio – same operating point – the increase in capacity caused by the IGVs reschedule is offset by the mentioned decay in aerodynamic speed.

For each operating point the program reaches a converged solution in around 3 hours, using dll libraries. This avoids calling the compressor performance code as an external executable saving a considerable amount of time.

## 5. Conclusions

The aim of the present paper is to divulge the discussed methodology rather than comment on the results obtained since these will undoubtedly depend on the particular compressor under study. Stochastic optimisation methods and in particular genetic algorithms have been found as a powerful and adequate methodology suited to derive the most flow efficient schedule of the variable geometry of an axial compressor or at least delimit the search range and hence minimise the need for expensive and time consuming engine tests in a quick manner.

A genetic algorithm has been developed and coupled with a compressor performance prediction tool to find the geometry schedule that maximises the adiabatic efficiency for a user defined value of the surge margin. Satisfactory results have been obtained using a 1D mean line code to predict the compressor efficiency. Besides, the modular character of the tool enables the researcher to substitute the compressor evaluation tool with 2D or 3D models for an enhanced accuracy of the results Furthermore, the tool enables the user to assess the impact of some design decisions at part speed operation during the design phase of the engine and in so doing promotes a better understanding of the expected performance of the compressor at part speed. This state of the art tool is suited to be upgraded to include the effect of bleeds and power of takes in the calculations for a greater applicability of the tool.

Results for a modern high bypass ratio engine eight stage axial compressor are shown as an example of the methodology employed and compared with experimental data obtained for the datum schedule from the compressor rig.

## Acknowledgments

## References

[1] Walsh P. and Fletcher P., Gas turbine performance (2nd ed), Blackwell Science Ltd, Oxford, 1998

[2] Despierre, A., Gas turbine combustor design using genetic algorithms, MSc thesis Cranfield University, 1996.

[3] Despierre, A., Stuttaford, P.J. and Rubini, P.A., Preliminary gas turbine combustor design using a genetic algorithm, International gas turbine and aeroengine congress and exhibition, ASME 97-GT-72, 1997.

[4] Gaiddon, A. and Knight, D.D., Multicriteria design optimization of integrated three-dimensional supersonic inlets, Journal of propulsion and power, Vol 19, pp. 456-463, 2003.

[5] Keskin, A. and Bestle, D., Application of multi-objective optimization to axial compressor preliminary design, Aerospace science and technology 10, pp. 581-589, 2006.

[6] Changduk Kong, J.K. and Lee, C., Components map generation of gas turbine engine using genetic algorithms and engine performance deck data, GT2006-90975, 2006.

[7] Gardner, B.A. and Selig, M.S., Airfoil design using a genetic algorithm and an inverse method, AIAA 2003-0043, 2003.

[8] Obayashi, S., Tsukahara, T. and Nakamura, T., Cascade airfoil design by multiobjective genetic algorithms, Genetic algorithms in engineering systems: innovations and applications, No 446, 1997.

[9] Duvigneau, R. and Visonneau, M. Single and multiobjective optimisation for high fidelity CFD using genetic algorithms, Evolutionary methods for design optimisation and control, 19-21 September, Athens, Greece, 2001.

[10] Whellens, M.W., Singh, R. and Pilidis, P., Genetic algorithm based optimisation of intercooled recuperated turbofan design, AIAA 2003-1210, 2003.

[11] Chipperfield, A. and Fleming, P., Multiobjective gas turbine engine controller design using genetic algorithms, IEEE Trnasactions on industrial electronics, Vol 43, No. 5, 1996

[12] Ghisu, T., Parks, G.T., Jarret, J.P and Clarkson, P.J., Integrated design optimisation of gas turbine compression systems, in 4th AIAA Multidisciplinary Design Optimization Specialist Conference, Schaumburg, Illinois, USA, 2008. AIAA-2008-1979.

[13] Kipouros, T., Jaeggi, D.M., Dawes, W.N., Parks, G.T., Savill, A.M. and Clarkson, P.J., Biobjective design optimization for axial compressors using Tabu Search, AIAA Journal, Vol. 46, No. 3, pp. 701-711, 2008.

[14] Kipouros, T., Jaeggi, D.M., Dawes, W.N., Parks, G.T., Savill, A.M. and Clarkson, P.J., Insight into high-quality aerodynamic design spaces through multi-objective optimization, CMES: Computer Modeling in Engineering & Sciences, Vol. 37, No. 1, pp. 1-44, 2008.

[15] Shahpar, S., Automatic aerodynamic design optimisation of turbomachinery components - an industrial perspective. VKI Lecture Series on Optimisation Methods & Tools for Multicriteria/Multidisciplinary Design, pp. 1-40, 2004.

[16] Dennis, J.E. and Schnabel, R.B., Numerical methods for unconstrained optimisation and nonlinear equations, Prentice Hall, 1983.

[17] Fletcher, R., Practical methods of optimisation, John Wiley, 1987.

[18] Rao, S.S., Engineering optimisation:theory and practice, John Wiley, 1996.

[19] Holland, J.H., Adaption in natural and artificial systems, University of Michigan Press, 1975.

[20] Goldberg, D.E., Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley Professional, 1989.

[21] Kirkpatrick, S., Gelatt, C.D. and Vecchi, M.P., Optimization by Simulated Annealing, Science, Vol 220, Number 4598, pp. 671-680, 1983.

[22] Kennedy, J. and Eberhart, R., Particle swarm optimization, Proceedings of the IEEE Int. Conf. on Neural Networks, Piscataway, NJ, pp. 1942–1948, 1995.

[23] Glover, F. and Laguna, M., Tabu Search, Kluwer Academic Publishers, Boston, MA, 1997.

[24] Jaeggi, D.M., Parks, G.T., Kipouros, T. and Clarkson, P.J., The development of a multi-objective Tabu Search algorithm for continuous optimisation problems, European Journal of Operational Research, Vol. 185, pp. 1192-1212, 2008.

[25] Kipouros, T., Jaeggi, D.M., Dawes, W., Parks, G.T. and Savill, M., Multi-objective Design Optimisation for Axial Compressors, in 3rd Aerodynamic Design Optimisation Seminar (ADOS 2005), Rolls-Royce plc., UK, 2005.

[26] Wright, P.I. and Miller, D.C., An improved compressor performance prediction model, ImechE C423/028, 1991.

[27] Lieblein, S., Analysis of experimental low-speed loss and stall characteristics of two-dimensional compressor blade cascades, NACA RM E57A28, 1957.

[28] Swan, S.C., A practical method of predicting transonic compressor performance, Transactions of the ASME, pp. 322-330, July 1961.

[29] Gallar, L., Pachidis, V. and Singh, R., Compressor IGV off design performance and loss modelling, International Symposium of Air Breathing Engines 2009, Paper 1221, 2009.

## Nomenclature

### Abbreviations

| | |
|---|---|
| GA | Genetic algorithm |
| IGV | Inlet guide vane |
| RL | Running line |
| SM | Surge margin |
| VIGV | Variable inlet guide vane |
| VSV | Variable stator vane |

### Greek symbols

| | |
|---|---|
| $\eta$ | Adiabatic efficiency |
| $\varphi$ | Angle of rotation – IGV and VSV settings |
| $\lambda$ | Constant of proportionality |
| $\pi$ | Pressure ratio |

### Subscripts

| | |
|---|---|
| 0,1,2 | IGV, first or second row of VSV's respectively |
| * | Design conditions |

### Latin symbols

| | |
|---|---|
| $a$ | Axial |
| N | Spool speed |
| NRT | Compressor aerodynamic speed $N/\sqrt{T}$ |
| P | Total pressure |
| T | Total temperature |
| U | Blade speed |
| V | Flow absolute velocity |
| W | Mass flow / Flow relative velocity |

# Stochastic axial compressor variable geometry schedule optimisation

Gallar, L.

2011-07-01T00:00:00Z