Proceedings of ASME Turbo Expo 2011
GT2011
June 6-10, 2011, Vancouver, British Columbia, Canada

GT2011-45499

AN OPTIMIZATION PROCEDURE FOR THE AERODYNAMIC MODEL TUNING OF CENTRIFUGAL COMPRESSOR STAGES

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ABSTRACT

This paper presents an automated optimization procedure for tuning and optimizing the performance parameters of centrifugal compressor stages in order to improve the accuracy of a 1D performance prediction tool and performance database. An in-house, well-validated 1D tool is used to predict the performance of centrifugal compressor stages. The stages are usually tested under similitude conditions in order to verify the predicted performance with the experimental data. Continuous improvements have been done on the tool to improve its accuracy, but the tuning to test data is still done manually and separately for each tested design flow coefficient. As a further leap in this activity, an in-house developed optimization code (PEZ) is interfaced with the 1D prediction tool to provide the best possible solution within the given tuning limits. This provides the possibility to use an extended number of tuning parameters and to tune the entire design family simultaneously, thereby ensuring a smooth evolution of the tuning parameters within the database. The optimization plan consists of a Differential Evolution (DE) genetic algorithm followed by a simplex-based optimization method (AMOEBA) with an objective of reducing the **R**oot **M**ean **S**quare (RMS) value of the error with the specified constraints. The procedure was successfully challenged with several families of similar stages but with various design corrected mass flows, by setting different objective/constraints combinations. The Optimizer was able to reduce the total RMS value of the error by approximately 80% with respect to the baseline for one of the recently tuned families. The result is a minimal deviation between predicted and experimental data for entire families, as well as a significant time reduction compared to the previous tuning methodology.

INTRODUCTION

At a customer request for a machine design, an extensive design database is used, together with an in-house 1D design tool in order to prepare the optimal design to fit the request. The complete machine configuration procedure from customer request to a complete offer takes usually a few weeks (sometimes less), making it impossible for extensive use of more elaborate modelling tools (for ex 2D and 3D CFD) at this stage. Therefore, a well calibrated database and an accurate 1D prediction tool are essential to meet the stringent turnaround time requirements. Continuous improvements are done to create a better prediction tool with minimal deviation from measured data. Model tests and fleet feedback are then effectively utilized in developing correlations and improving the tuning of both the 1D tool and the database to achieve a better accuracy.

In order to populate the database with a new family design, the complete aero design cycle of centrifugal compressor stages starts with 1D performance predictions of the polytropic head, polytropic efficiency, work coefficient etc. followed by 2D and 3D detailed analyses and tests to validate the predictions. Each level in the design phase has a significant impact by itself and also carries the impact of the previous phases [11]. Once the family design is finalised and the model tests are performed, the database and the 1D prediction tool need to be tuned to the test data in order to achieve a good match

Traditional tuning of the 1D tool is typically a manual experience-dependent process that utilizes the data from the tests conducted for different stages. A limited number of tuning parameters is typically used to keep the process under control. This is due to the fact that the more the tuning parameters that

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need to be optimized, the higher the number of iterations required by the user to reach an acceptable, although not necessarily optimum, level of improvement with respect to the baseline[1]. A small increase of the number of tuning parameters will lead to a very rapid increase in the number of iterations needed. Moreover, parameters that prove effective for one particular stage may not be suitable for others, indicating the necessity of a multi-stage tuning approach that ensures smooth evolution of the tuning parameters for the different stages. Therefore an automatic multi-stage tuning Optimizer becomes a necessity for a more detailed analysis, especially if the true optimal solution is sought for.

Optimization strategies have been used in recent years for the aerodynamic and mechanical design of turbo machine components [1]. In particular, numerical optimization techniques seem to be one of the most promising tools for the aerodynamic design of new generation turbo machinery components [2]. The current study focuses on efficient implementation of these optimization techniques in the performance tuning of centrifugal compressor stages.

An optimization procedure, intended for new designs of centrifugal compressor stages, has already been developed [3]. Effectiveness of this optimization algorithm is however somewhat limited, since the 1D performance predictions for these new designs need to be calibrated first with test data in order to be able to reliably estimate the expected flow behaviour through these designs. Considering the dependability of other downstream design chain tools on the accuracy of 1D tool [11], an effort has been undertaken to develop an automated optimization algorithm that tunes the 1D tool predictions with respect to experiment.

This led to the development of an optimization algorithm that interfaces an in-house developed optimization tool (PEZ) with an internal 1D prediction tool in order to provide the best possible 1D prediction within the given tuning limits. The aim of the current study is to develop and test an automated optimization algorithm that utilizes more tuning parameters to improve the accuracy of the 1D tool predictions when used for the development of new centrifugal compressor stages.

NOMENCLATURE

P	Integration Correction Factor	[-]
R	Gas constant	[J/kgK]
T	Temperature	[K]
Z	Compressibility factor	[-]
d	Normal distance between test and Prediction curve normalized by head or Efficiency at design point	[-]
k	Polytropic exponent.	[-]
n	Total number of test data	[-]
p	Pressure	[Pa]
w	Weight as specified by the designer	[-]

Greek symbols

η	Polytropic Efficiency	[-]
τ	Work Coefficient	[-]
φ	Flow Coefficient	[-]
ψ	Polytropic Head	[-]

$$\psi = \frac{ZRT_1}{\frac{k-1}{k}} * \left[\left(\frac{P_2}{P_1} \right)^{\frac{k-1}{k}} - 1 \right] \text{ for real gas}$$

ξ	Factor segmenting a speed line as specified by user	[-]

Abbreviations

CC	Centrifugal Compressor
Devi	Deviation from Default
GA	General Algorithm
LL	Left limit $= \frac{\text{mass flow rate at surge limit}}{\text{mass flow rate at design point}}$ [%]
OF	Objective Function
OFMOD	Modified Objective Function
RL	Right limit $= \frac{\text{mass flow rate at choke limit}}{\text{mass flow rate at design point}}$ [%]
W_devi	Weight Factor

Subscripts

dp	design point

STAGE FAMILY DESIGN

Centrifugal compressors are usually designed in families intended to cover a specific use or demand (pipeline, high head, high efficiency, etc.). Each individual design within the family (family member) is of different size. The individual designs in a family stretch from low to high design flow coefficients and sometimes from low to high design Mach numbers. Each family member is defined with one design flow coefficient and speed, but also with a useable flow range and speed range (typically 60 - 180% on flow coefficient and +/-40% on speed ratio, with respect to the design point). A chosen number of the designs (test masters) are selected for testing and then tuned to test data. The choice of the test masters is done in such a way

[1] The baseline is represented by the default tuning parameter values

that the entire matrix of the stage family can be created by interpolation of data between tested and tuned masters. The tuned test masters are then transformed into database masters, which in turn are used to populate the design database. Following a customer order, the design database is used to model a multi-stage compressor based on the customer needs. The time between a customer demand and a complete offer is typically a few weeks. Within this time, it is not possible to perform very detailed analyses of the proposed machine. A well-calibrated database and 1D performance tool are therefore of essence.

PREDICTION TOOL DESCRIPTION

Performance assessment of the preliminary and trial designs is done using an internal 1D prediction tool. This tool is originally a commercial tool [4] but is now being developed in-house. It is extensively used for preliminary design and performance analysis of single-stage or multi-stage configurations at design point and off-design.

The tool computes quantities such as polytropic efficiency, polytropic head, pressure ratio, surge (LL), and choke (RL) limits with geometric outline of the stage and operating conditions (inlet pressure and temperature, mass flow, rotation speed, gas properties, etc.) as input. The geometry taken into consideration should at least be composed of an impeller, a diffuser, and an exit system but a wide variety of components can be used including [5]:

- Inlet guide vane
- Impeller with/without splitter vanes, shrouded or unshrouded
- Vaneless or vaned (low solidity, cascade, wedge) diffuser
- Return channel
- Exit system (scroll, collector, deswirl etc.)

For each component type, the user is requested to provide the geometrical data defining its outline (meridional and blade-to-blade). These parameters are written in an input file, while the results of the calculation are stored in the output file where the results are presented in modules repeated for all design and off-design conditions. By exercising the prediction tool with this geometry, the associated performance parameters can be extracted from the corresponding output file. Obviously the quality of the optimization strongly depends on the quality of the prediction tool.

Over the years, taking advantage of test feedback on both single-stage test vehicles and full-scale compressors from fleet, the models used for the computation have continuously been refined and the critical parameters have been fine-tuned in order to obtain the best possible prediction of performance parameters in alignment with the experiments. Until now, however, this refinement has been done manually and using a limited number of tuning parameters.

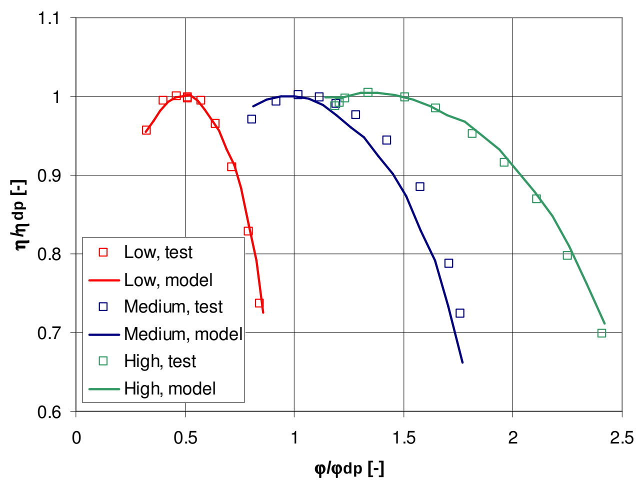

Figure 1 Comparison between predicted and tested efficiency

An experimental validation of the prediction tool for one of the older stage designs indicates the importance of family tuning that improved the accuracy as shown in Figure 1 and Figure 2, low, medium and high representing respective flow coefficient categories normalized by the medium design flow coefficient. The normalized polytropic efficiency and the polytropic head are plotted versus the flow coefficient normalized by the medium design flow coefficient. It can be seen that the family tuning does not necessarily mean an optimal tuning for all the individual family members, since the goal is to find an optimal overall match.

The measurement equipment used for the model tests are calibrated to traceable standards according to ISO 9000. The measurement accuracy is ±0.5% of max range for the pressures and ±0.1degK for the temperatures, leading to an estimated accuracy of ±0.5% of max range for the performance data.

USUAL TUNING PROCEDURE

In the usual in-house tuning, the main effort is put on the design point, which is tuned mainly with factors on the efficiency and the impeller exit flow angle. The intention is to match the polytropic efficiency and head as close as possible. Impeller inlet loss models are then adjusted to improve choke and stall limits. All this is done individually for each design flow coefficient stage. The shape of the performance curve is not necessarily followed.

The variations in speed ratio for each design flow coefficient are usually not tuned, only checked. Once all designs have been tuned, the resulting parameters are compared and in order to ensure a smooth evolution for the tuning parameters between the different design flow coefficients, some of them are adjusted at this point.

At one occasion, a manual tuning with six family members and seven tuning parameters per member was performed. This particular exercise took nearly two months to do, when performed by a highly experienced engineer. This is simply due to the fact that many tuning parameters are involved that need to be optimized keeping in mind several constraints (smoothness, off-design match, etc.) and objectives. There are also no guarantees that the solution found at the end of this manual process is the optimal one.

OPTIMIZATION APPROACH

The optimization algorithm (from here on referred to as “the Optimizer”) developed is capable of tuning the entire CC stage family with ‘n’ number of speed lines in both design and off-design conditions simultaneously. It can handle all the CC stage types and masters of different mass flows having the same design peripheral Mach number. The input details needed for the Optimizer are files defining the stage parameters and corresponding experimental data for all the stages that are to be tuned. The Optimizer works most effectively if the operating range from experimental data and the predicted curve (right and left limits) are in alignment. However, the Optimizer controls the number of points on the prediction curve while tuning the parameters. The positioning of the prediction points at surge and choke limits is taken care of by the engineer while preparing the input data for the stage parameters. The Optimizer is flexible enough to be used both for the tuning of single stage and for the entire CC stage family, handling any number of tuning parameters. The main objective of the Optimizer is to minimise the RMS value of the error between tested and predicted values. The error as stated here consists of two components, the first one indicating how far the predicted point deviates from the experimental data (Error); and the second one indicating how much the tuning parameters deviate from the default value as specified by the user (Devi).

These two factors can be given variable weights by the user, in specifying a W_devi factor, depending on whether the designer wants the parameters to be very close to the default values or to accept a larger deviation.

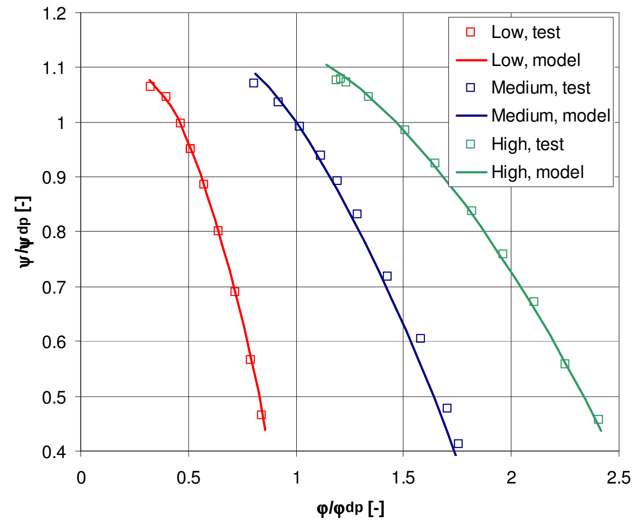

Figure 2 Comparison between predicted and tested head

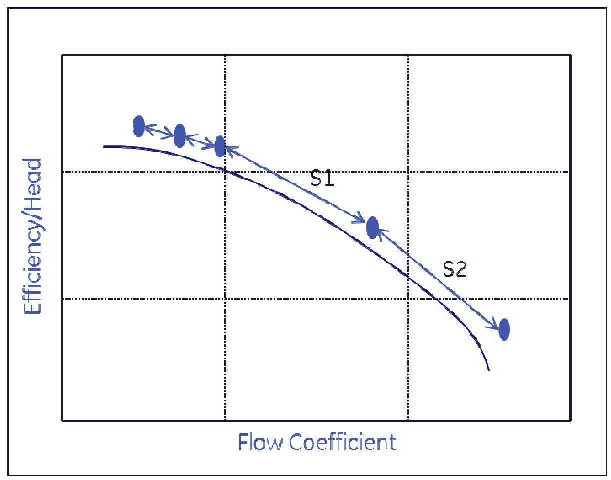

Figure 3 Error definition of individual points

$$P = \frac{S1 + S2}{2} \tag{1}$$

$$\text{error} = \frac{\sum_{n} (P * w * |d|}{\sum_{n} (P * w)} \tag{2}$$

In Figure 3, S1 and S2 are distances between the point currently being treated by the Optimizer and the two adjacent points, If the points are farther away, the values of S1 and S2 are greater and hence the contribution of this P value to the error will be higher compared to points that are located closer to one another. For the first and the last points, the P value will be equal to either S1 or S2 alone. In this way, the Optimizer handles also any uneven distribution of data points effectively. The Optimizer is also capable of handling variable weights for individual points for the experimental data as defined by the user in the input file.

Additionally, the design and off-design conditions can be handled separately by assigning them to different groups with different weights, if the user wants to concentrate on a specific part of the performance curve. The design speed itself is categorized into three groups, whereas the off-design speeds are categorized in to two separate groups as shown in Figure 4.

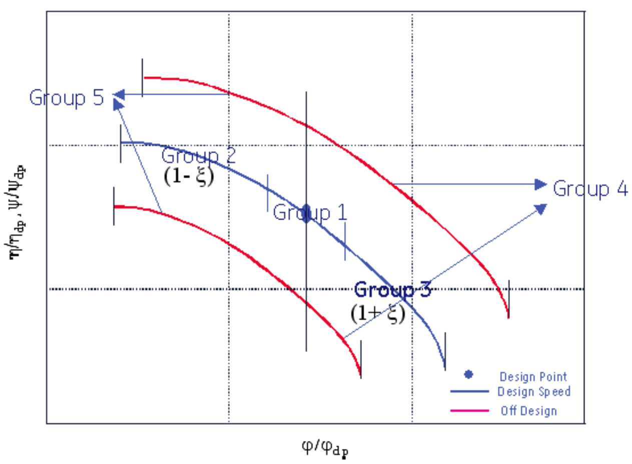

Figure 4 Group definitions inside the algorithm

When adjusting the tuning parameters the aim is to ensure a smooth evolution of them with design flow coefficient. This is achieved by means of defining a polynomial function (linear or quadratic) across each parameter for the entire family. The Optimizer is looking for this smooth evolution as close as possible to the default values by normalizing each parameter value by the user specified bounds. The normalized results are assigned each to a specific factor. The deviation is calculated as the sum of all the factors.

Figure 5 shows the behaviour of one tuning parameter, associated with the impeller performance correction, comparing two sets of automatic family tuning with two individual manual tunings. Family 1 (F1) was performed with four masters and a quadratic parameter fit and Family 2 (F2) used three test masters and a linear parameter fit. It clearly indicates the smooth evolution of the tuning parameter resulting from the family tuning, compared to the manual tuning. On top of that, the family tuned parameter values are varying less with design flow coefficient and are equal to the manually tuned value, or closer to the default value.

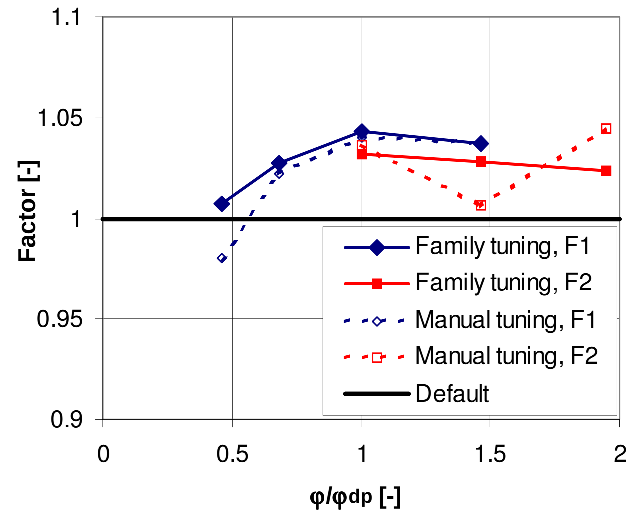

Figure 5 Comparison with manual tuning

In the algorithm, the 1D performance prediction tool has been interfaced and driven by an in-house developed optimization code (“PEZ”, Perl Version of Easy Optimizer)[9], [10]. The optimization plan used in this case starts with a differential evolution (DE) genetic algorithm [6], [10] step, followed by a second step that utilizes a simplex-based optimization algorithm (AMOEBA)[7], [8]. The genetic algorithm (GA) method is used because of its robustness and global search capabilities. The AMOEBA method is used to speed up the process of arriving at the final optimum design once the most promising part of the design space is identified using the first GA-based step.

The PEZ implementation of any of these two optimization methods consists of three main sections. Figure 6 shows the sequence of the optimization plan for both methods. In the first section, the objective function and constraints are defined based on user input values. Additionally, the initial design performance is computed. The second section is the optimization loop, in which the Optimizer will change the tuning parameters. The procedure effectively uses the prediction tool as a black box solver.

The GA method randomly generates the tuning parameters. Therefore, the initial set of parameters is needed only for performance normalization.

$$\mathrm{OFMOD} = \sum error + W\_devi * devi \tag{3}$$

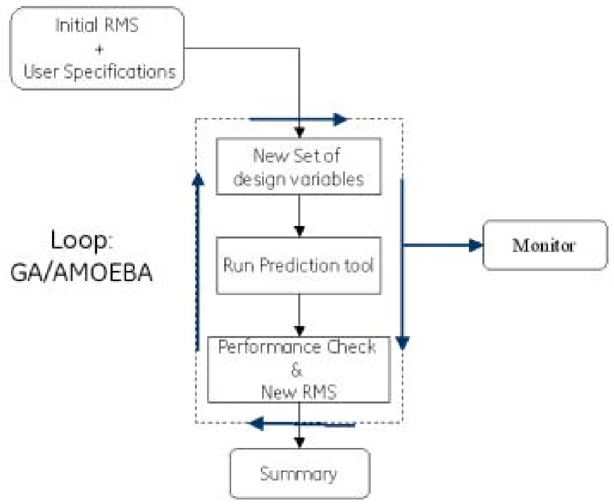

Figure 6 Optimization strategy plan

In the above equation (3), "error" accounts for the RMS value of the total error between predicted point and test data and "devi" accounts for the deviation of each tuning parameter from the default value. W_devi is the weight specified by the user in order to determine how stringent the demand to be close to default is. The higher the value, more the parameters are forced close to the default values.

The objective of the algorithm is to minimize the OFMOD function.

OPTIMIZATION RESULTS

The optimization algorithm was tested in two cases for in-house standard centrifugal compressor stage family masters. For both cases, seven tuning parameters were used. These included inlet loss coefficients, critical speed factors, separation factors, exit angle factors, efficiency correlation factors and blockage factors, but the Optimizer is not limited only to these parameters. The optimization was performed for polytropic efficiency and head. The design point was given a 20 times weight compared to the off-design points and a W_devi factor of 5:1 was used, meaning that the tuning parameters were kept very close to the default values. The CPU time needed was approximately one week per set of masters. This is to be compared to the two months spent by an experienced engineer performing the tuning manually in order to get an acceptable, although not necessarily optimal, tuning.

Case 1

For case 1, the optimization process tuned four masters, each with three speed lines. The variations in design were such that the largest design flow coefficient was approximately three times the smallest design flow coefficient.

Figure 7 shows the results of one of the four masters tuned with respect to experiment at design speed. The values are normalized with respect to the baseline design point value in order to show the existence of significant differences between predicted and experimental values.

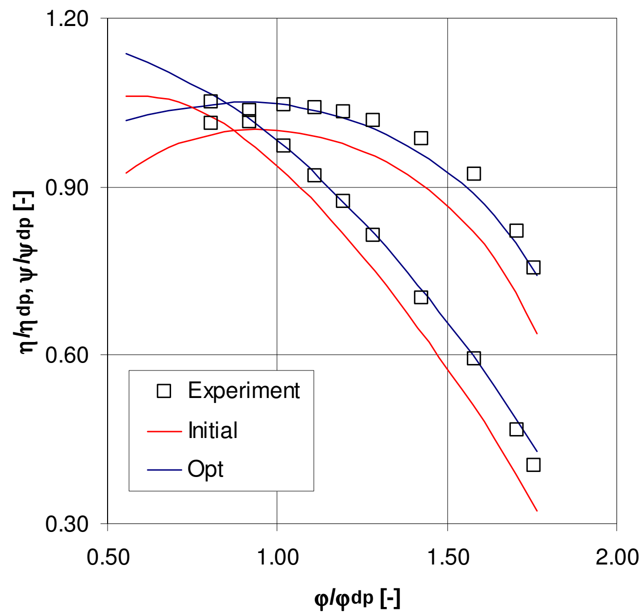

Figure 7 Optimization results for polytropic efficiency and head

This procedure was able to reduce the objective function value by almost 80% compared to the baseline.

Case 2

The second case was an investigation of various settings of the Optimizer. Six masters, each with four speed lines were used. The largest design flow coefficient was approximately six times that of the smallest design flow coefficient. An illustration of the total number of test data to be used in the tuning can be seen in Figure 8. All data have been normalized with the intermediate design flow coefficients values.

The Optimizer was set for either a linear or a quadratic evolution of the tuning parameters. In addition, only the two largest and the two smallest design flow coefficients were calibrated from true model test data. The test data for the two intermediate design flow coefficient was created from fleet feedback. The tuning was run both with and without these quasi-test configurations. Also individual tunings of each of the six masters were performed. Consequently, four sets of family tuning and one set of individual tuning were run:

1. Individual tuning of each of the six masters.
2. All six masters, linear parameter evolution
3. All six masters, quadratic parameter evolution
4. Only the four model test masters, linear parameter evolution

5. Only the four model test masters, quadratic parameter evolution

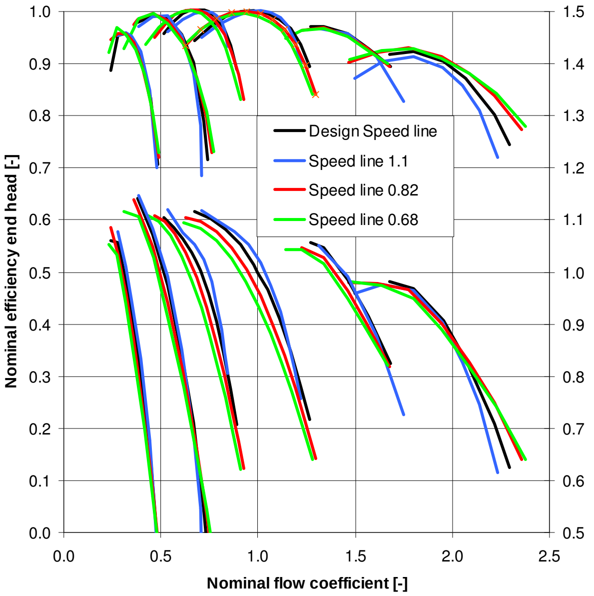

Figure 8 Test data used for the family tuning

In the individual tuning, there is no choice between linear or quadratic parameter evolutions, since only one design flow case is run at a time. The final value of each tuning parameter is what the Optimizer determines to give the optimal RMS value.

The results of these 5 tunings were compared with a previous tuning, performed by hand, using only three tuning parameters and performed only on the design speed line.

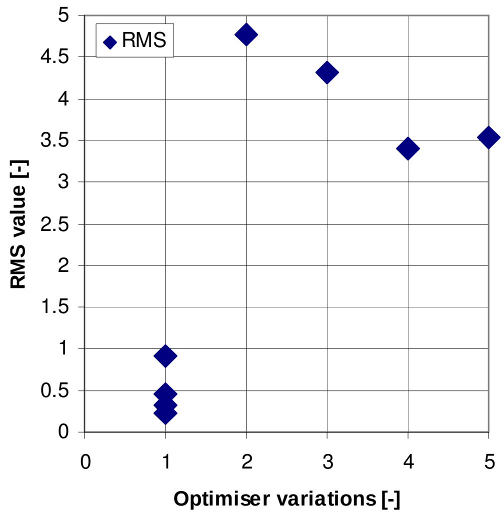

Figure 9 RMS values of tuning setups

Figure 9 shows the development of the RMS value for the five different calibrations. Please note that the individual master tuning consists of six individual tuning runs (some points are overlapping). As can be expected, the less number of masters, the lower the RMS value. In Figure 10, an example of a resulting tuning parameter is shown. The design flow coefficients have been normalized with an intermediate design flow coefficient value. All variations of tuning cases give the same general development of the parameter value, including the previous, manual tuning. It can be seen that although the RMS value of the individual tuning (Figure 9) is the lowest, the development of the parameter value with nominal design flow coefficient is not smooth and would be very difficult to use in the consequent creation of the design database.

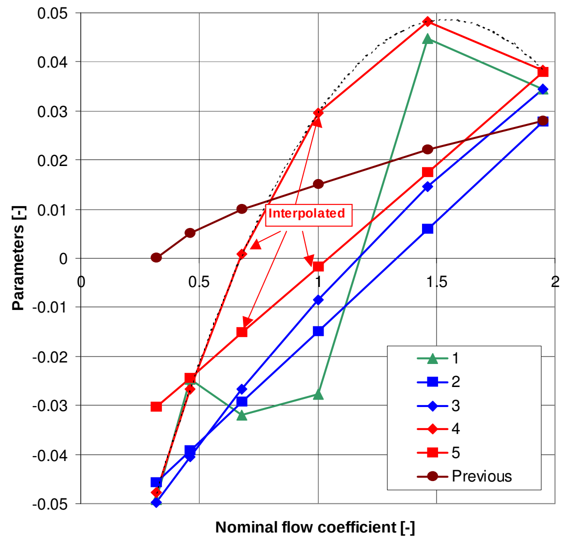

Figure 10 Example of tuning parameter evolution

The results of the various tuning options tested, can be found in Figure 11 for one master and the design speed line. It can be seen that, especially for the head, all the family tunings are better than the previous tuning. There are however cases, that for this particular speed line, could be done better. This is the moment when one must realize that this is just one part of the answer.

In order to determine which calibration is the most suitable, ALL of the masters and ALL of the speed lines have to be considered. In this particular case, this results in 24 efficiency and 24 head curves to be studied. This is an objective procedure. The engineer must use his/her experience and knowledge of the intended use of the particular family, in order to determine which of these calibrations is the optimal one.

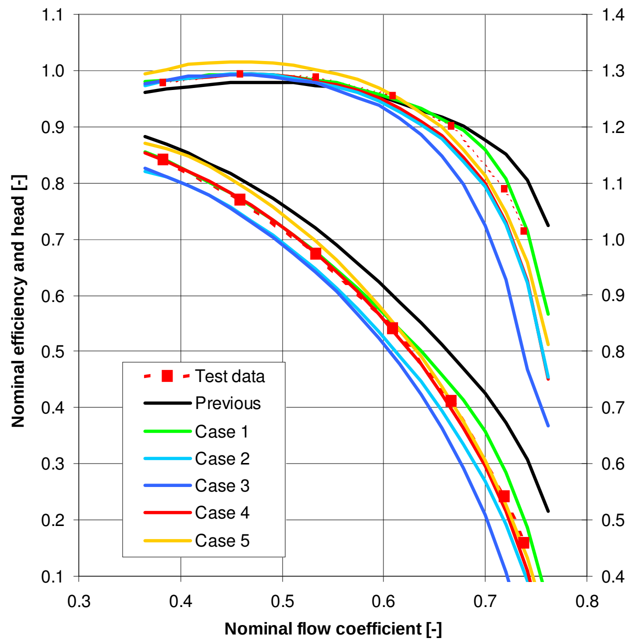

Figure 11 Result of tuning options on one master and one speed line

SUMMARY AND CONCLUSIONS

This paper presented an automated optimization procedure for model tuning of a 1D model of centrifugal compressor stages with respect to experimental data. The traditional tuning consists of manually tuning a limited number of parameters, for one stage at a time and concentrating mainly on the design point, the choke limit and the stall limit. The family grouping of the tuning parameters is thereafter done manually by adjusting chosen parameters afterwards, if needed, in order to get a smooth parameter evolution through the family. This process is subjective, time-consuming and non-optimal. A novel, automatic optimization method has been developed, which takes into account a larger number of tuning parameters, ensures an optimal matching with test data and allows for the tuning of the entire family together, thus ensuring a smooth evolution of the tuning parameters. Moreover, every test point is taken into account, resulting in a tuning that follows the actual shape of the test data curve. In this way, a more physical representation of the test data is achieved. The optimization method interfaces an in-house developed optimization code (PEZ) tool with the 1D prediction tool to provide the best possible solution within the given tuning limits. A global optimization technique (GA) was first employed. The obtained variables are further refined using a local optimization technique (AMOEBA). In the optimization process, the chosen set of variables is tuned with the objective of minimizing the RMS value of the total error between tested and predicted data. This algorithm was tested with in-house standard centrifugal compressor stage family masters and the total error value has been reduced by up to 80% with respect to the baseline. The Optimizer ensures smooth evolution of the tuning parameters close to the default criteria specified by the user. In general, the optimization process resulted in a significantly more accurate prediction of performance parameters, for an entire family, in alignment with the experiment and a quicker run-time for the optimization.

FUTURE WORK

Due to 1D modelling issues, both the usual manual tuning and the one presented here, automatic optimization, work only on impeller losses. That is, instead of attributing losses to where they actually occur (diffuser, return channel, etc.), all losses are imposed on the impeller in order to get a correct global performance. For stage performance predictions, this is good enough, but with future demands on improving individual components, there is a need to improve loss modelling on all components within a centrifugal compressor stage. For this work to be successful in the concept of automatic tuning, it is of essence to improve both the 1D modelling and to allow for an extended range of tuning parameters to be allowed in the Optimizer.

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