

Potential of Surrogate Modeling in Compressor Casing Design Focusing Rapid Tip Clearance Assessments

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ABSTRACT

Tip clearance-induced losses constrain decisive improvements in system efficiency and aerodynamic operational stability of aero engine axial compressors. The tendency towards even lower blade heights to compensate higher fluid densities aggravates their influence. Generally, it is emphasized to preserve the tip clearance at a minimum but large enough to prevent a collision of the blade tip and the casing during the entire engine mission. The present work concentrates on the development of a preliminary aero engine axial compressor casing design methodology involving metamodeling techniques. Previous research work at the Institute resulted in a 2D axisymmetric Finite Element model of a generic multistage high-pressure axial compressor casing. Subsequent sensitivity studies led to the identification of significant parameters important for fine-tuning the tip clearance via specific flange design. This work is devoted to explore the potential of Surrogate Modeling in preliminary compressor casing design with respect to rapid tip clearance assessments and corresponding precision compared to Finite Element results. Reputed as data-driven mathematical approximation models and conceived for numerical inexpensive simulation result reproduction, Surrogate Models evolve their capacity when linked with extensive design space exploration and optimization algorithms.

Compared with high-fidelity Finite Element simulations the reductions obtained in computational time amount to 99.9% in favor of the Surrogate Models. Validated via statistic methods and dependent on the training database size, the precisions of the Surrogate Models reach down to the range of manufacturing tolerances. Subsequent inclusion of the Surrogate Models in a parametric optimization process concerning tip clearance minimization rapidly returned adaptations of the geometric design variables.

Keywords: Surrogate Modeling; Compressor Casing Design; Finite Element Method;

NOMENCLATURE

Abbreviations

DSE	Design Space Exploration
FE	Finite Element
2D	Two-Dimensional
3D	Three-Dimensional

Symbols

r, φ, z	Components of the Cylindrical Coordinate System
H	Flange Height Selected for Parameter Variation
P	Flange Positioning Selected for Parameter Variation
p	Pressure
T	Sink Temperature
W	Flange Width Selected for Parameter Variation
α	Heat Transfer Coefficient
μ	Mean Value
σ	Standard Deviation

Subscripts

a	Surface of the Outer Side of the Casing
c	Stator Cavity Surfaces wetted with Leakage Flow
i	Surface of the Inner Side of the Casing
m	Surface of the Inner Casing Structures
p	Peripheral Surfaces of the Casing

1.0 INTRODUCTION

Reduced expenses linked with reduced time to market from the first concept towards the final product implementation are of major interest in aero engine development processes. Especially the multidisciplinary modeling in the preliminary design phase of aero engines includes significant potential for pioneering process optimization. The present project concentrates on the development of a preliminary aero engine axial compressor casing design methodology, involving metamodeling techniques and approaches for numerical model simplification. Proceeding from an initial casing geometry and based on given rotor expansions, a method allowing prompt tip clearance assessments is developed.

As a consequence of changed thermal as well as pressure driven expansion and centrifugal forces during engine operation, the tip clearance defined as the radial distance between rotor blade tips and the casing is of transient character. Generally, tip clearance-induced losses correlate with the relative ratio of blade height and tip clearance gap width [1-3]. The tendency of future compressors having lower blade heights exacerbates the impact of losses due to the increase of relative tip clearance values. A decrease in engine performance and limited operating range is the corresponding response. For enabling improved thrust-to-weight ratios and service life it is fundamental to preserve the tip clearance at a minimum but large enough to prevent a collision of the blade tip and the casing. The scope of this work is restricted to symmetrical variations in tip clearance.

Dedicated to develop promising approaches for numerical model simplification, previous studies at the Institute [4,5] investigated and quantified the effect of circumferentially repeated 3D features on radial displacement of a generic compressor casing assembly first. Bolted joints, bleed air ports, different types of stator stage and casing designs are just an example of many different 3D features compressor casings of modern aero engines involve. To obtain reductions in pre-processing and computational expense the transition from 3D to 2D axisymmetric Finite Element (FE) modeling was strived and fundamental parameter studies were conducted to prove validity. In terms of a concise review, initial

work [4] considered the effects related to variation of the circumferential quantity and diameter size of bleed air ports and bolted joints. Subsequent work [5] covered the effects associated with stator cavity leakage flows and stator geometry treatment variation, while the latter issue differentiates between supporting and non-supporting structure as a type of 3D features. Concerning project intended rapid tip clearance assessments, the evaluation part focused only selected paths located on the inner casing surface wetted with the compressed core flow. Calculation of the deviations in radial displacement caused by the 3D features investigated and corresponding result interpretation clarified, that the effects move within the magnitude of manufacturing tolerances. Consideration of stator cavity leakage flows was considered to be an adequate next topic for future work. Continuative work at the Institute [6] addressed the identification of parameters relevant for fine-tuning the tip clearance via specific flange design by means of sensitivity analysis. Referring to the rear section of the general arrangement given in Figure 1 and based on the results stated in [4,5], the 2D axisymmetric FE model of a generic multistage high-pressure axial compressor casing was created first. For parameter variation, a flange placed in the middle of the multistage compressor casing was selected and the effects on radial displacement were evaluated at different positions. As geometric parameters the flange height, width and positioning were taken into account. Modification of the heat transfer coefficient assigned at the surfaces of the selected flange served as thermal parameter variation. Flange height and width variations indicated similar tendencies in affecting the radial casing displacement. In case of preference, the first mentioned option manipulates the casing stiffness more intense. Modification of the flange positioning allowed for slight adaptations in casing stiffness including increased and dropped radial displacement characteristics at once. The effect of changed heat transfer coefficient values emerged to lead the sequence of parameter preference for fine-tuning the tip clearance, followed by flange height modification.

Present work focuses on the involvement of Surrogate Modeling in FE-based preliminary compressor casing design. Reputed as data-driven metamodeling technique this method represents an attractive option to allow inexpensive reproduction of numerical simulation results. For reasons of consistency with previous work [6], again the 2D axisymmetric FE model representing a generic multistage high-pressure axial compressor casing was used including all boundary conditions. For FE data generation the geometric casing flange design parameters were varied. The precision of FE simulation result prediction as well as the associated time expense were the key aspects evaluated. The inclusion of Surrogate Models in an optimization process with the objective to receive an optimized parameter set for tip clearance minimization very successfully solved the problem addressed here.

The structure of this paper is as follows. First, an introduction into Surrogate Modeling will be provided, including a brief literature review as well as an instruction of the procedure applied at the Institute. A description of constructional aspects in compressor casing design and the complete model setup will be presented in the next sections. Subsequently, the related results of this work will be described and discussed. Finally, conclusions of the present work and prospects for future work will be given.

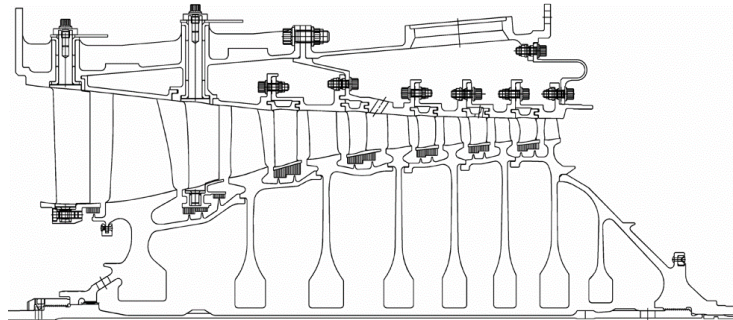


Figure 1: Generic Compressor General Arrangement [7]

2.0 SURROGATE MODELING

Detailed Finite Element Analysis of complete compressor casing assemblies are very time-consuming. Design Space Exploration (DSE) of the structural response across different parametric combinations help to understand the correlation of design variables and to optimize a design, achieved through the required large number of analyses. Compared with conventional Finite Element Analysis and especially when linked with DSE, Surrogate Modeling represents an attractive alternative. Based on the training data stored from previously analyzed designs, Surrogate Models are data-driven mathematical approximation models for numerical inexpensive result reproduction of new designs. Consequently, for providing the ability to predict reliable results of new designs with negligible additional effort, the initial expense of Surrogate Modeling lies in creating training data of specific designs. [8]

The number of reports dealing with applied Surrogate Modeling in turbomachinery engineering indicates an increased trend of interest in industry and academia. Recent work [8-12] utilized this technique to predict structural responses from Finite Element Analysis. In 2017, for instance, Zhang et al. [9] and Geller et al. [10] explored and optimized the design of various turbomachinery engine components. With concentration on the maximum stresses as single structural value rapidly emulated by a Surrogate Model the geometries considered were a turbine disk [9] and compressor impellers [10]. Both publications mention an accurate estimation at negligible computational cost compared to Finite Element simulation results. Furthermore, Heap et al. [11] and Walther et al. [12] derived innovative methods for the expansion from single-value towards a multi-value result prediction. By representing the stress of every node with a unique Surrogate Model, Heap et al. [11] found that entire stress distributions are predictable. Concurrently, this method required that the nodes of the mesh structure specified for FE result reconstruction via Surrogate Models shared an identical relative position across each of the FE models used in training. Implementation of a parametric mesh limited the study to simple parts. Next, Walther et al. [12] detected that Surrogate Models permit accurate predictions of nodal locations of very complex geometry. Instead of setting up a parametric mesh, as done by Heap et al. [11], mesh morphing was used. This meshing strategy granted Walther et al. [12] the prediction of more complex geometry. In 2018, Bunnell et al. [8] pooled the possibilities identified by Heap et al. [11] and Walther et al. [12]. A method for reproduction of the entire stress distribution and geometric shape of turbomachinery engine components was developed. Thus, each nodal stress value and position was emulated using a unique Surrogate Model. By means of mesh morphing the requirement of an identical FE model mesh structure was satisfied. An essential motivation was to perform DSE on compressor blades seeking to understand the full structural response across different parametric combinations. For visualization, Figure 2 compares the von Mises stress distribution at the suction side of a compressor blade calculated via Surrogate Models and FE simulation. The color scale was matched. X indicates the maximum stress position and O the minimum stress position. Referring to Bunnell et al. [8], the FE results and Surrogate Model predictions exhibited comparable geometric shape, stress distributions and magnitudes. FE result reconstruction via Surrogate Models correctly predicted a region of high stress located at the root of the blade at the middle of the chord. Less than 5% error was achieved on all the tested blades.

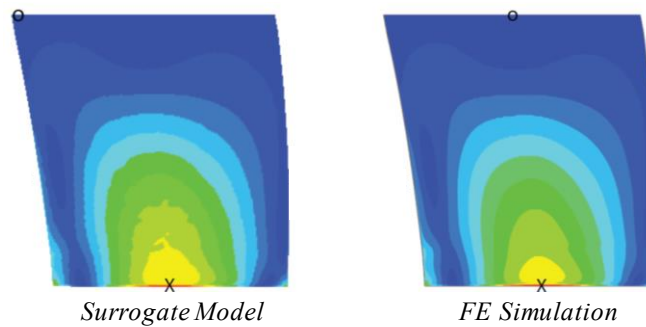


Figure 2: Von Mises Stress Distributions on the Suction Side of a Compressor Blade published by Bunnell et al. [8]

The procedure applied for Surrogate Model generation of this work is illustrated in Figure 3. Subsequent to the definition of variable design parameters, the Monte Carlo sampling method was chosen for extensive database creation. It relies on random sampling to explore the design space. Full Factorial, Fractional Factorial, and Basic Latin Hypercube are well-known alternative sampling methods, but not recommended in literature [13]. Next, FE models of the new design parameter combinations received from the Monte Carlo sampling method were set up and solved by means of the commercial software Abaqus FEA. Simulation result evaluation at specified nodes supplied the database with response values for given sets of design parameter combinations. Provisionally, the Gaussian Process Regression was selected as algorithm for generating the Surrogate Models. The Gaussian Process Regression, in the geostatistics field also known as Kriging, represents a nonparametric kernel-based probabilistic approach, widely used in applied mathematics, statistics and machine learning for constructing Surrogate Models [13-15]. Trained on the information stored in the database the Surrogate Models created allow for rapid result predictions of new design parameter combinations. The procedure was automated using the commercial software Matlab by MathWorks.

Implementation of alternative options for Surrogate Model algorithms has to be tested in future investigations with a focus on training time, robustness, predictive speed as well as accuracy. Consulting literature [8,16] the Radial Basis Function is rated as the most dependable method in terms of accuracy and robustness, performing well with sparse training data in design spaces including many parameters. In contrast, first studies applied to the case presented in this work proved much better results in terms of accuracy and time consumption when implementing the Gaussian Process Regression. A brief résumé of selected Surrogate Model algorithms extracted from literature [8,13,14,16,17] is given in Annex B of this document.

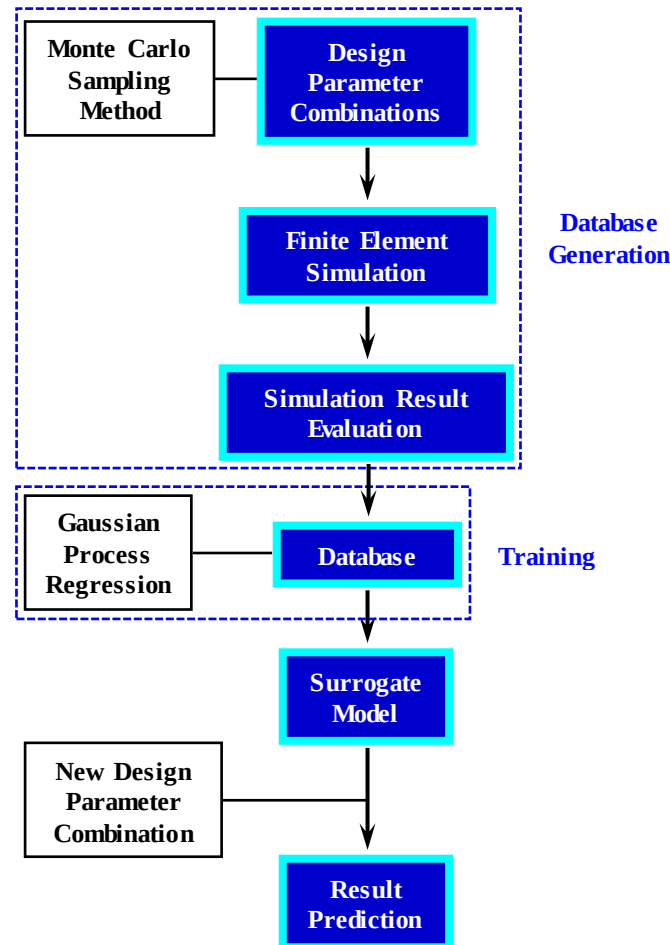


Figure 3: Procedure of Surrogate Model Generation

3.0 COMPRESSOR CASING DESIGN

Traditionally, designs of compressor casings are highly coupled to the technology available at the time of design, depending on technology-determining characteristics like the materials used or the manufacturing methods applied. Bretschneider et al. [18] identified a high level of similarity among compressor casing designs disclosed by aero engine manufacturers. Sustained by engine family concepts using a similar, scaled or further developed high-pressure system on the basis of high commonality, this tendency is a direct consequence, driven by saving development cost and simultaneously implementing mature successfully marketed component technologies [18].

In practice, mixed architectures between the four types of axial compressor casing design illustrated in Figure 4 are prevalent. Most of the current aero engine axial compressor casings feature an axial split in the front stages and change to a combination of double-walled ring style in the rear section. The axial split casing design provides the required access for assembling variable stator vanes and the corresponding actuating mechanism. The radial split casing is preferred when short local casing elements are preferred per stage. Well-defined axial load transmission linked with provision of a very high casing stiffness is one of the main duties of the double-walled casing design, beside the accommodation of bleed air off-take in different stages. Frequently, the inner casing wall is thermally designed to allow tip clearance optimization in stages where rotor blades are physically small and the stage efficiency is very sensitive to changes in tip clearance. [18]

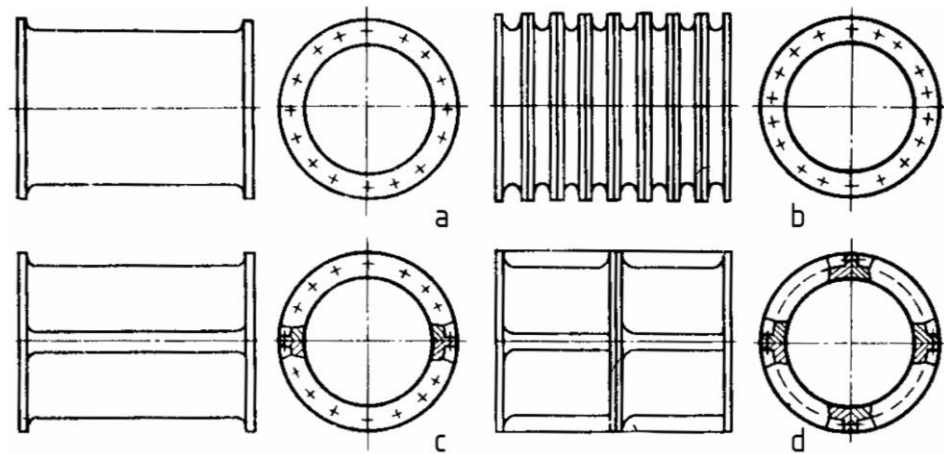


Figure 4: General Types of Axial Compressor Casings [18,19]

- a) Integral Case
- b) Radial Split Case
- c) Axial Split Case
- d) Double-Walled Case

For reasons of detailed categorization, literature [18] differentiates between mid-rotor split and inter-stage flange design as derived sub-elements. The mid-rotor split flange design is characterized by splitting the casing above the rotor and involves advantages for stiffness as well as blade-loss containment abilities. The abstraction of the inter-stage flange design stretches over a full stage, covering a stator and a rotor (or vice versa). Thus, it incorporates the rub-in liner for rotor blades as well as the T-Slot mount for stator vanes. A mix between both casing flange design shapes is possible but rarely found in existing aero engine arrangements. [18]

4.0 MODEL SETUP

This section describes the 2D axisymmetric FE model setup of the multistage high-pressure axial compressor casing assembly conceived for training database generation. Figure 5 visualizes the substantial architecture and a schematic of the boundary and load conditions implemented. Created referring to the rear section of the general arrangement illustrated in Figure 1, it represents a double-walled casing construction, combining radial split as well as inter-stage flange design. With respect to future work involving the extension of a given casing arrangement, a standardized component design process was established to allow addition of more casing rings and stators. Detail A defines the geometric parameters (height H , width W and positioning P) selected for modification of each flange within the restrictions listed in Table 1 and the red colored arrows indicate the corresponding directions of geometry variation. In order to avoid unfeasible geometry modifications linear inequality constraints had to be imposed between the flange widths and positions. If not specified differently, the flange dimensions used in the figures of this section correspond with the default values listed in Table 1.

Table 1
Geometric Flange Parameter Variation

	H	W	P
Minimum	1 mm	4 mm	1 mm
Maximum	25 mm	10 mm	12.75 mm
Default	14 mm	5.75 mm	3 mm

By means of the commercial FE software Abaqus FEA coupled thermo-mechanical implicit simulations were solved. As already mentioned, Figure 5 graphically summarizes the boundary and load conditions implemented as well. Index a describes the outer side of the casing, index i the inner side of the casing exposed to the compressed core flow and index m the surface of the inner casing structures wetted with bleed air. Considering leakage, index c characterizes those surfaces being in contact with the stator cavity leakage flow driven by the pressure gradient across the stator row. Index p designates the peripheral surfaces of the model. T symbolizes the temperature, p the pressure and α the heat transfer coefficient. The corresponding set of parameter values inserted is registered in Table 2. With reference to part contact definition between the involved components of the casing assembly the implementation was configured in consistency with previous work [4-6]. For heat transfer analysis tie constraints were introduced and subsequent substitution by surface-to-surface contact interactions permitted the transaction of thermo-mechanical analysis with allowed part separation. Moreover, an additional fixation is installed to lock the degree of freedom in φ - z -direction.

Provisional material selection for the complete casing assembly resulted in high temperature resistant Inconel 718. The isotropic material model implemented contains temperature dependent data for Young's modulus, Poisson's ratio, density, specific heat capacity, thermal expansion coefficient as well as thermal heat conductance sourced from [20-22]. Validation attempts ensured the correct reproduction of the material characteristics and an upgrade to a multi-material definition will be part of future work.

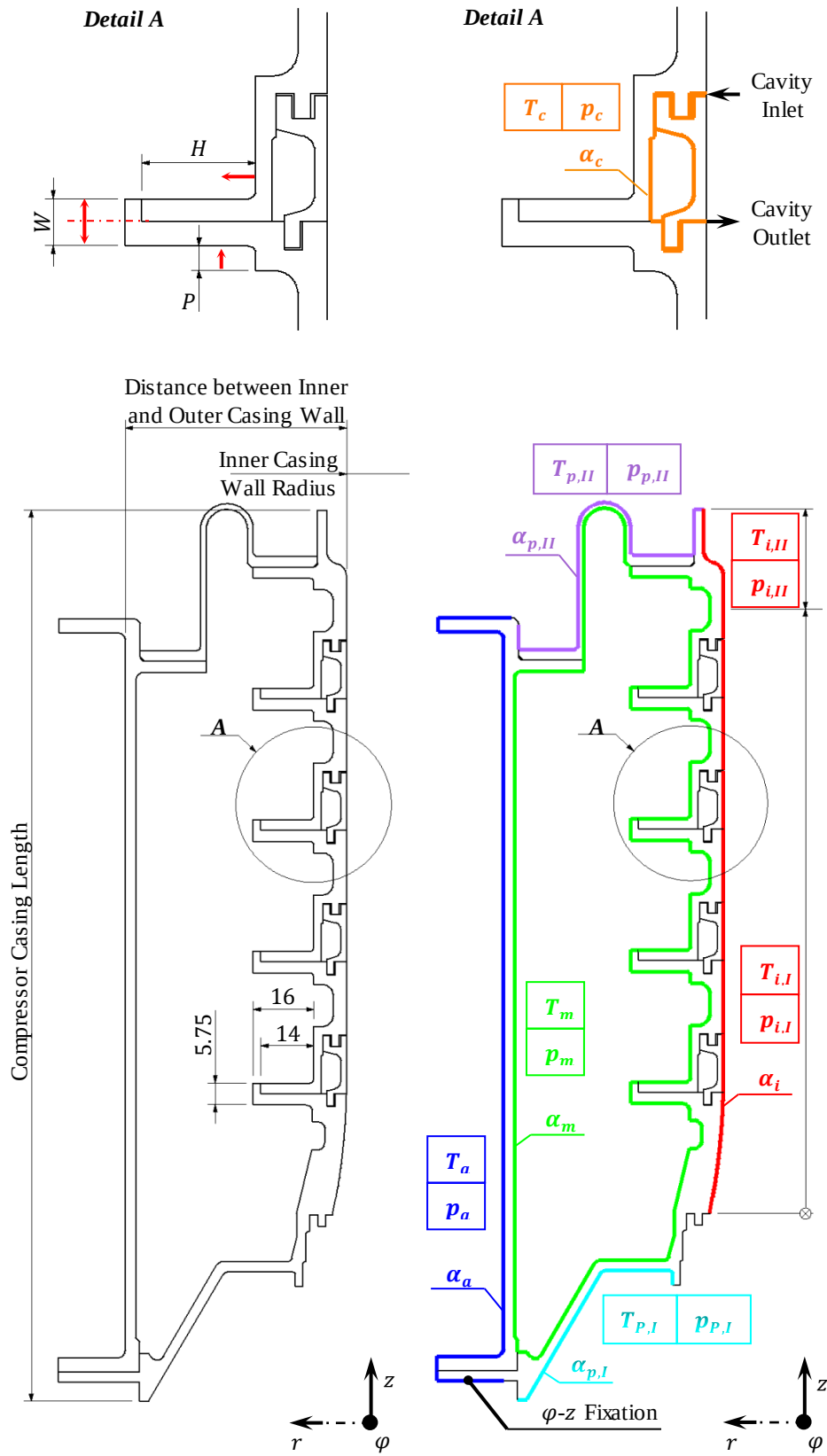


Figure 5: High-Pressure Compressor Casing Geometry (left) and Schematic of the Boundary and Load Conditions Implemented for the Compressor Casing Assembly (right)

Table 2
Parameter Settings Imprinted on the Surfaces of the
Generic High-Pressure Compressor Casing Structure

Parameter	Initial Condition	Initial Load
p_a	0 bar	1.01325 bar
p_c	0 bar	$p_{i,I}(z)$
$p_{i,I}$	0 bar	5.24 – 50 bar
$p_{i,II}$	0 bar	50 bar
p_m	0 bar	6.434 bar
$p_{p,I}$	0 bar	2.5 bar
$p_{p,II}$	0 bar	50 bar
T_a	273 K	293.15 K
T_c	273 K	$T_{i,I}$ at Cavity Inlet
$T_{i,I}$	273 K	490 K – 983 K
$T_{i,II}$	273 K	983 K
T_m	273 K	500 K
$T_{p,I}$	273 K	350 K
$T_{p,II}$	273 K	983 K
α_a	–	
α_c	–	
α_i	–	Depending on the Surrounding, the α Values Selected
α_m	–	Amount Between 10 and 1000 W/m ² K
$\alpha_{p,I}$	–	
$\alpha_{p,II}$	–	

The parameter settings registered in Table 2 are considered to be steady-state. They first define the case for an unloaded structure (Initial Condition). Subsequent an Initial Load Condition represents the load setting resulting from design point operation of a modern high-pressure compressor. The core flow pressure $p_{i,I}$ and temperature $T_{i,I}$ assigned were defined as z-dependent functions. Both increase linearly in flow direction. Compared with $p_{i,I}$ and $T_{i,I}$ the transition to $T_{i,II}$ and $p_{i,II}$ constitutes the end of the compression induced by the rotor. Consequently, $T_{i,II}$ and $p_{i,II}$ remain constant. In compliance with previous work [5,6] even pressure gradient driven leakage flows through stator cavities were considered via T_c and p_c . By setting p_c equivalent to the expression used for $p_{i,I}$ the corresponding pressure compensations from the cavity inlets towards the cavity outlets were configured. Constant values calculated for $T_{i,I}$ at the respective z-positions of cavity inlets were taken for T_c .

Exemplary for the hybrid computational grids generated and used in this work, Figure 6 shows the mesh of the 2D axisymmetric FE model of the compressor casing assembly for the case of default flange dimensions used. It consists of approximately 12,800 second-order elements and the mesh resolution is capable to provide smooth and converged computational solutions. Moreover, attention was paid to each contact surface in order to ensure node-to-node match between the part instances involved. The area within the red frame provides a zoomed detailed view of the meshed geometry.

The expansion behavior of the inner casing surface during engine operation is particularly relevant for an adequate tip clearance assessment. With a focus on radial casing displacement the measurement sites colored in red and displayed in Figure 7 were considered for FE simulation evaluation and training data supplementation. R represents the centered position right above rotor blades and S the centered position of the stator vane shrouds, respectively. Thus, resulting tip clearance formed by the rotor blade tips and the compressor casing will be calculated at the measurement sites R1, R2, R3, R4 and R5. The clearances described by the vane tips radially inboard of the stator vanes and the rotor drum will be calculated at the measurement sites S1, S2, S3 and S4.

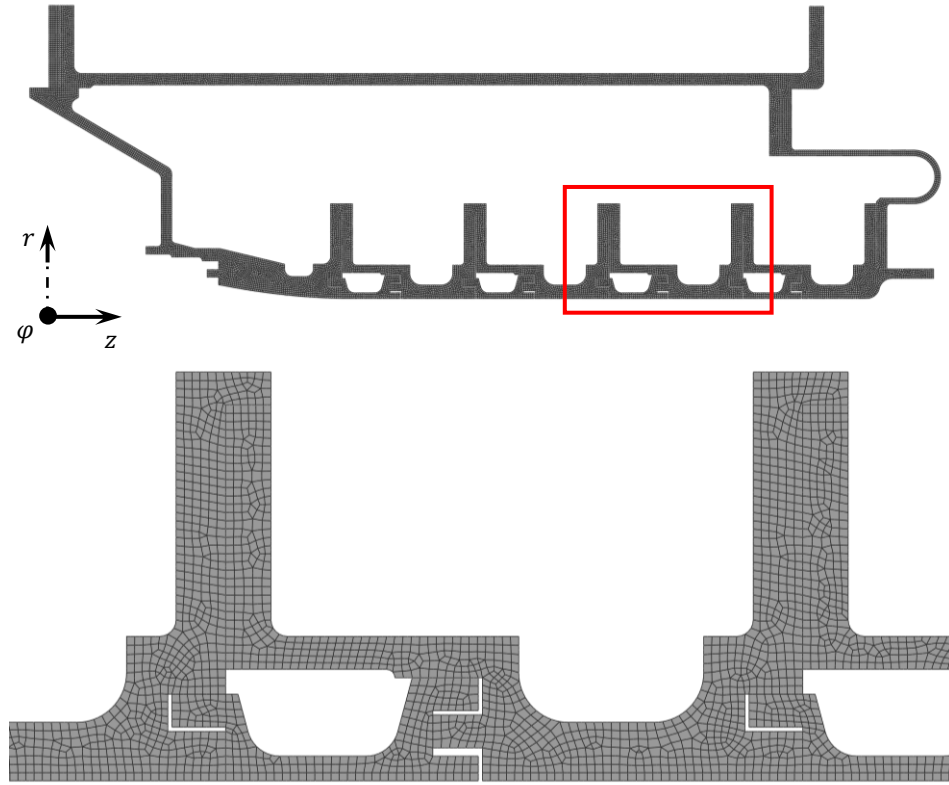


Figure 6: Generated Mesh of the 2D Axisymmetric High-Pressure Compressor Casing Assembly with Detail View

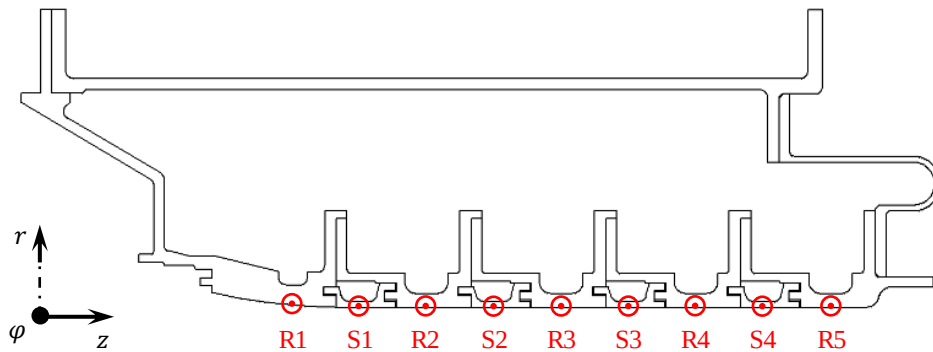


Figure 7: Measurement Sites Selected for FE Simulation Result Evaluation

5.0 RESULTS AND DISCUSSION

Referring to Figure 3 the database generated for this work covered the evaluation of 1,000 FE simulation results and stored 21 variables per FE simulation. For categorization, 12 variables involving the geometric parameter data H , W and P of 4 flanges were linked with 1 variable per measurement site containing data of the radial casing displacement. In total, this required to train 9 individual Surrogate Models.

5.1 Computational Expense

A summary of the elapsed times for the complete procedure with reference to Figure 3 is given in Table 3. The option to distribute FE simulations simultaneously on multiple computers and to combine the results subsequently allows for an even faster database generation than listed. Another correlation detected and shown in Figure 8 provides the increase in time required to train all of the 9 Surrogate Models when an increasing amount of data is stored. Due to the exponential escalation, the time required is considerable for even larger databases. Temporarily, the Gaussian Process Regression is responsible for this fact and future work will perform a comparison with alternative algorithms. Once the Surrogate Models training process is finished, there is no need for repetition unless the database is complemented. Compared to an individual high-fidelity FE simulation the reductions attained in computational time for prediction of new design parameter combinations amount to 99.9% in favor of the Surrogate Models.

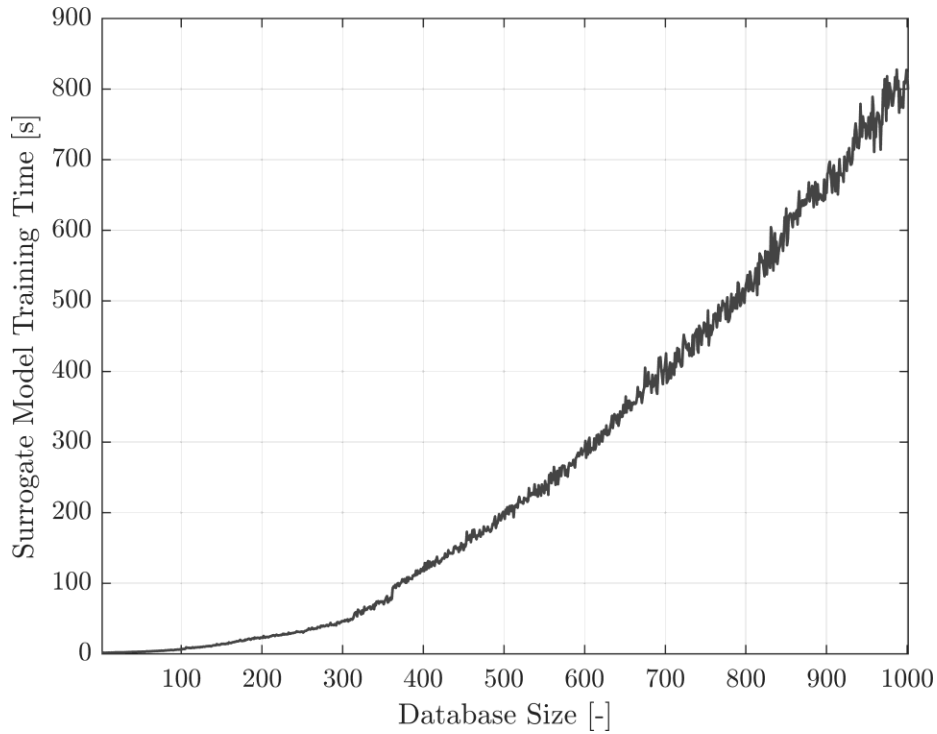


Figure 8: Evolution of the Elapsed Time for Training the Surrogate Models with Growing Database Size

Table 3
Elapsed Times for the Individual Processes in Surrogate Model Generation
Calculated with an Intel® Core™ i7-6700 3.4GHz Quad-Core Processor

Process	Time [s]
<i>FE Training Database Generation</i>	126,941.71
<i>Surrogate Model Training</i>	828.72
<i>Result Prediction</i>	0.15
<i>Total Procedure</i>	127,770.58

5.2 Validation and Precision

For validation of the results predicted by Surrogate Models, a verification database was generated. In total, it stored the FE simulation results calculated out of 50 different model setups with varied flange parameter sets randomly selected by means of the Monte Carlo sampling method. Subsequent to feeding in the equivalent parameter sets, the responses in radial displacement received from the Surrogate Models were compared with the FE results saved in the database used for verification. The precision the Surrogate Models provide was evaluated by determining the mean values μ and standard deviations σ of the complete set of verification cases. Both, μ and σ , were required to ascertain what type of distribution the errors in result prediction follow. In case of a normal distribution the $\mu \pm \sigma$ spectrum would indicate that approximately 68.3% of the calculated values lie within it, while for the $\mu \pm 2\sigma$ spectrum this percentage would increase up to approximately 95.4%. The Annex A of present work visualizes the histograms of both the dimensional and the percentage error in radial displacement result prediction determined for each measurement site. The mean values μ as well as the $\mu \pm \sigma$ and $\mu \pm 2\sigma$ restrictions are labelled and in Table 4 the percentage of values assessed within these spectra are registered. Compared with the normal distribution the number of cases within the confidence range were largely similar or even higher. In total, more than 90% of the verification cases were predicted correctly within the $\mu \pm 2\sigma$ spectrum.

Involving the complete set of measurement sites, the dependency of precision in result prediction via Surrogate Models based on the information stored in the training database is illustrated in Figure 9. Initiating with a $\mu \pm 2\sigma$ standard deviation spectrum of $\pm 0.2 \text{ mm}$ the precision in reproducing the radial displacement improves significantly with each supplementation until the database contains simulation results of 100 cases. As displayed in the magnified section, only slight improvements manifest within database sizes between 200 and 1000 cases. Precisions down to the range of manufacturing tolerances were achieved.

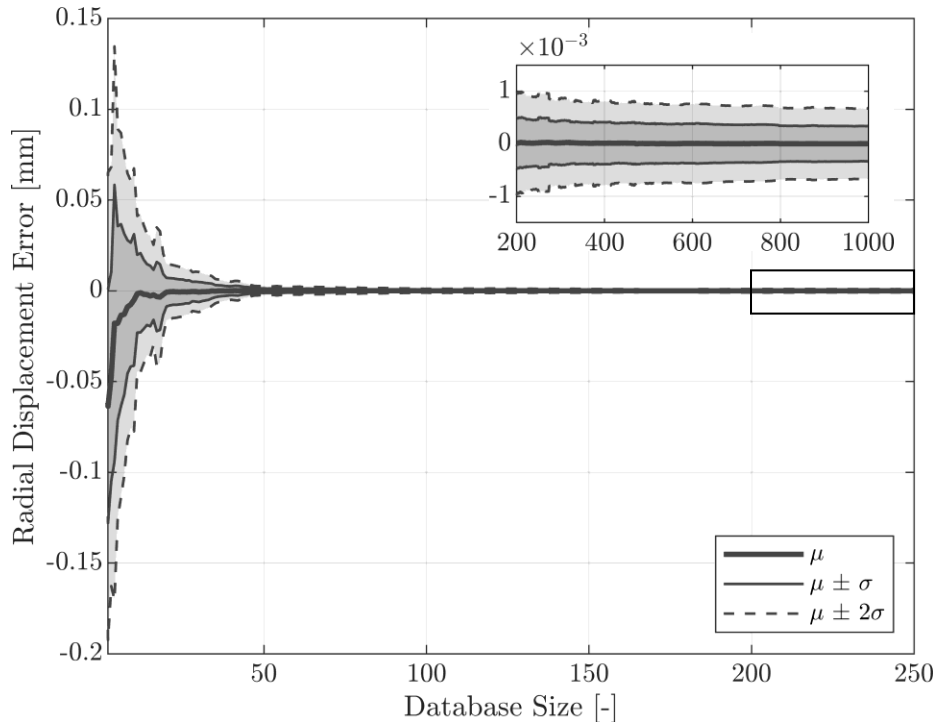


Figure 9: Dependency of Precision in Result Reproduction on Training Database Size

For reasons of completing the validation and precision section, the diagrams in Figure 10 reproduce the statistical measurement site based dimensional and percentage error spectra in radial displacement prediction via Surrogate Models. The results are based on a training data set of 1000 FE simulation results. A precise tendency of the mean value μ towards

negative or positive values is not to detect and when approaching measurement site R3 the standard deviation σ tends to reach peak values. The majority of statistic errors, which fall inside the $\mu \pm 2\sigma$ spectrum, are still in the micrometer range or in relative terms to the corresponding radial casing displacement values below 0.07%. Nevertheless, for a different verification data set the estimated mean values μ and standard deviations σ are expected to slightly change.

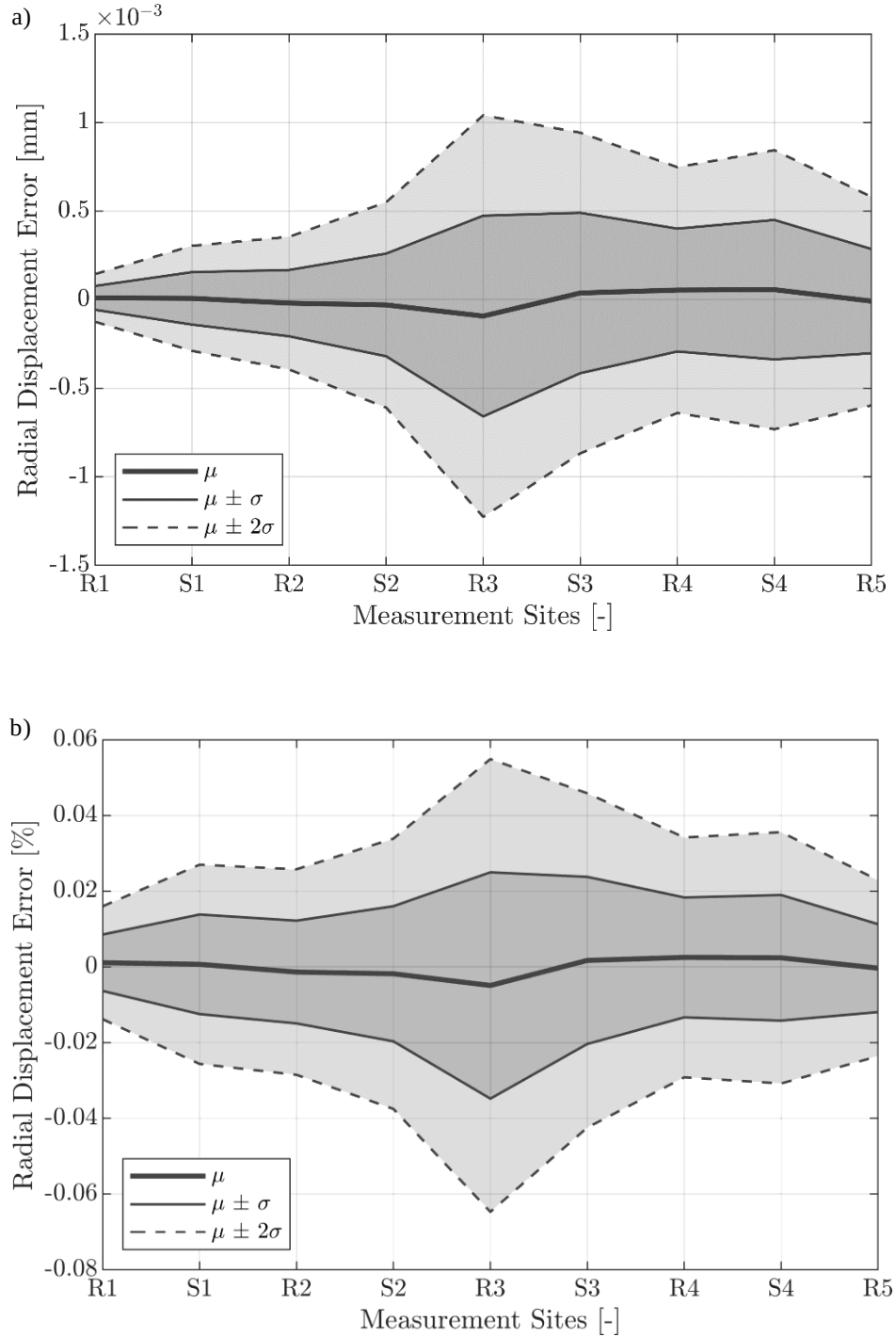


Figure 10: Statistic Error Spectra in Radial Displacement Prediction at the Measurement Sites Specified (a) Dimensional Error Spectra, b) Percentage Error Spectra)

Table 4
Percentage Error in Radial Displacement Prediction within the Considered Confidence Spectra $\mu \pm \sigma$ and $\mu \pm 2\sigma$ at the Measurement Sites Specified

Measurement Site	$\mu \pm \sigma$	$\mu \pm 2\sigma$
R1	92%	96%
S1	92%	94%
R2	76%	96%
S2	90%	94%
R3	98%	98%
S3	86%	96%
R4	66%	96%
S4	80%	96%
R5	74%	94%
Normal Distribution	68.3%	95.4%

5.3 Parametric Optimization

Surrogate Models develop their potential when linked with an extensive DSE and optimization algorithms. Up to this point, the Surrogate Models generated for present work have been proven to deliver highly precise radial displacement predictions. This section covers the inclusion of Surrogate Models to derive an optimum H, P, W parameter set for specific radial casing displacement adaption and tip clearance minimization. For reasons of consistency with previous sections of present work, the height H , positioning P and width W of 4 flanges constituted the design variables. The minimum and maximum values given in Table 1 described the constraints of the design variables selected for parametric optimization. Additional linear inequality constraints were imposed between the flange widths and positions in order to avoid unfeasible geometry modifications. Total tip clearance minimization was implemented as single-objective optimization problem. During the optimization process, the Surrogate Models were used to rapidly evaluate the radial casing displacements at the measurement sites specified. Furthermore, a provisional rotor expansion was set for each measurement site. Consequently, the tip clearances were calculated as the difference in radial displacement between the casing and the rotor. Subsequent summation returned the total tip clearance value, which was destined to be minimized. For the stopping criteria of the optimization process a constraint tolerance of $5 \cdot 10^{-5} \text{ mm}$ has been considered sufficient, given that the error linked to the Surrogate Models is even larger than this tolerance. Table 5 provides an insight into the main results. For brief categorization, in Matlab already predefined global as well as local optimization algorithms have been tested, coupled and compared with each other. In general, all of the local optimization algorithms provide input data dependent solutions within nonlinear or nonconvex tasks. Thus, beginning with a global parameter optimization and feeding in the received data set in subsequent local optimization allows to identify the best solution within the complete design space. In case of local optimization, the Active Set as well as the Interior Point algorithm were implemented. The genetic algorithm provided by Matlab was used for global optimization. Referring to Table 5, the key aspects in the analysis of results consider the ability of tip clearance minimization, the corresponding flange weight difference as well as the elapsed time. With respect to the first aspect mentioned, setting up an initial global and subsequent local optimization definitely returns the preferable parameter sets and total tip clearance values within an acceptable additional time expense. When considering weight as well, a trade-off has to be solved. In the present case, the Active Set algorithm performed slightly better to meet the objective of tip clearance minimization. In contrary, the Interior Point algorithm identified the configuration leading to a lighter weight design.

A résumé of the optimum H , W and P parameter dimensions obtained from tip clearance minimization is given in Figure 11. Solid curves denote the flange dimensions obtained from global genetic optimization. Dashed (Active Set) and dotted (Interior Point) curves characterize the results achieved from subsequent local optimization using the global optimized parameter set as input data. When comparing the dimensional development of the additionally local optimized H , W and P parameter sets from the first to the last flange of the multistage compressor casing a predominantly good agreement can be observed. In contrast to this, a dimensional match with the parameter configuration proposed by the genetic algorithm rarely exists. For the sake of completeness, Figure 12 presents the resulting compressor casing geometries identified via coupled global and local optimization.

Table 5
Results from Tip Clearance Optimization

Optimization Algorithm			
Genetic	Genetic		Genetic
	Active Set	Interior Point	
Tip Clearance Values [μm]			
R1	13.9	9.9	14.5
S1	48	47.7	50.2
R2	~0	~0	0.1
S2	109.3	88.4	87.4
R3	37.8	0.4	0.8
S3	~0	~0	0.1
R4	60.8	67.7	66.8
S4	~0	~0	0.1
R5	1.8	~0	0.8
Total Value	271.6	214.1	220.8
Reduction in Total Tip Clearance in Relation to Default Flange Configuration [%]			
	35.49	49.14	47.55
Relative Weight Difference to Default Flange Configuration [%]			
	+8.61	+12.94	+8.2
Optimization Time [s]			
	167.8	175.1	194.8

In this work it is assumed, that the rotor expansion data already exists. The rotor data can be derived either from a separate rotor model simultaneously calculated with the casing or from previous designs available. For instance, the case of reusing the data from a previous aero engine compressor design appears attractive, when only an already existing casing construction is retrofitted or modified and the rotor assembly remains unchanged. The casing modification may include measures for active clearance control or other equivalent technologies identified.

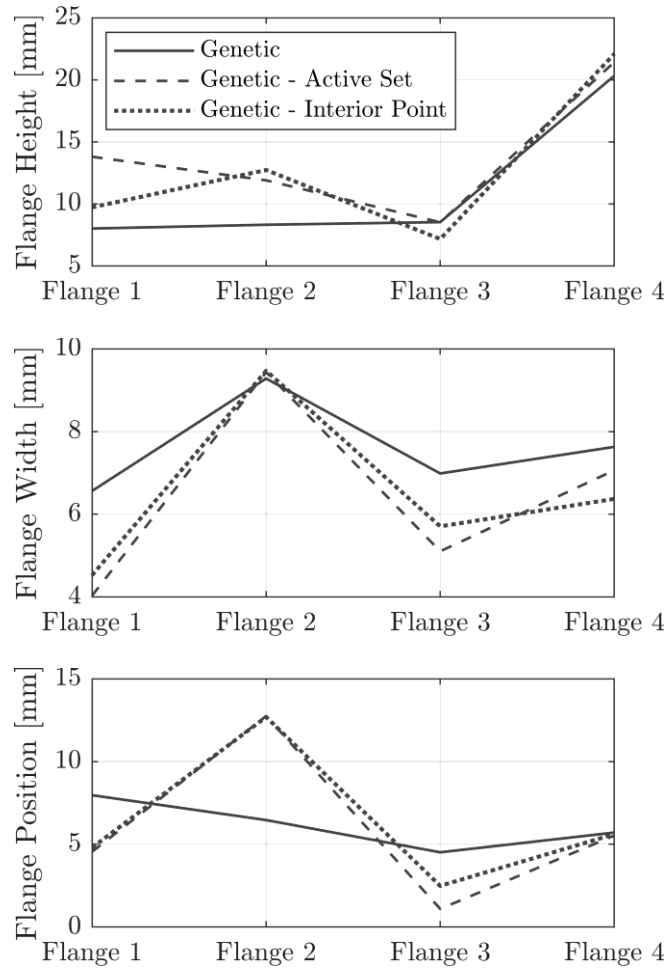


Figure 11: Optimized Flange Parameter Sets for Tip Clearance Minimization

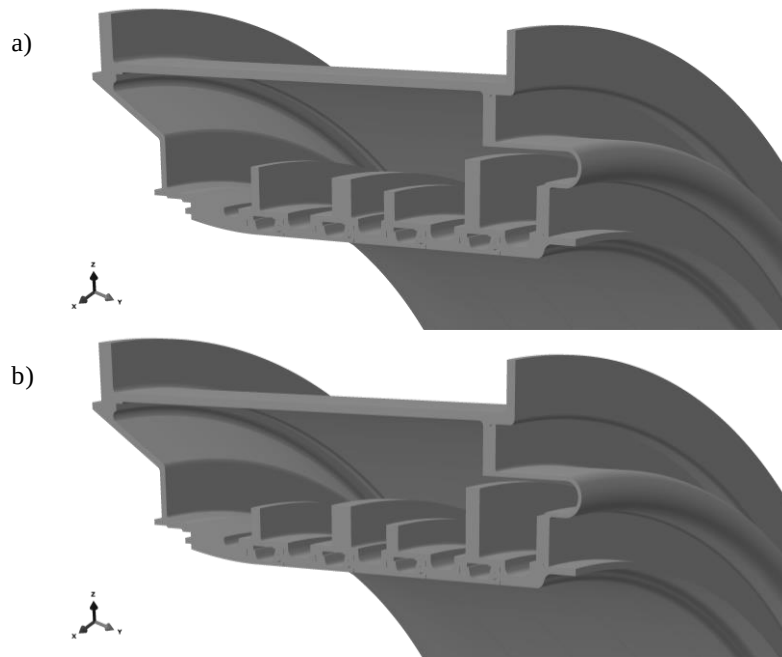


Figure 12: Optimized Compressor Casing Geometries
a) Genetic - Active Set, b) Genetic - Interior Point

6.0 CONCLUSION AND PROSPECTS

The present work explored the potential of Surrogate Modeling in FE-based preliminary compressor casing design. The key aspects of the evaluation mainly concentrated on the capability of performing rapid tip clearance assessments and on the correlating precision of FE result reproduction of the radial displacements. For this purpose, the 2D axisymmetric steady-state FE model of a generic multistage high-pressure axial compressor casing available from previous work [6] was re-used. Modification of geometric flange design parameters (H , W and P) via the Monte Carlo sampling method was used for FE data generation and DSE. The Gaussian Process Regression was chosen as algorithm in order to generate Surrogate Models trained on the data sets received from DSE and stored in a dedicated database.

Within the investigations executed, and once the Surrogate Models were trained, the time required for surrogate model prediction and full FE computations could instantaneous be compared. Followed by the training process, DSE and database generation emerged to be the most time-consuming tasks of the overall procedure in creating Surrogate Models.

Regarding validation of the accuracy of Surrogate Models in FE result reproduction, statistical methods were applied. In dependence of the database size precisions down to the range of manufacturing tolerances were achieved.

Motivation for completion was given by the previous findings. Thus, the Surrogate Models were included in an optimization process in order to receive an optimized H , W and P parameter set for tip clearance minimization. Coupling global with local optimization algorithms returned the most promising results.

Overall, Surrogate Modeling can contribute to a better understanding of design problems across different parametric combinations [8]. The fact, that trained Surrogate Models are computationally inexpensive in relation to numerical FE simulations, makes them attractive for the inclusion in parametric optimizations. The prediction error related to Surrogate Models depends on the number of training samples as well as the number and type of parameters emulated [8]. Also, the time required to train the Surrogate Models is affected by the magnitude and quality (noisy data) of the training database [16] as well as by the algorithm used for Surrogate Model construction [8]. An additional criterion influencing the prediction error and training time correlates with the tendency of specific Surrogate Model algorithms to become overfitted, resulting in increasing irregularity and larger local errors [13].

Future work related to the present project covers the implementation of additional optional features in the process of database generation. Specific selection of the flange design, the number of compressor stages, the material combination of the casing assembly and the upcoming load conditions (transient or steady state) are in progress of planning. Moreover, alternative sampling methods as well as Surrogate Model algorithms qualify for continuative parameter studies.

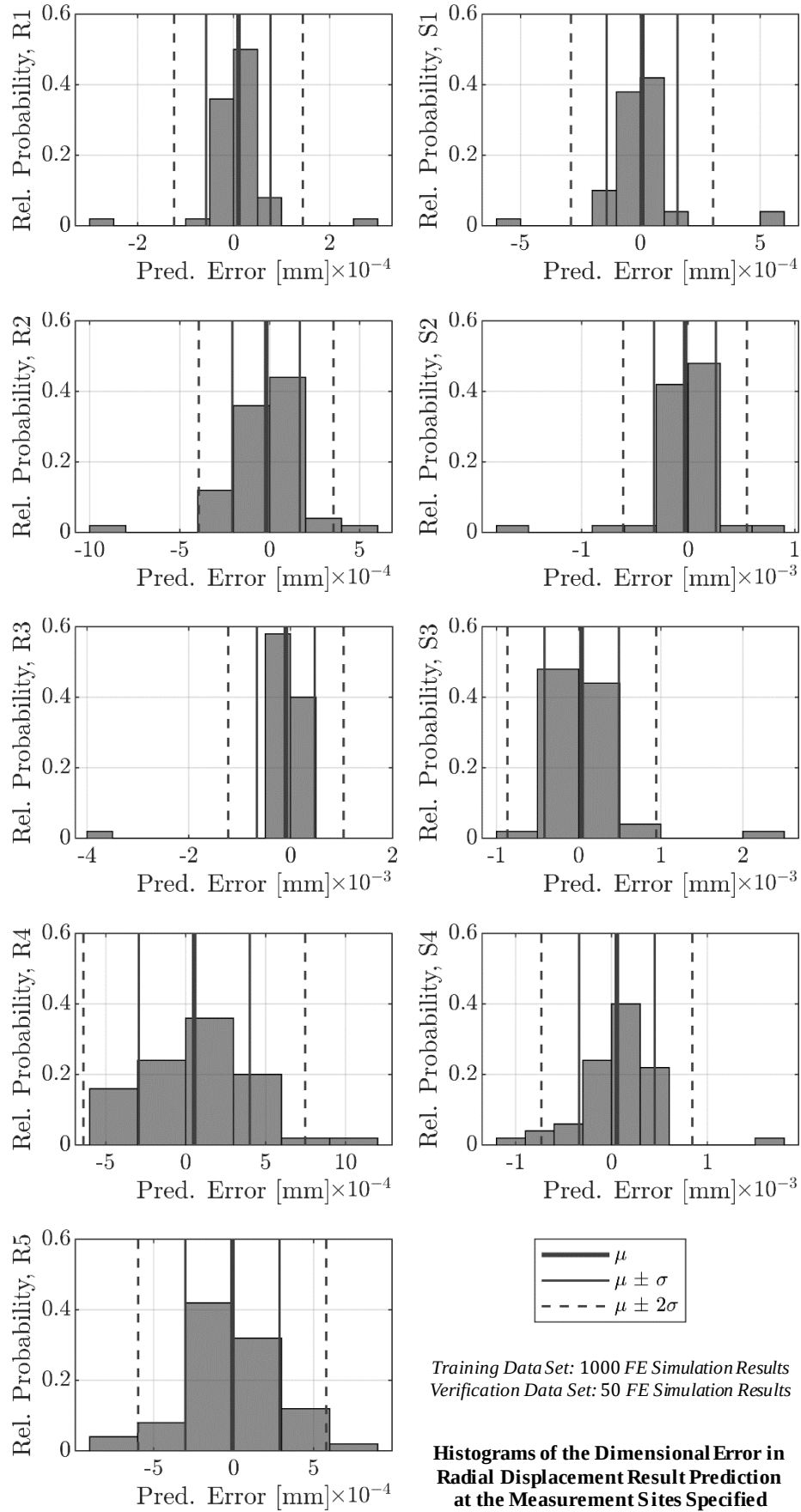
With respect to capturing the transient character of tip clearances during transient engine operation, changes of the procedure presented in this work will occur primarily in the database generation and evaluation. For brief classification, steady state FE simulations only return results for a single parameter set relevant for evaluation. When performing transient FE simulations for database generation, result evaluation can be based on several time-resolved parameter sets. For each time increment considered and for each measurement site evaluated a unique Surrogate Model can be generated. Considering tip clearance minimization based on geometric parameter optimization of the compressor casing, only the time increments representing the pinch points, where the minimum tip clearances during transient engine operation occur, are relevant. In order to avoid unnecessary expense, it is advisable to concentrate the result evaluation of transient FE simulations only on relevant time increments and to proceed with Surrogate Model generation as presented in this work. Additional techniques for further improving the tip clearances during transient engine mission would involve active control approaches.

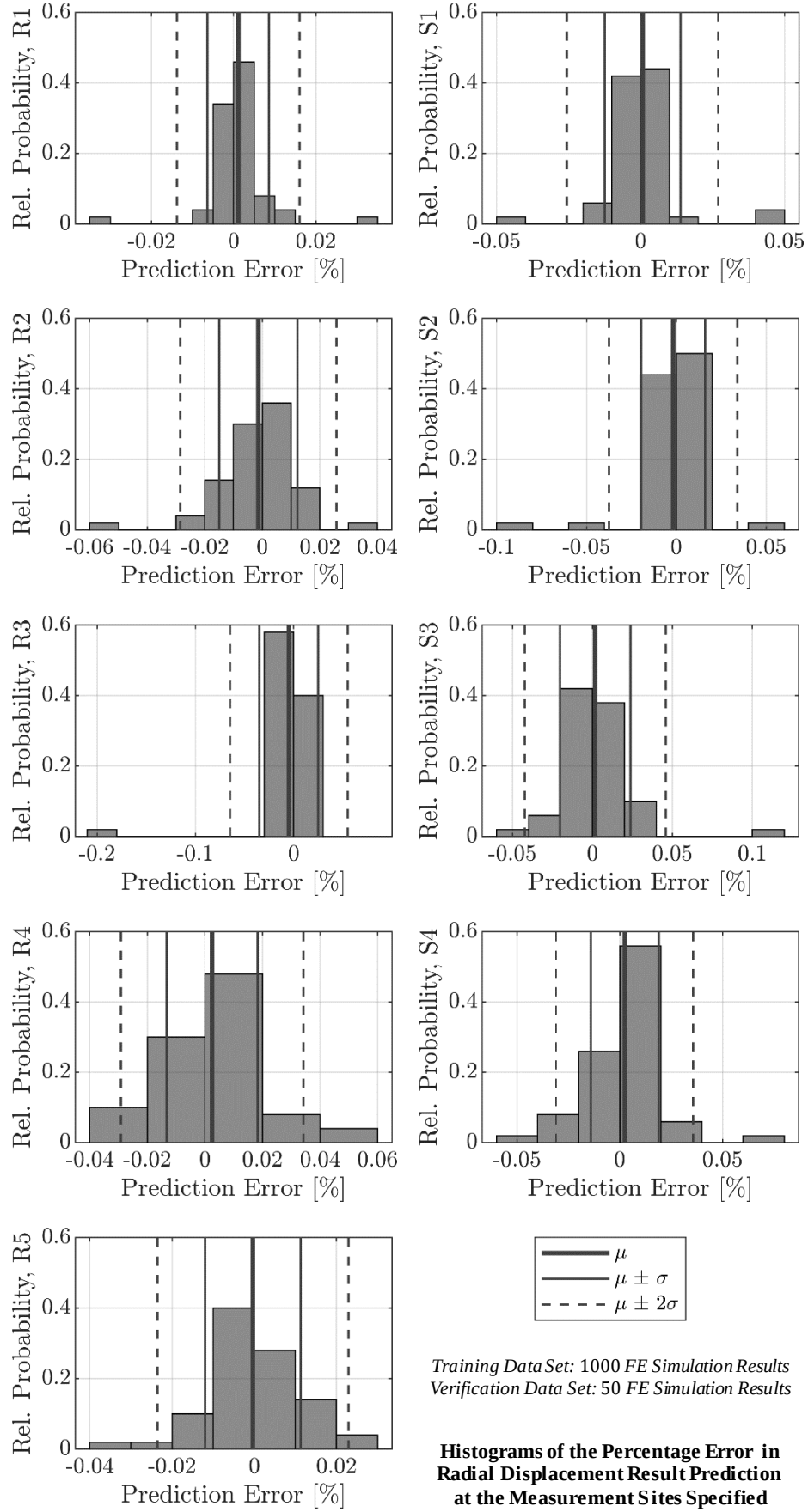
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ANNEX A





ANNEX B

A Résumé of Selected Surrogate Model Algorithms Extracted from Literature

Gaussian Process Regression	• Nonparametric kernel-based probabilistic approach, also known as Kriging. [14,17] • Due to its high prediction quality and its stochastic property, the method facilitates the estimation and measurement of the prediction error. • Generally, the method is well suited for the approximation of high-order nonlinear functions. • The method exhibits a flexibility in interpolating the sample points and filtering noisy data. • It is reported, that this technique performs consistently better than others with sparse training data in design spaces with many parameters. [8] • The major disadvantage of the method is, that Surrogate Model construction can be very time consuming. [16]
Radial Basis Function	• Depending on the weighted sum of Radial Basis Functions, theoretically every function can be emulated. • Radial Basis Functions represent a type of single-layer network with reasonably fast training and compact networks. • Radial Basis Functions exhibit the ability to learn. A prior knowledge of the behavior of the response is not necessary. • Radial Basis Functions are useful in approximating a wide spectrum of nonlinear spaces and provide good fits to deterministic as well as stochastic response functions. • It is reported, that Radial Basis Functions work consistently better than others with sparse training data in design spaces with many parameters. [8] • Radial Basis Functions are very efficient in modeling irregular behaviors. The tendency to overfit the model, which leads to increasing irregularity and larger local errors, can be noted as the major disadvantage.
Radial Basis Function Network	• Radial Basis Function and Radial Basis Function Network share the same approximation model formulation. The only difference originates in the way to determine the number and the centers of the Radial Basis Functions as well as their corresponding weight factors. In case of the Radial Basis Function Network, the inherent neural network estimates these data. • Based on a training database the inherent neural networks can learn a task without having explicitly being programmed for that specific problem. • The inherent neural networks suit for the approximation of high-order nonlinear functions. • High error tolerance, parallel computation of the information processing and distributed knowledge representation belong to the further advantages reported in literature. • If a sufficient number of Radial Basis Functions is given, Radial Basis Function Networks can approximate arbitrarily well any multivariate continuous function on a compact domain

If not specifically cited, the information in Annex B refers to reference [13].