Mitteilung

Projektgruppe / Fachkreis: Numerische Simulation
Modeling the Pressure-Strain-Correlation in Differential Reynolds Stress Models using Feature Engineering and a Genetic Evolution Algorithm

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Simulating turbulent flows using Reynolds-Averaged-Navier-Stokes-Equations (RANS) models is a very efficient approach for most practical applications, as they aim to produce accurate results, while being more performant than scale-resolving methods. However all RANS approaches require the modeling of unknown terms, one of them being the pressure-strain-correlation (PSC) in the differential Reynolds Stress Model.
A state-of-the-art model for this is the Speziale-Sarkar-Gatski (SSG) model [1], which tries to represent the PSC term using a set of basis tensors and (in its simplest form) five coefficients that need to be calibrated to achieve the desired behavior.
These coefficients are usually assumed to be constant, however, theoretical considerations suggest they should be functions of the current flow-state [2], considerably increasing the models complexity and capabilites.

In order to determine such functional dependencies, a machine learning approach referred to as Genetic Evolution Programming (GEP) [3] has successfully been employed by Alaya et al. [4]. This method uses evolutionary principles to evolve a set of possible equation-candidates for the coefficients over multiple iterations. For that, each candidate is evaluated via a predefined fitness-criterion and multiple techniques such as mutation, cross-combination or overwrites are applied to the less successfull candidates to explore the search-space of possible functions in a directed manner [3].
The method has advantages over traditional black-box-style neural networks, as it produces interpretable and easily implemented equations and allows the usage of complex fitness-criteria that would otherwise be very difficult to optimize via classical gradient-descent.
On the other hand, the convergence of this method is less predictable and controllable than other machine learning techniques and shows a high sensitivity to its initialization, inputs and training parameters.

To improve on these issues, a multi-step feature engineering process has been designed to select the most promising input features to be considered for the functional dependencies, effectively reducing the search-space the GEP has to explore.
In the first step data from a Large Eddy Simulation (LES) simulation, in this case the curved-backward-facing step of Bentaleb et al. [5], is used to reconstruct reference fields for each of the coefficients of the SSG term as a basis for further statistical analysis. Afterwards, five input variables identified as relevant for characterizing the flowfield are selected:

$$II_b, \quad III_b, \quad II_S, \quad Re_t, \ L = k^{3/2}/\epsilon, \quad r = \sqrt{S_{ij}S_{ji}/\Omega_{ij}\Omega_{ij}}$$

The variables are the second and third invariants of the Reynolds stress anisotropy tensor, the second invariant of the strain-rate tensor, the turbulent Reynolds number, turbulent length scale and strainrate- to vorticity-magnitude-ratio.

Their predictive capability for the previously reconstructed reference coefficient fields is determined by two different methods: A random forest approach and gradient boosting. Both methods estimate the predictive power each of the input variables has on the coefficient fields and form an importance-ranking based on this. To increase the procedures robustness, the rankings of both methods are averaged.
Next, the space of considered inputs can be expanded further by applying a multitude of transformations such as trigonometric, exponential and polynomial functions to the previously selected features. Then for each feature individually the most useful transformation is ranked using the Spearman-correlation between the transformed feature and the reference coefficient field as a criterion.
Finally, this feature engineering- and ranking method yields a set of 3-4 features and their most favourable transformation per coefficient that can be used as inputs for building functions with GEP.

In alignment with the work of Alaya et al. [4], the method is evaluated on the curved-backward-facing step test case [5], which was already used for the feature engineering, and the skin friction- and pressure-coefficients at the surface are identified as target-variables, that the optimization should try to match. Preliminary results for this procedure are shown in Figure 1, displaying the reference LES data, the predictions made by the original SSG model with constant coefficients and the improved SSG model utilizing the feature engineering and genetic evolution process (SSG GEP).

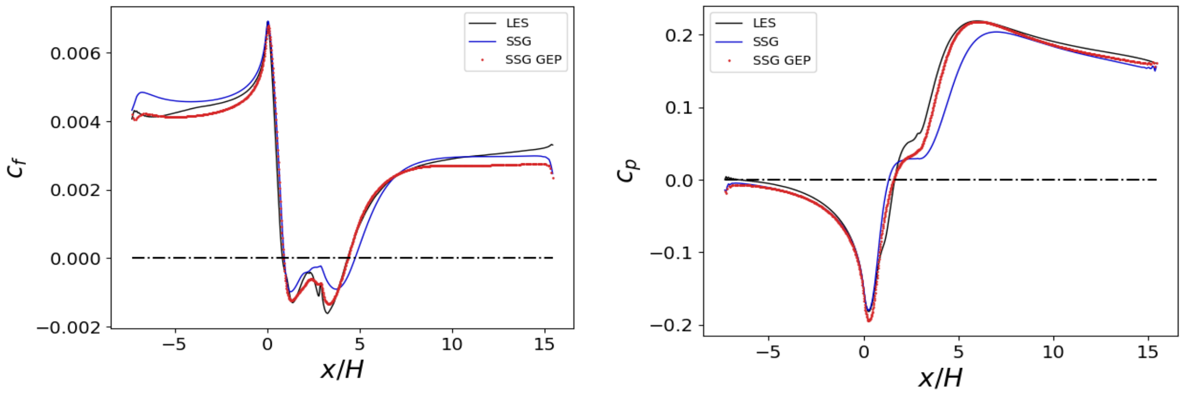

Figure 1: Preliminary Results of the GEP with Feature Engineering

Future work will focus on determining the limits and capabilities of the designed process by evaluating the GEP-trained models on other test-cases that were not used during training.

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