Isight process for automatic data match on an Aero Engine Thermal Model

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The aim of the work is to define an automatic process and to combine specific Isight tools that allow engineers to match the thermal performance of an aero-engine turbine module with a thermal aero-engine FE Model. The thermal behaviors of a complex system are the result of strong interactions between the fluid-dynamics aspects and the heat balance within each component. All those phenomena are strictly connected and they are subjected to approximations coming from the input of the simulation model and from the interactions of different variables. These approximations are reflected on the final results. The problem is to tune a high number of variables to match a high number of target results. For long time the industrial approach in turbine design has been based on Thermal FE analyses followed by manual iterations to match the simulation of physical phenomena and to reach acceptable solutions. The new requirements in reducing the product time-to-market together with the need of higher accuracy in the design have driven the development of new approaches based on the automation and automatic search of the target solution. This paper will summarize the AVIO approach developed in collaboration with Exemplar to automate an Isight process for an automatic data match on an aero-engine thermal model. The activity has been performed within the regional project GREAT2020 – (GReen Engine for Air Transport in 2020) - co-funded by the Regione Piemonte.

Keywords: Heat Transfer, Aero Engine, Data Match

1. Introduction

The thermal behaviors of a complex system such as an aero engine turbine module are the result of strong interactions between the fluid-dynamics aspects and the heat balance within each component. All those phenomena are strictly connected and they are subjected to approximations coming from the input of the simulation model and from the interactions of different variables.

The integrated simulation model takes into account different codes running in co-simulation. The fluid-dynamic simulation code calculates mass flow distribution and pressures in the turbine chambers. These data are used from the thermal code that, through user defined correlation calculates the heat transfer coefficients to be applied on model surfaces. The results obtained from thermal simulation are the temperatures distribution on the finite element model and the heat balance within each component.

Usually the thermal analyst is requested to provide a judgment on a fluid-thermal integrated solution and to understand if the physical thermal exchange phenomena have been calculated with a good approximation with the correlation supplied. This procedure is performed by the thermal analyst, most of the times, manually. This means that the analyst manually tunes the FE Fluid-

Thermal integrated model to match the simulation of physical phenomena and to reach acceptable solutions. This tuning involves a high number of variables, because the thermal models are usually very detailed, and it is normal to apply hundreds of different heat thermal correlations. Each correlation contains about ten inputs that can cause an approximation on the final evaluation of the heat transfer coefficients. In the same time there are a high number of outputs to match, corresponding to the different experimental measured points. Doing this operation manually can take weeks, because all the parameters are strictly connected and impact one on the other. Moreover a manual approach cannot take into account all the possible solutions and so, mainly due to mutual interaction of the variables, the final data match is not the optimal one.

This paper presents the research of improvement of this manual process, consisting in the automation of the Thermal run by means of Isight, and listing the different approaches tested to guide the automatic process modifying the input variables to automatic match the target output.

2. Automatic Thermal run implemented in Isight

The first step of the improvement is to put in an Isight loop the actual Thermal simulation of an aero engine turbine module and to define the input and output parameters.

The input variables defined are the input to the thermal heat transfer coefficient correlation that can easily tune the HTC calculated; in the model studied, these variables are the HTC multipliers contained into the thermal correlations. These inputs can increase or reduce with a scale factor the heat transfer coefficient calculated for each correlation. This choice helps to maintain the simulation of the physical phenomena, but allows the change of its numerical entity.

The outputs defined are the temperatures calculated by the simulation in correspondence of the points on which experimentally temperatures are measured. The output temperatures (as results of the thermal run) and the target temperatures (coming from experimental measures) are collected in an Excel spreadsheet implemented in the process after the thermal run.



Figure 1. Input CAD and output FEM to the automatic process

The automatic Isight loop in which the thermal run has been implemented is represented in figure 1. The process consists in:

- An optimization component that guides the data match.
- The Simcode component that launches in batch mode the thermal code (Thermal).
- The Excel component that allows the user to work on an Excel spreadsheet built ad hoc to collect thermal results from Thermal Simulation and to collect the thermal target coming from experimental measurements

The components used are shown in figure 2.



Figure 2. Isight components involved in the process

3. The Automatic Process

The process, developed in Isight, is constituted by the components described in the previous paragraph. The parameters (Input variables) that have been parsed from the optimization component are those corresponding to HTC multiplier in the thermal correlation. Those parameters have a default values that can be perturbed and varied to match the target outputs.

The allowable range assigned to the variables is set from the optimization component interface. The variables have been automatic parsed and named with an identification number that comes from the thermal model thanks to a java script that has been written at the optimization component level.

Concerning the output variables, they have been collected in an Excel spreadsheet that has been developed to guide the data match tests. This Excel spreadsheet contains:

- Output temperatures calculated from the thermal simulation in the previous step of the process
- Target temperatures coming from experimental measurements
- Formulas that calculates the sum of the errors between calculated temperatures and target temperatures

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ID	TEMP calculated	TEMP desired	Difference	Weights	Weighted values
		945	945	0.2	189
		941.9253544	941.92535	0.8	753.5402835
		939.1521139	939.15211	0.3	281.7456342
		936.1829912	936.18299	0.4	374.4731965
		935.3060141	935.30601	0.2	187.0612028
		925.2401333	925.24013	0.6	555.14408
		925.1388076	925.13881	0.1	92.51388076
		925.0159122	925.01591	0.8	740.0127298
		915.5875208	915.58752	0.4	366.2350083
		914.2814148	914.28141	0.472222	431.7440014
		950	950	0.482222	458.1111111
		910.8085566	910.80856	0.492222	448.3202117
		500	500	0.502222	251.1111111
		501.337417	501.33742	0.512222	256.7961658
		509,9382385	509,93824	0.522222	266.3010801
		501,4565913	501,45659	0.532222	266.8863414
	++	505 1527471	505 15275	0.542222	273 9050451
		00011027471	000.10270	UIDTLLLL	270.000401

Figure 3. Excel spreadsheet

The Excel spreadsheet allows the user to specify how many temperatures must be considered as output variables and to assign a weight to each error between temperature calculated and target on each node. In fact the implemented process updates the Excel spreadsheet with the complete thermal model temperature results. In this way the process has been kept general, and the user is in charge to specify the node on which the data match must be performed (this means that the user is in charge to specify the output variables and to assign the precision – weight – of the data match).

4. Different approaches for automatic thermal data match

Using the Isight process described above, different tests have been performed to evaluate a methodology to improve the actual manual data match. A significant test case has been used, consisting in a three stages test article (figure 4) of a turbine static part, used on an experimental bench developed thanks to a local regional research project (GREAT2020 - GReen Engine for Air Transport in 2020) used to characterize the thermal behavior of the turbine casings, measuring mass flows, temperatures and other thermal data.



Figure 4. Excel spreadsheet

The thermal model has been implemented in the Isight loop described, and the first approach has been used to perform an optimization that minimize the function "sum" of errors between calculated temperatures and target.

As target some points of the nominal thermal maps have been chosen. Starting from a perturbed temperature distribution, the effectiveness of the used approach has been evaluated considering the capability to minimize the difference between the identified values and the targets one.

The use of the Excel spreadsheet, in fact, allows building function that can be used as objectives of the optimization. This allows reducing the number of objectives to minimize.

The following tests have been performed:

- One objective function that collects the sum of 25 temperatures error and 30 input variables
- One objective function that collects the sum of 75 temperatures error and 90 input variables
- Three objective functions each one collecting the sum of 25 temperature and 90 input variables

The first test gave excellent result producing an optimized configuration after about 180 runs (5 hours) and matching all 25 target temperatures.

The second test produced an optimized configuration after 450 runs (15 hours) but the thermal profile calculated still contained sensible deviation from the target. This is due to the high number of variables and target taken uniformly on the thermal model. It is, in fact, hard to find an optimized solution with sparse variables and target on the model.

Thus the third test came, that divided the targets by model region. The first configuration has been repeated for each stage, so three functions "sum" of errors has been built, one for each test article stage. In this way we built an optimization in three steps, one for each stage. The third approach allows reaching good match result in 20 hours, against about one week of manual tune.

4.1 First Approach

In the first approach the data match process is focused only on one limited region corresponding to a single stage of the model. The location chosen as target for the data match are shown in figure 5.



Figure 5. Thermal location considered for data match

The Excel function built as objective of the optimization is the sum of errors between calculated temperatures and target. In this approach a single function is considered, only one objective is defined during the run.



Figure 6. Isight process – approach 1

In the first graph shown below, the objective function optimization behavior is diagrammed vs. the number of Thermal runs. It is possible to see that the best configuration has been found after 180 runs. In the second graph the temperature error in the optimized configuration is diagrammed vs. the percentage of nodes of the model. It is possible to see that in this case the error is in a temperature range of ± 2 K. This approach gave an acceptable result, and validates this approach, but the target nodes of the data match has been chosen in a limited location.



Figure 7. Isight process results graphs

4.2 Second approach

In the second approach the data match process is focused on the entire model. The location chosen as target for the data match are shown in figure 8.



Figure 8. Thermal location considered for data match

The Excel function built as objective of the optimization is the sum of errors between calculated temperatures and target. In this approach a single function is still considered, only one objective is defined during the run.

In the first graph shown below, the objective function optimization behavior is diagrammed vs. the number of Thermal runs. It is possible to see that the best configuration in this case has been found after 450 runs. In the second graph the temperature error in the optimized configuration is diagrammed vs. the percentage of nodes of the model. It is possible to see that in this case the error is in a temperature range of ± 60 K and the number of nodes with a temperature error over 30 K is not negligible. This approach does not give an acceptable solution.



Figure 9. Isight process results graphs

4.3 Third approach

In the third approach studied the data match process is focused on the entire model. The location chosen as target for the data match are shown in figure 5.

The approach number 2 demonstrates that a data match process on locations sparse on the model, using one single objective function does not reach an acceptable solution. This is due to the complexity of the system, in which each input variable impacts on different outputs due to the complex interactions between the physical phenomena considered. For this reason the third approach uses the methodology studied in the first test (focusing the data match on a limited region, one single stage) and replicates it for every stage of the model. This means in this case that the model has been divided in 3 regions for data match (the three stages). In this way three objective functions have been created, and three different data match loops in cascade have been studied.



Figure 10. Thermal location considered for data match

For this approach it has been necessary to modify the iSight process as shown in the following figure.



Figure 11. Isight process – approach 3

In this case the three different regions have been optimized individually. The final solution has been verified with a final TEST run. Each optimization loop (single region) passes the updated input variable to the optimization loop of the following region.

The best configuration in this case has been found after 200 runs for each optimization loop. The run time is 20h. In the first graph shown below, one of the three objective functions optimization behavior is diagrammed vs. the number of Thermal runs. It is possible to see that the best configuration in this case has been found after 200 runs. In the second graph the temperature error in the optimized configuration is diagrammed vs. the percentage of nodes of the model. It is possible to see that in this case the error is in a temperature range of ± 10 K with a negligible number of nodes with a temperature error of 20 K. This approach gives an acceptable solution in about 20 hours of simulation.



Figure 12. Isight process results graphs

5. Final considerations

Managing a data matching between experimental data and simulation is a time consuming job, that requires also a deep expertize of the physical behavior of the aero engine turbine system. Moreover a manual approach cannot guarantee to reach the best matching solution. The research of an automated way to perform a data match of a simulation model involving a high number of variables that are physically correlated one each other, improves the accuracy of simulation models and helps to increase the product time to market. The approaches described in this paper are the synthesis of a study aimed to find out a general methodology to perform an automatic data matching. The first approach has been used only to evaluate the problem, while the third one pointed out that the right way to face the data matching in the field of fluid-thermal simulation is to divide the optimization loop of data matching in limited regions and to evaluate the impact of the best solution found on one region on the other locations.

The whole procedure will be used to match the model on the experimental data available from the GREAT2020