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Advances in automatic thermal model to test correlation in space industry

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In space industry thermal models are an important tool to predict, analyze and understand the thermal behaviour of components, subsystems and whole spacecrafts. Most parameters of these models have a limited accuracy and consequently the models results are uncertain. In order to reduce this uncertainty to a required level the model parameters are adjusted (correlated) by fitting the model to test results obtained during thermo vacuum tests. This is often a difficult long lasting manual process. In order to perform these correlations automatically many different methods have been developed and analyzed. Two of these methods are analyzed regarding their requirements, efficiency and limitations. A genetic algorithm is compared to a method based on non-linear equations solving algorithms of the Broyden class.

I. Introduction

Thermal mathematical models are currently an important tool to reduce the risk, cost and time of a spacecraft design, development and testing. Consequently limited accuracy of models leads directly to technical risks, costs and delays. Therefore, it is important to have accurate models. A usual method to improve the quality of thermal spacecraft models is to test with the corresponding real hardware in a thermo vacuum chamber and measure the temperature at several points. This test is then simulated using the mathematical model. By comparing the results of the test and the corresponding calculated results from the mathematical model the accuracy of the model can be evaluated. As many parameters of the model have an uncertainty these can be adjusted so that the deviation to the test results is minimized. This model correlation procedure leads to more reliable models.

The procedure of adjusting the parameters can be very complex and time consuming as many parameters influence many results. Normally this task is performed manually requiring a lot of knowledge, manpower and time. Several mathematical methods have been studied attempting to automatize this task. First gradient based minimization methods where analyzed Ref. 5,8,6. Then stochastic algorithms like genetic Ref. 1,7,9,14,15,16, particle swarm algorithms Ref. 3,16 and other stochastic algorithms Ref. 2,13,17 where studied. Normally all these methods merge the deviations to a single objective function which is then minimized using a minimization algorithm. All have been proven to be able to fulfil the task for reduced models. The large amount of iterations would lead to very large

on level. In the cited urs depending on the case, the method and the accuracy level reached. These times are not short but they are a good improvement compared to conventional manual correlation.

Another approach has been proposed in Ref. 10 and 12. A practical illustrated explanation of the approach has been presented in Ref 11. Instead of minimization algorithms quasi newton equation solving algorithms of the Broyden class Ref 4 are used. The advantage of this approach is that it uses a whole vector of information for each iteration

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while the other minimization algorithms analyzed use only one single scalar. Also it handles a set of simpler functions instead one very complex objective function. It has been shown that the algorithm is able to adjust parameters of thermal models using considerably less iterations than normally published for other methods making it possible to correlate even complex models within a reasonable time. Also the results from the algorithms where compared to typical results from stochastic algorithms a direct comparison between stochastic algorithm and this method using the same model was missing.

This paper presents an improvement of thermal model correlation method using Broyden class methods and a direct comparison to the method based on a genetic algorithm developed by Ref 7.

II. The Broyden class method

In Ref. 10 the usage of algorithms of the Broyden class to correlate thermal models is described and analyzed for two members of this class. One member is Broyden's first method, also known as "good Broyden method" Ref. 4. The other member is a completely new method published in the paper. This method is called self developed method in Ref. 10 and is called K2014 method in this paper.

This method can be described that it linearly approximates the model at a starting point based on the gradients (Jacobian matrix) obtained from a parameter variation. The optimum of this linear approximation can be found comparatively easily and fast. At this optimum the model is solved. By evaluating the differences between the expected values from the linear approximation and the obtained values of the model a new linear approximation is obtained (approximate Jacobain update). This procedure is repeated until the optimum of the linear model converged to a desired accuracy. The members of the Broyden class are different methods to update the linear model using the secant condition.

The big advantage of these algorithms is that the number of iterations after the jacobian matrix generation does not depend on the number of parameters itself. It depends only on their non-linearity and the parameter interaction. For a fully linear model the model is solved once for the initial condition, then it is solved once for each parameter to generate the jacobian matrix and after the first iteration already the minimum is reached. For typical non-linear thermal models a good result is already achieved after 3 to 20 iterations after the jacobain matrix generation.

III. Implementation of a new linear equation solver

The Broyden class methods are for unconstrained determined equation systems. But the thermal correlation problem is a constrained equation system which is normally over determined. In Ref. 10 the boundaries have been considered by limiting the parameter change of the unconstrained solution to the boundaries. If the equation system is under- or overdetermined a least squares solution is used.

As an improvement the solution of the linear equation system is replaced by an optimization algorithm which minimizes the least squares of the linear equation system with the Nelder Mead simplex algorithm considering the boundaries.

IV. The genetic algorithm

The continuous improvement that takes place on the computation capacities has made possible to apply stochastic methods to the optimization of complex problems in spite of the high computational effort required. Although they do not guarantee the finding of the global optimum, usually they are able to give a good enough answer in a reasonable time. The major advantage of this type of methods is that they are independent of the mathematical properties of the function, so they can be applied to almost any problem including non-monotonic functions with local minima.

One of these stochastic approximations are the genetic algorithms (GAs). They are search algorithms of general purpose, based on the principles of natural evolution of the populations. The basic concept consists of generating a random population of chromosomes or individuals, where each chromosome represents one possible solution to the problem. The algorithm process the chromosomes population by means of three types of operators: selection, crossover and mutation, converging to better solutions with the successive generations.

The GA used in this study is an in-house developed algorithm combined with a thermal analysis software called TK, also in-house developed. This software, called GAC-TM, is able to correlate TMMs in both a steady state and transient analysis and can also perform the simultaneous correlation of several cases (i.e., hot and cold cases). The details of the algorithm implementation can be found in the Ref. 1 and 7. The cited algorithm has been slightly modified to be used in this study in order to use the same error criterion used in the Broyden's class method for comparative purposes. So, two different GA have been used. The first one, referred as original GA, uses the original fitness function used in Ref. 7 and provides the RMS error as additional information. The second one, referred as RMS GA, uses a modified fitness function based on the RMS error.

TK solves the set of N non linear algebraic transient equations that are obtained when the thermal lumped parameter method is used. TK uses the Newton-Raphson technique for problem linearization and solves the set of N equations by the iterative methods contained in the ITPACK 2C public domain software package. The sparse storage scheme is used in TK, minimizing the amount of RAM memory employed.

V. Comparison of the algorithms

The main target of the algorithms is finding a solution which fits best to the results with a minimum of time. The algorithms where executed on different systems and used different solvers for the thermal model, so the calculation times cannot be compared directly. For all models analyzed and for nearly all other thermal models, the time to solve the model is considerably longer than all other parts of the algorithm. Consequently for comparison purposes the time needed for the correlation can be assumed nearly proportional to the total number of times the model had to be solved although in fact the hardware and solver used may affect to the real calculation time. For this reason and for the sake of clarity, only the root mean square evolution over the number of model executions has been chosen for this comparison.

For the Broyden class Methods, the total number of executions includes the first solving of the initial model, plus the executions needed for the initial Jacobian matrix and all subsequent solving iterations. The first point of the curves corresponds to the initial guess and the second (at 2+nr of parameters), corresponds to the first calculation after the Jacobian matrix generation. The RMS evolution during Jacobian matrix generation is not displayed.

For the genetic algorithm the number of executions corresponds to the number of generations (also called iterations in Ref. 1) times the number of individuals for each generation plus the first solving of the initial model. The displayed RMS is the lowest for each generation.

A. Description of the models

4 models have been used to compare the behaviour of the algorithms. The first 3 models are the test models used in Ref. 10 and the last model is the Tribolab model from Ref. 1. These models have been selected as they represent typical complex behaviour of full thermal models but are simple enough for to enable many iterations. Also neither the complexity of the models nor the correlation up to a few millikelvins is relevant for the practical application the comparison of these cases delivers a basis to choose the most efficient methods. As their definition Ref. 1 and 10 and code Ref. 11 is published it is possible to use them as benchmark for other correlation methods. Due to the large number of iterations needed it is unpractical to perform such an analysis for large full size practical space industry models. Never the less the results of the usage for practical models are given in chapter VI.

The undetermined, the determined and the over determined simple model from Ref. 10 are test models designed to have a non linear interaction between all parameters representing difficult configurations to correlate. Their exact definition is described in Ref. 10 and their code is included in the appendix from Ref. 11. These 3 models are based on the same configuration shown in Figure 1. The difference between them is the number of parameters (GL) to be correlated so that the 3 possible situations are investigated. The undetermined model has 6 parameters but only 4 results. This means that there are infinite solutions. This configuration occurs when it is tried to correlate parameters while not enough relevant data is available. A situation which should be avoided often resulting from inappropriate test setups. Unfortunately these situations occur in practical applications and therefore the robustness of the algorithms is analysed. Results from these configurations can be very distant from the physical reality despite an accurate correlation; the most important aspect is that the algorithm does not become unstable so that one single underdetermined node of a whole model does not prevent the correlation for the remaining model.

The determined model has exactly the same number of parameters as results (four). For this case there is one single solution where all temperature differences are 0K. A rare practical situation occurring normally only for simple models and simple test setups, but it is a good case to investigate the behaviour of the algorithm because the optimal solution is known.

The over determined model is the normal case for a thermal model correlation, there are more results (4) available than parameters (3). These configurations normally never have an exact solution therefore the RMS will never converge to 0.

The Tribolab model is based on a real space instrument. Tribolab is a materials tribology experiment, non-pressurized, to test new solid lubricants which was located in an external platform called EuTEF (European Technology Exposure Facility), outside the European Columbus module, part of the International Space Station. The detailed Tribolab TMM is formed by 47 nodes but the Tribolab model used in this paper corresponds to the reduced model of 7 nodes shown in Figure 2 which is based on this instrument.

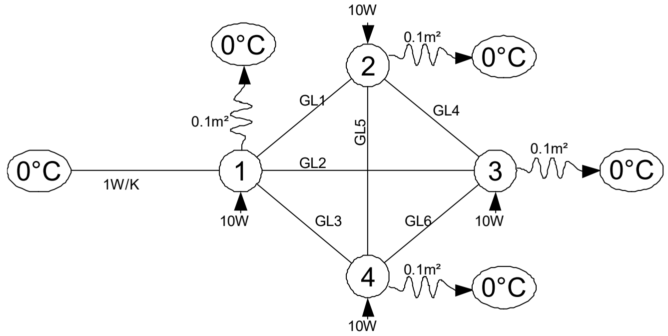

Figure 1 Schematics of the undetermined, determined, and over determined simple model

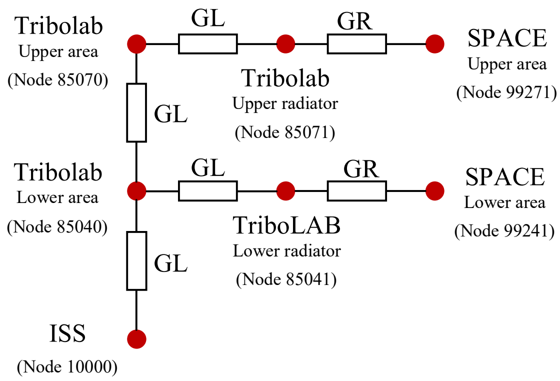

Figure 2. Tribolab model

B. Definition of the optimization target

The root mean square of the temperature deviations is used to compare the convergence of the algorithms.

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(t_{i\,mdl} - t_{i\,mes})^2}{n}} \quad (1)$$

Where

$t_{i\,mdl}$ is the temperature result number i according to the model

$t_{i\,mes}$ is the temperature result number i according to the measurement

n is the number of temperature results. This corresponds to the number of nodes (4) for the simple undetermined, determined and the over determined model as it is a static calculation. For the transient Tribolab model, it corresponds to 4 nodes times 120 time steps times 2 load cases (cold and hot) = 960.

For the Broyden class methods the results were evaluated with a limited numerical resolution of $10^{-5}K$. Therefore below $10^{-4}K$ for the RMS the numerical resolution is poor and the inconstancy caused by rounding leads to instability. Therefore $10^{-4}K$ is considered as the lowest limit achievable and RMS values below $10^{-4}K$ are not evaluated. It can be seen that all gradient based algorithms become unstable below this limit

C. Results for the undetermined simple model

As can be seen in Figure 3 the undetermined model converges for all methods analyzed.

For this model the fastest algorithms were the original methods from Ref. 10. These methods are followed by the Broyden class methods with the new linear solver. The first step of the methods with the original linear solver leads to a lower RMS than expected for a linear system. This is a seldom coincidence which enabled these algorithms to converge faster than the algorithms with the new solver. Normally the new solver leads to a lower RMS for the first iteration as can be seen in Figure 3.

This is also the only case tested where the good Broyden method was partially faster than the K2014 method.

The stochastic nature of the genetic algorithms makes possible that each execution of the algorithm may provide a different solution for the same problem. For this reason, it is advisable to execute them more than once for each

optimization problem, as it is possible to reach solutions that could be better than those obtained until that moment. In this work, for each correlation problem studied, the algorithm has been executed 5 times.
The number of times that the model has been solved has been higher in the case of the genetic algorithms and the differences between both implementations studied are not significant. It is remarkable that the correlation target used in this study (10^{-4}K) is really demanding, which is very interesting to evaluate the studied methods but in real situations the typical correlation target use to be about 2K or 3K and many more nodes.

Algorithm	Total nr of times the model was solved to reach a RMS below 10^{-4}K		
good Broyden (Ref. 10)	**16**		
good Broyden new lin. Solver	37		
K2014 Ref. 10	18		
K2014 with new lin solver	20		
	Min	Average	Max
Genetic original (Ref. 1)	6831	8669	9351
Genetic Fitness =RMS	6831	7997	9481

Table 1 Number of model calculations to reach a RMS limit for the undetermined model

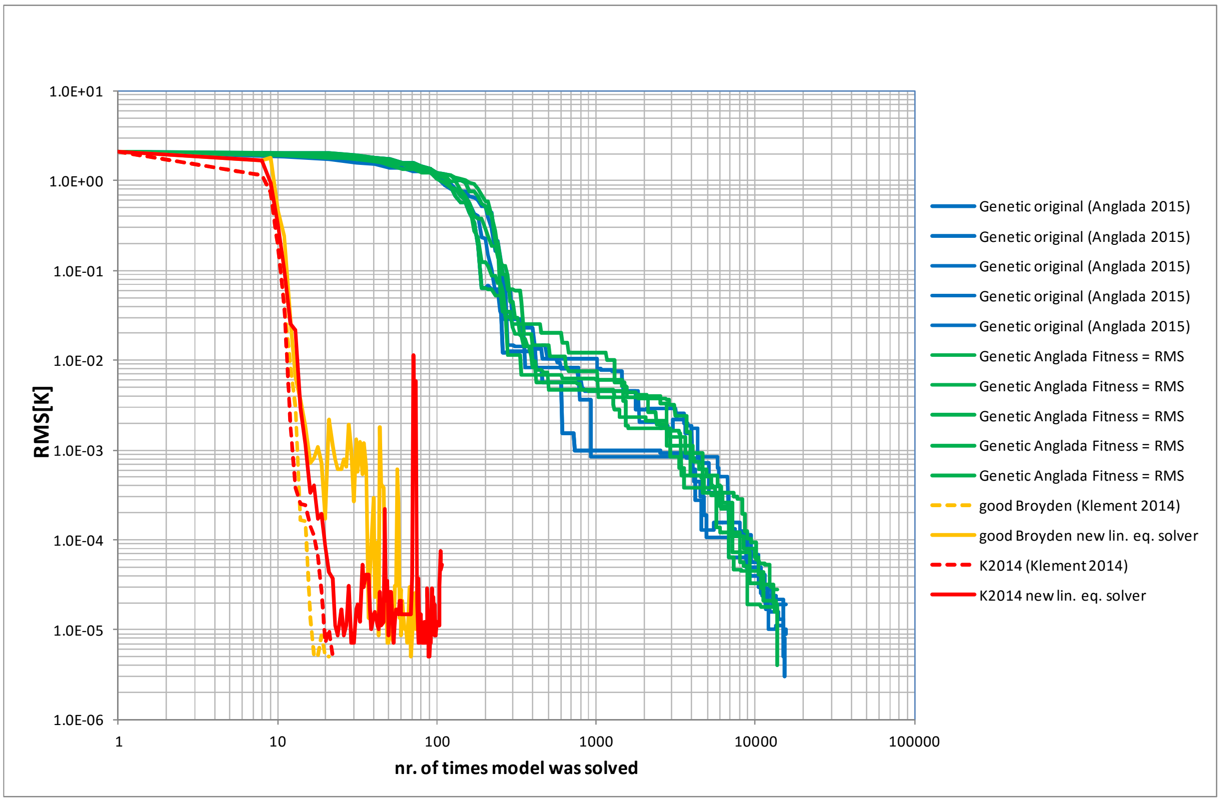

Figure 3. Convergence of the undetermined model correlation

D. Results for the determined simple model

The K2014 algorithm with the new solver linear solver was the fastest to correlate the simple determined model.

Algorithm	Total nr of times the model was solved to reach a RMS below 10^{-4}K		
good Broyden (Ref. 10)	31		
good Broyden new lin. solver	64		
K2014 (Ref. 10)	26		
K2014 with new lin solver	**19**		
	Min	Average	Max
Genetic original (Ref. 1)	5531	6677	10491
Genetic Fitness =RMS	5941	10037	14501

Table 2 Number of model calculations to reach a RMS limit for the determined model

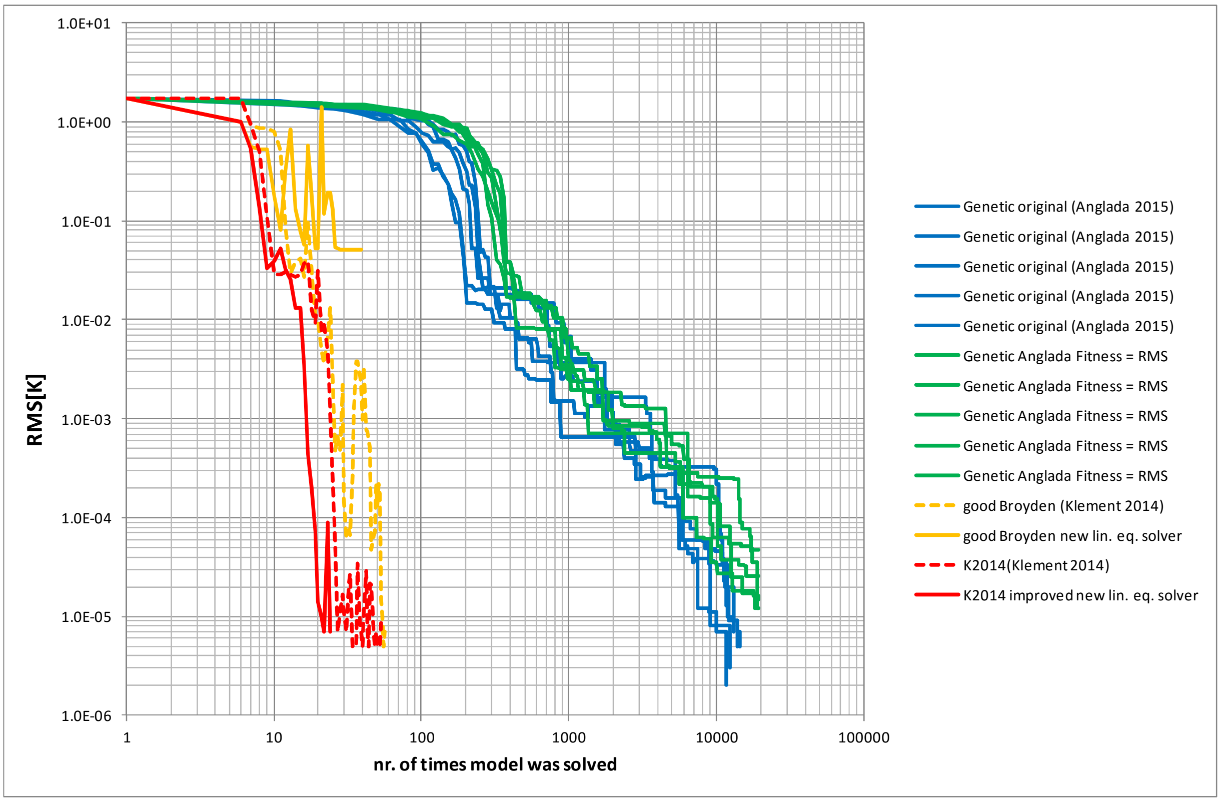

Figure 4 Convergence of the determined model correlation

E. Results for the simple over determined model

The K2014 algorithm with the new solver linear solver was the fastest to correlate the simple over determined model.

Algorithm	Total nr of times the model was solved to reach a RMS below 0.03K		
good Broyden (Ref. 10)	19		
good Broyden new lin. solver	9		
K2014 (Ref. 10)	11		
K2014 with new lin solver	**8**		
	Min	Average	Max
Genetic original (Ref. 1)	351	465	661
Genetic Fitness =RMS	1701	2021	2201

Table 3 Number of model calculations to reach a RMS limit for the over determined model

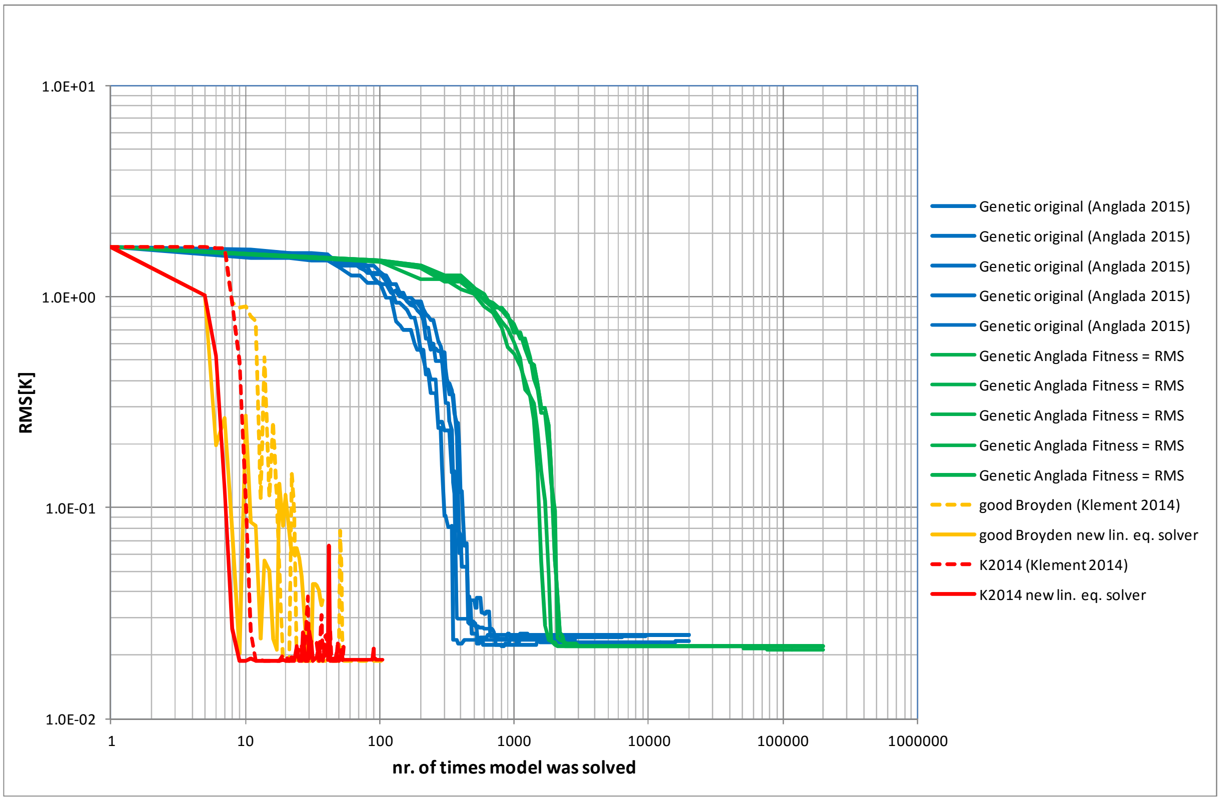

Figure 5 Convergence of the over determined model correlation

F. Results for the Tribolab Model

The Tribolab model showed the largest differences between the Broyden class methods (here the good Broyden and K2014 method) and the genetic methods. The K2014 method with the old linear and with the new linear solver converged nearly with the same speed. It can be seen that at the first iteration the new linear solver had an advantage over the original method from Ref. 10.

Algorithm	Total nr of times the model was solved to reach a RMS below 1K		
good Broyden (Ref. 10)	15		
good Broyden new lin solver	15		
K2014 (Ref. 10)	16		
K2014 with new lin. solver	**14**		
	Min	Average	Max
Genetic original (Ref. 1)	650	1584	2320
Genetic Fitness =RMS	650	1332	1890

Table 4 Number of model calculations to reach a RMS limit of 1K for the Tribolab model

Algorithm	Total nr of times the model was solved to reach a RMS below 10^{-4}K		
good Broyden (Ref. 10)	Not reached after 211		
good Broyden new lin solver	143		
K2014 (Ref. 10)	32		
K2014 with new lin. solver	32		
	Min	Average	Max
Genetic original (Ref. 1)	Not reached after 500000		
Genetic Fitness =RMS	Not reached after 500000		

Table 5 Number of model calculations to reach a RMS limit of 10^{-4}K for the Tribolab model

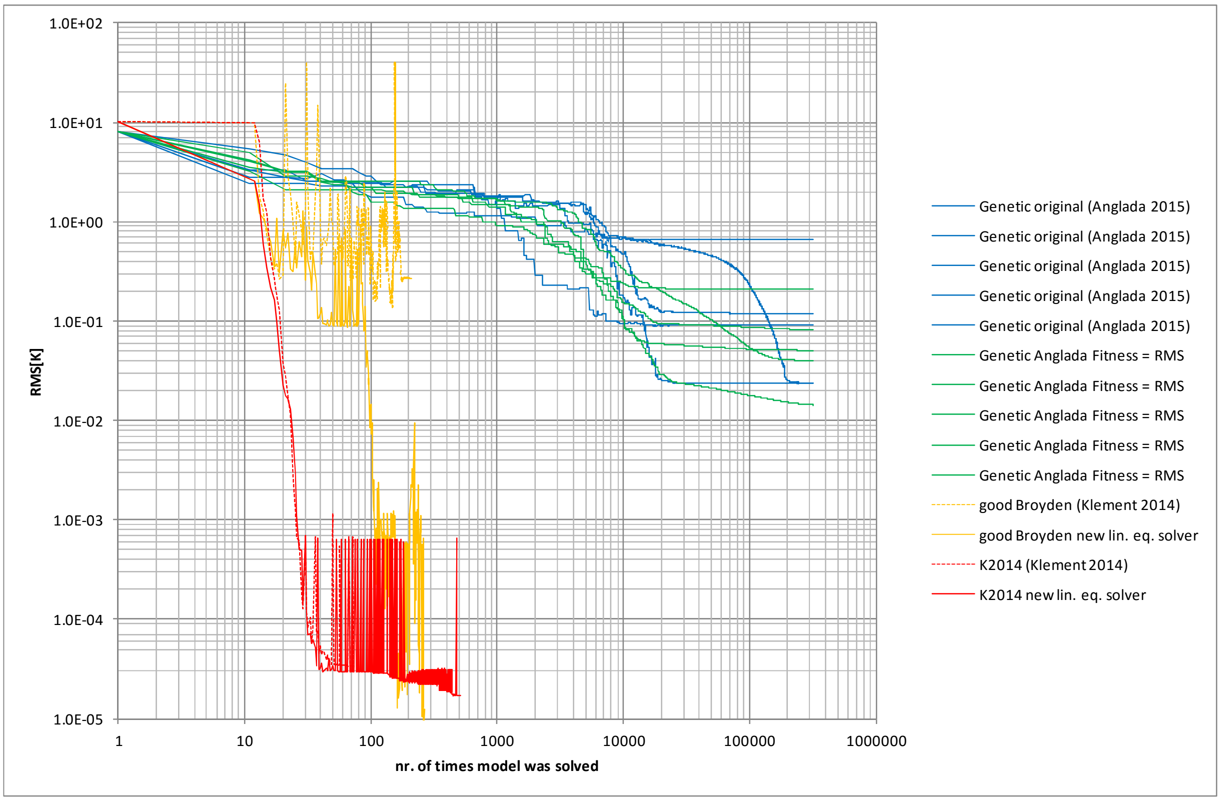

Figure 6 Convergence of the transient Tribolab model correlation

G. Calculation time

Also not relevant for the comparison between the correlation algorithms the calculation time is reported here
The calculations corresponding to the genetic algorithm have been performed in a conventional laptop (1 processor Intel ® Core ™ i7-2720QM @ 2.20 GHz and 4 Gb RAM) while the calculations of the Broyen class where performed on a workstation (1 processor used from a AMD Quad-core Opteron@2.7GHz and 16 Gb RAM). The calculation times corresponding to the undetermined, determined and over constrained models are included in Table 6 and the values corresponding to the Tribolab model in Table 7 these include all the process from model solving, file transfer operations and code compilation. For these small models the differences of the actions not related to solving the thermal problem dominate over the real solver time. Also this is not a fair comparison due to many factors(solver parameters, check out of the licence, compilation approach, file transfer over the network, postprocesing) it is obvious that the thermal solver used for the genetic algorithm was considerably faster, even being executed on a slower System. Therefore a dedicated comparison of the solvers might be interesting for the future.

model	Thermal solver code	fitness method	Time (s)/ Calculation	Total number of calculations (average)	Total time (s)
Undetermined	TK	Genetic original	0.004	8669	35
Undetermined	TK	Genetic fitness = RMS	0.005	7997	40
Undetermined	Thermica 4.5.3a	Good Broyden	1.5	19	28
Determined	TK	Genetic original	0.005	6677	33
Determined	TK	Genetic fitness = RMS	0.008	10037	80
Determined	Thermica 4.5.3a	K2014 with new lin. solver	1.5	16	24
Over determined	TK	Genetic original	0.004	465	2
Over determined	TK	Genetic fitness = RMS	0.004	2021	8
Over determined	Thermica 4.5.3a	K2014 with new lin. solver	1.5	8	12

Table 6 Calculation times for 4 nodes models

fitness method	Objective (K)	Time (s)/ Calculation	Total number of calculations (average)	Total time (s)	Total time (h)
Genetic original	1	0.04	1584	63.36	0.018
Genetic fitness = RMS	1	0.04	1332	53.28	0.015
Genetic original	10^{-4}	0.04	500000	20000.00	5.556
Genetic fitness = RMS	10^{-4}	0.04	500000	20000.00	5.556
K2014 with new lin. solver	10^{-4}	120	14	1680	0.46

Table 7 Calculation times for Tribolab model

VI. Practical Application of the Broyden class methods to complex models

The Broyden class methods have been used to correlate transient complex models with several thousand nodes to real thermal vacuum test results and in orbit telemetry data. Also correlation of reduced models to fine full models has been performed. But as these models contain protected knowledge their detailed results will not be shown here only a brief summary is results is given in Table 8. All correlation cases presented are transient load cases. Also transient correlation is unusual in space industry has been proven to be very efficient. It has many advantages:
It needs a long time to reach a steady state in a test setup, by correlating transient results instead test time and costs can be saved. Thermal capacities can be measured quite accurately if the power dissipation is well known. And with accurate thermal capacities small couplings like heat leaks trough MLI and cables can be accurately measured by evaluating the temperature change over time instead of temperature differences. Several parameters can be observed with a single sensor as long as there are independent effects over time. Last but not least considerably more data is used delivering accurate models.

Type	Approximated Number of nodes	Number of Parameters	Loadcases correlated	Total Timesteps evaluated	Sensors	Temperatures used for correlation	RMS initial[K]	RMS final[K]	Total Iterations	Total Time	Algorithm
Model to test	1000	13	6	6	25	150	8.8	2.3	28	34h	K2014
Model to test	2500	7	4	8425	1	8425	4.5	1.3	unknown	1.5h per iteration	K2014
Model to telemetry	2500	5	1	100	2	200	3.9	1.5	17	19h	K2014

Table 8 example of results obtained for practical applications

VII. Conclusion and outlook

6 different algorithms to correlate thermal models have been compared to 4 test models. All algorithms showed to be able to correlate thermal models. It is shown that the algorithms for the Broyen class analyzed correlated the thermal models faster than the genetic algorithms. For 3 of 4 of the cases analyzed the algorithm published in Ref. 10 combined with a new linear solver described in this paper was the most efficient one. For the under constrained model the methods with the original linear solver converged slightly faster, but this is probably a coincidence. Therefore this algorithm can be considered the most effective one of the methods analyzed.
Apart from being fast there are also limitations and disadvantages for this method. The main limitation is that it will work well only with monotone functions. A non-monotone function leads to instability as can be observed near the numerical accuracy limit of 10^{-4}K. Normally Thermal models are monotone but there are exceptions like a controlled heater switching on at a temperature level. Fortunately this can be avoided by mapping the heater power instead of simulating the heater logic. There are some configurations where quasi Newton methods do not converge. If these configurations are possible or likely to occur for thermal models still has to be investigated. Up to now no case could be observed.
The number of times that the model has been solved by the genetic algorithm has been higher in all cases with the implementations used in this study. Results obtained with the fitness function based on the RMS are similar to the obtained with the fitness function used in the original genetic algorithm. Only in the over determined model the differences between them are significant and best results correspond to the original fitness function. This is remarkable, because the RMS is a more relaxed criteria and it would seem more easy to reach the target value. But it seems that the algorithm have more difficulties to “find the correct path” and reach the correlation target. The major advantage of the genetic algorithms is that they are independent of the mathematical properties of the function, so they can be applied to almost any problem including non-monotonic functions with local minima.
From the investigated methods the K2014 with the new linear solver was the most efficient one. Also it is not shown in detail it has also proven to be the most efficient Broyden class method for complex models in practical applications.

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