Appendix G

Correlating thermal balance test results with a thermal mathematical model using evolutionary algorithms

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Abstract

The results of a series of thermal balance tests have been correlated with a thermal mathematical model. Three different optimization algorithms have been used for this: Monte Carlo simulation, Genetic Algorithm and Adaptive Particle Swarm Optimization. Based on a correlation criterion that minimizes the temperature difference between tests and model, the correlation can be optimized. APSO proved to be most useful, for its ability to optimize both locally and globally, its ability to search in a continuous search space, and its fast convergence. In this research, an average residual error of only 1.1°C was found. In general, optimization algorithms are feasible for thermal balance test results correlation. Comparing to manual correlation, optimization algorithms take less time, yield better results since they scan the entire search space, and are more flexible since several uncertain parameters can be varied at the same time. However, optimization techniques tend to find mathematical solutions rather than physical solutions, so boundaries on the parameter space are needed, for example from other tests. Even though this research indicates a good correlation, the set-up was relatively small (only 129 nodes and 24 relevant temperature measurements and comparisons) and comprehensible. For larger (satellite) test programs, the thermal network might be less easily understood and contain more unknowns and uncertainties. In that case a correlation using optimization techniques might be less optimal. Some engineering judgement of the thermal engineer will always be needed.

Note: An article explaining the method in more detail is included behind the presentation.

Correlating thermal balance test results using optimisation algorithms

Niek van Zijl, Bruin Benthem, Barry Zandbergen

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Use (evolutionary) optimisation algorithms for TB test correlation!

- In industry so far **TB test correlation** was always done **manually**
- Nowadays, with **increase in computer speed** optimisation algorithms are possible
- This research shows that **optimisation algorithms,** in particular **APSO**, are very much **suited for this correlation**!
- This presentation will prove this, based on a series of tests performed at Dutch Space

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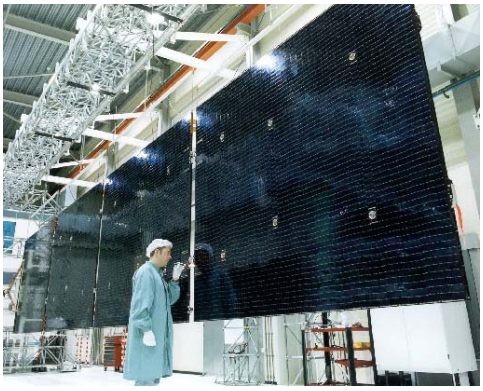
A solar panel is stacked before launch

Unfolded solar panel



Stacked solar panel

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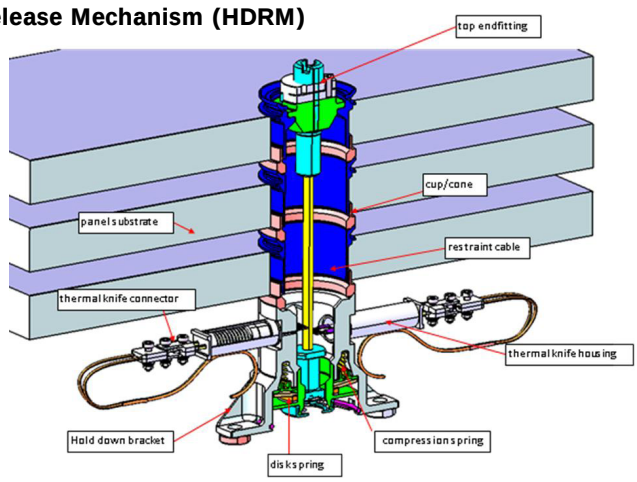
The panel is held together using an HDRM

Hold Down and Release Mechanism (HDRM)



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Several TB tests were performed for TMM validation

Test goals

- Validate the TMM of the HDRM by determining the unknown couplings and optical properties
- Reduce endfitting temperature uncertainty

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In total 4 dedicated tests were performed

- In total 4 tests have been performed
  - 3 dedicated tests on parts of an HDRM to determine 8 thermal parameters
  - Final test on entire HDRM to validate earlier found values and correlate 8 other parameters
- First two tests at Dutch Space (1 week)
- Last two tests at ESTEC (2 weeks)

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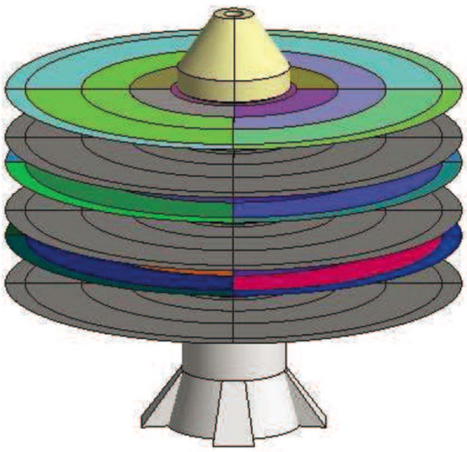
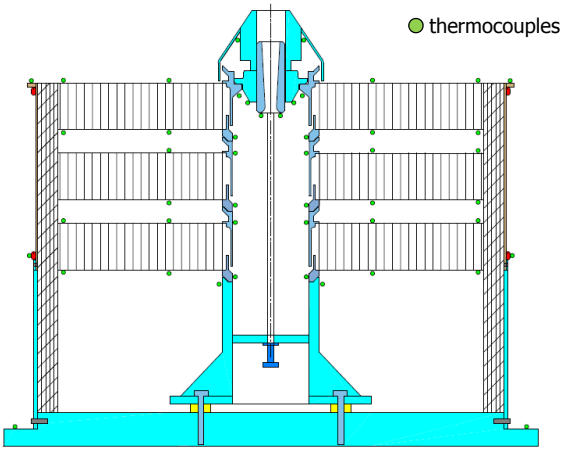
Thermocouples were placed in accordance with the TMM

HDRM model versus measurement locations





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6 test phases have been performed on the total set-up

Phase	Cold plate [°C]	Solar simulator flux	White cap
D1 T1	60°C	1423 W/m^2	no
D1 T2	60°C	1322 W/m^2	no
D1 T3	40°C	1423 W/m^2	no
D2 T1	60°C	1423 W/m^2	yes
D2 T2	60°C	1322 W/m^2	yes
D2 T3	40°C	1423 W/m^2	yes

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Thermal balance test correlation aims to minimise ΔT

Thermal balance test correlation:

*"The process of **adaptation of TMM parameters** in order to **minimise** the **difference** between the temperature **measurements** and the temperature **predictions** of the TMM"*

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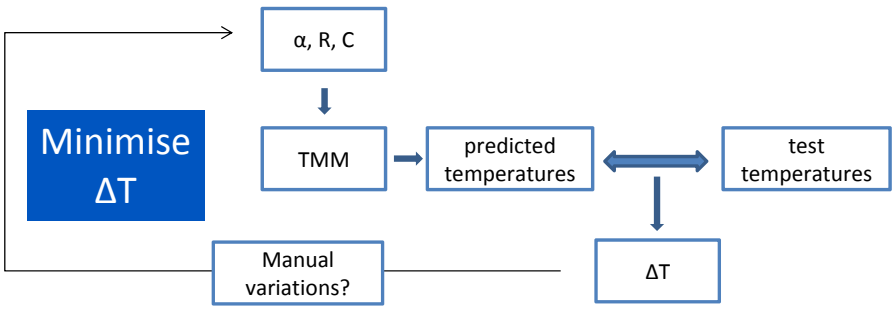
The correlation process: minimising through adaptation



Manual correlation:
1) It takes ages, 2) Goal of average ΔT < 3°C often not reached!

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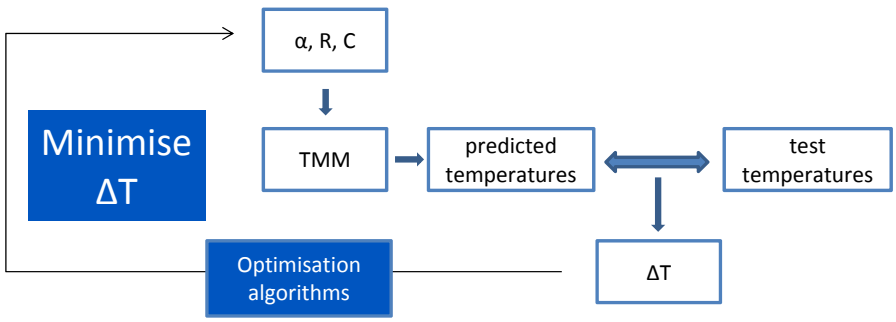
The correlation process: minimising through adaptation



Use optimisation algortihms!

Correlation goal is to minimise temperature difference over all 6 phases and all thermocouples

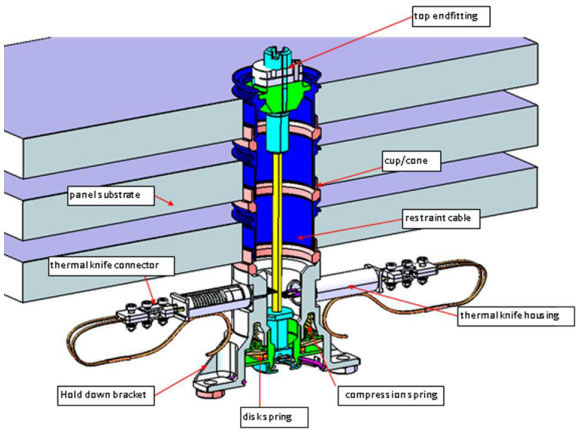
$$\min \Phi = \sqrt{\frac{\frac{1}{N}\sum_{i=1}^{N}(T_{model_i} - T_{test_i})^2 + (T_{model_{ef}} - T_{test_{ef}})^2}{2}}$$

$$\min \Phi_{allPhases} = \sqrt{\frac{1}{6}\sum_{phase=1}^{6} \Phi_{phase}{}^2}$$

In the correlation process, 16 thermal parameters were varied

Parameter
C_cup2panel
C_cone2panel
C_intra-panel
C_inter-panel
α_endfitting
ε_endfitting
α_WhiteCap
ε_WhiteCap

Parameter
C_bracket2baseplate
C_endfitting2cup
C_endfitting2whitecap
ε_baseplate
ε_TiCup
ε_Kapton
ε_CFRP
α_Kapton (outerPanel)



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Several optimisation algorithms have been compared

- Monte Carlo simulation
  Random picking of parameter values
- Genetic Algorithm
  Simulates natural selection (survival of the fittest)
- Adaptive Particle Swarm Optimisation
  Simulates behaviour of school of fish

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APSO allows to search in a continuous search space

- Algorithm introduction by Zhan (2009), for TB tests by Beck (2012)
- APSO imitates the **swarm behavior** of fish or birds
- A set of **mathematical rules** allows the swarm to **explore**, but also **follow the 'best' particle**
- Advantage is it can **search in a continuous space**

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Genetic Algorithm is widely-used optimisation algorithm, based on natural selection

- Algorithm introduction for TB tests by Jouffroy (2007)
- GA mimics **natural selection**, allowing 'best fit' solutions to **survive and produce offspring**
- **Genetic operations** allow the population to **evolve** and differ slightly from the previous, **allowing new (better) solutions**
- Method is widely used, for example in orbit optimisation

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The practical application of these algorithms involved linearisation and .csv dump to MATLAB

- ESATAN-TMS model is linearised around test temperatures
- L, R and Q matrices dumped as .csv and imported in MATLAB

- TMM is evaluated and compared to test temperatures
- Thermal parameters are changed (linearly) using algorithms and substituted in L / R / Q matrices

- If model is converged, stop

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Correlated model has average temperature difference of 1.1°C only, and almost 0 on the endfitting

Average temperature difference between model and test [°C]	
Endfitting	All nodes
0.24	1.1

From literature: a goal of average ΔT < 3°C, but it is often not even reached!

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APSO is best algorithm to use for TB test correlation

	Monte Carlo	GA	APSO
Φ [K]	1.0171	0.789	0.783
Number of evaluations	10000	25600 (256 individuals x 100 generations)	6000 (20 particles x 300 iteration)
Search space	discrete	discrete	continuous
Required calculation time (s)	515	1298	263
Algorithm set-up	easy	difficult population operation	difficult swarm operations

APSO best algorithm to use:
- ability to optimise both locally and globally
- able to search in a continuous search space
- leads to fast convergence

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Discussion

- The first series of TB tests on parts only, have certainly helped in converging the result of the entire HDRM correlation
- Calculation time on this set-up was limited. With larger models, the thermal network grows, increasing computation time enormously
- Re-running the algorithm yielded the same objective function, but with different solution (thermal parameter set). Some of these sets were physically impossible, so engineering judgements is still important!

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Conclusion

- Established good correlation (1.1°C average) with test results
- Shown feasibility of optimisation algorithms
- APSO came out as best algorithm:
  - ability to optimise both locally and globally
  - able to search in a continuous search space
  - leads to fast convergence

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(Test) experience quotes

In theory, theory and practice are equal. In practice, theory and practice appear not to be equal

free from Flip Zijdemans, Dutch Space

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Correlating thermal balance test results with a thermal mathematical model using evolutionary algorithms

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***Abstract*— The results of a series of thermal balance tests have been correlated with a thermal mathematical model. Three different optimisation algorithms have been used for this: Monte Carlo simulation, Genetic Algorithm and Adaptive Particle Swarm Optimisation. Based on a correlation criterion that minimises the temperature difference between tests and model, the correlation can be optimised. APSO proved to be most useful, for its ability to optimise both locally and globally, its ability to search in a continuous search space, and its fast convergence. In this research, an average residual error of only 1.1°C was found. In general, optimisation algorithms are feasible for thermal balance test results correlation. Comparing to manual correlation, optimisation algorithms take less time, yield better results since they scan the entire search space, and are more flexible since several uncertain parameters can be varied at the same time. However, optimisation techniques tend to find mathematical solutions rather than physical solutions, so boundaries on the parameter space are needed, for example from other tests. Even though this research indicates a good correlation, the set-up was relatively small (only 129 nodes and 24 relevant temperature measurements and comparisons) and comprehensible. For larger (satellite) test programs, the thermal network might be less easily understood and contain more unknowns and uncertainties. In that case a correlation using optimisation techniques might be less optimal. Some engineering judgement of the thermal engineer will always be needed.**

I. Introduction

When a series of thermal balance tests is finished, the results need to be correlated with a thermal mathematical model. For long this correlation process has been a manual process as described clearly in [1], but the correlation often does not yield satisfactory results. The general correlation goal is a correlation within 3K [2],[3], but many correlations do not reach that criterion [1],[4]-[6]. Besides that, manual correlation can be very time consuming. As the correlation process actually is an optimisation problem, several optimisation techniques could be used to (semi-) automatically solve this problem. With computer speed increase over the past few years, optimisation algorithms have become more attractive to use. A literature study of several algorithms in [7] showed that Genetic Algorithm (GA) and Simulated Annealing (SA) proved promising for thermal correlation. In [8] a general study of GA parameters is performed. [9] is the first paper describing the use of Adaptive Particle Swarm Optimisation (APSO) for correlation.

In this paper the feasibility of the use of Monte Carlo techniques, GA and APSO is investigated. All techniques are tested using the results of a series of performed thermal balance tests.

II. Test Set-Up

A series of four thermal balance tests was performed on the Hold Down and Release Mechanism (HDRM). This system, developed by Dutch Space, clamps a stack of solar panels together during launch and deploys them once in orbit. The stack is held in place with a cable under tension, running through a hole in every panel. On both ends it is clamped with two endfittings. On the top part, the endfitting is exposed to solar radiation. To lower this endfitting temperature, also a white cap can be used.

Fig. 1. HDRM side-view during test integration

The first three tests have been performed on parts of the HDRM, to determine 8 sensitive thermal parameters. Dedicated test set-ups and tests were designed to determine these values.

The last test was performed on an entire HDRM. The set-up consisted of an HDRM with 3 circular panel parts of 210 mm diameter as seen in Fig. 1. All around the panels 5 layers of 2-mm insulating foam and double-sided aluminised Kapton in between [10] are placed, while an Aluminum/CRES cylinder was placed around the foam, equipped with guard heaters, reaching the same temperature gradient as in the stack. This combination of foam and guard heating reduced the heat leak to the sides, leading to less than 0.3°C influence on the test temperatures.

On the bottom the HDRM was fixed to an aluminium baseplate, mounted on the chamber cold plate. A solar simulator was present to deliver the heat flux to the sample. It was calibrated using a solar cell.

Six different test phases were tested as described in TABLE I. Three tests phases are performed with white cap, and three without. Steady state (<0.1°C/ 2hrs) was reached for all test phases.

TABLE I
Test Phases

Phase	**Cold plate** [°C]	**Solar sim** [W/m^2]	**White cap**
D1 T1	60	1423	no
D1 T2	60	1322	no
D1 T3	40	1423	no
D2 T1	60	1423	yes
D2 T2	60	1322	yes
D2 T3	40	1423	yes

III. Correlation Problem/Criterion

A geometrical model of the test set-up was made in ESATAN-TMS, including the test chamber (shroud, door, window) and the insulating foam. The insulating foam was modelled as a fully IR-reflective surface. This geometrical model led to a thermal mathematical model of 109 nodes, plus 20 nodes for the environment. The test item was modelled rotationally symmetric and split in 4 quarters. Due to this rotational symmetry, a pair of thermocouples (for redundancy) was placed under 180° from the other. There were 48 thermocouples used on the set-up, plus about 10 in the chamber (facility thermocouples). Averaging redundant test thermocouples, and taking into account the shroud, door and window, there were 24 relevant locations of which the temperatures could be compared between test and model. As the model is rotationally symmetric, the temperatures of every four rotationally symmetric nodes were averaged as well.

To check the quality of the correlation, a correlation criterion was defined. [11] defines this as the average temperature difference, while [12] defines it in a least squares fashion. For this test two aspects were important: correlation over all nodes and the correlation of the endfitting temperature only (since this is the critical aspect of the HDRM). As a result, both aspects count for 50% in the correlation criterion, while still using a least squares approach:

$$\Phi = \sqrt{\frac{\frac{1}{N}\sum_{i=1}^{N}(T_{model_i} - T_{test_i})^2 + (T_{model_{ef}} - T_{test_{ef}})^2}{2}}$$

Where N is the amount of temperatures that are compared. As the shroud, door and baseplate serve as heat sinks, they are the boundary conditions of the system. Consequently these same temperatures are fed in the model as well, so they do not count for the correlation criterion. As a result, N = 20 when no white cap is present, and N = 21 if there is a white cap. The endfitting is included in N, since it then counts for the average error in the system.

As there are 6 test phases, this correlation needs to be checked for all 6 test phases (again root-mean-square, RMS), so:

$$\Phi_{allPhases} = \sqrt{\frac{1}{6}\sum_{phase=1}^{6}\Phi_{phase}{}^2}$$

IV. Implementation

To correlate the model, a set of 16 thermal parameters was varied. These consist of optical properties (UV absorption and IR emissivity) and conductive couplings (including some contact conductances). The different correlation methods were applied by making a .csv dump of the ESATAN-TMS model and reading these in MATLAB to accommodate for automatic correlation. This leads to three matrices: L, R and Q. L is the (square) matrix of conductive couplings, R is the (square) matrix of radiative couplings, and Q is the one-dimensional matrix of heat inputs (i.e. solar power, αAS).

The different algorithms (Fig. 2 and Fig. 3) work by varying parts of these matrices. If a conductive coupling is varied, it can just be replaced in the L-matrix. If the absorption α of a node is varied, the heat input on that node is scaled linearly with the new α. And if the emissivity ε of a node is varied, the entire radiative coupling from that node to all other nodes is scaled linearly with the new ε. Scaling these optical properties linearly with heat input or radiative couplings is not entirely representative, since reflections to other nodes are then not taken into account. This small error can be checked at the end of the correlation by back-substituting the found parameters from the optimal correlation in ESATAN-TMS and comparing the resulting temperatures.

The main advantage however is that varying optical properties becomes much faster this way, since not every time a new radiative analysis needs to be performed, like in ESATAN-TMS. There the entire geometrical model needs to be reloaded, after which a radiative analysis over all nodes needs to be performed. This is done by firing rays from every surface and counting the amount of rays that hit each other surface. The radiative analysis uses a Monte Carlo scheme, so a large amount of rays (~10000) per surface is fired, leading to a total 10-20 seconds needed per radiative analysis.

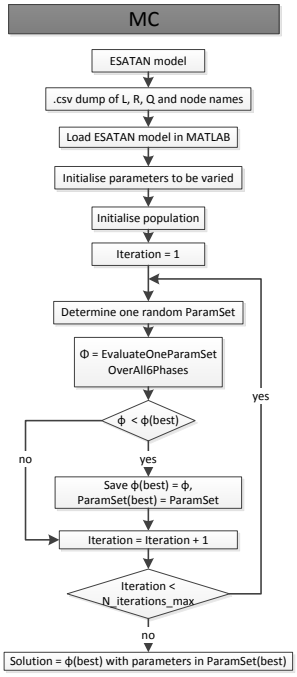

Fig. 2. Monte Carlo implementation

Besides the faster alterations of optical properties, MATLAB is also faster than ESATAN-TMS in calculating steady state results, because it is able to work with matrices better.

Variations of the parameters happened within certain limits. For 8 out of 16 parameters, their uncertainty ranges had been determined in the earlier 3 tests. Another 4 optical properties were known from Dutch Space heritage, while taking into account the guidelines from ESA [13] of ±0.03. The last 4 parameters were varied in a very large range: -100% to +100% of the estimated value. This allowed the search space to become limited, but large enough to find the optimal solution.

In the end, every algorithm chooses a set of parameters, which are then inserted in the model. The model is solved for steady state of each phase using the boundary conditions from TABLE I. The resulting temperatures are compared on the 24 relevant nodes, which gives a solution for the objective function.

Three algorithms are used for correlation: Monte Carlo (MC), Genetic Algorithm (GA) and Adaptive Particle Swarm Optimisation (APSO).

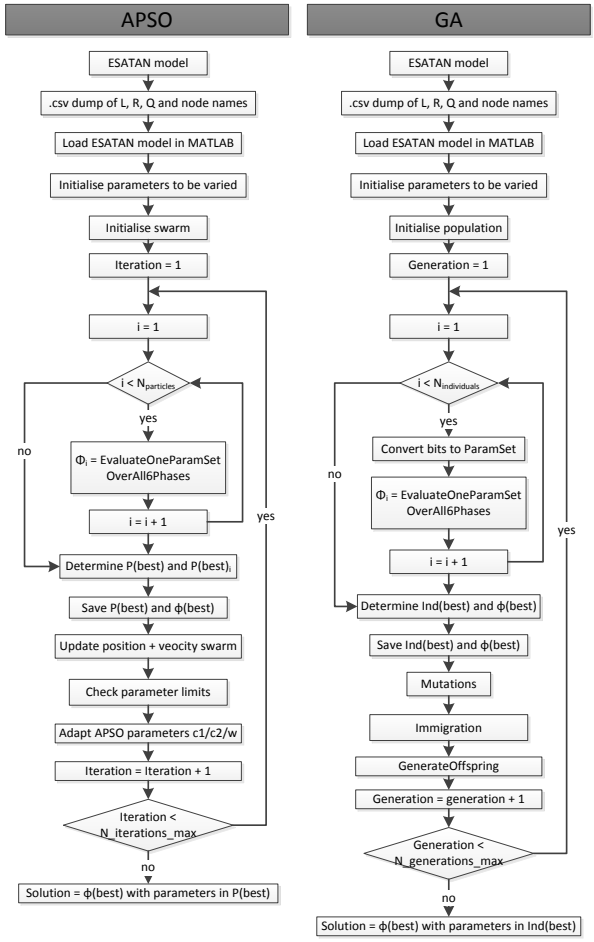

Fig. 3. GA and APSO implementation

V. Monte Carlo Method

The Monte Carlo method is quite straightforward. Per trial, each parameter value is randomly (uniform) chosen from its parameter range. This is evaluated and yields a value for the objective function. The more trials are performed, the larger the chance is a lower value for the objective function is found. On the other hand it is never clear whether this is a true optimum. A correlation with $\Phi = 1.0171$ is found, after 10000 trials, taking 515 seconds.

VI. Genetic Algorithm

The genetic algorithm simulates natural selection. A population consisting of solutions (parameter sets) evolves over generations, while the ones with the best fitness (lowest value for objective function) survive. Fig. 3 presents the algorithm in more detail.

In this research, each parameter had a resolution of 7 bits, leading to an individual length of 112 bits. A mutation rate of 0.1% per bit, an immigration rate of 2% and an elitist survival principle of 5% was used. On top of that, the most fit individual has a 2 times higher chance to generate offspring than the least fit individual. For all individuals in between this scales exponentially. In the next generation, parents are fully replaced with children (i.e. there is no fitness check, since this would require a full function evaluation, increasing the computation time).

In Fig. 4 the best correlation of 100 generations and a population size of 256 individuals is presented. This run took 1298 seconds and yielded a value for the objective function Φ = 0.789.

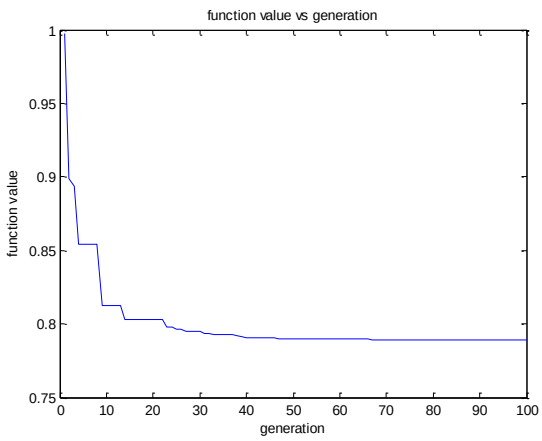

Fig. 4. Objective function improvement with more generations in GA correlation

VII. Adaptive Particle Swarm Optimisation

The APSO algorithm is described in [14]. APSO is an adaptation of Particle Swarm Optimisation (PSO) [15],[16]. PSO is based on the behavior of a flock of birds or school of fish. The movement of each particle (parameter set) is influenced by its local best known position but is also guided toward the best known position in the search space, which is updated when other particles find better solutions. The swarm searches the entire search space, but is also able to converge when an optimum has been found. This combination of both global and local optimum search makes PSO very useful.

The adaptive part in APSO comes from two extra parameters only, which identify the evolutionary state, and enforce an elitist learning principle. These parameters are adapted during the search. The evolutionary state determination increases the search efficiency and speed, while the elitist learning principle allows the swarm to jump out of the local optima.

The algorithm is presented in Fig. 3. During the correlation process, the swarm consisted of 20 particles, and the maximum amount of swarm iterations was 300. The development of the APSO parameters during the process is presented in Fig. 5. This resulted in Φ = 0.783 after 263 seconds.

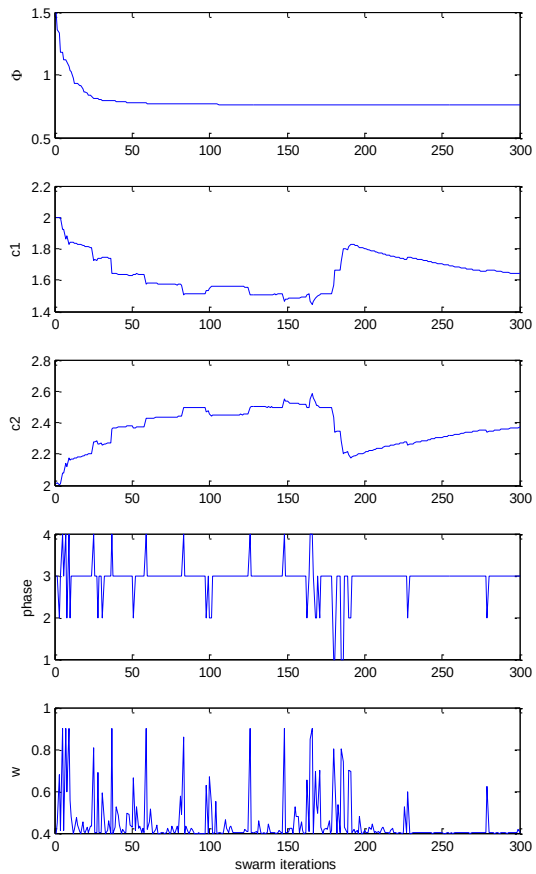

Fig. 5. Development of APSO parameters during correlation

VIII. Optimal Correlation

The optimal correlation can be found by selecting the one with the lowest value for the objective function, which is the one from APSO. The resulting temperature differences ΔT between model and test are presented in TABLE II.

TABLE II
REMAINING TEMPERATURE DIFFERENCES BETWEEN CORRELATED MODEL AND TEST FROM OPTIMAL CORRELATION (APSO)

Phase	ΔT on endfitting [°C]	ΔT over all nodes [°C] (RMS)
D1T1	0.16	1.20
D1T2	-0.17	1.11
D1T3	0.25	1.25
D2T1	-0.07	0.92
D2T2	-0.46	0.95
D2T3	0.05	1.04

The remaining ΔT over all nodes (RMS) is 1.1°C, which is far within the goal of correlation within 3°C [2],[3],[13]. So the correlation can be considered sufficient.

The residual between test and model temperatures is not zero. There always remains an error between test results and model. For now, several sources are:

- Errors in thermocouple measurements: even though the thermocouples are calibrated, still redundant thermocouples are now averaged, so there is always a residual error.
- Modelling errors which simplify reality: optical properties of finite surfaces and simplifications of the geometry.
- Material/manufacturing errors/assumptions: the panel is never fully homogene in all directions, for example due to different directions of the carbon fibres. On top of that, adhesives and/or pottings are not equally thick in all directions. This is assumed in the model however, so this might lead to errors.
- Couplings are linearised: the couplings through the panel are modeled as linear with temperature, whereas they are a combination of conduction (linear) and radiation (quartic).

IX. DISCUSSION

A comparison of the three different optimisation techniques is presented in TABLE III. From this table it becomes clear that APSO is the best method for correlating the test results. It reaches a better correlation due to its ability to combine both local and global search. On top of that, it can search the parameter space in a continuous search space, i.e. the parameter space does not have to be discretized and thus a global optimum is also a local optimum (you are in the Himalayas, but you also know you are exactly at the top of Mount Everest). APSO has a short calculation time, since the swarm can be very small, and there is no time involved in converting the parameters to bits and vice versa, like in GA. The solution also converges rather quickly, compared to GA. The main disadvantage of GA is the resolution of the parameters. More bits means a more accurate solution, but requires much more calculation power. Setting up the APSO correlation is not more difficult than setting up the GA correlation. Both methods have several swarm/population operations, but once the algorithm is set up, it can be applied rather easily.

TABLE III
COMPARISON OF DIFFERENT ALGORITHMS

	Monte Carlo	GA	APSO
Φ [K]	1.0171	0.789	0.783
Number of evaluations	10000	256 individuals x 100 generations = 25600	20 particles x 300 iterations = 6000
Search space	discrete	discrete	continuous
Required calculation time (s)	515	1298	263
Algorithm set-up	easy	difficult population operation	difficult swarm operations

However, some remarks can be made. Four aspects are considered.

A. *Amount of relevant temperature locations*

The amount of relevant temperature locations is limited in this test compared to large satellites programs. This means there are less nodes and couplings, which makes the correlation of the model easier. As a result, the correlation of the model can be on average 1.1°C, where several others have failed to correlate within 3°C [1],[4]-[6]. It can be concluded the correlation in this particular test has been good, but it cannot be concluded that this will hold for other (larger) satellite tests. The amount of temperature locations in this test was relatively small, compared to 49 in Monte Carlo correlation [11], 17 in APSO correlation [9], 35 in GA correlation [8] and 105 in manual correlation in [1]. For larger models or more measurement points the correlation might be more difficult.

On the other hand, in the correlation performed in this research, a set of 16 parameters was varied. This is relatively large, compared to 5 in Monte Carlo correlation [11], 10 in APSO correlation [9], and 5 in GA [8] (no data available from the manual correlation in [1]). More specific, using the optimisation techniques, the set of 16 parameters can easily be expanded. It will increase the computation time a little, but that is all. This makes optimisation algorithms again more favourable over manual correlation. Also, the total computation time is only in the order of several minutes, whereas [9] speaks of 50 hours for 600 iterations in a TMM with 650 nodes and only 10 varying parameters.

B. *Diversity in found correlations*

Running the different algorithms several times yielded several parameter sets with similar objective function values (0.783 to 0.790). These parameter sets however differed significantly. It shows that there are several solutions possible in this optimisation problem. Some of these parameter sets

present mathematically possible solutions, but not physically possible ones, for example emissivities larger than 1. The challenge is to determine which of all these parameter sets is in fact the set that approached the physical parameters the best. In this research, three dedicated tests were performed to determine 8 of the 16 parameters. The values found with their uncertainty margins were used as inputs. The APSO solution that showed the best correspondence to these results (only few percent difference between earlier results and correlation results) was finally selected as the optimal correlation. However, if these 3 dedicated tests had not been performed, it would have been much harder to determine which physical solution to take. This is where ultimately also engineering judgement of the thermal engineer is needed!

A concrete example during this correlation process was the coupling of the HDRM to the baseplate. Normally the HDRM is isolated from the baseplate with some thermal washers, but mechanically fixed in place with several bolts. During the correlation, the temperature at the bottom part of the HDRM was always higher than was expected, in the order of 10°C. This showed in fact much less power was flowing to the baseplate than was predicted. By making this coupling a varying parameter, the optimisation algorithms directly converged to a solution a factor 3 lower than was expected. Inspection of the test set-up also revealed that the bolts had not been torqued properly, explaining this lower conduction. The fact that the correlation algorithms converged to this much lower value proves their strength. On the other hand, the thermal engineer should notice that the temperature is always higher during every correlation run, i.e. the optimisation algorithm cannot lower this temperature difference further (and the influence on the objective function of a 10°C difference is big!). The thermal engineering should thus know how the thermal model is built and which parameters could affect the correlation. A combination of engineering judgement and the optimisation algorithm yields the optimal correlation then.

C. Failure to reproduce found correlation

The result of running an optimisation algorithm is a certain set of values for all 16 parameters. But vice versa, the questions rises whether for a certain optimal correlation, this correlation can be reproduced? In a practical sense, this means the optimal correlation parameters yield the temperatures on the 20/21 (without/with white cap) relevant node locations (boundary conditions are kept the same). Now a correlation starts with these temperatures as reference temperatures, instead of the test temperatures. In a theoretical sense, this correlation should lead to an objective function of 0, since there exists a perfect fit to the temperatures.

This reproduction correlation process has been performed for GA and APSO. Fig. 6 presents these results. It is clear that the function value (i.e. the objective function) does not become 0, even after 1000 iterations, so both algorithms are not that perfect that they can always find the true optimum. This might have to do with the large set of parameters. Considering the 16 parameters and the 7 bits per parameter, an individual in GA consists of 112 bits, so there are 2^{112} = $5.2 \cdot 10^{33}$ parameter sets possible. For APSO, the amount of combinations is infinite due to its continuous search space.

On the other hand, already after 100 generations (GA) or 200 iterations (APSO) an objective function value of 0.1 has been found, which comes down to an average residual error per temperature location of 0.1°C. This residual error is so small, that it is also safe to say the correlation algorithm does find useable optima.

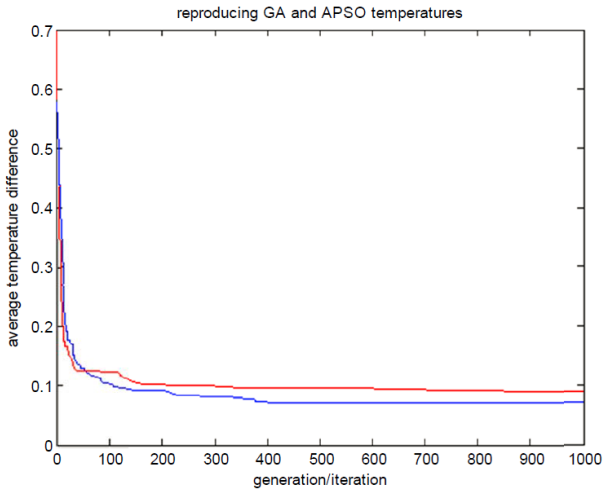

Fig. 6. Effort to reproduce the thermal parameters from the GA (blue) and APSO (red) optimal correlation

X. Conclusion

For the correlation of thermal balance test results with a thermal mathematical model, APSO proved to be most useful, for its ability to optimise both locally and globally, its ability to search in a continuous search space, and its fast convergence.

In comparing manual correlation with the use of optimisation techniques, it can be said that optimisation techniques are favourable: they take less time than manual correlation, they yield better results since they scan the entire search space, and they are more flexible since several uncertain parameters can be varied at the same time.

On the other hand, optimisation techniques tend to find mathematical solutions rather than physical solutions, so boundaries on the parameter space are needed, for example from other tests. As more parameters are being varied, the search space becomes very big. As there are several possible solutions, the algorithms do not necessarily find their own optimum again. And finally, the results from this research indicate a good correlation (average residual per node of

1.1°C), but the set-up was relatively small (only 129 nodes and 24 relevant temperature measurements and comparisons) and comprehensible. For larger (satellite) test programs, the thermal network might be less easily understood and contain more unknowns and uncertainties. In that case a correlation using optimisation techniques might be less optimal. Some engineering judgement of the thermal engineer will always be needed.

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References

[1] Z. Jin, S. C. Joshi, G. J. J . Nesamani, P.K. Chan, T.M. Ying & C. H. Goh, "Data analysis and correlation for thermal balance test on a micro-satellite model," *Heat Transfer Engineering*, vol. 31, no. 2, pp. 222-233, 2010.

[2] D. G. Gilmore, *Satellite Thermal Control Handbook*. The Aerospace Corporation Press, 1994, ISBN 1-884989-00-4.

[3] R. D. Karam, *Satellite Thermal Control for Systems Engineers*. American Institute of Astronautics and Aeronautics, 1998, vol. 181 of Progress in Astronautics and Aeronautics, ISBN 1-56347-276-7.

[4] Z. Sherman, "The thermal balance test of AMOS-2 spacecraft," *Proceedings of the 5th International Symposium on Environmental Testing for Space Programmes, ESA SP-558*, pp. 127-135, 2004.

[5] E. van den Heuvel & J. Doornink, "Thermal balance testing of the European robotic arm," *Proceedings 4th International Symposium on Environmental Testing for Space Programmes, ESA SP-467*, pp. 439-444, 2001.

[6] S. Miller & E. Marotta, "Thermal modeling and testing of a nanosatellite's avionics board," *Journal of Thermophysics and Heat Transfer*, vol. 21, no. 3, pp. 496-504, 2007.

[7] F. Jouffroy, "Bibliographical study of optimisation methods with focus on genetic algorithm techniques wrt post-test thermal model correlation problem," document available from https://exchange.esa.int/restricted/model-correlation, 2006.

[8] F. Jouffroy & N. Durand, "Thermal model correlation using genetic algorithms," *21st European Workshop on Thermal and ECLS Software*, 2007.

[9] T. Beck, A. Bieler & N. Thomas, "Numerical thermal mathematical model correlation to thermal balance test using adaptive particle swarm optimization (APSO)," *Applied Thermal Engineering*, vol. 38, pp. 168-174, 2012.

[10] S. Tachikawa, R. Takagi, Y. Mizutani, Y. Hiasa, and A. Ohnishi, "Performance evaluation of new thermal insulation system with polyimide foams," in *41st International Conference on Environmental Systems*, pp. 52-57, 2011.

[11] W. Cheng, N. Liu, Z. Li, Q. Zhong, A. Wang, Z. Zhang & Z. He, "Application study of a correction method for a spacecraft thermal model with a monte-carlo hybrid algorithm," *Chinese Science Bulletin*, vol. 56, no. 13, pp. 1407-1412, 2011.

[12] B. A. Cullimore, "Dealing with uncertainties and variations in thermal design," *Proceedings of InterPack '01, International Electronic Packaging Conference*, 2001, IPACK2001-15516.

[13] ECSS, "ECSS standard, Space Engineering, Mechanical Part 1: thermal control," ECSS-E-30 Part 1A, 2000.

[14] Z-H. Zhan, J. Zhang, Y. Li & H. S-H. Chung, "Adaptive particle swarm optimization," *IEEE Transactions on Systems, Man, and Cyberneticspart B: Cybernetics*, vol. 39, no. 6, pp. 1362-1381, 2009.

[15] J. Kennedy and R. C. Eberhart, “Particle swarm optimization,” in Proceedings of IEEE International Conference on Neural Networks, vol. 4, pp. 1942–1948, 1995.

[16] R. C. Eberhart and J. Kennedy, “A new optimizer using particle swarm theory,” in Proceedings of the 6th International Symposium on Micro Machine and Human Science, pp. 39–43, 1995.