Dynamic Compact Thermal Model with Neural Networks for Radar Applications

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ABSTRACT

This article deals with the creation of a compact thermal model. In this aim, we apply some well-known methods such as FEM model reduction and identification of RC networks. To go further than already existing approaches, we also introduce the use of artificial neural networks (ANNs) to cope with nonlinearities which may appear in thermal phenomenons. A new hybrid model, trying to gather the advantages of ANNs and RC networks, is applied on a simple thermal problem. The need of samples will also lead us to carry out, in parallel, the FEM model reduction. The reduced FEM model will then be used to generate the required databases and validate the compact model results.

1. INTRODUCTION

The increase of power density and the constant miniaturization of electronic elements have generated an growing requirement of thermal management. Thus, in active antenna, the junction temperature of power modules, typically high power amplifiers (HPA), should be carefully evaluated. Indeed, this temperature affects both the reliability and the efficiency of the components and taking into account this parameter becomes more and more important. The Finite Elements Method (FEM) seems to bring a solution for this problem. Indeed, a fine modeling makes possible to predict quite accurately the heat repartition inside all kinds of components and/or cooling systems. Nevertheless, build a fully-detailled model is impossible and the resolution of the numerical system can be really time-consuming, mainly if the model is accurate and hence complex.

Lots of tips are of course available to reduce the complexity of an FEM model. Using symmetries of the model or neglecting some thermal effects could simplify the problem and accelerate calculations. Those techniques could be very useful, but the FEM offently stays too slow to be really efficient. A step forward in the reduction of complexity is done with Compact Thermal Models (CTMs). Those methods have no direct link with the real structure of the system and only preserve a notion of "level". A complete part of the system is then often replaced by a single node in an equivalent electronic circuit. The parameter of the circuit are calculated to imitate the response of the real system. Many studies have been achieved on this way, and the results have shown CTMs could be a very attractive method for thermal prediction [1] [2] [3].

For dynamic responses, and when the conduction is not the main thermal phenomenon, the nonlinearities of the real systems are however more perceptible and some improvements of CTMs seem possible. Given the fact that this method can be viewed as a linear model identification, it appears sensible to use nonlinear models identification (such as ANN) in order to surmount current limitations of CTMs.

To cover all the aspects of this question, we will reduce the real case of power modules to a simpler one with only one electronic component mounted on a cooling system (Fig 1). The problem of temperature prediction is hence much easier but the thermal effects involved are similar. The FEM model of the system will be used to evaluate each steps of the compact model creation and to provide simulated measurements. As all the others in the article, this FEM model has been build with TAS (Thermal Analysis System) Software.

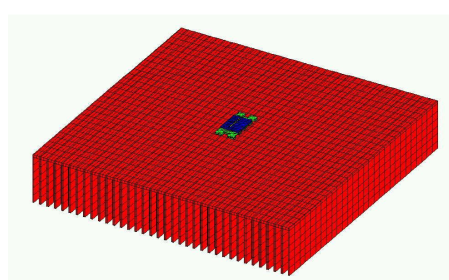

Figure 1: Global view of the system.

2. RC NETWORK AS COMPONENT MODEL

The FEM model is voluntarily simple. The junction temperature prediction is thus very coarse and low. The model is only composed of a silicon bar on a block of BeO brased on a support made of CuW (Fig 2). The support will next be used to screwed the ”component” on the radiator.

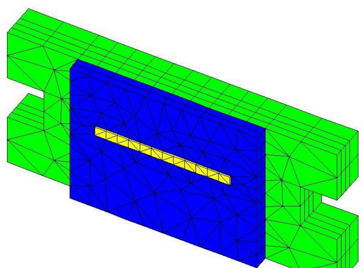

Figure 2: FEM model of the component

For this model, the main thermal effect is due to conduction. In this case, for small dimension elements, some assumptions could be very useful to simplify the model. If the heat flow is supposed to be one-way, the thermal behaviour of a homogeneous block of material can be summarized by its thermal resistance R_{th} and its thermal capacitance C_{th}.

$$R_{th} = \frac{\Delta x}{\lambda S} \tag{1}$$

$$C_{th} = \mu c S \Delta x \tag{2}$$

Δx : length of the block in the direction of heat flow
λ : conductivity of the material
S : surface perpendicular to the direction of heat flow
μ : volumetric mass of the material
c : specific heat of the material

The dynamic response of the component can then be reproduced by a network with 3 RC elements (one for each homogenous block). To identify thermal resistances, the static response for a fixed boundary condition is sufficient (Fig 3). However, the calculation of capacitances requires the temperature transcients (Fig 4) at each level. Thanks to FEM, it is possible to easily extract all those data. The parameters of an equivalent model can so be computed. This kind of approach is used by the majority of the CTMs methods [4] [5] [6].

3. FEM MODEL REDUCTION

TAS allowes the introduction of a RC network inside the structure of a model. Hence, the equivalent circuit can be inserted in the FEM model. The substitution with the true

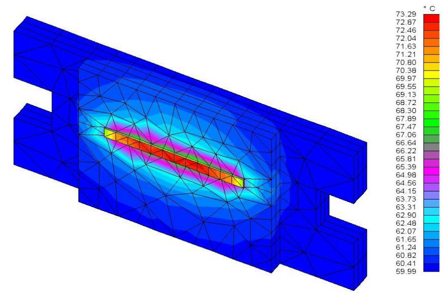

Figure 3: Temperature of the component in steady case

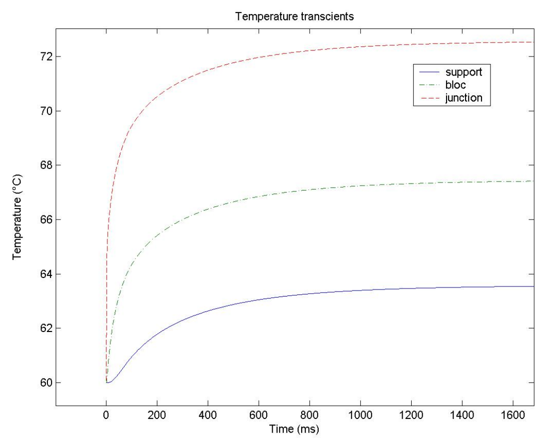

Figure 4: Temperature curves for a 20 W power-step

component model saves about 700 nodes. But the majority of nodes are still dedicated to model fins. A second simplification is also available on the FEM model. The convective effects are characterized by a heat exchange coefficient which is linked to surface area. Thus, a plate with fins is equivalent to a simple plate with the same global heat exchange coefficient. This modification is however not sufficient. Indeed, the fins also change the conductivity of the cooling system. So, the parameters of the equivalent plate can not stay isotropic. The use of this replacement also enables us to reduce the numbers of convective flows.

The numbers of nodes has thus decreased from about 16000 for the initial complete model to less than 1000 for the simpliest one, with only a small deformation on the heat repartition (Fig 5 and 6). The latter will help us to generate databases for the learning of the neural network.

4. ANN COMPACT MODEL

Even if RC networks have shown their efficiency, they are not applicable in all cases. For the cooling system, the heat direction could not be considered one-way. Moreover, at first, the conduction is the main thermal phenomenon in the radiator but, after a while, the tempera-

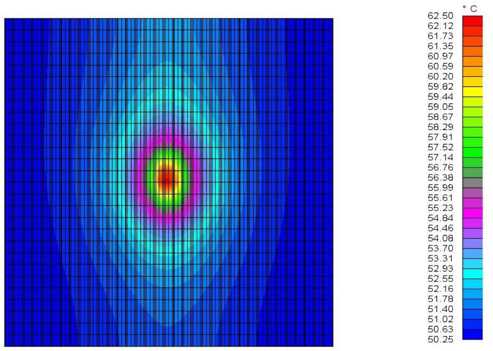

Figure 5: Repartition on heat exchanger with real component model and fins

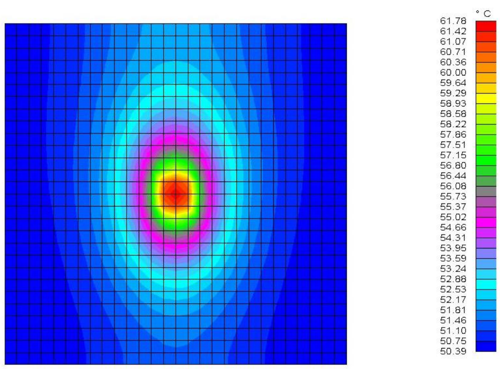

Figure 6: Repartition on heat exchanger with equivalent RC network and without fins

ture in the radiator increases and therefore the heat exchange coefficient. The convection then becomes predominant. So, the radiator acts initially like a simple plate and stores the heat. When it reaches a specific temperature, the heat load can then be evacuated. The cooling system could thus not be replaced by a simple RC circuit between the bottom of the component and the ambient temperature (Fig 7).

ANNs are able to accomplish this task of nonlinear regression. They have indeed been applied on various problems of pattern recognition, temporal series prediction or modelisation [7] [8]. A neuron is composed of several entries and one ouput. The output of the neuron is calculated with an activation function (usually non linear) from an aggregation of the inputs. For our model, a single layer perceptron, the aggregation function is a weighted-sum and the activation function is the logistic function. The parameters of the network (the weights of the sums) are at first randomly initialiazed, and an output is computed. Then, a gradient descent method, which is called the learning algorithm, calculates the parameters correction that leads to a lowest error. This step is repeated until a specific error.

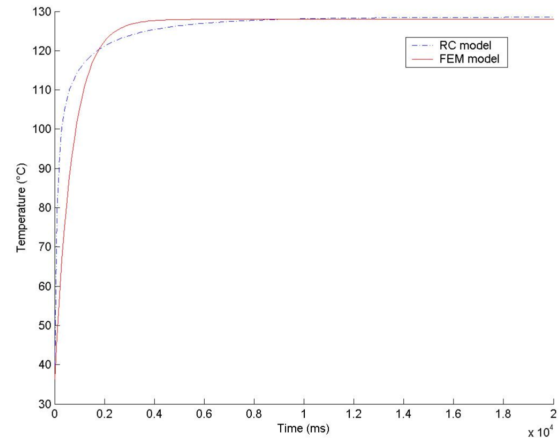

Figure 7: FEM model and RC model responses comparision for the radiator

ANNs are often presented as black-box models. However, if their parameters are not linked to the real system, physics thoughts have a prominent weight in the choice of the neural network structure. The characteristics of the modeling problems force us to choose a specific form of dynamic neural network, called NNOE (Neural Network Output Error) [9]. NNOE use multi-delayed signals and their past outputs as inputs. The value of the time-step in the network should be carefully selected in function of system dynamics. The previously calculated RC network is really helpful in this aim. The circuit is indeed a low-pass filter and gives us directly the maximum frequency of power pulses that can be transmitted to the cooling system. Endly, the dimensions of the radiator and the conductivity of the aluminium bounds the size of cooling system ”memory” and thus the number of delays. The ANN is simulated with MATLAB and the NNSYSID toolbox.

For our ANN model, the only input is the mean power injected in the component (Fig 8). After the physical analysis, some parameters still remain to be selected. The number of delays have been bound but the neural network should rarely need all information. The input delays have then been limited to 10. For stability reasons, the number of delays on the reinjected output has been fixed to 1. Ten neurons are located in the hidden layer. This parameter can be analysed as a measure of the nonlinearity degree of the system, but it should also be related to the number of inputs. The reduced FEM model has been used to generate 3 measurements of 1 minut (learning, validation and test databases) of the temperature under the component for random power signals (only the active periods are the sames). The results are compared with the FEM model (Fig 9).

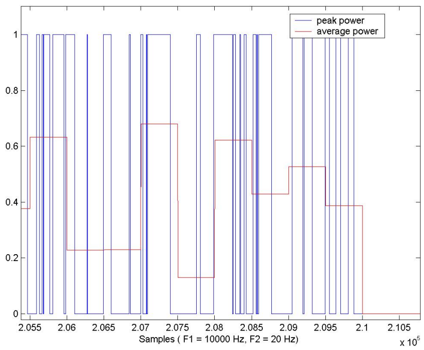

Figure 8: The real power peaks used in the RC model and the mean power, the input for the ANN

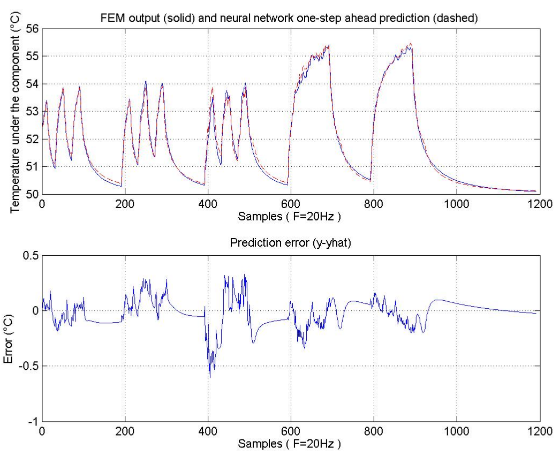

Figure 9: Output comparison of neural network model and FEM model for the temperature under the component

5. HYBRID MODEL AND RESULT

The merging of the two compacts models is quite trivial. For the ANN, the RC network acts as a filter on the power pulses, so the variation of the junction temperature will not impact the output of the neural network. For the RC network, the neural network output is just a boundary condition fixed under the component during a time-step. The two models can then be considered as independant and the junction temperature will just be the sum of their outputs. The only drawback of this method is on the update of the neural network output where a kind of ”discontinuity” may occur on the predicted junction temperature signal. The hybrid model is then just the superposition of the ouputs of the 2 compact models.

A new set of data is generated to compare the output of the compact model and of the FEM model for both high and low frequencies (Fig 10). As the two parts of the model predict accurately their component parts of the signal, the combination of their outputs obviously predicts quite well the junction temperature.

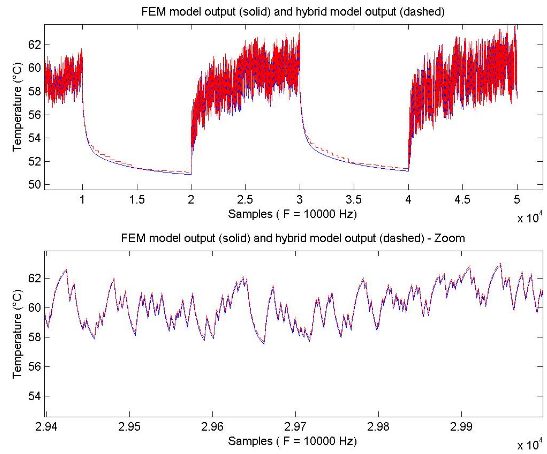

Figure 10: Output comparison of hybrid model and FEM model for the junction temperature

6. CONCLUSIONS

The ANN compact model has shown its efficiency. The neural networks have then been able to deal with thermal non-linearities, like the convection in fins. Added to the RC network effective method, ANN and other statistical models, which will be tried in further works, provide a nice opportunity to improve compact models. The first improvement will be to use this method in the multiple components case.

Moreover, the hybrid model has been learnt only from data, even if some parameters have to be manually selected. Since there is no link between the physical model and the compact model, the latter can also be learnt from measurements and this method could create directly a model from a real system. Furthermore, neural networks can be adapted for control applications. As linear models [10], the hybrid model can so be used to limit the junction temperature. Another advantage of neural networks is to allow multiple inputs problem and thus some other variables, such as ambient temperature or air velocity, could be taken into account.

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