Black–Box Modeling to Estimate Tissue Temperature during Radiofrequency Catheter Cardiac Ablation: Feasibility study on an Agar Phantom Model

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Abstract

The aim of this work was to study linear deterministic models to predict tissue temperature during radiofrequency cardiac ablation (RFCA) by measuring magnitudes such as electrode temperature, power and impedance between active and dispersive electrodes. The concept involves autoregressive models with exogenous input (ARX), which is a particular case of the autoregressive moving average model with exogenous input (ARMAX). The values of the mode parameters were determined from a least squares fit of experimental data. The data were obtained from radiofrequency ablations conducted on agar models with different contact pressure conditions between electrode and agar (0 and 20 g) and different flow rates around the electrode (1, 1.5 and 2 L/min). Half of all the ablations were chosen randomly to be used for identification (i.e. determination of model parameters) and the other half were used for model validation. The results suggest that: 1) a linear model can be developed to predict tissue temperature at a depth of 4.5 mm during RF cardiac ablation by using the variables *applied power*, *impedance*, and *electrode temperature*; 2) the best model provides a reasonably accurate estimate of tissue temperature with a 60% probability of achieving average errors better than 5ºC; 3) substantial errors (larger than 15ºC) were found only in 6.6% of cases and were associated with abnormal experiments (e.g. those involving displacement of the ablation electrode); and 4) the impact of measuring impedance on the overall estimate is negligible (around 1ºC).

Keywords agar phantom, autoregressive modeling, black–box modeling, cardiac ablation, catheter ablation, non–structured model, temperature prediction, radiofrequency ablation, temperature measurement.

Introduction

Radiofrequency (RF) catheter cardiac ablation (RFCA) is a minimally invasive procedure for destroying a zone of the myocardial tissue causing an arrhythmia. The procedure uses an active electrode placed at the tip of a percutaneous catheter. The RF (≈500 kHz) electrical current is delivered to the patient through the active electrode and a dispersive electrode placed on the patient's back or thigh. RFCA is generally performed by means of a constant–temperature protocol, which means that RF power is modulated by the RF generator to maintain a constant target temperature value (T_e) measured by a sensor embedded in the active electrode (see Fig. 1A). The thermal effect (i.e. tissue necrosis) occurs exclusively in the cardiac tissue underneath the active electrode, as the current density is highest in that zone. Consequently, the maximal temperature reached in the tissue is located at 1–2 mm from the electrode–tissue interface using dry (i.e. non cooled) electrodes [1]. Unfortunately, no information can be obtained on tissue temperature (T_t) during RF heating by means of direct measurement. Only the progress of T_e and the electrical parameters (power, voltage, current and impedance) can be displayed and recorded with conventional RF generators. However, the estimation of T_t could avoid excessive heating or thermal injury to contiguous tissues during RFCA.

We hypothesized that the progress of T_e, RF power (P_e) and electrical impedance (Z_e) could provide enough information to estimate T_t (on which the other electrical variables would be dependent). The rationale for this hypothesis is based on:

(1) Once RF power raises the temperature in the tissue, a thermal flux is created and heat is transferred towards the electrode by thermal conduction. It could therefore be assumed that T_e and T_t will be directly related by the thermal conductivity of the in–between tissue.

(2) During a constant–temperature ablation, RF power requirements are directly related to the convective cooling effect on the electrode and tissue surfaces caused by the circulating blood [2]. In addition, there is also a direct relation between RF power and depth of the lesion [2]. For these reasons, RF power changes could provide information on changes in this cooling effect, and hence on T_t.

(3) Impedance changes are closely associated with tissue heating [3].

Previous work has been conducted to estimate lesion progress on–line by studying the impedance progress [3–5]. Numerical modeling (based on e.g. finite element method) has also been proposed to estimate tissue temperature during RFCA [6]. However, as far as we know, no study has attempted to estimate T_t from the combined progress of all the above mentioned variables.

Our interest lies in creating linear deterministic models to predict T_t (i.e. $\hat{T}_t$) from the progress of all the variables (see Fig. 1B). The structure of the proposed models is not defined a priori, moreover they are completely data–driven as both the model parameters and structure are obtained from the data, so that neither physical constant determination nor mathematical simplification are needed [7,8]. If required, a number of local linear models can be obtained to eventually predict non–linear behavior. In general, non–structured models, also known as *black–box models*, have been employed to predict dynamic behavior in different scientific areas. To date, previous works have reported the use of black–box modeling to predict tissue temperature in therapeutic ultrasound [7,9] and hyperthermia cancer treatment [8]. These studies employed neural networks to estimate the temperature change using the temporal echo–shifts extracted from collected backscattered ultrasound signals.

The main aim of the present research was the study of linear deterministic models to predict tissue temperature during RFCA processes by measuring related magnitudes

(i.e. electrode temperature, power and impedance).

Experimental set-up

The experimental setup was based on an agar phantom as tissue–equivalent material [10]. This methodology (previously employed in similar studies [10,11]) facilitates the precise positioning of very small temperature sensors (e.g. micro–thermocouples), and achieves reproducible conditions between RF ablations. Details on the phantom construction can be found in [11]. Figure 2 shows a diagram of the phantom and experimental setup. The agar phantom was constructed utilizing a methacrylate tube container with 50 mm external diameter and 30 mm in height. We situated a T–type thermocouple IT–21 of 0.41 mm diameter (Physitemp Instruments, Crifton, NY, USA) at a depth of 4.5 mm to measure tissue temperature (T_t), which is the prediction target. The thermocouple tip was always placed on the catheter axis. The phantom was submerged in a bath (polycarbonate container of 25×20×18 cm) containing 12 L of 0.5% NaCl solution as blood–equivalent [12], and maintained at 37ºC throughout the experiments with an immersion thermostat Microtherm 3000423 (JP Selecta, Abrera, Barcelona, Spain). A hydraulic circuit (see Fig. 2) was set up to simulate blood flow inside the cardiac chamber, and consequently removed heat from the agar and cooled electrode surfaces during ablation. This circuit was set up using a Stöckert roller pump (Shiley, Irvine, CA, USA) which re–circulated the saline solution from the bath and irrigated the phantom surface and the ablation electrode by means of an 18 mm diameter tube located 25 mm from the ablation catheter [12]. Three flow rate values were considered: 1.0, 1.5 and 2.0 L/min.

The ablations were conducted using a Blazer II 7Fr/4 mm ablation catheter (Boston Scientific, Natiok, MA, USA). A methacrylate scaffold was used in order to accurately

locate the axis of the catheter on the symmetry axis of the phantom, establishing a total distance of 4.5 mm between the point of RF application (i.e. the electrode tip) and the tissue temperature measurement point (T_t). The scaffold allowed the ablation electrode to apply constant pressure on the agar, ensuring good reproducibility throughout the experiments. Two values of pressure were considered: 0 (zero pressure) and 20 grams, so that six experimental groups were considered (3 flow values × 2 pressure values). An ablation generator EPT−1000XP (EP Technologies, Boston, MA, USA) was utilized to deliver unmodulated 500 kHz sinusoidal current between the ablation electrode and a large metallic plate (20×20 cm) located on the bottom of the bath. The ablations were conducted by programming a constant temperature of 55ºC at the electrode tip (T_e), simultaneously limiting the output power to 50 W. The duration of the ablations was 120 s in all the experiments. Twenty ablations were conducted for each group (i.e. 120 ablations in all). The signals provided from the thermocouple (T_t) and from RF generator (P_e, Z_e and T_e) were sent to a PowerLab 8sp data acquisition system (ADInstruments, Colorado Springs, CC, USA), sampled to 100 Hz and digitalized with 16−bits resolution for subsequent analysis.

Analytical methods

Proposed ARX model

The initial hypothesis of this work was based on the assumption that tissue temperature rise in RFCA can be adequately predicted with a linear dynamic model. I.e. the tissue temperature can be predicted by a linear combination of previous measurements of tissue temperature, electrode temperature, ablation power and recorded impedance. This model can be expressed as follows:

$$T_t(k\Delta t) = a_1 T_t((k-1)\Delta t) + a_2 T_t((k-2)\Delta t) + a_3 T_t((k-3)\Delta t) + \ldots + a_n T_t((k-n)\Delta t) +$$
$$+ b_1 T_e((k-1)\Delta t) + b_2 T_e((k-2)\Delta t) + \ldots + b_m T_e((k-m)\Delta t) +$$
$$+ c_1 P_e((k-1)\Delta t) + c_2 P_e((k-2)\Delta t) + \ldots + c_o P_e((k-o)\Delta t) +$$
$$+ d_1 Z_e((k-1)\Delta t) + d_2 Z_e((k-2)\Delta t) + \ldots + d_p Z_e((k-p)\Delta t) +$$
$$+ e((k-1)\Delta t)$$

where T_t represents the present tissue temperature at evenly spaced instants in time (Δt), T_e corresponds to the electrode temperature, P_e delivered power, and Z_e measured impedance, again at evenly spaced instants in time. e corresponds to a white noise signal uncorrelated to any of the above variables, whereas $k = 0, 1, 2\ldots$ The choice of a linear model to predict tissue temperature, rather than other more complex (e.g. a non–linear) model, is a reasonable hypothesis by taking into account previous results obtained from ex vivo RFCA experiments in which a linear model was found between T_e and P_e [13].

For the proposed model to be useful for prediction, not only have the values of the different parameters to be calculated ($a_1 \ldots a_n$, $b_1 \ldots b_m$, $c_1 \ldots c_o$, $d_1 \ldots d_p$), but also an estimation must be made of the number of parameters, i.e. n, m, o and p. The total number of parameters of each model is $\Psi = n + m + o + p$. However, different combinations can provide the same value of Ψ. These combinations are known collectively as "model structure". It can be shown that m, o and p are always smaller or equal to n for physically consistent models. The integer value n is also known as the order of the model.

The proposed model corresponds to the widely known Autoregressive Model with exogenous input (ARX). This model is a particular case of the Autoregressive Moving Average Model with exogenous input (ARMAX). The values of the different constants are obtained from a least squares fit of experimental data. However, the order of the model and the integer values m, o and p have to be fixed. A careful choice of the

aforementioned parameters is paramount for the validity of the model, as small n, m, o and p values will yield high prediction errors, whereas too large values of these parameters will lead to unrealistic small errors and poor extrapolation performance due to overparametrization.

Parameter identification

In the most general case, the model parameters (a_1,a_2,…,a_n; b_1,b_2,…,b_m; c_1,c_2,…,c_o, d_1, d_2,…d_p) are calculated using non-linear optimization techniques aiming at minimizing the error between estimated ($\hat{T}_t$) and measured (T_t), tissue temperature. The procedure carried out to calculate the model parameters can be explained briefly as follows. For each instant in time, the difference between actual and estimated tissue temperature is obtained:

$$\varepsilon(k\Delta t) = T_t(k\Delta t) - \hat{T}_t(k\Delta t)$$

where the temperature estimate is obtained from:

$$\begin{aligned}\hat{T}_t(k\Delta t) &= a_1\hat{T}_t((k-1)\Delta t) + a_2\hat{T}_t((k-2)\Delta t) + a_3\hat{T}_t((k-3)\Delta t) + \cdots + a_n\hat{T}_t((k-n)\Delta t) + \\ &+ b_1T_e((k-1)\Delta t) + b_2T_e((k-2)\Delta t) + \cdots + b_mT_e((k-m)\Delta t) + \\ &+ c_1P_e((k-1)\Delta t) + c_2P_e((k-2)\Delta t) + \cdots + c_oP_e((k-o)\Delta t) + \\ &+ d_1Z_e((k-1)\Delta t) + d_2Z_e((k-2)\Delta t) + \cdots + d_pZ_e((k-p)\Delta t)\end{aligned} \quad (1)$$

Then, the model parameters are estimated by minimizing the cost function:

$$J = \sum_{k=0}^{N-1}\left[\varepsilon(k\Delta t)\right]^2 = \sum_{k=0}^{N-1}\left[T_t(k\Delta t) - \hat{T}_t(k\Delta t)\right]^2 \quad (2)$$

where N is the number of data points to be considered, which may correspond to different samples (see later for details).

The cost function can be minimized analytically considering:

$$\frac{\partial J}{\partial a_h}=0;\quad \frac{\partial J}{\partial b_i}=0;\quad \frac{\partial J}{\partial c_j}=0;\quad \frac{\partial J}{\partial d_l}=0; \qquad (3)$$
$$h=1,2,\ldots,n;\quad i=1,2,\ldots,m;\quad j=1,2,\ldots,o;\quad l=1,2,\ldots,p$$

In the most general case, the cost function is minimized using optimization techniques, such as the Newton–Raphson method.

Influence of sampling frequency and decimation

Initial parameter estimations were carried out from signals sampled at 100 Hz. However, the results obtained were not entirely satisfactory because:

(1) The sampling frequency was far too high for the evolution of the tissue temperature. Tissue temperature usually reaches an almost constant value after 120 s, so consecutive measurements at 100 Hz show little difference, leading to a model very sensitive to measurement noise and calculation errors due to truncation.

(2) The number of calculations required for cost function optimization greatly increases with the length of the data samples used for parameter identification. With 100 Hz and 120 s samples, a total of 12,000 data points are considered for each ablation experiment. As a minimum of 10 ablation experiments are simultaneously used for parameter identification, it is clear that the number of required calculations vastly increases with sampling frequency, without any clear advantage in terms of the accuracy of the prediction model obtained.

To avoid these problems, the measured signals were downsampled (decimated) by factors of 10, 20, 50 and 100, obtaining sampling intervals (Δt) of 0.1, 0.2, 0.5 and 1 s. The decimation was always performed after the corresponding anti-aliasing filtering of all the downsampled signals. The use of longer sampling intervals served the purpose of solving the numerical, computational and noise problems. On the other hand, the proposed method provides tissue temperature estimates for $t=k\Delta t$ from measurements at

$t=(k-1)\Delta t$, hence successive predictions will be calculated at Δt increments. Therefore, the use of larger sampling intervals implies larger prediction intervals.

Estimation of the number of parameters and construction of local models

The values of the different parameters were obtained from a least squares fit of experimental data [Equations (2) and (3)]. However, the number of parameters to be used for the least squares fit (i.e. $\Psi = m+n+o+p$) had to be fixed. A small number of parameters will yield high prediction errors whereas too many parameters will lead to unrealistic small errors and poor extrapolation performance due to overparametrization. It is therefore necessary to ascertain the influence of sampling time and model complexity, with the goal of finding the simplest model (with the fewest possible number of parameters) which could adequately predict the behavior of the tissue temperature.

The first step was to build local models using only data from each experimental group. I.e., half of the experiments (60 ablations including 10 from each group) were chosen randomly for identification, whereas the other half were used for validation purposes. In each case, five sampling intervals were considered: 0.01, 0.1, 0.2, 0.5 and 1 s. In order to determine the influence of the number of parameters, n was varied from 1 to 5 and each of m, o and p varied from 0 to n. Consequently, more than 6,000 different models were calculated for each group of 20 ablations, which makes an overall total of more than 60,000 different models. Each of these models was validated against the subset of experiments in the corresponding group that was not used for parameter estimation.

During the validation stage, the prediction error was calculated for each experiment i as:

$$\varepsilon_i = \frac{1}{N}\sum_{k=0}^{N-1}\left|\varepsilon\left(k\Delta t\right)\right| \quad (4)$$

The average prediction error for each model ($\bar{\varepsilon}$) was defined as:

$$\bar{\varepsilon} = \frac{1}{M}\sum_{i=1}^{M}\varepsilon_i \quad (5)$$

where M is the number of experiments used for the construction of the model. In the case of the local models, M=10 since ten experiments were used for parameter validation. All the models with the same number of parameters (Ψ) were ordered by their average prediction error value. The minimum average prediction error of each group was considered to be the best average prediction error ($\bar{\varepsilon}_{\min}$) and this value was distinctive for each value of Ψ.

Construction of a global model

The procedure described in the previous section was also applied to determine whether a single model can adequately predict tissue temperature without explicit information of electrode pressure and liquid flow, i.e. by grouping together samples from the six experimental sets. In this case all the ablations (120 experiments) were grouped, after which 60 experiments were chosen randomly to be used for identification, whereas the other half were used for validation purposes. In this case M=60 in Equation (5). Once more, all the models with the same Ω (number of parameters) were ordered by the average prediction error, and of these the model with the minimum value was considered (i.e. the value of $\bar{\varepsilon}_{\min}$ was determined).

Finally, in order to asses the potential a single global model, we searched for the optimum model by using the following criterion: 1) models with high $\bar{\varepsilon}_{\min}$ were discarded; 2) the smallest values were chosen from models with similar $\bar{\varepsilon}_{\min}$, and 3) of

these, the model with the fewest number of parameters (Ω) was selected.

Information content of the measured magnitudes

As previously stated, the developed models consider the contribution of P_e, Z_e and T_e to estimate temperature rise ($\hat{T}_t$) . However, whereas all three quantities are known to influence or be affected by tissue temperature, they do not provide the same amount of information when estimating tissue temperature. In order to ascertain the contribution of each measurement to the overall estimate, the contribution factor for each measurement was calculated, so the overall estimate can be expressed as:

$$\hat{T}_t = C(T_e) + C(P_e) + C(Z_e) \quad (6)$$

where $C(T_e)$, $C(P_e)$ and $C(Z_e)$ are the contribution factors of each of the measured magnitudes.

Results

Local models and estimation accuracy

First, the effect of changing the sampling intervals was assessed. The values of 0.01, 0.1, 0.2, 0.5 and 1 s were considered, and corresponded to the cases of non–decimated, and decimated by factors of 10, 20, 50 and 100, respectively. The decimated sampling interval of 1 s was chosen for two reasons: 1) smaller prediction error and 2) reduced parameter calculation time.

Figure 3 shows the best average prediction error ($\bar{\varepsilon}_{\min}$) as a function of the number of parameters (Ψ) for each experimental group (i.e. for flow rates of 1, 1.5 and 2 L/min and pressure values of 0 and 20 g). For the same flow rate the obtained models clearly yield improved prediction when 20 g of pressure was applied to the ablation electrode. This result implies that the ablation experiments with higher pressures have less

variability and indicate that the electrode–tissue pressure is relevant for experiment repeatability. On the other hand, prediction errors are clearly smaller when the flow rate is 1.5 L/min.

Global model

The procedure described in the previous section was also applied to determine whether a single model can adequately predict tissue temperature without explicit data of electrode pressure and liquid flow, i.e. by grouping together samples from the six experimental groups. Figure 4 shows the best average prediction error ($\bar{\varepsilon}_{\min}$) as a function of the number of parameters to be identified. As the number of free parameters was increased, $\bar{\varepsilon}_{\min}$ decreased up to a point where a higher number of parameters did not lead to lower prediction errors. Based on this result, the model with 11 parameters and the smallest prediction error was chosen. Table 1 shows the parameters of Equation (1) for this model.

The $\bar{\varepsilon}_{\min}$ for the global model is higher than that of the models for the group of 1.5 L/min, however, its value is in line with the $\bar{\varepsilon}_{\min}$ obtained in the local models for 2 L/min and definitively better than the ones obtained at 1 L/min. The reason could be a higher variability of the experiments with 1 L/min being compensated by experiments with higher liquid flows.

Figure 5A shows the actual and predicted temperature increase for a validation experiment (i.e. an experiment not used for model estimation). The graph shows a temperature increase over 37.5ºC. This particular validation experiment had the highest accuracy of tissue temperature estimation, with estimation errors (ε_i) smaller than 0.7ºC during the whole ablation process. Figure 6 shows the cumulative probability of the average prediction error for the selected model. There was a 60% probability of

achieving average errors better than 5ºC. Out of the 60 ablations used for validation, four (6.6%) showed average prediction errors larger than 15ºC, which can be considered abnormal. One of the abnormal experiments is shown in Fig. 5B. The actual tissue temperature rose only about 14ºC, which could have been caused by a slight displacement of the ablation electrode.

Information content of the measured magnitudes

Regarding the assessment of the contribution of each measurement (P_e, Z_e and T_e) to the overall estimate, Figure 7 shows the typical evolution of contribution factors ($C(T_e)$, $C(P_e)$ and $C(Z_e)$) during the ablation process shown in Fig. 5A. The contribution of impedance measurement to the overall estimate is clearly around 1ºC, and although this contribution helps to improve overall accuracy, most of the estimated tissue temperatures are calculated from information provided by the electrode temperature and ablation power. This behavior was observed in all the prediction experiments. Moreover, $C(P_e)$ was always higher than $C(T_e)$ at the early stages of ablation. However, the crossing points between $C(T_e)$ and $C(P_e)$ ranged from 30 to 120 s.

Discussion

Our attention was focused on estimating tissue temperature during RFCA for two clinical reasons: 1) To avoid excessive temperatures (above 80ºC) and hence thermal injury to adjacent tissues, and 2) To avoid the lack of thermal lesion (temperatures lower than 50ºC). In fact, the information on estimated tissue temperature could be very useful as an input parameter in the closed-loop control that modulates RF power during constant–temperature RFCA [14]. Specifically, this feasibility study presents the proof-of-concept development of a black-box model to predict tissue temperature for the RF

cardiac ablation process from measurements of electrode temperature, ablation power and impedance. A methodology has been presented to calculate and select a suitable linear model. The selected model provided a reasonably accurate estimate of tissue temperature, although substantial errors were observed in some experiments (e.g. those in which the ablation electrode had been displaced).

Regarding the contribution of each variable to the estimation, the presented results show that in the early stages of ablation, the power contribution factor $C(P_e)$ was always higher than that of electrode temperature $C(T_e)$, whereas later in the ablation process $C(P_e)$ gradually decreased while $C(T_e)$ increased. The behaviour of $C(P_e)$ could be explained by the constant–temperature protocol employed in this study, which initially augments the applied voltage until reaching the target temperature in the electrode and then slowly reduces it to balance power losses (due to blood flow and thermal conduction towards deeper tissue) to maintain the target temperature. Once the target temperature is approximately constant and there are no changes either in external conditions (blood flow, pressure, etc.) or applied voltage, the relation between target and tissue temperature is only dependent on thermal conductivity. This could be the explanation for the increase in $C(T_e)$.

It was also observed that the contribution of the impedance measurement to the overall estimate is small (around 1ºC), which suggests(at least in agar phantoms) that a reasonable estimate can be obtained without impedance measurement, unlike the procedure employed in intraoperative bipolar RF cardiac ablation to control lesion transmurality [15]. In this respect, our results are in close agreement with the model proposed by Mattingly et al [8] to predict tissue temperature in hyperthermia, which considered only the temperature and applied power variables.

Although we considered some variability by using three flow rate and two pressure

values (which correspond to two electrode-tissue contact values, i.e. insertion depth), the application of the proposed method in clinical practice should allow for a high degree of variability. In this respect, and although we have focused on prediction models not defined a priori and completely data–driven, future work could be conducted to include physical information in the parameters, so that the parameters of the model are not completely data-driven. This approach could improve prediction accuracy, as we consider that the proposed technique could be improved by incorporating additional information from other variables. For instance, the application of a low power RF pulse prior to RF ablation has been suggested as a method to determine and monitor efficiency of heating during ablation [16]. Since this efficiency is closely related to the cooling effect of the blood on the electrode and tissue surface, this pre-ablation measurement could provide information on flow rate, and hence reduce the variability in $\hat{T}_t$ associated with this external variable. Likewise, we only used the impedance progress measured at 500 kHz in the study to estimate tissue temperature. Measuring at lower frequencies (5–50 kHz) could therefore be considered since they have been shown to have a close correlation with lesion size [5] and heating efficiency [17]. On the other hand, the proposed technique could be improved to cope with unusual situations in which substantial prediction errors were observed, or at least, provide some information on the validity of the current estimate. This is especially relevant if the proposed models are to be used for in vivo ablation processes, although our models were developed using agar phantoms so that the effect of physiologic variability was not taken into account. This methodology could also be applied to other RF ablation techniques in which there is even less variability in some external factors. For instance, in RF hepatic ablation to destroy tumors, a needle electrode is inserted into the liver totally surrounded by tissue, hence controlling the quality of contact between

electrode and tissue.

It is also important to point out that we focused on the prediction of tissue temperature at a depth of 4.5 mm. Although future experiments could be conducted at other depths, the clinical value of an accurate estimation of tissue temperature at ≈5 mm is without doubt very important.

Conclusions

The results from this feasibility study suggest that:

1) A suitable linear model can be developed to predict tissue temperature during RF cardiac ablation by using the variables of applied power, impedance between active and dispersive electrodes, and electrode temperature.
2) The best model provides a reasonably accurate estimate of tissue temperature (a 60% probability was found of achieving average errors better than 5ºC).
3) Substantial errors larger than 15ºC were found in 6.6% of cases associated with abnormal experiments (e.g. those showing displacement of the ablation electrode).
4) The contribution of impedance measurement to the overall estimate is small (around 1ºC).

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Table 1. Parameters [following Equation (1)] of the global model chosen. The number of parameters (Ψ = n + m + o + p) was 11.

Related variable			
Estimated tissue temperature ($\hat{T}_t$)	Electrode temperature (T_e)	Power (P_e)	Impedance (Z_e)
a_1 = 2.82 a_2 = – 3.311 a_3 = 2.467 a_4 = – 1.312 a_5 = 0.3358	b_1 = 0.001847 b_2 = – 0.001377	c_1 = 0.002383 c_2 = – 0.002128	d_1 = – 0.001326 d_2 = 0.001257
n = 5	m = 2	o = 2	p = 2

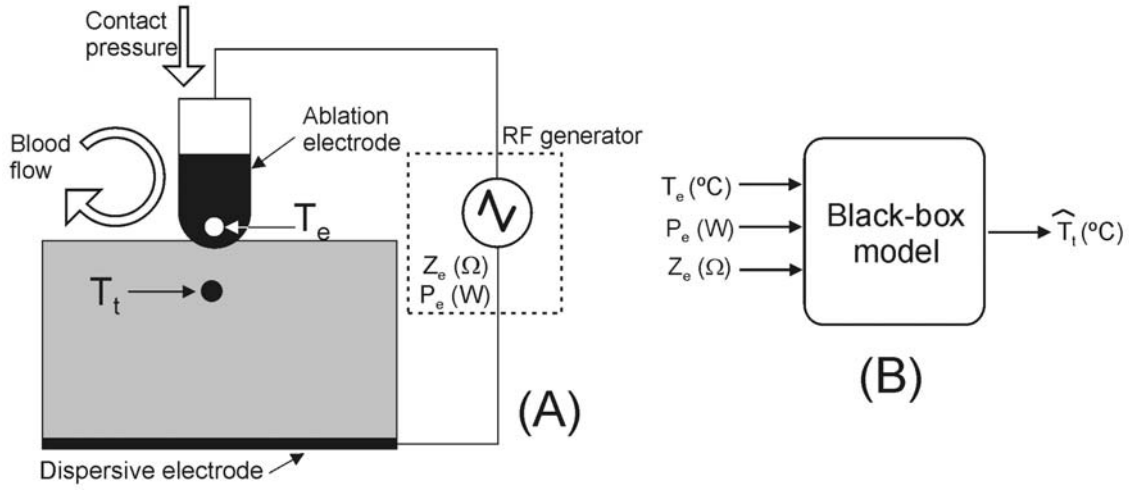

Figure 1 A: Diagram of the physical situation during RF catheter cardiac ablation, which is conducted by constant−temperature, i.e. RF generator adapts the RF power (P_e) to maintain electrode temperature (T_e) to a target value. No information about tissue temperature (T_t) can be obtained by direct measurement. B: The progress of these two variables (P_e and T_e) during RF heating, along with the electrical impedance measured between the ablation and dispersive electrodes (Z_e) could be employed to predict tissue temperature ($\hat{T}_t$) by means of a black−box model.

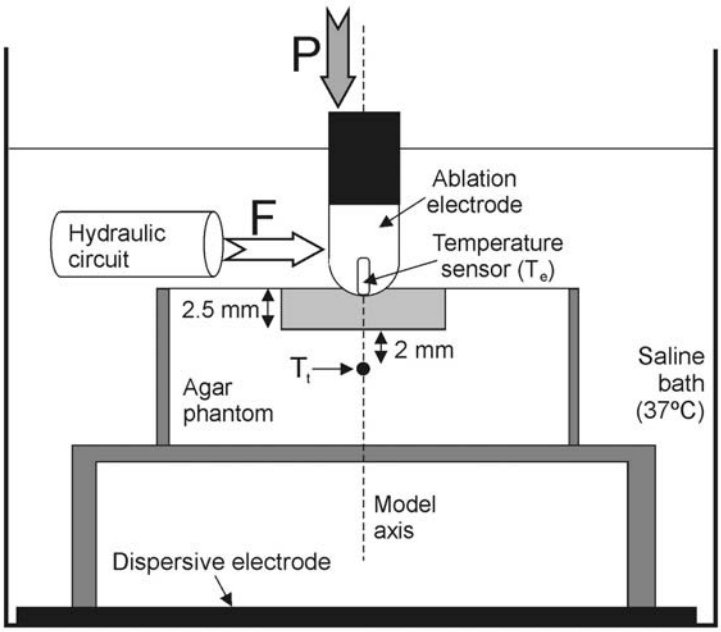

Figure 2 Schematic side view (not to scale) of experimental set-up. The agar phantom included a temperature sensor at a distance of 4.5 mm to measure tissue temperature (T_t). The ablation electrode included a temperature sensor at its tip to measure electrode temperature (T_e). The phantom also included a 20×20×2.5 mm compartment placed at top center in the phantom, in which agar fragments of equal dimensions (gray rectangle) were replaced after each ablation (since the agar closest to the RF electrode often melted during ablation). The phantom was submerged in a saline bath maintained at 37ºC. A hydraulic circuit simulated blood flow (F) inside the heart. The effect of varying the pressure of the electrode on the tissue was assessed by adding a weight on the catheter (P).

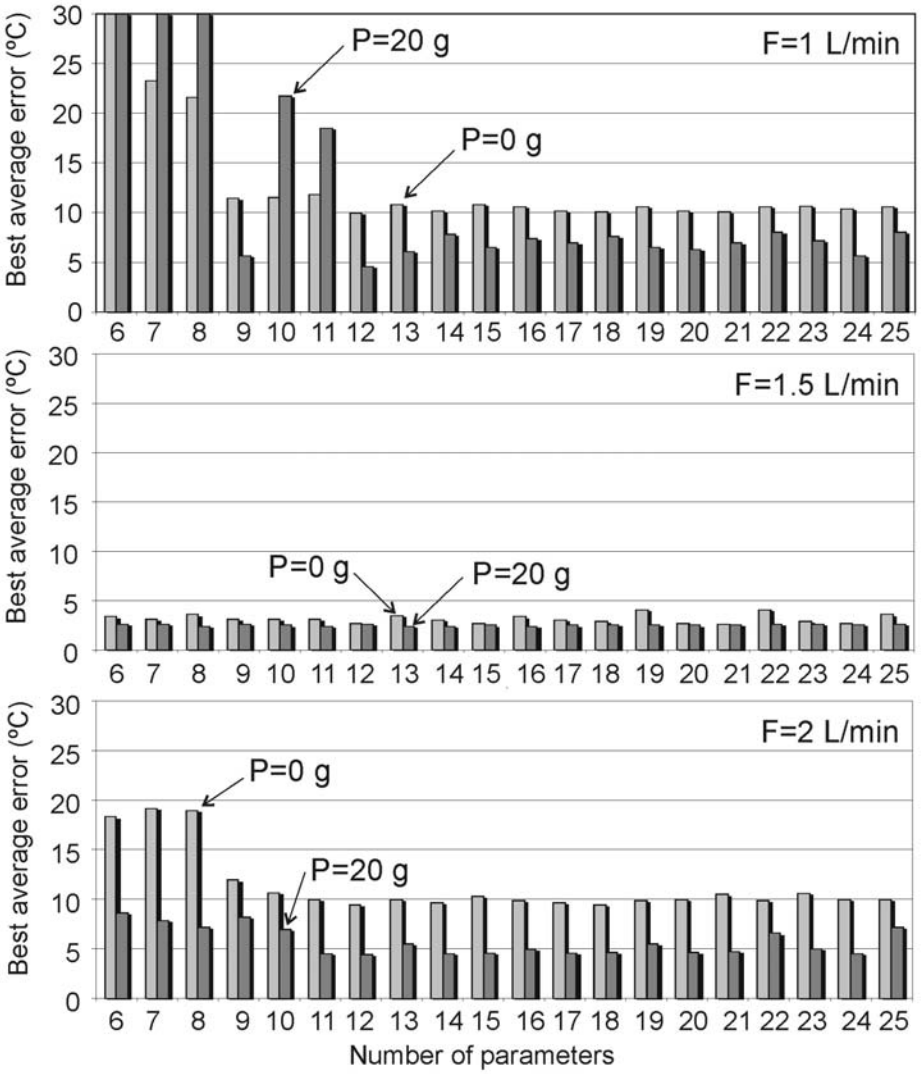

Figure 3. Best average prediction errors as a function of the number of parameters (Ψ = m + n + o + p) employed in the models for each experimental group.

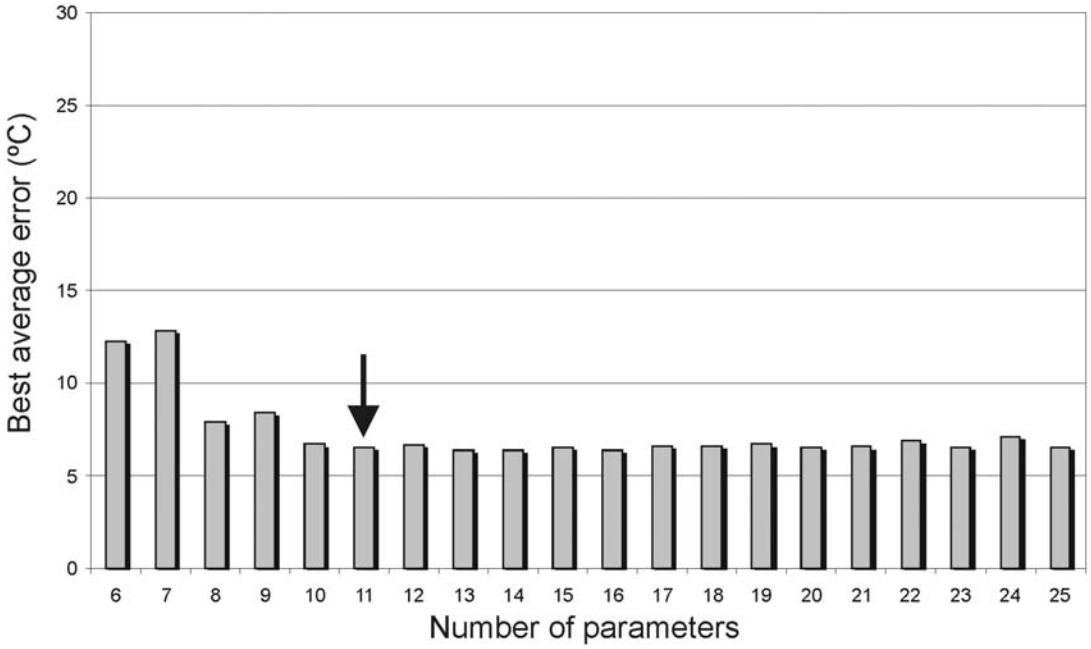

Figure 4 Best average prediction error as a function of the number of parameters (m + n + o + p) employed in the global model. As the number of parameters was increased, the average prediction error decreased until an increase in the number of parameters did not lead to better prediction errors. The model with 11 parameters (arrow) and smallest best prediction error was chosen.

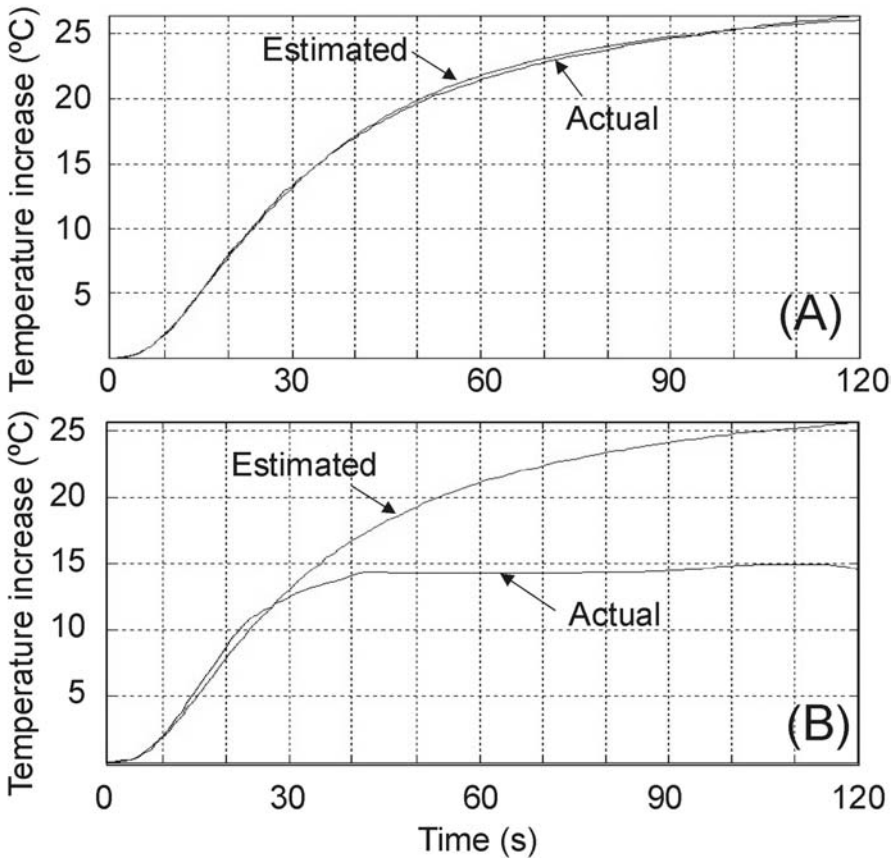

Figure 5 (A) Example of progress in actual (T_t) and estimated ($\hat{T}_t$) temperature increase. This example corresponds to a 1.5 L/m flow and 20 g pressure and was the one with the highest accuracy in tissue temperature estimation, giving estimation errors smaller than 0.7ºC during the whole ablation process. (B) Example of irregular experiment where the actual tissue temperature rose only about 14ºC, which could have been caused by a slight displacement of the ablation electrode.

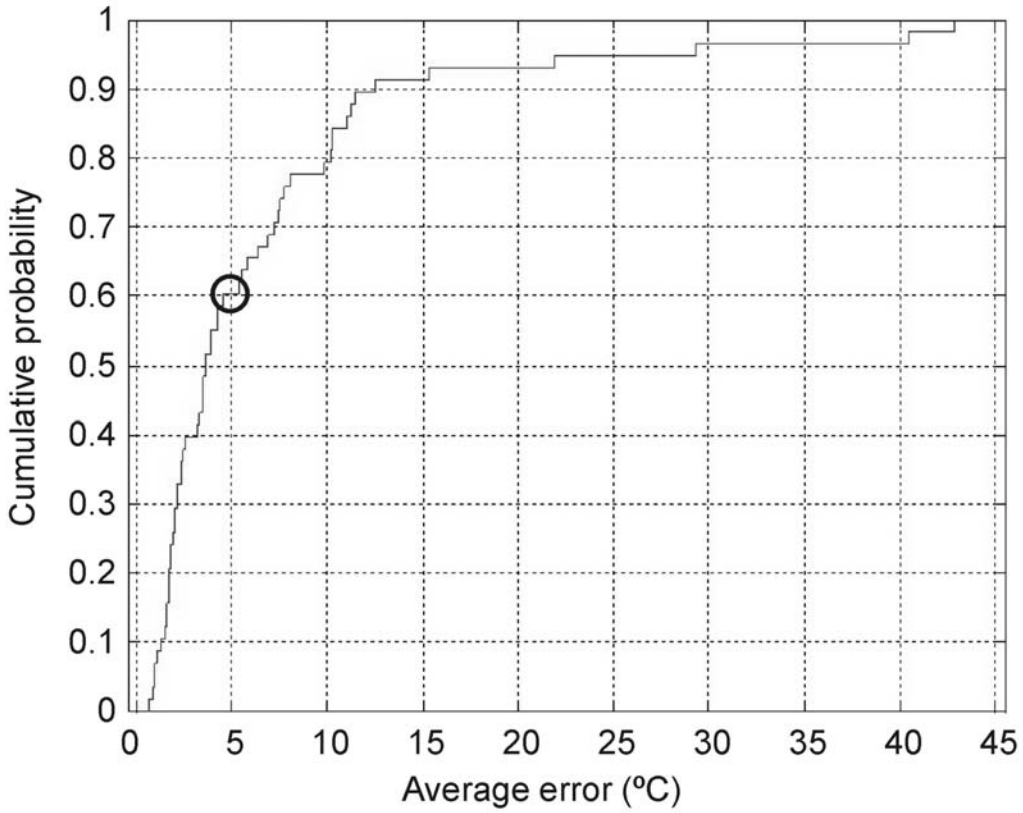

Figure 6 Average estimation error cumulative probability. Notice that there was a 60% probability of achieving average errors better than 5ºC (circle). Out of the 60 ablations used for validation, four (≈6.6%) showed average prediction errors larger than 15ºC, which can be considered abnormal.

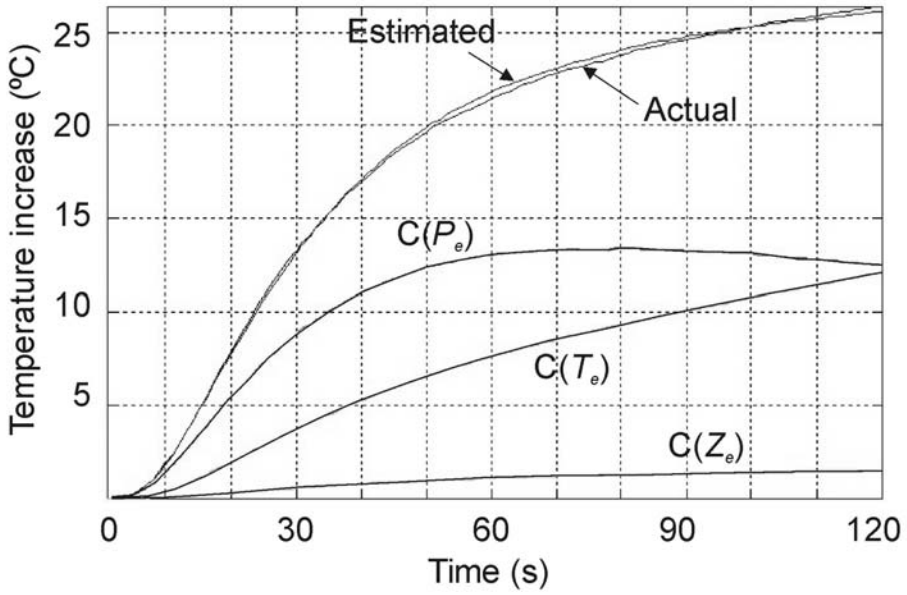

Figure 7 Typical evolution of contribution factors ($C(T_e)$, $C(P_e)$ and $C(Z_e)$) during the same ablation process shown in Fig. 4. Note that the contribution of impedance measurement to the overall estimate is around 1ºC. Although this contribution helps to improve the overall accuracy, most of the estimated tissue temperature is calculated from information provided by electrode temperature and ablation power.