

# A NEW APPROACH OF THE NEURAL PREDICTIVE CONTROL APPLIED IN A THERMOELECTRIC MODULE

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**Abstract:** This article presents an efficient solution for predictive control based on neural networks with feedforward multilayer, as a model for a thermoelectric module. It is shown the capability of a neural network to learn the entire nonlinear dynamics and the advantage of using these nonlinear models for the calculation of the predicted variables. It is also suggested a new control law capable of minimize the cost function using the Newton-Raphson and the descendent gradient optimization rules. For this application it is shown that a significant reduction in the number of iterations and application in real-time systems when compared to other optimization techniques.

## 1 INTRODUCTION

The recursive neural networks have shown to be a very important tool in several control applications in nonlinear dynamic systems. This article has the objective of presenting a development and its results obtained from a prediction-based algorithm through a recursive neural network applied in a thermoelectric chamber with nonlinear dynamics.

The Generalized Predictive Controller (GPC) was introduced by (Clarke, 1994) and is being used for control of industrial process with profitable performance in the control of non-minimum phase plants, unstable plants or plants with unknown dead time (Clarke, 1994). The GPC uses initially a linear prediction model. If a nonlinear model is used then it is also necessary to make use of a nonlinear algorithm. Expressive results are obtained regarding efficiency and computational performance. The prediction feature of the GPC when using a neural model, with the capability of learning the entire dynamic of the plant, it is more efficient than the standard nonlinear modelling techniques. It is well known that the plant model is directly related to the accuracy of the prediction (Fontes et al., 2008). The most used techniques to modelling nonlinear plants, as the linearization around the operating points (Lee and Ricker, 1994; Li and Biegler, 1988) or approximated models, do not guarantee the required accuracy when compared to the neural models.

The control signal update rule in the present work

is based on the first and second derivatives of the cost function. A new hybrid control law is proposed based on the Newton-Raphson rules and the decendent gradient. The computational cost related to the computation of the control signal is associated to the Hessian. However, the reduced number of iterations guarantee an excellent performance of the algorithm when it is applied in real-time control systems.

For simulation and real trials of the proposed control technique a Peltier cell was mounted in a set named the thermoelectric chamber. The results obtained characterize a suitable solution for the proposed system, as well as the potential of this tool in the modelling and control of nonlinear systems, whenever it is real-time or not. In the section 2, the structure of a recursive neural network is presented as well as the equations that describe it. In the section 3, the necessary equations for the determination of the proposed control law. The section 4 presents the description and modelling of the system as well as the results obtained in the trials.

## 2 NEURAL NETWORK ARCHITETURE

The model of a plant used in a neural generalized predictive controller (NGPC) is a neural network and it is important to evaluate the architecture of the network to be used. It is known that a recursive neural net-

work with three layers, one of them hidden, is capable of representing any linear or nonlinear function. The Figure 1 describes a multilayer feedforward neural network with all its structure of delayed inputs and outputs signals. In (Hao et al., 1993), it was presented in details the mathematical representation of nonlinear plants and the respective considerations in order to determine the order of the neural model in terms of the regressors of the inputs, disturbances and outputs, namely,  $u(n)$ ,  $t(n)$  and  $y(n)$ . For each perceptron of the hidden layer there is an activation function. The neural network is described by the following equation:

$$y(n+1) = f(y(n), y(n-1), \dots, y(n-n_y), t(n), \dots, t(n-n_t), u(n), \dots, u(n-n_u)), \quad (1)$$

or, in a detailed view,

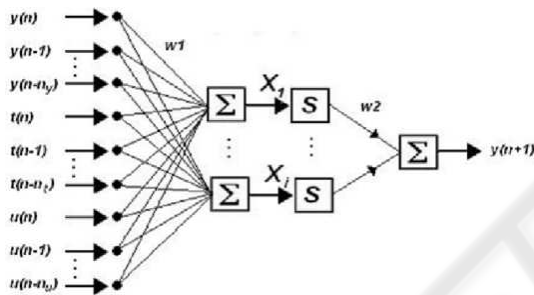


Figure 1: The recursive neural model structure.

$$y(n+1) = \sum_{i=1}^N w_2(1, i) S(X_i), \quad (2)$$

with,

$$X_i = \sum_{j=1}^{n_y} w_1(i, j) y(n-j) + \sum_{j=0}^{n_t} w_1(i, n_y + 1 + j) t(n-j) + \sum_{j=0}^{n_u} w_1(i, n_y + n_t + 2 + j) u(n-j), \quad (3)$$

where:

- $y(n+1)$  is the output of the neural network;
- $S(\cdot)$  is the output function of the  $i$ -th nodes of the hidden layer;
- $N$  is the number of nodes in the hidden layer;
- $n_y$  is the number of inputs nodes associated to  $y(\cdot)$ ;
- $n_t$  is the number of inputs nodes associated to  $t(\cdot)$ ;
- $n_u$  is the number of inputs nodes associated to  $u(\cdot)$ ;

- $w_1(i, j)$  represent the weights associated of the  $j$ -th input to the node  $i$ ;
- $w_2(1, i)$  represent the weights associated of the  $i$ -th hidden node to the output node;
- $y(\cdot)$  represents the output past values;
- $t(\cdot)$  represents the ambient temperature past values;
- $u(\cdot)$  represents the input past values.

### 3 OPTIMIZATION

For the presented application it is necessary the use of a cost function with finite prediction horizon. The NGPC algorithm must satisfy the following optimization problem:

$$\Delta u(k) = \min_{\Delta u} \left\{ J = \sum_{i=N_1}^{N_2} \|ref(n+i) - \hat{y}(n+i)\|_2 + \lambda \sum_{i=1}^{N_u} \|\Delta u(n+i)\|_2 \right\}, \quad (4)$$

where:

- $N_1$  is the minimum prediction horizon;
- $N_2$  is the maximum prediction horizon;
- $N_u$  is the control horizon;
- $ref(n+i)$  is the reference signal;
- $\hat{y}$  is the output signal predicted by the neural model;
- $\lambda$  is the weight at the control signal;
- $\Delta u(n+i)$  is the variation of the control signal defined as  $u(n+i) - u(n+i-1)$ .

For the cost defined in (4) there are four tuning parameters:  $N_1$ ,  $N_2$ ,  $N_u$  and  $\lambda$ . As the dead time is much smaller than the sampling time, it is fair to admit  $N_1 = 1$  and, as a consequence,  $N_2 = N_u$ . It may be verified also that, while the cost is minimized, the resulting control signal allows the plant to track the reference signal.

As mentioned before, the proposed control law presents an update algorithm based on the rules of Newton-Raphson and the decresent gradient. The use of two methods allows the adding of the weight  $\alpha$ , according to (5). This way, the control law contemplates one more degree of freedom and as a consequence a gain in the dynamics of the controller. The control law proposed for the update of the control signal  $U(k+1)$  is given by,

$$U(k+1) = U(k) - \alpha \frac{\partial J}{\partial U} - \left(\frac{\partial^2 J}{\partial U^2}\right)^{-1} \frac{\partial J}{\partial U} \quad (5)$$

It is easily observed that there's an addition of a new degree of freedom  $\alpha$ , besides the one defined in (4). The optimal value of  $J$  in terms of  $U$  is obtained after each iteration of the optimization algorithm. In the iterative process, for each value of  $J$  the future inputs vector  $U(k)$  is also calculated, with the Jacobian and Hessian matrices defined as:

$$\frac{\partial J}{\partial U} = \begin{bmatrix} \frac{\partial J}{\partial u(n+1)} \\ \frac{\partial J}{\partial u(n+2)} \\ \dots \\ \frac{\partial J}{\partial u(n+N_u)} \end{bmatrix}, n = 1, \dots, N_u \quad (6)$$

$$\frac{\partial^2 J}{\partial U^2} = \begin{bmatrix} \frac{\partial^2 J}{\partial u(n+1)^2} & \dots & \frac{\partial^2 J}{\partial u(n+1)\partial u(n+N_u)} \\ \dots & \ddots & \dots \\ \frac{\partial^2 J}{\partial u(n+N_u)\partial u(n+1)} & \dots & \frac{\partial^2 J}{\partial u(n+N_u)^2} \end{bmatrix}, \quad (7)$$

and the predicted output is given by:

$$\hat{y}(n+k) = \sum_{i=1}^N w_2(1,i)S(X_i). \quad (8)$$

The iterations are interrupted when the percentage of the variation  $U(k)$  is smaller than a given  $\epsilon$ . For each iteration  $k$  the elements of the Jacobian and the Hessian are calculated for the given control law.

It is necessary that efficient routines are elaborated for the calculation of the gradient, used in the minimization of the cost, when the iterations of the optimization algorithm are used in real-time.

## 4 TRIALS

### 4.1 System Description

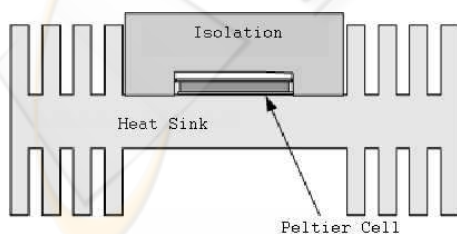


Figure 2: Thermoelectric module.

A Peltier cell, also known as thermoelectric module (TEM), is a component composed of several semiconductor plates placed side-by-side and electrically

isolated from the external environment by a ceramic coat. Through two terminals connected to the cell, an electric current flows, causing the heat to pump between its faces. This phenomenon is known as the *Peltier effect* and it is the opposite of the *Seebeck effect*, which characterizes the thermocouples. The heat pumping direction depends on the direction of the current flow, which allows the Peltier cells to be used as actuators in cooling systems as much as in heating systems.

The TEM is widely used in temperature control in specific applications (Fontes et al., 2008). In some of them a physical model is used, (Fontana, 2001; Almeida, 2003). These applications vary from cooling modules, medical instruments, composition and small refrigerators, etc (Mel, 1999).

A thermoelectric module is composed of a thermic chamber, where the Peltier cell is associated to a heat sink. The Figure 2 presents an illustration of the set used in the experiments of heat pumping. The process variable is the upper face temperature, controlled by the manipulation of the applied current. The information of the ambient temperature is also informed to the neural net as a load disturbance. Other works involving the thermic chamber present a characterization of the module by nonlinear parametric models (Sobrinho et al., 2006; Lima, 2007; Almeida, 2004) and bilinear state-space models (Garcia, 2008).

### 4.2 Neural Network Training

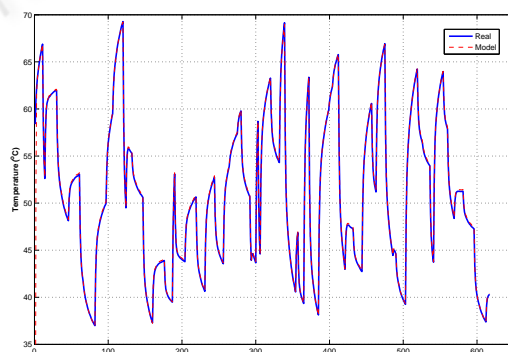


Figure 3: Neural model plot versus system's real data.

For the network training, the system response for a Pseudo-random signal input (PRS) was obtained along the entire operation range ( $30^{\circ}\text{C}$  a  $80^{\circ}\text{C}$ ). The proposed architecture for the neural model contemplates 3 layers, with 3 regressors in the hidden layer and one in the output layer, 3 exogenous regressors and the Hyperbolic Tangent as the activation function;

During the training phase the weights were adjusted iteratively, as proposed in (Hagan and Men-

haj, 1994). For the feedforward architecture proposed, the performance was measured in accordance with the minimization of the squared error criterion between the network and the system's real outputs for the same input signal. Several training algorithms were used, as the resilient backpropagation, the Fletcher-Reeves rule with backpropagation of the conjugated gradient, the Polak-Ribiere rules, the decrescent gradient, among others. The algorithm of Levenberg-Marquardt presented the best overall results and it was used for the system modeling. The Figure 3 presents the output of the neural model compared to the real system's output.

For validation, another PRS was generated and applied to the system and its response was compared to the model response. *The mean squared error* between the system ( $y_r$ ) and the model ( $\hat{y}_m$ ) outputs for the  $N$  points, defined as

$$E_{mq}(\%) = \frac{\sqrt{\sum_{i=1}^N (y_r - \hat{y}_m)^2}}{N} * 100, \quad (9)$$

was 1,148%

The closed-loop system was implemented according to the well-known *receding horizon principle* (Propoi, 1963; Camacho and Bordons, 2004; Zammarero and Vega, 1999). It is fair to say that the good computational performance of the proposed controller is based on the choice of the algorithm defined in the optimization block. The choice of the controller parameters can be done by several criteria: Number of iterations for the resolution of the control signal, computational cost and accuracy of the solution. It is necessary though, to develop fast optimization algorithms. In this work a solution is presented, which applies the Newton-Raphson method added by the decrescent gradient which can be implemented as optimization technique in highly nonlinear real-time applications. A computational analysis showed that there was no significant increase in the computational cost associated with the optimization of the control signal with the increment of the decrescent gradient method. The terms of the decrescent gradient to be calculated are the same as the onset of the Newton-Raphson's method.

### 4.3 Results

The trials were performed for three distinct cases: The algorithm 01 represents the system proposed in this article with parameters  $\lambda = 2000$  and  $\alpha = 0.00008$ . The algorithm 02 refers to the same algorithm with a more aggressive tuning ( $\alpha = 0.0000955$ ). The algorithm 03 refers to an existing algorithm, without the addition of the term related to the decrescent gradient,

with  $\lambda = 2000$ . The prediction horizon is  $N_y = 10$ . The small values of  $\alpha$  are due to the system's large static gain, but the variation of these parameters between the algorithms 1 and 2 is 20%.

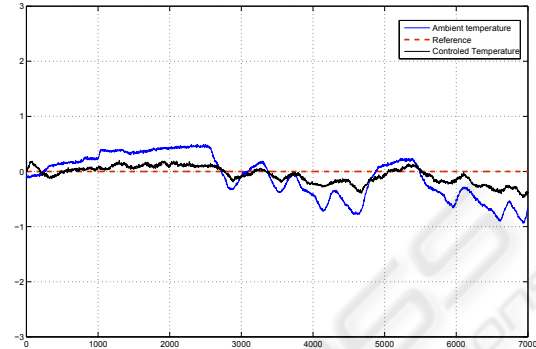


Figure 4: System response to load disturbances.

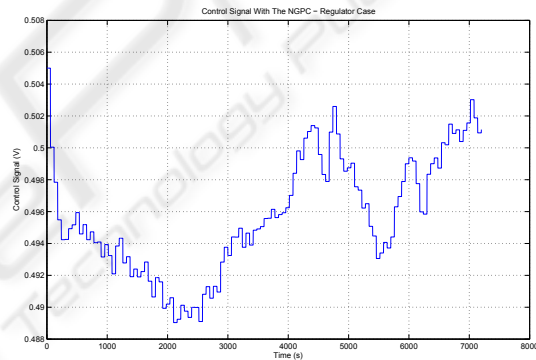


Figure 5: Control signal for the regulator case.

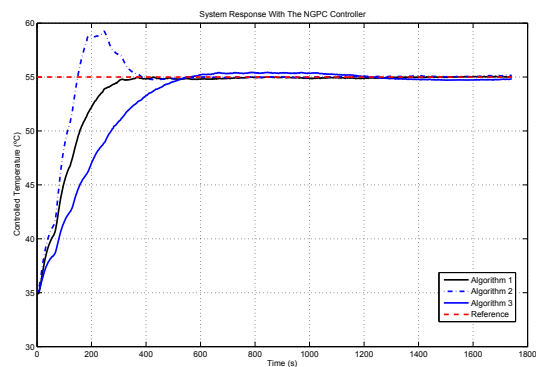


Figure 6: System response for a step in the reference.

The Figure 4 shows the system response to a disturbance caused by the variation of the ambient temperature. It is easy to observe that the controller is capable of rejecting the disturbance, keeping the system

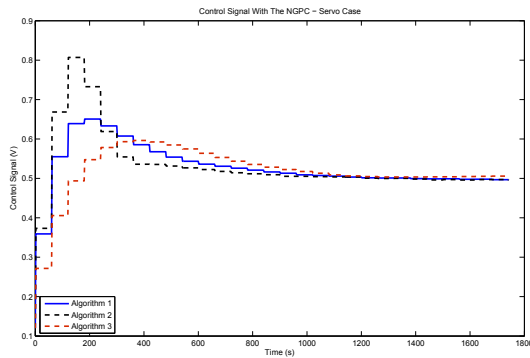


Figure 7: Control signals for the servo case.

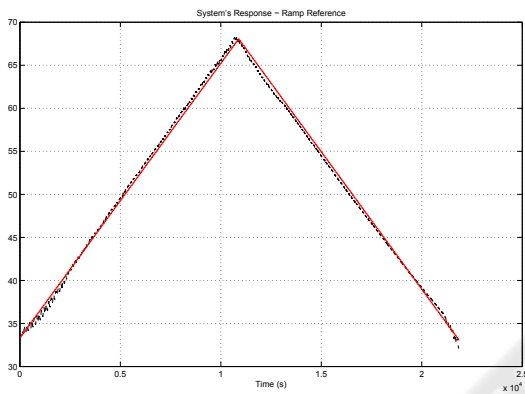


Figure 8: System response for a ramp reference.

output inside the desirable range, presenting a very small offset of  $0.3^{\circ}\text{C}$ , inside the accuracy range of the sensors, for an ambient temperature variation of  $1.5^{\circ}\text{C}$ . The output signal of the controller for this case is shown in the Figure 5.

The system response for a deviation of  $20^{\circ}\text{C}$  in the setpoint for the three controllers implemented is shown in the Figure 6, in which the dashed line represents the system output for the algorithm 02, while the black and blue lines represent the algorithms 01 and 03 respectively. The control signal for the three algorithms are expressed in the Figure 7.

For better evaluation of the performance of the controllers, the indices presented in (Goodhart et al., 1994) were used, which are the mean and variance of the controller outputs ( $\bar{u}$  and  $\sigma_u$ , respectively), the *Integral of the Absolute Error* (IAE), which penalizes the error between the reference and the system variable and the *Integral with Time of the Absolute Error* (ITAE), which penalizes the absolute error throughout the time line. The calculated indices are shown in the Table 1 and the time parameters of the closed-loop system is presented in the Table 2. It is easy to see that the algorithm proposed in the present work presents

a better performance in relation to the tracking error and a smaller mean control effort ( $\bar{u}$ ). The settling time is also smaller. The rise time for the second algorithm is smaller, but it also presents a large overshoot which may not be viable in real applications. For the regulatory trial, the results obtained were  $E_{qm} = 0.0755\%$ ,  $IAE = 0.104$ ,  $ITAE = 145.108$ .

The third and last trial was the analysis of the system response for a ramp reference. The control law does not contemplate a second integral action, necessary for the ramp tracking. Still, the algorithm provided good results when compared to other techniques. In this work, the proposed methodology was compared to three other results obtained for different controllers for the same case: The algorithm B is a single model based GPC presented in (Lima, 2007). The algorithms C and D are described in (Santana, 2008) in a multi-model environment, with the controllers based on gain margin and phase margin metrics, respectively. The algorithm A is the one proposed in this work, with  $N_y = 2$ ,  $\lambda = 3000$  and  $\alpha = 0.000095$ . The ramp started in the temperature of  $33.5^{\circ}\text{C}$  covering all modeled range with variation of  $0.1915^{\circ}\text{C}$  at each 60 seconds, which corresponds to one sampling time. The overall results are shown in Table 3

Table 1: Performance indices for the controllers.

	Alg. 01	Alg. 02	Alg. 03
$\bar{u}$	0.5295	0.5332	0.5196
$\sigma_u$	0.0031	0.0063	0.00038
IAE	0.6728	0.6226	1.1550
ITAE	77,1668	81,7647	244,9661

Table 2: Time indices for the controllers.

	Alg. 01	Alg. 02	Alg. 03
Rise Time	200s	118s	358s
Settling Time	296s	354s	972s
Max. Overshoot	0%	21.66%	2.21%

Table 3: Mean squared error for a ramp reference.

	Alg. A	Alg. B	Alg. C	Alg. D
Eqm	0.3191%	2.214%	1.482%	1.418%

The neural networks is capable of capturing the entire dynamic of the system. Performance indices based on the number of iterations and the computational effort when only the jacobian is used was presented in (Soloway and Halcy, 1996). It is fair to affirm that the reduced number of iterations performed by the NGPC algorithm ranges from 6 to 12 times

faster, even with the calculation of the Hessian requiring a high computational effort.

## 5 CONCLUSIONS

In this work a new approach of the Neural GPC was presented which complies a little modification in the control law, given by the adding of one more degree of freedom associated to the decrecent gradient. This modification caused a significant improvement in the control effort and in the general system's closed-loop response without significant increase of the computational effort. Furthermore, the algorithm becomes much more flexible when compared to other one-degree of freedom based strategies.

The trials were executed in a real-time nonlinear physical system with complex dynamics, with non-minimum phase states and highly nonlinear static gains along the different operation ranges. The neural model was able to represent with very good accuracy the system dynamics, which shows the efficiency of the neural networks when applied in the nonlinear system identification. The system was implemented to prove in practice the superior performance of the proposed technique. The same algorithm may be applied in the control of important industrial process, as in multivariable control, level, concentration and temperature. The developed algorithm may stimulate new applications involving the ideas presented in this work. The low computational cost allows the practical implementation of the proposed algorithm in real-time existing embedded systems.

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