HYBRID STRUCTURE TO SIMULATE THE THERMAL BEHAVIOR OF POOLS FOR DIFFERENT CLIMATE CONDITIONS AND PROFILE OF HUMAN ACTIVITY

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Abstract – In this work is proposed a hybrid structure to simulate thermal behaviors of pools. The structure uses neural representation to model the climatic data and parametric estimation to determine the variation in volume due the human activity. The new structure allows adapting the theoretical dynamic models, with variations over time for specific regional weather conditions. As a case of study, data of state of Minas Gerais (MG) – Brazil were used.

Keywords – Artificial Neural Network, Parametric Estimation, Thermal Model of Pool, Simulation

Resumo – Neste trabalho é proposta uma estrutura híbrida para simular o comportamento térmico de piscinas. A estrutura utiliza representação neural para modelar dados climáticos e estimação paramétrica para determinar a variação do volume causada pela atividade humana. A estrutura permite adaptar modelos teóricos dinâmicos para variações no tempo para regiões com condições climáticas específicas. Como estudo de caso foram utilizados dados do estado de Minas Gerais (MG) – Brasil.

Palavras-chave – Redes Neurais Artificiais, Estimação de Parâmetros, Modelo Térmico de Piscina, Simulação

1. Introduction

With the reduction of watersheds and with the population growth, it is observed that conventional systems to generate energy may not be to meet future world demand. The study of the use of new forms of alternative energy, the development of mathematical models and simulation of structures, for the systems that use them, allows better use of these resources in urban and rural areas.

In this work, a system based on renewable solar energy is considered. The system operates with the heating and cooling pool through directly solar energy. It proposed a structure that allows a model thermal of swimming pool is used to simulate their dynamic behavior in different locations and different climatic conditions. The proposed simulation structure consists in an hybrid adaptation of a model that combines a system dynamic model, neural networks and parametric estimation. Neural models are constructed to represent climate data and the parametric estimation is used to obtain the pool volume and, consequently, the impact of human activity.

Human activity is a factor that directly influences the thermodynamic behavior of pools and, therefore, must be considered. In this work, changes of volume are estimate in order to track losses due to human activity. The volume is indirectly determined by parametric estimation of the model of pool through the method of the random-walk least squares.

In the proposed simulation structure, a neural representation for the climate system, that allows map geographically distinct regions (for the state Minas Gerais located in Brazil) will be presented. The estimation of the volume parameter will be determined indirectly from a parametric estimation model. With this objective, a simulation structure based on equation of differences was developed to simulate

and estimate the parameters of the process. This structure allows simulate different environmental conditions, different location and different size of swimming pools.

In section II, the thermal model for pool is discussed. In section III, the hybrid structure, which incorporates the dynamic model, ANN and parametric estimation will be presented. In section IV, the procedures to represent the climate system through neural networks will be discussed. In section V, the structure for parameter estimation will presented; and in section VI, results of simulations are shown. Finally the conclusions of this work are presented.

2. Thermal Model of Pool

In literature various mathematical models have been proposed to describe the dynamic behavior of thermal pools [1-12].

Almanza and Lara [1] proposed a model for calculating the energy needed to maintain constant the temperature of the pool. Croy and Peuser [2] studied various sources of energy (solar, oil and gas) to heat swimming pools and found that the use of solar energy is attractive and presents a competitive cost.

The calculations of solar radiation and insolation which affects the thermal behavior of pools were studied by Elmina, Areed and Elsayed [3] and Melliti [6] respectively. Both studies used ANN to model the solar radiation and insolation, showing satisfactory results.

Haafa, Luboschik and Tesche [4] described a model of pool that was validated with data collected over three years. Molineaux, Lachal and Guisan [7,8] also developed a model of pool that use as source of heating the solar energy. Hahne [5] proposed a model of pool where can observe that the evaporation is the factor that most influences the energy loss of the swimming pools.

As analyzed by Hahne, Sartori [9] also examines the energy loses of pools through evaporation. Smith, Jones and Löf [10], also identified that evaporation is the main cause of energy loses of pools. Some of these models can be simulated using the software RETSCREEN [11]. But for simulations in other regions of different climatic conditions, for which the models were not developed, the models may not be adequate. In this study, the structure of simulation proposed allows simulate different weather typical conditions of the state MG-Brazil. This is possible because the neural representations, which adjust a mathematical model to climate, was used to map the climate with data collected from the regions concerned. The procedures adopted for obtain the neural representation to the climate in the state of MG can be applied and extended to other regions and countries.

The model proposed by Govaer e Zarmi [12], which determines the variation of temperature of the pool due to climatic parameters, such as ambient temperature and solar radiation, was selected to compose the hybrid structure of simulation. The temperature of the pool is the monitored parameter to examine the influence of climatic conditions and human activity.

The equation that describes the thermal model of pool is given by:

$$\overline{(\tau\alpha)}A_p I_{(t)} = (U_c + U_r)A_p(T_{(t)} - T_{a(t)}) + U_s A_s(T_{(t)} - T_{s(t)}) +$$
$$cU_c A_p(P_w - P_a) + \varepsilon R A_p + \rho_\rho V C_\rho \frac{dT}{dt} \tag{1}$$

Where:

A_p : pool of area (m^2); A_s : area of soil (m^2); c : constant of loses of heat by evaporation ($°C/kPa$); C_p : specific heat of water (KJ/kgK); I : annual change in insolation (W/m^2); P_a : vapor pressure of water (kPa); P_w : saturation vapor pressure of the water in air temperature (kPa); R : radiation (W/m^2); T : temperature of pool ($°C$); T_s : temperature of soil ($°C$); T_a : variation annual of ambient temperature ($°C$); U_c : coefficient of convective heat loss ($W/m^2°C$); U_r : coefficient of heat loss by radiation ($W/m^2°C$); U_s : coefficient of heat loss by contact with the ground ($W/m^2°C$); V : volume of pool (m^3); $\overline{(\tau\alpha)}$: product of the transmittance and absorption; ε : emissivity; ρ_ρ : density of water;

Let Consider:

$$A = \overline{(\tau\alpha)}A_p$$
$$B = (U_c + U_r)A_p$$
$$C = U_s A_s$$
$$D = cU_c A_p(P_w - P_a)$$
$$E = \varepsilon R A_p$$
$$F = \rho_p V C_p$$

It is possible obtain:

$$AI_{(t)} = B(T_{(t)} - T_{a(t)}) + C(T_{(t)} - T_{s(t)}) + D + E + F\frac{dT}{dt} \tag{2}$$

Therefore, the representation of the model can be given by:

$$F\frac{dT}{dt} + (B + C)T_{(t)} + U_{(t)} \tag{3}$$

Where:

$$U_{(t)} = -BT_{a(t)} - CT_{s(t)} + D + E - AI_{(t)} \tag{4}$$

The pool's volume can be calculated using parameters $(B+C)/F$ or $1/F$. The value 1162.6388 is used to convert units of the model. The Equations (3) and (4) will be used at the section V, to estimate the pools volume front of human activity.

$$V = \frac{-(B+C)*h}{1162.6388*\left(\frac{(B+C)}{F} - 1\right)} \tag{5}$$

$$V = \frac{-h}{\frac{1}{F}*1162.6388} \tag{6}$$

To calculate the solar radiation (R) is necessary to determine the temperature of the sky (T_{sky}). The terms for calculating the temperature of the sky and the solar radiation were proposed in [17] and [18] respectively. T_{dw} is the temperature of dew point. The terms are shown below:

$$T_{sky} = (273 + T_a)(0.711 + 0.0056T_{dw} + \tag{7}$$
$$0.00073T_{dw}^2 * 0.013\cos(90))^{0.25} - 273$$
$$R = 0.96 * 0.00000005697 * (T^4 - T_{sky}^4) \tag{8}$$

The equation proposed by Govaer and Zarmi, to calculate the ambient temperature was modified in this work, in order to represent the hourly variation in temperature. Eq (9):

$$T_a = \overline{T_a} + T_{max} * sen(2\pi * k * h / 24 - 2.03) \tag{9}$$

3. Hybrid Structure of Simulation Proposed

The structure of simulation that adjusts the theoretical model of swimming pools to operate in specific climatic conditions is shown in Fig. 1. It may be noted that the resulting structure incorporates the physical model, the neural representation of climate data in the region considered and estimation of parameters of the process. As a case study, were considered climate data of the state of Minas Gerais - Brazil.
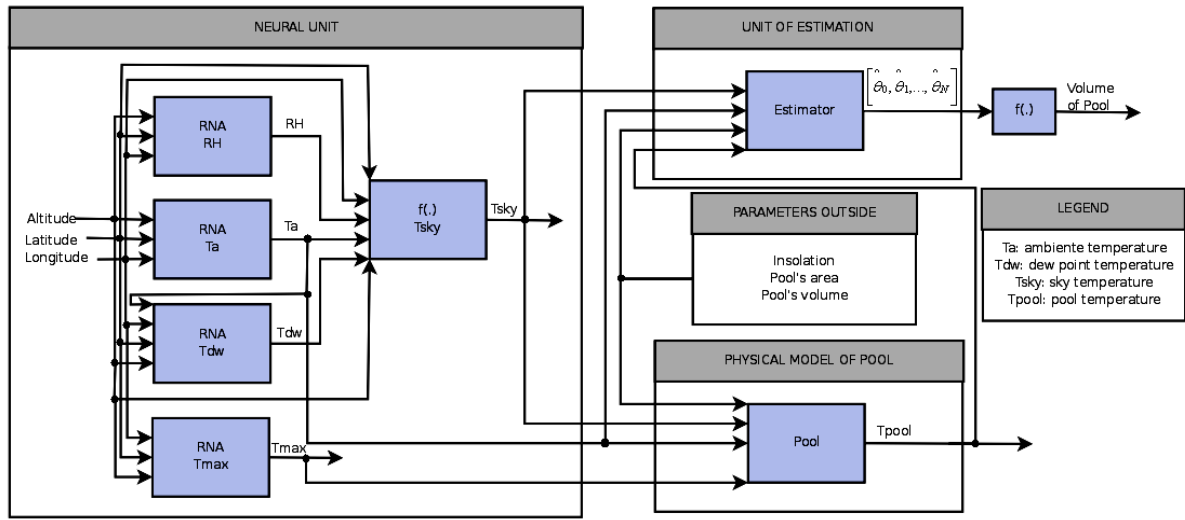
Figure 1 – Hybrid structure adaptation of the models of thermal pool

As can be seen in Fig. 1, the neural representation provides data from the relative humidity (RH), ambient temperature, maximum ambient temperature (Ta) and dew point temperature (Tdw) of the physical model of pool, which, in turn, provides the water temperature $T_{(t)}$ of the pool and provides to the parameters estimator the value of entry $U_{(t)}$. From the module of estimation, the volume V is extracted through the equations (5) e (6).

4. Artificial Neural Networks

Artificial neural networks are parallel and distributed systems [13] that are able to adjust a mathematical function to represent a physical process. Through examples, the ANN is capable to learn and generalize the information of a system which it was trained and adjusted.

According to Hecht-Nielsen in [14] there is always a continue and differentiable function, for any neural representation of three layers, able to represent it, where the layer of entry has *n* neurons, the hidden layer 2n +1 and *m* for the layer of output, that corresponds to the number of exits. These comments were considered in this work.

The following procedure was adopted to normalize the input data:

a) In order to improve convergence of the ANN training process, the normalization interval [0, 1] was reduced to [0.2, 0.8], because in the log-sigmod function the values [0, 1] are not reached: $f \to 0$ for $net \to -\infty$ and $f \to 1$ for $net \to +\infty$. Moreover, this can give to ANN an extrapolation capacity. As the logarithmic scale compacts large data values more than smaller values, when the neural network contains nodes with log-sigmoidal activation function (considered in this work), better results can be achieved if the data are normalized within the interval [0.2, 0.8], [15,16];

b) The data was normalized through the following formula:

$$f^a(Lo) = Ln = (Lo - Lmin) / (Lmax - Lmin) \qquad \text{10a}$$
$$f^b(Ln) = Lo = Ln * Lmax + (1 - Ln) * Lmin \qquad \text{10b}$$

where *Ln* is the normalized value, *Lo* is the value to normalize, *Lmin* and *Lmax* are minimum and maximum variable values, respectively.

c) *Lmin* and *Lmax* were computed as follows:

$$Lmin = (4 \ x \ LimiteInf. - LimiteSup) / 3 \qquad \text{11a}$$
$$Lmax = (LimiteInf. - 0.8 \ x \ Lmin) / 0.2 \qquad \text{11b}$$

4

The Eqs. (11a) and (11b) are obtained substituting in the Eq. (10a) *Ln* = 0.2 and *Lo = LimiteInf*; and *Ln* = 0.8 and *Lo = LimiteSup*. Where *LimiteInf* and *LimiteSup* are the minimum and maximum values of the original data sets respectively.

In this work the algorithm used training was Levenberg-Marquardt, due to a rapid convergence.

4.1   Neural representation of climate data

Four neural models were built. One to represent the relative humidity (*RH*), another for ambient temperature (T_a), the third one for maximum temperature (T_{max}) and the fourth to map the temperature of the dew point (T_{dw}):

$$RH = f_{ANN}(latitude, longitude, altitude)$$
$$T_a = f_{ANN}(latitude, longitude, altitude)$$
$$T_{max} = f_{ANN}(latitude, longitude, altitude)$$
$$T_{dw} = f_{ANN}(latitude, longitude, altitude, T_a)$$

It is consider acceptable a error of ±1ºC for *Ta, Tmax* and *Tdw* and ±5% for *RH*. Was observed during experiments that errors in these proportions cause little impact on the system of a thermal pool.

The representations were considered climate data measured during 10 years. The training set was conducted with the average monthly information of relative humidity, ambient temperature, maximum ambient temperature and the dew point temperature of twenty-five cities in the state of Minas Gerais and validated with three cities that were not considered in the training. The results of training and validation are presented below:

Table 1 – Error obtained during the process of training and validation

	AVE Trein	AVE Val	STD-DV Trein	STD-DV Val
Ta	0.0790	0.1339	0.0642	0.0516
Tmax	0.0085	0.3220	0.0082	0.2621
Tdw	0.0156	0.4200	0.0233	0.4691
RH	0.0910	1.5674	0.0758	1.1413

In Table I it is possible to see a satisfactory neural representation of climate data. The parameter T_a, for example, presented average error of 0.1339 ºC for the validation. The parameters T_{max}, T_{dw} and *RH* obtained, respectively, 0.32ºC, 0.42ºC e 1.5674%.

The validation of neural representation to three cities that were not considered in the training set is shown in Tables II to V. As can be seen in the results of the validation of neural networks T_a, T_{max}, T_{dw} and *RH*, the neural networks had an average error satisfactory to the problem addressed in this work.

Table 2 – Results of validation for T_a

	Ta	Ta ANN	Error
Belo Horizonte	24.31	24.12	0.19
Formoso	24.29	24.40	0.11
Frutal	25.52	25.62	0.09

Table 3 – Results of validation for T_{max}

	Tmax	Tmax ANN	Error
Belo Horizonte	29.69	29.09	0.60
Formoso	31.58	31.51	0.07
Frutal	31.26	31.66	0.30

Table 4 – Results of validation for T_{dw}

	Tdw	Tdw ANN	Error
Belo Horizonte	18.20	18.32	0.11
Formoso	18.68	17.72	0.96
Frutal	21.42	21.61	0.18

Table 5 – Result of validation for *RH*

	RH	RH ANN	Error
Belo Horizonte	68.56	71.44	2.88
Formoso	69.57	70.50	0.93
Frutal	75.74	76.62	0.88

From Tables II to V, it is possible to observe that the error in all cases was below of the limits for each parameter, i.e., neural models are able to represent climatic data in a satisfactory form. In many cases, the values obtained through these models were very close to the original data, which shows the good performance of the representations.

5. Parametric Estimation

In this work the method of the least squares random-walk to determine the variation of volume in the pool due to human activity was considered.

As the algorithms of estimation of parameters are usually implemented in computer, it is required a representation of the theoretical model in equations of differences. Thus, the equation (3) was rewritten in order to meet this requirement:

$$T_{(k+1)} = a_1 T_{(t)} - b_1 U_{(t)} \tag{12}$$

The real values of the parameters that will be estimated are given by $a_1 = (B+C)/F$ e $b_1 = 1/F$.

The method of estimation considered applies to systems that can be represented in the form $y = \varphi\theta$, where θ represents the parameters to be estimated. This representation is given by the expression below:

$$\begin{bmatrix} T_{(k)} \\ T_{(k+1)} \end{bmatrix} = \begin{bmatrix} -T_{(k-1)}, -T_{(k-2)}, U_{(k-1)}, U_{(k-2)} \\ -T_{(k)}, -T_{(k-1)}, U_{(k)}, U_{(k-1)} \end{bmatrix} \begin{bmatrix} [a_{(k)}, b_{(k)}]^T \\ [a_{(k)}, b_{(k)}]^T \end{bmatrix} + \begin{bmatrix} e_{(k)} \\ e_{(k)} \end{bmatrix}$$

The algorithm of estimation is given by the expressions [13-15]:

Start $\hat{\theta}_{(0)}$ e $P_{(0)} = \alpha I (\alpha >> 0)$; $[Q]$, $k = 0$

$$k_{(k+1)} = \frac{P_{(k)} \varphi_{(k+1)}}{\lambda + \varphi_{(k+1)}^T P_{(k)} \varphi_{(k+1)}} \tag{13}$$

$$\hat{\theta}_{(k+1)} = \hat{\theta}_{(k)} + k_{(k+1)} \left[y_{(k+1)} - \varphi_{(k+1)}^T \hat{\theta}_{(k)} \right] \tag{14}$$

$$P_{(k+1)} = \frac{\left\{ P_{(k)} - K_{(k+1)} \varphi_{(k+1)}^T P_{(k)} \right\}}{\lambda} + [Q] \tag{15}$$

$k = k + 1 \rightarrow equation (13)$

Where P is the covariance matrix, Q is a characteristic matrix of adjustment of the random-walk technique and I is a diagonal matrix with the value of 10^7 or more.

6. Simulations and Analysis of the Results

There were proposed two simulations ranging (reducing) the volume to represent human activity. One follows the type ramp variation and the other the type exponential variation. The functions that represent these variations are given, respectively, by equations (16,17), where v is the volume in instant t:

$$f(v) = \begin{cases} v & 0 < t \le 168 \\ -0.0015873vt + 1.266v & 168 < t \le 672 \\ v & t > 672 \end{cases} \tag{16}$$

$$f(v) = \begin{cases} v & 0 < t \le 168 \\ 0.8ve^{(-(t-169)/100)} + 0.2v & 168 < t \le 672 \\ v & t > 672 \end{cases} \tag{17}$$

In Fig. 2 and Fig. 3, the data variations of the temperature of the pool during January when the volume varies according to functions (16) and (17), respectively are presented. These two simulations were conducted for the city of Belo Horizonte / MG (-19.93 latitude, longitude, altitude -43.94 and 850m).

It may be noted that the temperature of the pool varies stronger in Fig. 3. This is because the fall in volume is more aggressive and, as the volume is related directly with the reaction time of the system (the smaller the volume faster the temperature will vary). But, it can be seen that the final value of temperature is the same and this is consistent since the final volume is also the same.

In Fig. 4 and Fig. 5, are shown real values of volume and the estimated values.

The estimation of the volume from the parameter a using the equations (16) and (17) is represented, respectively, in Fig. 4 and Fig. 5. As can be seen, in both cases, the estimated volume was very close to reality. Therefore, the result that was obtained was considered satisfactory.
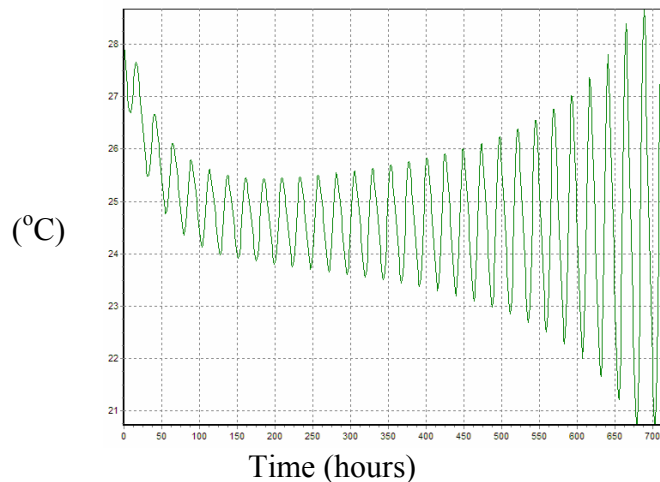

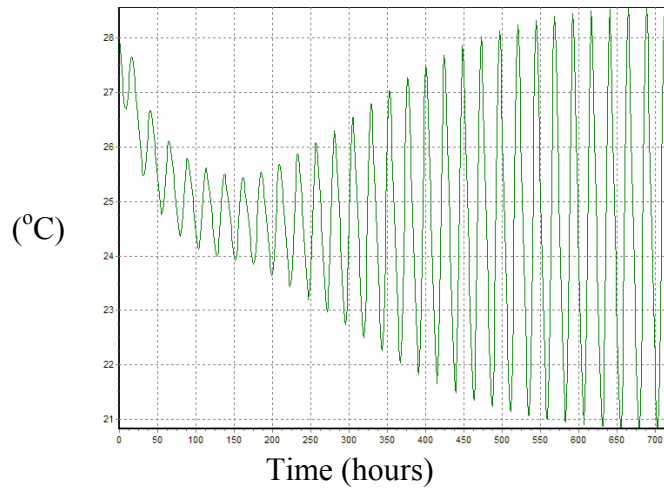Figure 2 – Variation of the temperature of the pool over a month with a volume-type ramp

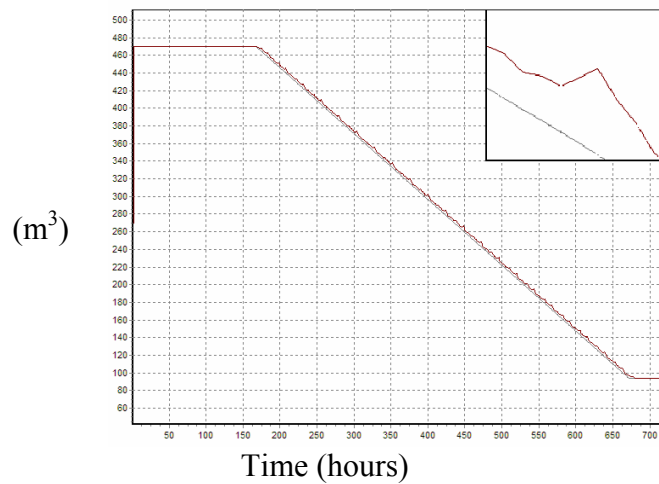**Figure 3** – Variation of the temperature of the pool over a month with a volume-type exponential

Figure 4 – Variation and estimation of volume-type ramp obtained by parameter *a* over a month
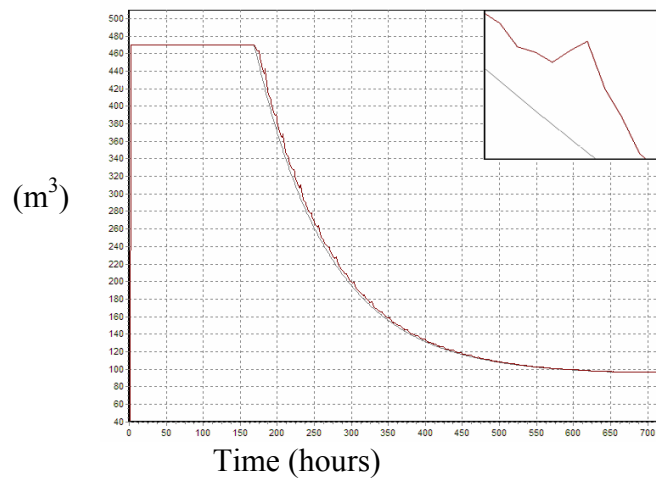

Figure 5 – Variation and estimation of volume exponential type obtained by parameter during a month

The change in volume can be also estimated by the parameter *b*. However, the values of *b* have very low scale and the mistakes of estimating the volume became more evident, indicating that a is the best parameter for estimating the volume of the pool.

In Fig. 6 the change of the temperature of the pool - band of smaller magnitude - against the change of temperature for the period January- June is shown. It is possible to see that there is, as expected, a direct relationship between both of them.
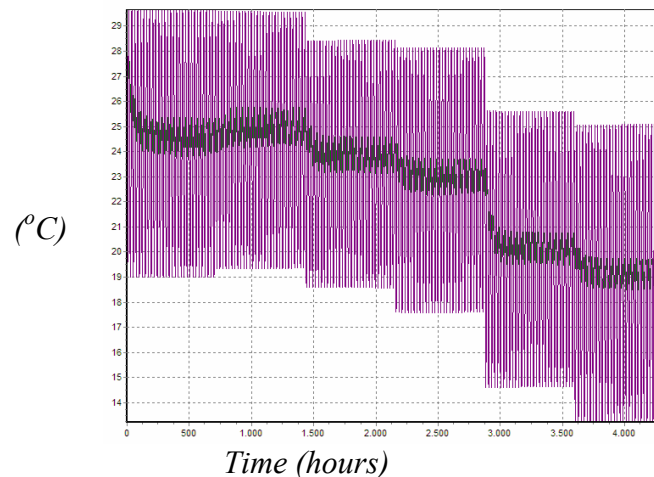
8

(^{o}C)

Time (hours)

Figure 6 – Variation in the temperature of the pool against variation in ambient temperature without variation in volume

7. Conclusions

In this work a structure of simulation that combines theoretical model of pool, artificial neural networks and parametric estimation was presented. The structure allowed adapting the theoretical model to operates in regions with specific weather conditions.

The neural representation of climate data presented results highly satisfactory when they were validated for MG-regions in Brazil. For reasons of space these results were not presented in this work.

The parametric estimation permitted to follow the change in the volume of the pool against human activity. This condition has been incorporated into the simulation through generic mathematical functions. In future works we expect to shape this human behavior through intelligent agents. It can be observed in simulations using the hybrid structure proposed in this paper that the results were satisfactory.

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