A thermodynamical model study for an energy saving algorithm

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Abstract. A local Spanish company that produces electric heaters needs an energy saving device to be integrated with the heaters. It was proven that a hybrid artificial intelligent systems (HAIS) could afford the energy saving reasonably, even though some improvements must be introduced. One of the critical elements in the process of designing an energy saving system is the thermodynamical modelling of the house to be controlled. This work presents a study of different first order techniques, some taken from the literature and other new proposals, for the prediction of the thermal dynamics in a house. Finally it is concluded that a first order prediction system is not a valid prediction model for such an energy saving system.

Keywords: Fuzzy systems, Hybrid Artificial Intelligence Systems, Real World Applications, Thermodynamical Modelling, Electric Energy saving.

1 Motivation

In Spain, a local company has developed a new dry electric heaters production line and a device for electric energy saving (EES) is to be included in the catalogue. In previous works, the development of such a device has been analyzed, and a multi agent hybrid fuzzy system has been proposed [12] [13] [11]. There are two stages in defining the proposed energy distribution algorithm that goes in the CCU: the design stage and the run stage. In the design stage a wide range fuzzy controller is trained and validated out of the hardware device, while in the run stage the whole algorithm is executed in the embedded hardware (CCU)

The first preliminary EES was proposed in [12]. In that proposal, a thermodynamical model (from now on TM) of the house to be controlled was not required, because the fuzzy energy distribution controller (FC) was defined directly by a team of experts.

In our next work, [13], a new system design was presented (see Figure 1) and two improvements were introduced: an optimization step to improve the Experts FC

(MOSA) and a TM based on the estimation of thermal parameters by the Simulated Annealing algorithm (SA).

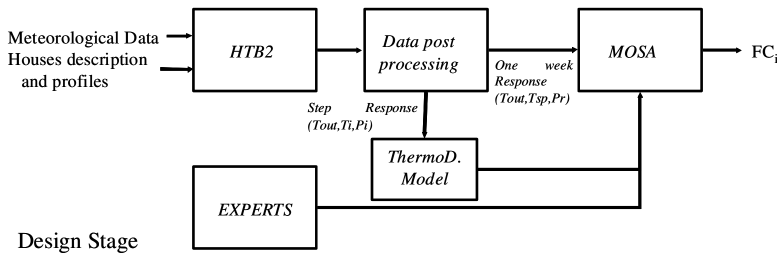

Fig. 1. . The Design stage procedure. A fuzzy controller is trained for each configuration pair of climate zone and building topology

Although in [13] a TM was used and the FC was proven to make a suitable distribution of the available energy with this temperature model, we realised that the TM (based on SA) must be studied in depth. In the present work, techniques for indoor temperature forecasting based on thermodynamical theory [2], SA, GAs and ANNs [8], [10], are to be used and compared to be included in the EES proposed.
The work is organized as follows. The Design stage of the ESS proposed is detailed in Section 2. Section 3 presents the new different TMs. A comparison of the proposed TM is carried out in Section 4. Finally, conclusions and future work are presented in Section 5.

2 The Design stage

The Design stage includes several steps: the HTB2 simulation, the data post-processing, the identification of the TM and the generation of the best suite FC.
The HTB2 simulation software [7] in following HTB2, is a well known tool suitable to analyze the dynamics of heating systems and the energy consumption in buildings using the concentrated parameter model [5] [1]. Also a simulation for determining the thermodynamics of each room in the building is needed. This simulation is the *step response of the house,* where a change in the temperature set point is analyzed.
The post-processing step has two tasks: one consists on preparing the training data for the TM (the step response simulated with HTB2 during one day); and the second task is to prepare a dataset obtained from one week of HTB2 simulation; this will represent the training and validation datasets to be used in the Thermo D. and MOSA steps. A TM for the house is required, because the optimization algorithm (MOSA) needs to calculate an approximation of temperature in a room when a FC is evaluated.
Finally, the MOSA step is the 10 k fold cross validation multi-objective simulated annealing for training the fuzzy controller. The MOSA is the multi-objective adaptation of the simulated annealing presented in [14]. Each individual is the consequent part of the fuzzy controller, and the fitness function is the Distribution algorithm execution. The two objectives to reach are minimizing the energy

consumption and keep the house in comfort minimizing the difference between the TM output and temperature set point. The initial individual has been obtained from expert knowledge, and the antecedents and rules are kept the same for all individuals.

3 Definition of the thermal dynamics

Firstly, the main question to consider in the thermal dynamics modelling is that the temperature control in a house is a first order control system [10] [2], which means that no past data [Ti(t-n), P(t-n), etc] must be used in the estimation models.
The thermal dynamics of a house was described by P. Davidsson in his work [2]. This model was the TM used in our work [13], based on the calculation of the thermal resistance and the thermal capacitance for each room from the step response of the house. Using the simulated annealing heuristic the best pair of thermal parameters for each room was found.
Here, it's formalized the SA+Davidsson combined proposal presented in our work [13] and presented a set of typical solutions taken from the literature [8] [10].

Identifying the parameters of the Davidsson proposal with the SA

The Davidsson' proposal is based on the consideration that all the thermodynamical characteristics of a room are described by two constants: the thermal resistance, R, which captures the heat losses to the environment, and the thermal capacitance, C, which captures the inertia when heating up/cooling down the entities in the room. (in our experiments we use the sample time of 1 min.) The temperature, $T_{xi,}$ in room x at time i is described by formula (1):

$$T_{xi} = \frac{1}{1+\frac{1}{R_x C_x}} \cdot \left(T_{x(i-1)} + \frac{P_i + \frac{T_{outi}}{R_x}}{C_x} \right) \quad \mathbf{(1)}$$

where P_i is the heating power, T_{outi} the outdoor temperature, and $T_{x(i-1)}$ is the temperature in room x 1 min ago.
It must be considered that the Davisson' work did several simplifications that we didn't: constant outdoor temperature is assumed (10ºC), radiation from the sun is negligible (i.e., weather cloudy), [2]. Thus, it's needed to estimate the suitable pair of thermal parameters R and C for each room. Here the Simulated Annealing is used, one of the simplest and fastest optimization algorithm.

Identifying the parameters of an exponential thermal function with the Simulated Annealing (SA)

We have stated that the Davisson'model has a too fast response of the temperature evolution to the influence of the power, despite of having identified the factors R and

C ad-hoc for each room. Thus, we think that the exponential model of equation (2) would be more adequate than the Davidsson' alternative.

$$T_{xi} = a_x + b_x \cdot T_{xi-1} + c_x \cdot P_{xi-1} + e^{d_x \cdot T_{xi-1} + e_x \cdot P_{xi-1}} \qquad \mathbf{(2)}$$

where P_{xi-1} is the heating power in room x 1 min ago, and $T_{x(i-1)}$ is the temperature in room x 1 min ago.

The parameters a_x, b_x, c_x, d_x and e_x are estimated running the SA algorithm for each room x. The fitness was the mse of the multi-step prediction. The training-testing scheme used is 5x2CV.

Identifying a TM with a Genetic Algorithm

A simple generational GA [3] was proposed to learn the parameters of the exponential function (2) too. The individuals are vectors of five real numbers (a_x to e_x parameters) and fitness is the MSE of the multi-step prediction. The configuration of the GA is: an initial population of 100 individuals, crossover probability of 70%, mutation probability of 1% and tournament selection of size 4. The training-testing scheme used was 5x2CV.

Identifying a TM with a fast-forward Artificial Neural Networks

The use of ANN to define prediction models for building variables as indoor temperature or relative humidity, has grown in last years [10] [8]. Our proposal is based on a two-layer network of fast-forward type, with tan-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. This is a useful structure for function approximation (or regression) problems. As an initial guess, we use the inputs <$Tindoor_t$, $Tout_t$, $Power_t$>, thirty neurons in the hidden layer. The network should have one output neuron since there is only one target, the indoor temperature. We will use the Levenberg-Marquardt [6] [9] algorithm for training.

4 Experiments and commented results

This work deals with the comparison of different approaches of the thermodynamical modelling of the indoor temperature in a house with the one proposed based on the Davisson' model and SA [13]. The climate zone chosen for the experiment is the city of Avila, an E1[1] city, and the building topology is a three bedrooms condominium house, with orientation North-South, composed of seven heated spaces.
The environmental data such as the outdoor temperature or the solar radiation have been gathered from statistical data of the city of Avila in the winter of the year 2007. Other files, as the occupancy, the temperature set point profile for each room in the house, small power devices profile, etc. have been designed attending to realistic

[1] The Spanish regulations define 5 climate zones, from the less severe –A3– to the most severe –E1–.

profiles. Finally, files like ventilation file have been generated attending to the regulations.

The HTB2 simulation produces two datasets: the step response of the house for one day (training dataset) and the evolution of the heating power required to keep the comfort level (21ºC for all the rooms) and temperature in the house during one week (testing dataset). The training and testing error of the selected thermal prediction techniques applied over the seven simulated rooms are shown in table 1.

	David.	SA+David	SA+Expo	GA+Expo	ANN
Train	247,6/158,0	27,0/7,2	16,2/8,9	5,4/0,6	26,2/14,5
Test	130,1/59,8	58,2/18,3	23,9/5,3	28,7/5,4	38,6/28,4

Table 1. Training and testing mean/standard deviation of the percentual error of the thermal models

The original Davidsson thermal model [2] with parameters R and C for a typical small room (R = 0.1, C = 3000) were applied to all the rooms. It can be observed that the testing error is lower than the training error, but it's still too high (130,11%). Thus, we think that the Davidsson's formula parameters can be optimized and a meta-searching algorithm SA was used to learn the Davidsson' parameters. However, the results of the SA was better than the direct Davidsson' model (58,23%) but not good enough to be used in the Fuzzy Controller Optimization Algorithm (MOSA). The remaining proposals overpass the Davidsson' proposals but the testing errors are too high again. In spite of the results of the table 1, we consider important to analyze the distribution of the error between the testing ticks (one tick per minute during seven days).

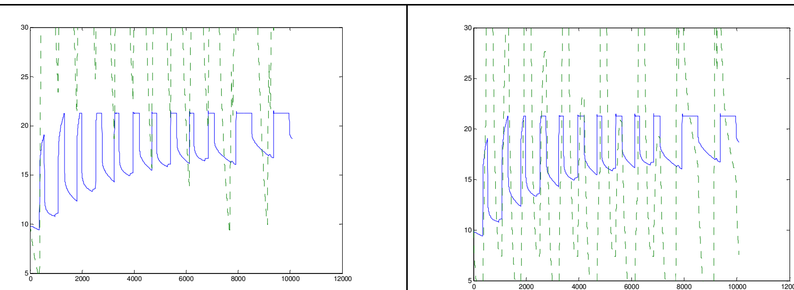

Fig. 2-3 Left side is the TM estimated for a bedroom with the original Davisson function with R = 0.1, C = 3000; Right Side is the TM estimated for a bedroom with the Davisson function parameters optimized with SA.The Solid line is the reference temperature and dotted line is the estimated temperature.

In Figures 2 to 6 we can see the comparison of the reference temperature evolution (solid line) with the predicted temperature (dotted line) for a bedroom. We can state that the Davidsson's models confirm the high error of Table 1, may be the SA+David proposal (Figure 3) follows better the crests than original function (Figure 2), but both models are not suitable temperature models. The exponential models (Figures 4-5) are not good enough, because they follow the crests with a variable amplitude lag. Finally the solution based on ANN is presented in Figure 6, this proposal fits with high precision the last crests but it's not a valid model for the FC learning step (MOSA) because of its high medium error.

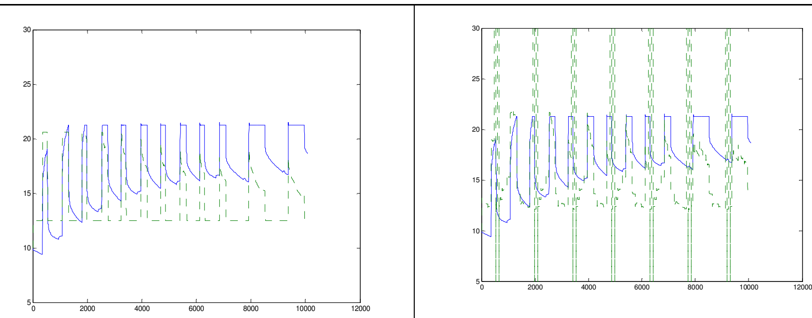

Fig. 4-5 Left side is the TM estimated for a bedroom with the exponential function parameters optimized with SA Left side is the TM estimated for a bedroom with the exponential function parameters optimized with GA. The Solid line is the reference temperature and dotted line is the estimated temperature.

In short, all the first order solutions presented here have an unstable behaviour due to the recursive evaluation so they can be used in a real context. This fact was published in [14], where it said that a recursive evaluation (multi-step prediction) in a learning algorithm usually may not converge to an appropriate model, unless we include some terms that depend on estimates of certain properties of the model (so called 'invariants' of the chaotic series).

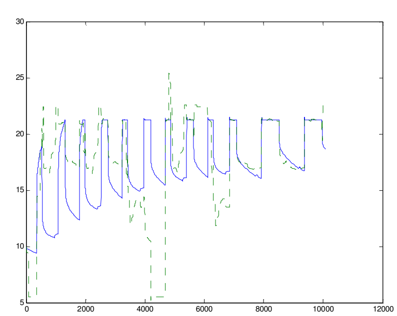

Fig. 6 TM estimated for a bedroom with an ANN. The Solid line is the reference temperature and dotted line is the estimated temperature.

5 Conclusions and Future work

This work compares the thermal prediction proposal presented in preliminary works based on the SA algorithm against with first order prediction AI techniques. Although the results of the new AI technique improve the preliminary work results, the multi-step prediction evaluation used in all of them give very unstable prediction of the temperature.

As Villar and Sanchez stated in [14], the recursive evaluation (multi-step prediction) of a model in a learning algorithm usually needs to estimate the invariants of the series to predict.

Future work will include two working lines: the researching in invariant learning algorithms and the training and validating of the FC with the new thermal models for the validation of the ESS.

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