THE DESING OF CONTROL OF A KITCHEN REFRIGERATOR

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Abstract: The article provides an example of how to design an digital control for maintaining the temperature at a predefined level in a common kitchen refrigerator. The control works on the basis of modeling a thermostatic appliance and the use of fuzzy logic. Thermostatically simulated and fuzzy controlled model are presented successively. The latter is set-up on the basis of the Sugeno's type of fuzzy rules and the Jang's procedure of learning. MATLAB, SIMULINK and Fuzzy Logic TOOLBOX (FLT) are the programming environments used for realization of the model. The principal aim in designing the control is to assure the fastest and best transition possible from an analogue to digital control of the refrigerating appliance, which represents the basis of a functional expansion demanded by the present market.©

Keywords: fuzzy logic, refrigerator control, modelling, simulation.

1. INTRODUCTION

The concept of designing digital control of a compressor in a common kitchen refrigerator is described in the article. Fig. 1 introduces a three-level concept of our design, which was used for a specific refrigerating appliance - the HZOS 3361 model. Although, household appliances also contain freezing compartments, we do not discuss their particularities, so as to provide a more concise survey. The compressor control for the freezing compartment was set-up equally in the project. In view of potential technological changes in the product, all procedures mentioned below lead to the replacement of mechanical thermostats with microprocessor controls, which slightly increases the price of a refrigerating appliance; however, it enables better control and the possibility of introducing new functions. The Internet and mobile telephony, enabling remote communications, stress the importance of these functions even more. The concept of the control design can be divided into the following phases:

• the analyses of the observed, thermostatically controlled refrigerator;

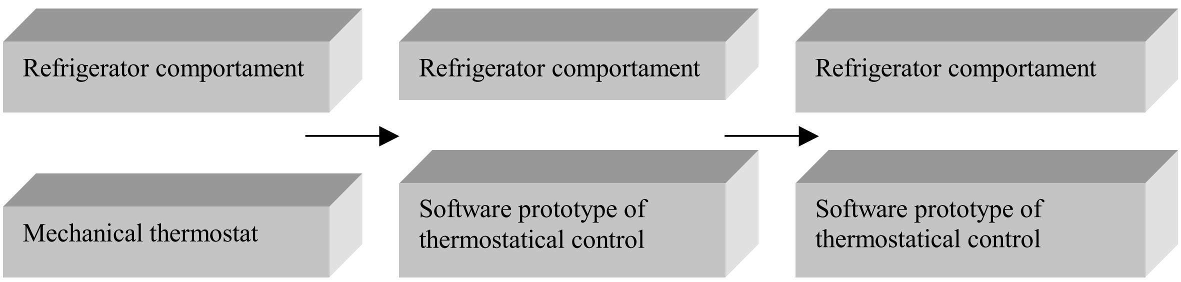

Fig. 1. Three phases of the control design of a kitchen refrigerator.

• the set-up of the software model of thermostatic control with reference to MATLAB and SIMULINK tools; and

• the set-up of fuzzy control with reference to MATLAB, SIMULINK and Fuzzy Logic TOOLBOX (FLT) tools.

In the first design phase, we are able to analyse the basic issues related to the control process. One is the temporal relation between the operative and non-operative mode of the compressor, which we observe in the phase of a normal (not start-up) mode of the refrigerating appliance. Depending upon the external temperature and the actual configuration of the power system, the ratio varies between 1:1 and 1:5. The second characteristic, resulting from the compressor, is the 7 min latency after each cycle of the compressor operative mode. Consequently, potentially “higher” granulation of control is not possible within a controlling period with a predefined lower limit. A programming model of thermostatic control was built in MATLAB (Matalab, 1994) and SIMULINK (Simulink, 1998) environments, in the second phase. The purpose of this model was the ability to change the response time of the thermostat and the refrigerating compartment. Various outgoing time functions of the ON/OFF thermostat were thereby acquired. In the third phase we set-up a software prototype of fuzzy control with the help of the Jang’s concept of learning (Fuzzy Logic TOOLBOX, 1998, J.R. Jang, 1993), on the basis of the time dependent thermostatic output functions. In this phase we also tested it on the real appliance under specific standardized conditions of measurement. A procedure was set-up, which rapidly leads us from thermostatic control to the qualitatively equivalent and digitally devised fuzzy control. With further adjustments of fuzzy control (in the example described, this means expansion on contraction of the entire length of the ON/OFF cycle), an improved version of control was achieved, for which decreased amplitude of oscillation around the desired temperature is typical. Concurrently, an approximately 3% decrease in the consumption of electric energy was attained (M.C. Popescu, 1996). The latter results were achieved on a couple of compressors for refrigerating and freezing parts. In view of the European classification of refrigerating appliances into five classes, which regards the consumption of electric energy (from A to E), the specific product of the producer mentioned above would, thus, be promoted from class C to B. This would also assure a higher sales price on the market for the product.

2. THE MODEL OF THERMOSTATIC CONTROL

The HZOS 3361 is a typical example of the refrigerating-freezing appliance that is used in the average household. It consists of the refrigerating part (205 dm^3 of the volume) and the freezing part (103 dm^3 of the volume). The external measures of the appliance are 177 cm × 59 cm × 59 cm. The basic characteristics of the performance, established in the first phase, are the following (besides a compulsory 7 min latency of the compressor): a relatively slow response time of the cooling system in relation to the compressor start time, and a relatively large amplitude of oscillation around the desired temperature (± 3^0C). Within the model set-up of thermostatic control, the ratio of 1:1 was selected as the proportion between the ON/OFF time of the control cycle. The ON part of the cycle represents time in which the compressor is switched-on, and the OFF part of the cycle defines time in which the compressor is switched-off. In practice, the described proportion occurs in the summer period of the year, when external temperatures vary from 25^0C up. This proportions were measured under laboratory conditions in the analysis phase of the real system operation. The second phase of designing intelligent control represents the model building and simulation of thermostatic control on the grounds of the basic characteristics of the controlled object, which were attained during the first phase. Due to large inertia of the controlling system and long duration of standardized measurements, 1 min was chosen as the basic simulation temporal unit or simulation step. The fundamental components of the model, presented in fig. 2, are

• the *Switch* block, which switches the compressor ON

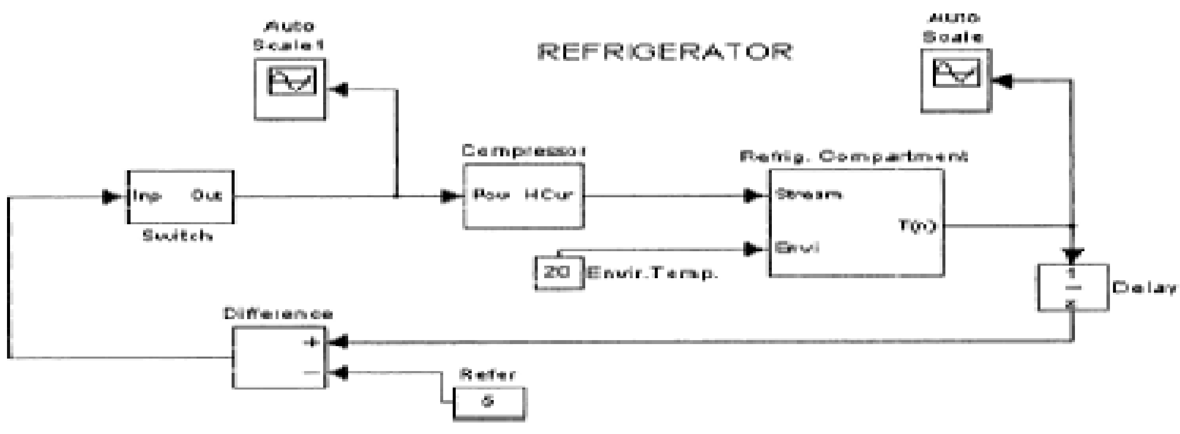

Fig. 2. The basic model of thermostatic control of the refrigerating compartment.

and OFF according to the positive or negative error *e(t+1)* (the difference between the temporary and referential temperature); the eventual switching of the compressor occurs upon a check-up of the status in latency; or in other words, the switching-on of the compressor does not occur as a result of compressor latency during the previous time cycle, where the entire time of latency is not yet 7× cycles; the sensitivity of the thermostat has a deviation of 0.1^0C from the desired temperature;

• the *Compressor* block generates the cooling power, which is transferred to the *Refrigerator Compartment* corresponding to the ON-OFF cycle;

• the *Refrigerator Compartment* represents the refrigerating place; it decreases the cooling power (Stream) from the environmental factors (Envi), in delay, according to the received cooling power; correspondingly, the internal temperature of the object is calculated and then, with a certain delay, released into the next decision cycle, in which a new error is calculated in the *Difference* block, expressed by

$$e(t+1)=T(t)-T_{desired} \tag{1}$$

The model is beneficial in control testing as results can be accomplished much faster using a model compared to the results obtained from the control of a real object. The model was set-up in a simulating environment applying MATLAB and SIMULINK tools. fig. 3 presents the efficiency of the results of the control simulation and the compressor triggering through 600 simulation steps. The left segment of the picture evidences that the amplitude and frequency of oscillation around the desired temperature ($T_{desired}$ = 5^0C) are approximately equal to the result, achieved during real-object control with thermostatic regulation. The right segment of the picture presents the triggering function of the compressor.

3. SOFTWARE PROTOTYPE OF FUZZY CONTROL

On the basis of the stepwise function, portrayed in the right segment of fig. 3, which represents the temporally conditioned output from the *Switch* block (a thermostat), fundamental laws of the relationship between the ON and OFF part of a controlling cycle for the given modeled appliance can be established. From here, there is only one more step towards fuzzy control. Two alternatives are at hand: fuzzy control can be set-up intuitively (M.C. Popescu and Petrişor A., 2005, M.C. Popescu and Degeratu Pr., 1996), or automatically. We are primarily interested in the latter alternative. Following the learning concept, we can leave the design of fuzzy-control parameters to the FLT module, which represents one of the applicative modules of the MATLAB tools. Routines from Yang's principles of learning described in (M. Sugeno, 1985) are provided within tools. It uses a hybrid or back-propagation gradient descent algorithm for the identification of parameters of the Sugeno's rule type fuzzy inference system (FIS). As input of the learning procedure, left function from fig. 3 is submitted to the module. The left function represents input of fuzzy control, and the right one the desired output, or response of fuzzy control. Both functions are submitted to the learning system as vectors, in 600 value length. Learning within the FLT tools is performed in the following steps:

• automatic preparation of the input/output vectors in MATLAB and SIMULINK environments;

• within FLT, we primarily open a new Sugeno FIS model, determine the number of input/output variables and then run the ANFIS editor;

• within the ANFIS editor, we primarily load the learning vectors and then generate the FIS matrix; finally, the learning procedure is executed for n steps; the number n is chosen subjectively.

Before learning procedures may start, the criterion parameters need to be determined. Those are the type and the number of input membership functions and the mode of output formation (the linear function or constant). We selected the default option given by FLT: four membership bell functions for the single input variable input1, demonstrated in fig. 4, and the linear formation of output value. While the input variable still represents the error *e(t + 1)*, the output variable represents the directive for switching the

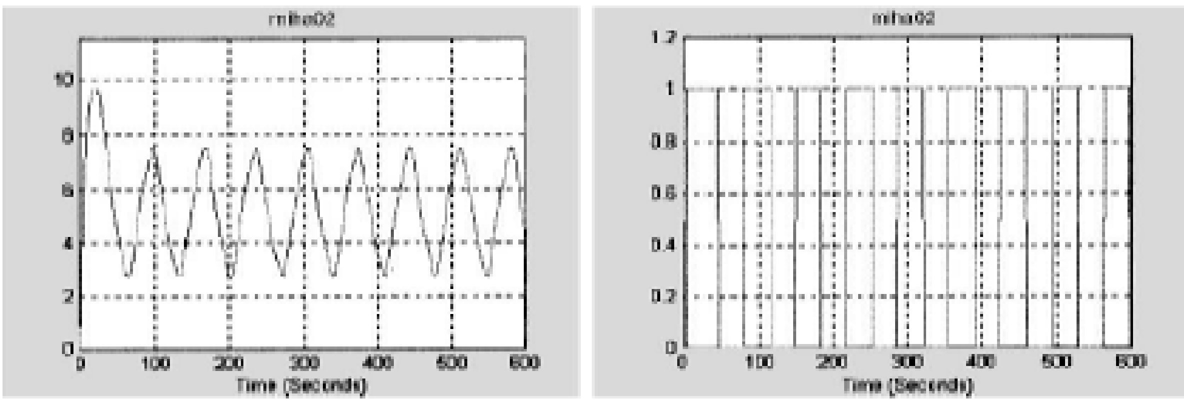

Fig. 3. The results of control (T(n) /refrigerating compartment and out/switch).

compressor on at value 1, and the directive for switching the compressor off at value 0. figs. 5 and 6 demonstrate plots of translation functions as the result of learning after 3, 10, 400 and 1400 steps.

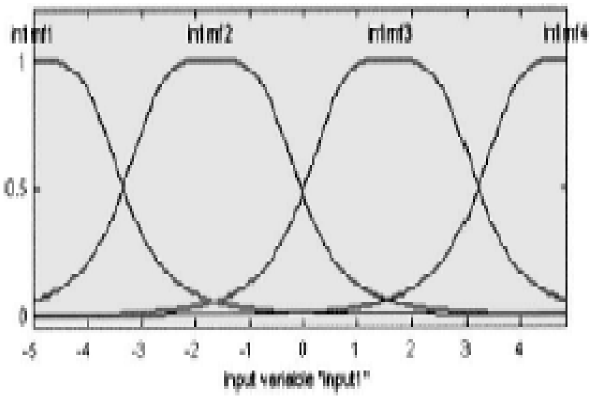

Fig. 4. Selected membership bell functions for the input variable.

It is evident that by extending the learning time, a more ideal translation of the stepwise function is achieved. However, due to obligatory compressor latency, we can not achieve completely precise matching of the actual stepwise function. The object of learning is in fact the output part of the Sugeno's type rule. The latter (M. Sugeno, 1985) can be written with the eq. (2) as

$$\textit{if } (x_1 \textit{ is } A_1) \textit{ and } (x_2 \textit{ is } A_2) \textit{ and,} \ldots \textit{,and } (x_n \textit{ is } A_n) \textit{ then } y_j = f(x_1, \ldots, x_n) \quad (2)$$

where, A_i represents the fuzzy set (term), x_i the input value, and output functions y_j the object of learning. In most cases, FLT forms so many rules and concurrently output functions as there are given input membership functions. The function $y_i = f(x_1, \ldots ,x_n)$ can be either a constant or a linear function. The constant or coefficients of the linear function are the object of learning. The greater the number of epochs, the less the approximative error, or in other words, coefficients or constants come close to an ideal matching of the desired function. All details of learning are described in (M.C. Popescu and Petrişor A., 2000, M.C. Popescu, 2003). In our case, the learned rules are demonstrated in the eq. (3), while the learned parameters are demonstrated in the eq. (4).

$$\textit{if (input1 is in1mfi) then (output is out1mfi),} \quad 1 \le i \le 4 \quad (3)$$

$$y1 = .1.517x\ .\ 7.651,\ \ y2 = .0.521x\ .\ 0.702,$$
$$y3 = .0.252x + 1.602,\ \ y4 = .0.184x + 1.92 \quad (4)$$

Since we performed learning via a segmentialy derivative function, slight anomalies appear in the translation function, which can be avoided on the basis of the eq. (5). Thereby, a new model of a refrigerator, which is illustrated in fig. 7, can be established. The Switch block is exchanged with the Fuzzy Logic Controller and Balance blocks. The latter provides compensation for anomalies presented in the eq. (5). In the left segment of fig. 7, we can see the response of the fuzzy controller built on the basis of parameters achieved after the three learning steps. The result of annulated anomalies can be seen in the right segment of fig. 7.

$$\textit{if } f(t) \ge 0.5 \textit{ then } f(t) = 1 \textit{ else } f(t) = 0 \quad (5)$$

4. OPTIMISATION OF CONTROL AND RESULTS OF MEASUREMENTS

Due to the tendency towards the reduction of energy consumption, we tried to extend the cycle length ($x_{ON} + x_{OFF}$) linearly. The main reason for extension was to minimize the number of times the device was switched-on, which results in increasing the number of first overshoots and the consumption of electric energy. Reduction in energy consumption was achieved, as well as a greater amplitude deviation from the desired temperature as compared with the thermostat. In this respect, we linearly reduced the ON/OFF cycle ($x_{ON}+x_{OFF}$) to the extent of x_{OFF} = 7. The result was unexpected: a better preservation of desired temperature (if compared with fig. 3, we see the deviation is ± 1.^{0}C), and the reduction of energy consumption by approximately 1.5% have been achieved. The first result seems logical, yet the second seems less so. It originates from the mechanical and electrical characteristics of the compressor. On the basis of optimised

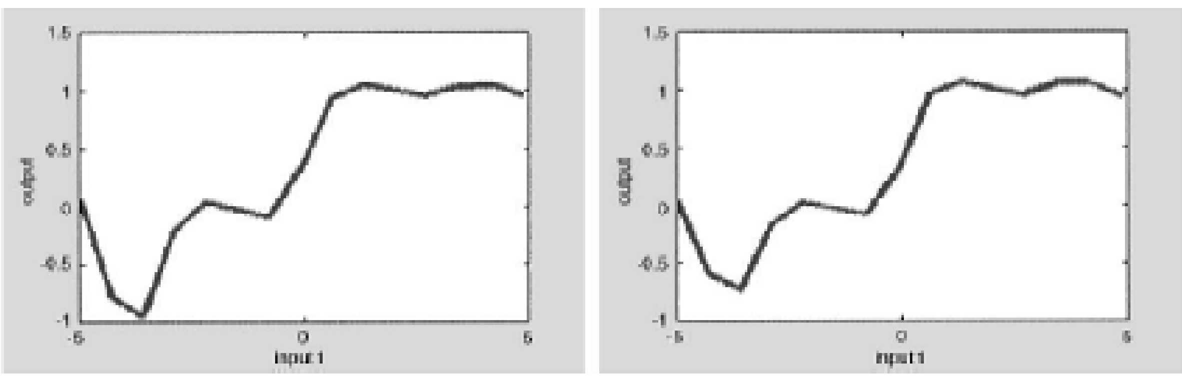

Fig. 5. The plot of the learned translation function after 3 and 10 steps.

fuzzy control, the fuzzy prototype was tested according to internationally established standards in special measuring environment located on

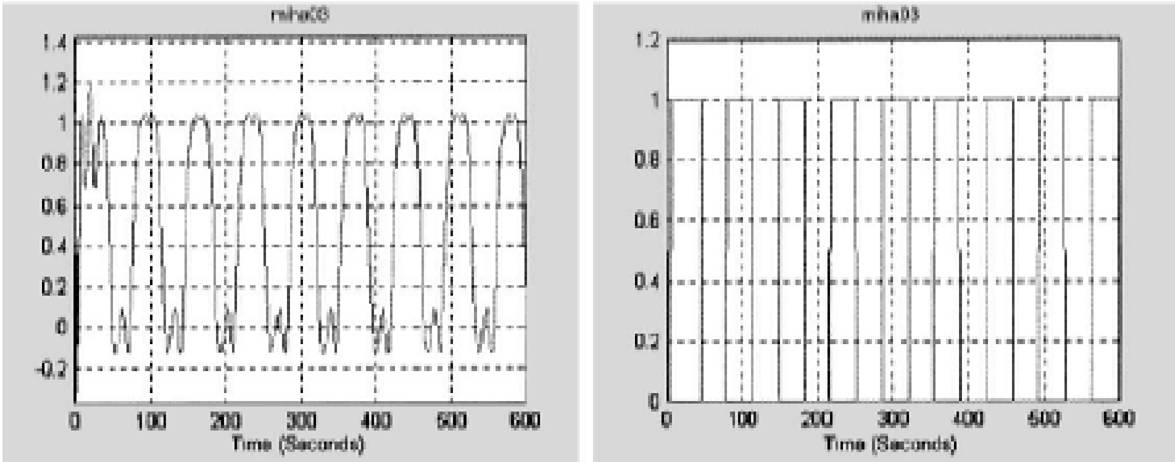

Fig. 6. The model of a fuzzy controlled compressor.

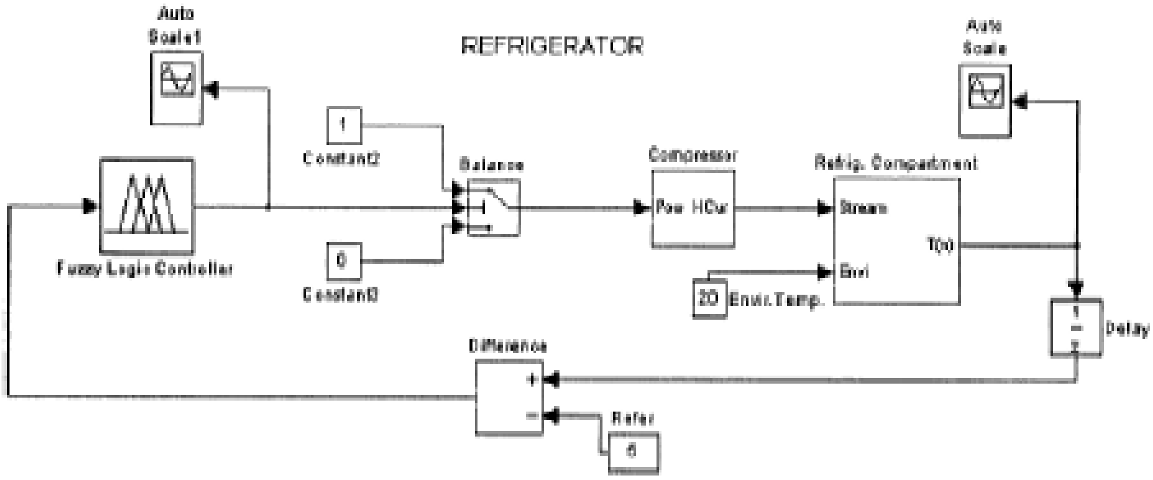

Fig. 7. The response of the learned and corrected function.

the premises of the appliance manufacturer. We also controlled the freezing compartment. Such measurements last longer in accurate and artificially preserved exterior conditions. The standardized measurements also demonstrated that fuzzy control results in the conservation of approximately 3% of electrical energy. The entire daily consumption of electric energy is shown in table 1.

Tabel 1

	Thermostatic control	Fuzzy control
Consumption (kwh/day)	1,64	1,59

5. CONCLUSION

The article presented one of the alternatives for a fast transition from classical thermostatic control to digital control of the refrigerating compressor on the basis of a fuzzy controller. The presented procedure enables the set-up of a translation function, which is copied from the thermostat's one. We can furthermore optimise the fuzzy controller on the basis of linguistic corrections in the set of rules, or by finding simple solutions, as was done in the case of reducing intervals. One of the reasons which justify the transition from thermostatic control to the digital one is also the inability to configure responding capabilities of the thermostat.

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