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A FUZZY LOGIC CONTROLLER FOR AN EMBEDDED POWER SWITCHING SYSTEM REGULATOR FOR TEXTILE WASHING MACHINE

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ABSTRACT

The contemporary textile washing machines do not have the features for temperature regulation and selection for different textile materials, and for the machine's voltage input regulation. This can be seen as one of the causes of the fast deterioration of new textiles and increase in the number of rags; which in turn causes the expenditure of more income in the purchase of textile materials.

The concern of this research is on the use of the Fuzzy Logic Control (FLC) methodology in the design of an automatic and dynamic voltage and temperature regulator controller for the textile washing machine. The fuzzy based controller for the washing machine will be able to automatically regulate the voltage and temperature into the machine washing tank. The best fit temperature for washing different clothing shall be automatically used for various washings and hence prolong the life-span of textiles as against the increasing trend in possession of rags due to improper washing mode.

1 INTRODUCTION.

Fuzzy Logic Control (FLC) methodology is a control system methodology that is applicable in the design of systems that requires the regulation and control of some parameters for effective and/or efficient performance of the system.

Fuzzy logic is basically a multi-valued logic that allows intermediate value to be defined between conventional evaluations like Yes/No, true/false, etc. Notions like "rather warm", "pretty cold" and the likes can be formulated mathematically and processed by Computers.

Fuzzy expert systems incorporates an IF-THEN rules approach to solving control problem rather than attempting to model a system mathematically as in Conventional Control System. For example rather than dealing with temperature control in terms such as *'SP = 500F", "T<IOOOF" or 210C<TEMP<220C, terms like "IF (process is too cool) AND (process is getting colder) THEN (add heat to the process)" or "IF (process is too hot) AND (process is heating rapidly) THEN (cool the process quickly) are used. These terms are imprecise and yet descriptive of what must actually happen

More and more incomes are expended in the purchase of textiles as a result of the increasing trend in the deterioration of new textiles. And the more new textiles we buy, the more rags we have as well. This abnormality is as a result of the mode of washing of these textiles. Most washing machines do not have features like temperature regulation and selection for different textile and cannot also control its input voltage. This research eliminates these shortcomings of washing machines.

2. RELATED WORK

Fuzzy Logic has been employed as a methodology for the design of Control Systems. It has served as a good (if not better) alternative methodology for Controller designs. Some of the related works identified in the course of this research work are:

- The Reactor Temperature Controller as reported in [15], where a product of Aptronix called FIDE was used to design fuzzy Controller for the control of the temperature in a Reactor.
- Temperature Control: PID vs Fuzzy Logic as reported in [6] where a Fuzzy Logic version of a PID Home Temperature Control System was reported designed and its advantage over the conventional PID system was highlighted.
- Balancing of an inverted pendulum in a vertical position on a Cart using Fuzzy Control as reported in [2] where a PD Fuzzy Control system was designed. Its performance evaluation was reported done using a simulation of the control system.
- Others as reported in [2] are: Vibration Damping for a Flexible-Link Robot, Rotationally inverted Pendulum, Machine Scheduling and A Fault Detection System for Aircraft. Also reported in [5] is a Fuzzy logic Speed Control which can also be referred to as Cruise Control.
- Reported in [15] is A Fuzzy Logic Temperature Controller for Preterm Neonate Incubator designed and simulated for the control of the incubator temperature in order to attain a thermoneutral condition for neonates.

Washing machines can be automated further than they are currently. This can be achieved by automating the washing machine process through the use of sensors to detect parameters including volume of clothes, degree and type of dirt and so on. The wash time and other measures can then be determined from these parameters.

3. DEFINITION OF TERMS

3.1 Fuzzy Logic

Fuzzy Logic is a form of logic used in artificial-intelligence applications in which variables can have degrees of truthfulness or falsehood represented by a range of values between 1 (true) and 0 (false). It provides a simple way to arrive at a definite conclusion based upon vague, imprecise, or noisy input information. Fuzzy Logic approach to control problems mimics how a person would make decisions.

3.2 Fuzzy sets

The input variables in a fuzzy control system are in general mapped into sets known as "fuzzy sets" by means of Membership Functions,. The process of converting a crisp input value to a fuzzy value is called "fuzzification". Strictly speaking, a fuzzy set A is a collection of ordered pairs:

$$A = \{(x, \mu(x))\} \qquad (1)$$

Item x belongs to the universe and μ(x) is its grade of membership in A. A single pair (x, μ(x)) is a fuzzy singleton

3.3 Fuzzy Controller

The structure of a Fuzzy Controller is shown in the block diagram in Fig. 4. The controller is between a preprocessing block and a post-processing block. Sections 3.3.1, 3.3.2, 3.3.3, 3.3.8 and 3.3.12 explain the diagram block by block.

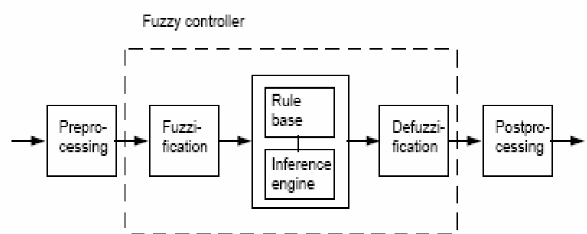


Figure 4: Blocks of a fuzzy controller.

3.3.1 Preprocessing

The inputs are most often CRISP measurements from some measuring equipment. A preprocessor, the first block in Fig. 4, conditions the measurements before they enter the controller. A quantiser is necessary to convert the incoming values in order to find the best level in a discrete universe. Assume, for instance, that the variable error has the value 4.5, but the universe is U= (-5, -4… 0… 4.5, 5). The quantiser rounds to 5 to fit it to the nearest level. Quantisation is a means to reduce data, but if the quantisation is too coarse the controller may oscillate around the reference or even become unstable.

When the input to the controller is error, the control strategy is a static mapping between input and control signal. A dynamic controller would have additional inputs, for example derivatives, integrals, or previous values of measurements backwards in time. These are created in the preprocessor thus making the controller multi-dimensional, which requires many rules and makes it more difficult to design. The preprocessor then passes the data on to the controller.[4]

3.3.2 Fuzzification

The first block inside the controller is fuzzification, which converts each piece of input data to degrees of membership by a lookup in one or several membership functions. The fuzzification block thus matches the input data with the conditions of the rules to determine how well the condition of each rule matches that particular input instance. There is a degree of membership for each linguistic term that applies to that input variable.[1,2,4,5]

3.3.3 Rule Base

Basically a linguistic controller contains rules in the IF - THEN format, but they can be presented in different formats. In many systems, the rules are presented to the end-user in a format similar to the one below,

If error is Neg and change in error is Neg then output is NB
If error is Zero and change in error is Neg then output is NM
If error is Pos and change in error is Neg then output is Zero

The names zero, pos, neg are labels of fuzzy sets as well as NB, NM, PB and PM (Negative Big, Negative Medium, Positive Big, and Positive Medium respectively). [1,2,4,5,8]

3.3.4 Universe

Elements of a fuzzy set are taken from a universe of discourse or just universe. The universe contains all elements that can come into consideration. Before designing the membership functions it is necessary to consider the universes for the inputs and outputs.

Take for example the rule

If error is Neg and change in error is Pos then output is 0.

Naturally, the membership functions for Neg and Pos must be defined for all possible values of error and change in error and a standard universe may be convenient. Some commercial controllers use standard universes; hence, the choice of data types may govern the choice of universe. For example, the voltage range [-5, 5] could be represented as an integer range [-50, 50] or as a floating point range [-5.0, 5.0]. A way to exploit the range of the universes better is scaling. If a controller input mostly uses just one term, the scaling factor can be turned up such that the whole range is used. An advantage is that this allows a standard universe and it eliminates the need for adding more terms. [1,2,4,5,6,8,9,10,11,12,13]

3.3.5 Membership Functions

Every element in the universe of discourse is a member of a fuzzy set to some grade, maybe even zero. The grade of membership for all its members describes a fuzzy set. In fuzzy sets elements are assigned a grade of membership such that the transition from membership to non-membership is gradual rather than abrupt. The set of elements that have a non-zero membership is called the support of the fuzzy set. The function that ties a number to each element x of the universe is called the membership function, μ(x).

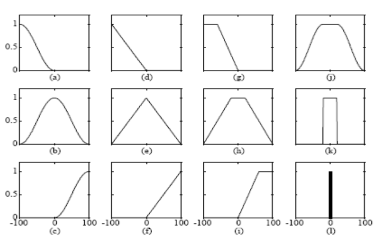


Figure 6: Examples of membership functions. Read from top to bottom, left to right: (a) s−function, (b) π− function, (c) z−function, (d-f) triangular versions, (g-i) trapezoidal versions, (j) flat π− function, (k) rectangle, (l) singleton.

Fig. 6 shows some typical shapes of membership functions. Fuzzy controllers use a variety of membership functions. A common example of a function that produces curve is:

$$gaussian(x:c,\sigma) = \ell^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \qquad (2)$$

This is the Gaussian type of MF, where c represents the MF center and σ is the MF's width.[1,3,5]. The designed fuzzy logic controller uses the equation

$$\mu(x) = 1 - \exp\left[-\left(\frac{\sigma}{x_0 - x}\right)^a\right] \qquad (3)$$

The extra parameter *a* controls the gradient of the sloping sides. It is also possible to use other functions, for example the sigmoid known from neural networks.

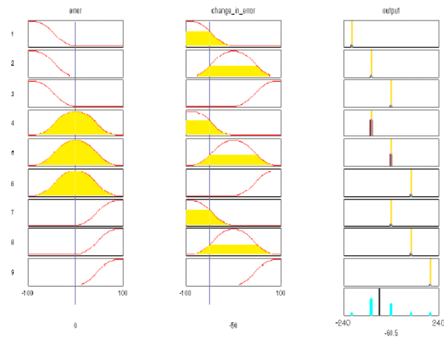


Figure 7: Graphical construction of the control signal in a fuzzy PD controler (generated in the Matlab Fuzzy Logic Toolbox).

3.3.6 Inference Engine

Figures 7 is a graphical construction of the algorithm in the core of the controller. Each of the nine rows refers to one rule. For example, the first row says that if the error is negative (row 1, column 1) and the change in error is negative (row1, column 2) then the output should be negative big (row 1, column 3). The picture corresponds to the rule base in (2). The rules reflect the strategy that the control signal should be a combination of the reference error and the change in error, a fuzzy proportional-derivative controller. We shall refer to that figure in the following. The instances of the error and the change in error are indicated by the vertical lines on the first and second columns of the chart. For each rule, the inference engine looks up the membership values in the condition of the rule.

3.3.7 Aggregation

The aggregation operation is used when calculating the degree of fulfillment or firing strength αk of the condition of a rule k. A rule, say rule 1, will generate a fuzzy membership value μe1 coming from the error and a membership value μ ce1 coming from the change in error measurement. The aggregation is their combination,

$$\mu_{e1} \text{ and } \mu_{ce1} \qquad (4)$$

Similarly for the other rules, Aggregation is equivalent to fuzzification, when there is only one input to the controller. Aggregation is sometimes also called fulfilment of the rule or firing strength.

3.3.8 Activation

The activation of a rule is the deduction of the conclusion, possibly reduced by its firing strength. Thickened lines in the third column indicate the firing strength of each rule. Only the thickened part of the singletons are activated, and min or product (*) is used as the activation operator. It makes no difference in this case, since the output membership functions are singletons, but in the general case of s-, π-, and z- functions in the third column, the multiplication scales the membership curves, thus preserving the initial shape, rather than clipping them as the min operation does. Both methods work well in general, although the multiplication results in a slightly smoother control signal. In Fig.7, only rules four and five are active.

A rule k can be weighted a priori by a weighting factor, $\omega_k \in [0,1]$, which is its degree of confidence. In that case the firing strength is modified to

$$\alpha_k^* = w_k * \alpha_k \qquad (5)$$

The degree of confidence is determined by the designer or a learning program trying to adapt the rules to some input-output relationship.

3.3.9 Accumulation

All activated conclusions are accumulated, using the max operation, to the final graph on the bottom right (Fig. 7). Singleton output (Fig. 7) and sum accumulation results in the simple output

$$\alpha_1 * s_1 + \alpha_2 * s_2 + ... + \alpha_n * s_n \qquad (6)$$

The alphas are the firing strengths from the n rules and s1…sn are the output singletons. Since this can be computed as a vector product, this type of inference is relatively fast in a matrix oriented language.

3.3.10 Defuzzification

The resulting fuzzy set (Fig. 7, bottom right) must be converted to a number that can be sent to the process as a control signal. This operation is called defuzzification. The resulting fuzzy set is thus defuzzified into a crisp control signal. There are several defuzzification methods:

Centre of Gravity (COG): The crisp output value *x* is the abscissa under the centre of gravity of the fuzzy set. [1,2,4,5]

$$u = \frac{\sum_i \mu(x_i) x_i}{\sum_i \mu(x_i)} \qquad (7)$$

Here xi is a running point in a discrete universe, and μ(xi) is its membership value in the membership function. The expression can be interpreted as the weighted average of the elements in the support set. For the continuous case, replace the summations by integrals. It is a much used method although its computational complexity is relatively high. This method is also called centroid of area.

Other defuzzification methods are Centre of Gravity Method for Singleton (COGS), Bisector Of Area (BOA), Mean Of Maxima (Mom), Leftmost maximum (LM) and Rightmost maximum (RM),

3.3.11 Post-Processing:

Output scaling is also relevant. In case the output is defined on a standard universe this must be scaled to engineering unit, for instance, volts, meters, or tons per hour. An example is the scaling from the standard universe [-1, 1] to the physical units [-10, 10] volts. The post-processing block often contains an output gain that can be tuned, and sometimes also an integrator.

4. THE DESIGN

4.1 Linguistic Variables for the Intelligent Washing Machine

Linguistic variables are used to represent a fuzzy logic system's operating parameters. The linguistic variables for this design include the following: "wash-time", "temperature" and "voltage". and variables like the turbidity rate and the spin rate shall be determined by the machine as the machine is put to operation. These linguistic variables shall be analyzed explicitly using the fuzzy-based rules. The fuzzy variables themselves are adjectives that modify the variable (e.g. "large positive" error, "small positive" error, “zero" error, "small negative" error, and "large negative" error). As a minimum, one could simply have "positive", "zero", and "negative" variables for each of the parameters.

4.2 Mode of operation of the Intelligent, Fuzzy-Based Washing Machine

The automatic fuzzy based dynamic voltage and temperature regulatory controller for an intelligent washing machine is designed and operates as follows: The intelligent washing machine has within it the following which are required for the its operation;

1) A textile quality feeler to determine different quality of clothing to be washed
2) A temperature controller tank with thermostat for temperature measurement.
3) A conductivity sensor to measure detergent level from the ions present in the wash.
4) A turbidity sensor to read the spin rate.
5) A voltage controller that controls the input voltage to the temperature sensor tank.-designed
6) A wash-time determinant sensor.

The intelligent washing machine is designed and functions such that when a cloth of any texture is dropped into the washing dish inside the washing machine, the textile quality feeler which will be made of a steel plate and which will form the base of the washing dish, will feel or test the texture and thickness of the clothing material and determine from the result of the test, the appropriate temperature which is best suitable to wash such textile material. This is then sent in a form of a transient signal to the temperature sensor tank. For instance IF (fabric-thickness > 1.0) AND (heating-process is getting colder) THEN (add heat to the process)" or "IF (fabric-thickness < 1.0) AND (heating-process is heating rapidly) THEN (cool the process quickly)" are used.

When the temperature controller receives the signal, it checks for the type of signal received so as to determine the kind of signal to be sent to the voltage controller which controls the input voltage to the temperature sensor tank. This in turn, returns the appropriate voltage value for the type of signal received and sends it to the temperature sensor. For example, if (signal = 1) then ((voltage =high) and (temp = Hot)). The conductivity sensor measures the detergent level from the ions present in the wash. The temperature controller in the washing tank increases or decreases the temperature of water in the tank depending on the signal received. Sensors and controllers are used to detect parameters including volume of clothes, degree and type of dirt, suitable wash temperature, input voltage and so on. The wash time is then determined from this data using few lines of fuzzy rules that relate some of the parameters/variables together. Once this is determined, it is sent as an electrical impulse to the washing-time determinant sensor. The machine determines the optimum wash cycle for any load using the washing-time determinant sensor. When the wash-time reaches the magnitude of the signal sent to the washing-time determinant sensor, then, the washing stops. The conductivity sensor is used to obtain the best result with the least amount of energy, detergent and water. It then estimates the number of cloth washed by the number of times the intelligent washing machine door was opened.

The diagram below is for the process blocks of the fuzzy-based washing-machine, with each block performing a special role towards a successful operation of the fuzzy-based washing machine. The controlled output from a network of sensors and linguistic variables controllers introduce the self-learning and tuning ability to the washing machine. The controlled output includes a controlled temperature, a controlled voltage, a controlled wash-time, a controlled detergent level suitable for the washing.

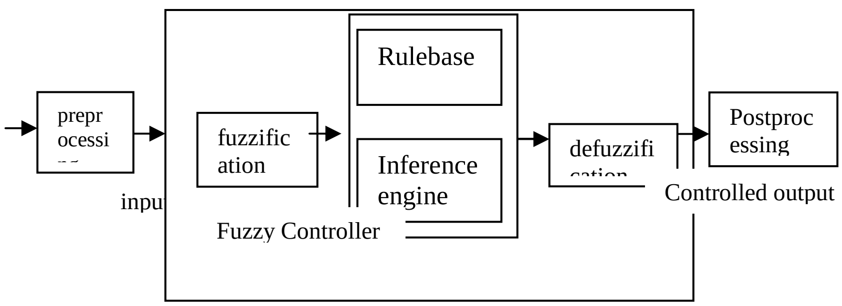


Figure 2: Blocks of the fuzzy-based washing machine controller

The preprocessor conditions the measurement of the reference input before it enters the fuzzy controller. This includes filtering of the input to remove noise and converting the incoming value in order to find the best level in a discrete universe.

The fuzzification block matches the input data with the conditions of the rules to determine how well the condition of each rule matches that particular input instance. There is a degree of membership for each linguistic term that applies to that input variable.

Rule base may use several variables both in the condition and the conclusion of the rules. The main function is to regulate a control signal based on an error signal. For each rule, the inference engine looks up the membership values in the condition of the rule. The resulting fuzzy set must be converted to a number that can be sent to the process as a control signal. This operation is called defuzzification where the resulting fuzzy set is thus defuzzified into a crisp control signal.

4.3 Fuzzy Logic Wash-Time Determinant Controller-Input/Output of the fuzzy logic wash-time determinant controller

Figure 3 shows a diagram of the wash-time fuzzy logic controller. There are two inputs: (1) the degree of dirt on the clothes and (2) the type of dirt on the clothes. These two inputs can be obtained from a single optical sensor. The degree of dirt is determined by the transparency of the wash water. The dirtier the clothes, the lower the transparency for a fixed amount of water. On the other hand, the type of dirt is determined from the saturation time, the time it takes to reach saturation. Saturation is the point at which the change in water transparency is close to zero (that is, below a given number). Greasy clothes, for example, take longer for water transparency to reach the saturation because grease is less water soluble than other forms of dirt. Thus, a fairly straightforward sensor system can provide the necessary inputs for our fuzzy controller.

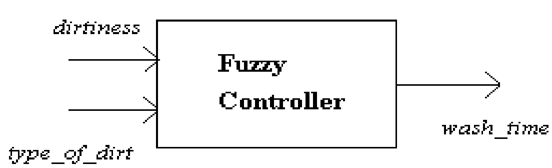


Figure 3: Fuzzy logic wash-time determinant Controller

4.4 Definition of Input/Output Variables

Before designing the controller, we must determine the range of possible values for the input and output variables. These are the membership functions used to translate real world values to fuzzy values and back. Figure 4 shows the labels of input and output variables and their associated membership functions. Values for the input variables dirtiness and type_of_dirt are normalized (range of 0 to 100) over the domain of optical sensor values. Wash_time membership functions are singletons (crisp numbers) as described in this design. We can use fuzzy sets or singletons for output variables. Singletons are simpler than fuzzy sets. They need less memory space and work faster.

4.5 Defining the Membership Functions

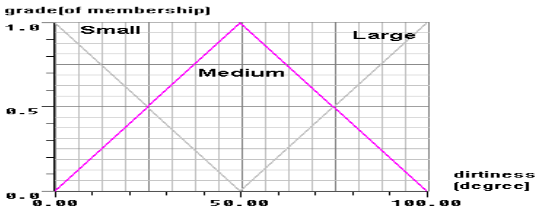


Figure 4a Labels and Membership Functions of Input Variable dirtiness

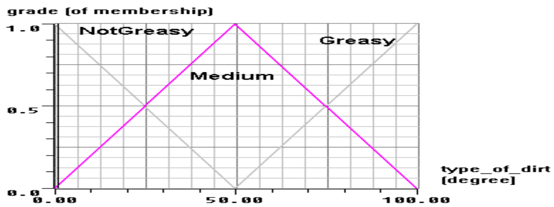


Figure 4b Labels and Membership Functions of Input Variable type_of_dirt

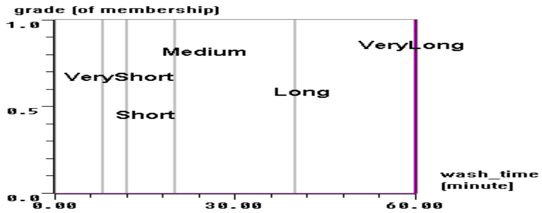


Figure 4c Labels and Membership Functions of Output Variable wash_time

4.6 Rules

The decision making capabilities of a fuzzy controller are codified in a set of rules. Rules for our washing machine controller are derived from common sense, data taken from typical home use, and experimentation in a controlled environment. A typical intuitive rule is as follows: **If** saturation time is long **and** transparency is bad **then** wash time should be long. From different combinations of these and other conditions, we derive the rules necessary to build our washing machine wash-time controller.

4.7 Controlling the Temperature Using the Temperature Controller

The variable "temperature" in this system can be subdivided into a range of states: "cold", "cool", "moderate", "warm", "hot", "very hot". The sensor input is the temperature. We start by defining the input temperature states using Membership Functions:

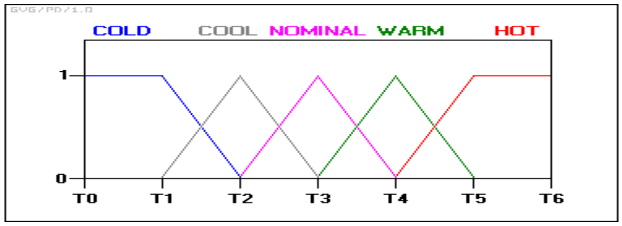


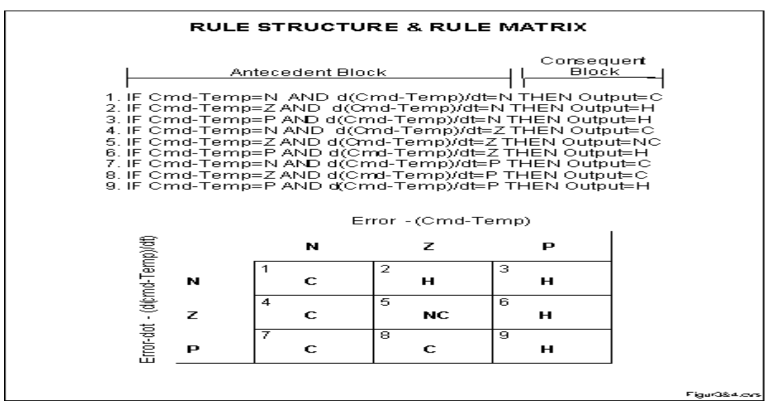
Figure 5: membership functions of the input temperature states

With this scheme, the input variable's state no longer jumps abruptly from one state to the next. Instead, as the temperature changes, it loses value in one membership function while gaining value in the next. In other words, its ranking in the category of cold decreases as it becomes more highly ranked in the warmer category.

4.8 System Operating Rules

Linguistic rules describing the control system consist of two parts; an antecedent block (between the IF and THEN) and a consequent block (following THEN). Depending on the system, it may not be necessary to evaluate every possible input combination (for 5-by-5 & up matrices) since some may rarely or never occur. By making this type of evaluation, fewer rules can be evaluated, thus simplifying the processing logic and perhaps even improving the fuzzy logic system performance.

It is necessary to establish a meaningful system for representing the linguistic variables in the matrix. Therefore, the following will be used:
"N" = "negative" error or error-dot input level, "Z" = "zero" error or error-dot input level, "P" = "positive" error or error-dot input level, "H" = "Heat" output response, "-" = "No Change" to current output, and "C" = "Cool" output response.



Figures 6: The rule structure.

After transferring the conclusions from the nine rules to the matrix there is a noticeable symmetry to the matrix. This guarantees a reasonably well-behaved linear system. Additional degrees of error and error-dot may be included if the desired system response calls for this. This will increase the rule base size and complexity but may also increase the quality of the control. Figure 6 also shows the rule matrix derived from the rules.

4.9 Error & Error-DOot Memebership Function

There is a unique membership function associated with each input parameter. The membership functions associate a weighting factor with values of each input and the effective rules. These weighting factors determine the degree of influence or degree of membership (DOM) each active rule has. By computing the logical product of the membership weights for each active rule, a set of fuzzy output response magnitudes are produced. All that remains is to combine and defuzzify these output responses. As inputs are received by the system, the rule base is evaluated. The antecedent (IF X AND Y) blocks test the inputs and produce conclusions. The consequent (THEN Z) blocks of some rules are satisfied while others are not. The conclusions are combined to form logical sums. These conclusions feed into the inference process where each response output member function's firing strength (0 to 1) is determined.

INPUT DEGREE OF MEMBERSHIP:"error" = -1.0: "negative" = 0.5 and "zero" = 0.5 "error-dot" = +2.5: "zero" = 0.5 and "positive" = 0.5. ANTECEDENT & CONSEQUENT BLOCKS (e = error, er = error-dot or error-rate). Now referring back to the rules, plug in the membership function weights from above. "Error" selects rules 1,2,4,5,7,8 while "error-dot" selects rules 4 through 9. "Error" and "error-dot" for all rules are combined to a logical product (LP or AND, that is the minimum of either term). Of the nine rules selected, only four (rules 4,5,7,8) fire or have non-zero results. This leaves fuzzy output response magnitudes for only "Cooling" and "No Change" which must be inferred, combined, and defuzzified to return the actual crisp output. In the rule list below, the following definitions apply: (e)=error, (er)=error-dot.

1. If (e < 0) AND (er < 0) then Cool 0.5 & 0.0 = 0.0
2. If (e = 0) AND (er < 0) then Heat 0.5 & 0.0 = 0.0
3. If (e > 0) AND (er < 0) then Heat 0.0 & 0.0 = 0.0
4. If (e < 0) AND (er = 0) then Cool 0.5 & 0.5 = 0.5
5. If (e = 0) AND (er = 0) then No_Chng 0.5 & 0.5 = 0.5
6. If (e > 0) AND (er = 0) then Heat 0.0 & 0.5 = 0.0
7. If (e < 0) AND (er > 0) then Cool 0.5 & 0.5 = 0.5
8. If (e = 0) AND (er > 0) then Cool 0.5 & 0.5 = 0.5
9. If (e > 0) AND (er > 0) then Heat 0.0 & 0.5 = 0.0

The inputs are combined logically using the AND operator to produce output response values for all expected inputs. The active conclusions are then combined into a logical sum for each membership function. A firing strength for each output membership function is computed. All that remains is to combine these logical sums in a defuzzification process to produce the crisp output.

4.11 The "Fuzzy Centroid" Algorithm

The defuzzification of the data into a crisp output is accomplished by combining the results of the inference process and then computing the "fuzzy centroid" of the area. The weighted strengths of each output member function are multiplied by their respective output membership function center points and summed. Finally, this area is divided by the sum of the weighted member function strengths and the result is taken as the crisp output. One feature to note is that since the zero center is at zero, any zero strength will automatically compute to zero. If the center of the zero function happened to be offset from zero (which is likely in a real system where heating and cooling effects are not perfectly equal), then this factor would have an influence.

(neg_center * neg_strength + zero center * zero strength + pos_center * pos_strength) = OUTPUT
(neg_strength + zero strength + pos_strength)
(-100 * 0.866 + 0 * 0.500 + 100 * 0.000) = 63.4%
(0.866 + 0.500 + 0.000)

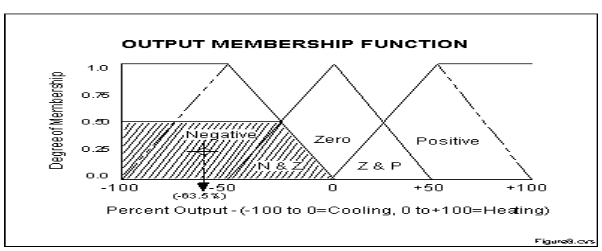


Figure 9 – The horizontal coordinate of the centroid is taken as the crisp output

The horizontal coordinate of the centroid of the area marked in Figure 9 is taken as the normalized, crisp output. This value of -63.4% (63.4% Cooling) seems logical since the particular input conditions (Error=-1, Error-dot=+2.5) indicate that the feedback has exceeded the command and is still increasing therefore cooling is the expected and required system response.

5 IMPLEMENTATION OF THE INTELLIGENT, FUZZY-BASED WASHING MACHINE

The potential considerations introduced in the implementation of the intelligent, fuzzy-based washing machine are concerned with the machine's sensitivity against the slope of the ground, automatic temperature and voltage control, the minimization of rinsing water sloshing and of the minor friction forces at the base standing support bearings. The machine controllers and sensors would check to see how much soap or detergent it needs, how much water to add, how fast and which direction it should spin, the wash time, the regulated voltage and temperature for a perfect wash

6. DISCUSSION OF RESULT, CONCLUSION & RECOMMENDATION

The fuzzy based controller for the washing machine was able to automatically regulate the voltage and temperature into the machine washing tank. The best fit temperature wash different clothing is automatically used for various washings and hence prolongs the life-span of textiles as against the increasing trend in possession of rags due to improper washing mode. The contributions of this research are:

1. Automatically regulate the voltage
2. Automatically regulate the temperature of water
3. Reduce costs or expenses on clothing materials
4. Automatically detect the texture of the material
5. Assist improves or prolongs the life-span of textiles.

The application of fuzzy control system makes the intelligent washing machine robust with several control abilities. The use of this machine is recommended for the washing of different fabric textures. All important parameters needed to be catered for have been handled during the design phase of the machine.

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