Design and Analysis of a Fuzzy Model Based Solar Classroom Heater

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Abstract
Fuzzy logic control was originally introduced and developed as a model free control design approach. However, it unfortunately suffers from criticism of lacking of systematic stability analysis and control design thought it has a great success in industry applications. In the past two decade or so, prevailing research efforts on fuzzy control have been devoted to model-based fuzzy control systems. This paper presents a linguistic approach taking into account non-linearity especially in multivariable application systems. The main benefit is better and more accurate decision making due to the model-based approach and systematic knowledge management. Insight to the process dynamic operation is the most important issue. Automatic generation of systems, model-based techniques and adaptation techniques are very valuable in developing tuning systems for fault diagnosis and forecasting. The linguistic approach increases the performance by combining various specialized models in a case-based approach. The linguistic equation (LE) approach is very efficient as a modeling technique because; models can be generated from data, various types of fuzzy rule-based models can be represented by LE models, and any LE model can be transformed to fuzzy rule-based models. The LE approach is successfully extended to dynamic modeling.

Keywords
Fresh air, solar energy fuzzy control, classroom heating

I. Introduction
The process industries face considerable control challenges, especially in the consistent production on high quality products, more efficient use of energy and raw materials, and stable operation on a different condition. The processes are nonlinear, complex, multivariable and highly interactive. Usually, the important quality variables can be estimated only from other measured variables. Constraints between process variable cause interactions between controllers. Various time delays depend strongly on operating conditions and can dramatically limit performance and even destabilize the closed loop system. Uncertainty is an unavoidable part of the process control in real world applications. With the help of a solar collector, an experimental system has been set up. In this system, the framework of the system is based on fuzzy algorithm. To provide a better precision of the fresh air temperature, the system works in three different which needs three different control rules. In this paper, these three modes are introduced firstly, and then a design of the three fuzzy controllers is described in detail. Meanwhile, the automatic transition process of the three modes in different conditions is studied. Finally, through the analysis of experimental data, it is proved that the system can provide stable fresh air temperature according to different setting temerities.

The fresh air system is a common phenomenon in developed countries. In some countries, it is especially regarded as one of the necessary equipment installed. Compared with traditional air conditioner, it will save much more energy. Moreover, solar energy is an ideal green energy as renewable energy. Nowadays, researching on the solar thermal applications has become a hot topic and a common trend. Another big advantage using the solar energy to heat fresh air into the room is to improve room air quality without a lot of heat loss which produces much influence on the existing air conditioning system. An experimental system has been built for this research. It uses solar as the only source, fuzzy tool box in the round sunshine. According to the practical application, the fresh air system should work in three different modes which are MATLAB control software is used to model and control the system. In this paper, the research platform is built in Kanye, Botswana which has abundant solar energy and solar energy and the long year round sunshine. According to the practical application, the fresh air system should work in three different modes which are Mode 1, Mode 2 and Mode 3. The transition Mode 1, Mode 2 and Mode 3. The transition process of the modes to each other can be controlled by electronic valves. Mode 1 is the solar energy only fresh air. Comparing with Mode 2. It is made up of branch 1 and branch 3, but without branch 2 as shown in Fig. 1. Mode 3 is made up of branch 2 and operation of the system can be still achieved just by automatic switching to mode 3. It contributes to prolonging the heating time. The key point is that, even if sunset or in the night, the stable. The whole process relies on the system’s own judgments, automatic selection and self regulation.

Fig. 1 : The operation of Mode 2

II. Fuzzy Controller Design

Fig. 2 : The Basic Structure of Fuzzy Logic Control
A. The variables of fuzzy controller

Taking error $\varepsilon$ and change in error $\Delta \varepsilon$ as the inputs and a voltage which is used to error adjust the frequency converter as the output, the manual control experiment must be done before the fuzzy controller design. The regulation law of the system can be got through the manual system experiment.

B. The Establishment of Membership Functions and Fuzzy Control Rules

Each mode has its own operating conditions and characteristics, which requires its own membership functions and control rules. In order to provide a better precision of the fresh air temperature and accelerate the response time, the system should work in three different modes.

According to the Mode 1 and the data obtained from manual experiments, the range of $\varepsilon$ is $[-4, 4]$, and the distribution after fuzzification is $[-4, -2, -1, -0.5, 0, 0.5, 1, 2, 4]$. The range of $\varepsilon_c$ is $[-0.02, 0.02]$, and the distribution after fuzzification is $[-0.02, 0.015, -0.005, 0, 0.005, 0.01, 0.015, 0.02]$. The range of $\Delta u$ is $[-0.04, 0.04]$, and the distribution after diffuzzification is $[-0.04, -0.02, 0.01, -0.01, -0.005, 0, 0.005, 0.01, 0.012, 0.02, 0.04]$. It is noteworthy that membership functions are mainly distributed near zero, which contributes to improving the control precision.

For the Mode 3, the range of $\varepsilon$ is $[-4, 4]$, and the distribution after fuzzification is $[-4, -2, -1, -0.5, 0, 0.5, 1, 2, 4]$. The range of $\varepsilon_c$ is $[-0.02, 0.02]$, and the distribution after fuzzification is $[-0.02, -0.015, -0.01, 0.005, 0.01, -0.005, 0, 0.005, 0.015, 0.02]$. The range of $\Delta u$ is $[-0.2, 0.2]$, and the distribution after fuzzification is $[-0.2, -0.08, -0.06, -0.04, 0, 0.04, 0.06, 0.08, 0.04]$. For the system characteristics of inertia and delay, the membership function $\Delta u$ should distribute near the positive and negative 0.0, it can help to improve the stability.

Table 1: The fuzzy control rules for frequency converter $\Delta u$

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<tr>
<th>$\varepsilon$</th>
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Table 2: The fuzzy control rules of Mode 2

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For the Model 2, the range of $\varepsilon$ is $[-2, 2]$ and the distribution after fuzzification is $[-2, -1, -0.5, 0, 0.5, 1, 2]$. For the Model 3, the range of $\varepsilon$ is $[-4, 4]$ and the distribution after fuzzification is $[-4, -2, -1, -0.5, 0, 0.5, 1, 2, 4]$. For the Model 4, the range of $\varepsilon$ is $[-4, 4]$ and the distribution after fuzzification is $[-4, -2, -1, -0.5, 0, 0.5, 1, 2, 4]$. The range of $\varepsilon_c$ is $[-0.02, 0.02]$, and the distribution after fuzzification is $[-0.02, -0.015, -0.01, 0.005, 0.01, -0.005, 0, 0.005, 0.015, 0.02]$. The range of $\Delta u$ is $[-0.2, 0.2]$, and the distribution after fuzzification is $[-0.2, -0.08, -0.06, -0.04, 0, 0.04, 0.06, 0.08, 0.04]$. For the system characteristics of inertia and delay, the membership function $\Delta u$ should distribute near the positive and negative 0.0, it can help to improve the stability.
III. Experimental and Data Analysis

A. Different set point of fresh air temperature control

According to the practical application, the fresh air system should provide different fresh air temperature for users to choose. The system must adjust automatically with the change of the setting temperature and has fast response speed. Meanwhile, the fuzzy control system must resist external interference and has robustness. For providing fresh air of different temperature, the Mode 1 is taken as example. The automatically controlled effect of different specified temperatures can be seen in Fig. 6. During that time, the outside air temperature was 7°C. The temperature of the water into the fan coil was between 38°C to 48°C. When the setting temperature is changed, the maximum temperature error is about 3°C, and a slight overshoot has occurred. It is about 10%, and this slight overshoot can help to accelerate response time. The time of the adjustment process is about 4-5 minutes, but it is already sufficient to meet the actual control demand. Analysis of data shows that stabilization error is between ±0.3°C.

B. The automatic transition process

The principle of transition process is briefly described as follow: firstly, according to inherent characteristics of the system, it should run in Mode 1 to start solar collector system to heat fresh air directly when sunshine is sufficient. Secondly, in order to provide enough energy at night, it should run mode 2 to store energy into tank when the temperature provided by solar energy collection system is 20°C higher than the set temperature. Lastly, it should run Mode 3 to start the tank to heat fresh air directly when sunset or solar energy is not enough. Taking the transition process of the Mode 2 to mode 3 as an example, it is easily found that the system can work very well from T7, T9 and T12. During the transition process, a little dynamic error has occurred. It is about between ±3.5°C. After about 4 minutes, the temperature of fresh air stabilizes at the setting temperature within the range of between ±0.3°C, which can be from the working process under Mode 3.

C. Fuzzy Logic (FL)

Fuzzy logic has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multivalued logic. However, in a wider sense, fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects unsharp boundaries in which membership is a matter of degree. In this perspective, fuzzy logic in its narrow sense is a branch of fuzzy theory. Even in its narrow definition,
Fuzzy logic differs both in concept and substance from traditional multivalued logical systems (MATLAB Fuzzy logic toolbox user’s guide). The following is a list of general observations about fuzzy logic:

- Fuzzy logic is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple. Fuzzy logic is a more intuitive approach without the far-reaching complexity.
- Fuzzy logic is flexible. With any given system, it is easy to add on more functionality without starting again from scratch.
- Fuzzy logic is tolerant of imprecise data. Everything is imprecise. Fuzzy reasoning builds understanding into the process rather than taking it on to the end.
- Fuzzy logic can model nonlinear functions of arbitrary complexity. Fuzzy system can be created to match any set of input-output data. This process is made particularly easy by adaptive techniques like Adaptive Neuro-Fuzzy Inference System (ANFIS), which are available in fuzzy logic toolbox software.
- Fuzzy logic can build on top of experience of experts. In direct contrast to neural networks, which use training data and generate opaque, impenetrable models, fuzzy logic lets the user to rely on the experience of people who already understand the system. Fuzzy logic can be blended with conventional control techniques. Fuzzy systems don’t necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.
- Fuzzy logic is based on natural language. The basis of fuzzy logic is human communication. The observation underpins many of the other statement about fuzzy logic. Fuzzy logic is built on the structure of qualitative description used in every day language, and hence easy to use.

Generally, a fuzzy logic model is a functional relation between two dimensional spaces. The relationship between input and output fuzzy spaces is known as fuzzy associative memories (FAM). Inside FAM, the linguistic variables and the attributes are specified and the associative rules between different fuzzy sets are elaborated in order to set up the following constructions:

- **IF (premise) THEN (conclusion)**
- **Every premise or conclusion consist of expressions as (variable) IS (attribute) connected through the fuzzy operator AND.**
- **To implement a fuzzy system, the following steps need to be followed:**
  - Fuzzication which is a coding process in which each numeral input of a linguistic variable is transformed in the membership function values of attributes.
  - Inference, which is a process done in two steps:
    1. The computation of a rule by intersecting individual premises, applying the fuzzy operator AND,
    2. Often, more rules drive to same conclusion. To obtain the confidence level of this conclusion (i.e. the membership function value of a certain attribute of output linguistic variable) the individual confidence levels are joined by applying the fuzzy operator OR.
    3. Defuzzification which is a decoding operation of the of the information contained in the output fuzzy sets resulted from inference process, in order to provide the most suitable output crisp value. There are a number of methods which can be used for defuzzification presented by Paulescu et al. (2008)

Based on the differences of fuzzy control rules and their generation methods, approaches to fuzzy logic control can be roughly classified into the following categories:

**1. Conventional fuzzy control**


**2. Fuzzy proportional-integral-derivative (PID) control**

Conventional PID controllers are still the most widely adopted method in industry for various control applications, due to their simple structure, ease of design and low cost in implementation. However it has shown that by combining conventional PID and fuzzy controllers give better and robust control scheme. Conventional fuzzy controller can be further classified as the direct action type (Mann G. K. I, Hu B. G and Gosine R. G, 1999) of fuzzy PID controllers, since its fuzzy inference reduces a control action output directly to control a system. In contrast with direct action, another type of fuzzy PID controllers is classified
as gain scheduling (Han Z. X, Feng G, Walcot B. L and Ma J 2000, Zhao Z. Y Tomizuka M and Isaka S, 1993), for the reason that controller gains change as operating condition or dynamics of a system varies.

3. Neuro-fuzzy control
   The combination of neural network control and fuzzy control is called neuro-fuzzy control, which is basically a fuzzy control augmented by neural networks to enhance it characteristics like flexibility, data processing capability and adaptability (Boroushaki M et al., 2003, Da F. P and Song W. Z, 2003). The process of fuzzy reasoning is realized by neural networks, whose connection weights correspond to the parameters of fuzzy reasoning (Chakraborty S, Pal K and Pal N. R, 2002, Jang J. S. R, 1993). Using back propagation type, or reinforcement type, or any other neural network learning algorithms, a neuro-fuzzy control system can identify fuzzy control rules and learn (tune membership functions of fuzzy reasoning, and thus realize the neuro fuzzy control. It should be noted that the T-S fuzzy model is one of the general fuzzy systems used to realize the neuro-fuzzy control (Juang C. F and Hsu C. H, 2005, Tzafestas S. G and Zikidis K. C, 2001).
   One main advantage of neuro-fuzzy control is that it does not basically require information on the mathematical model of the system controlled. Thus this class of fuzzy control offers a new avenue in solving many difficult control problems in real life where the mathematical model of a system might be hard, if not impossible to obtain. However, one of its major limitations is the systematic analysis of stability of the closed loop control system and convergence of the learning algorithms in the context of the closed loop control systems.

4. Fuzzy-sliding mode control

5. Adaptive fuzzy control
   Adaptive control refers to the control of partially known system with some kind of adaptation mechanism. Most works in adaptive control are based on the assumption of linear or simplified nonlinear mathematical models of systems to be controlled. Following the similar idea in neural networks, (Santibanez V, Kelly R and Llama M. A, 1992) for universal function approximation capability, it is shown (Wang L. X and Mendel J. M, 1992) that a fuzzy system is capable of approximating any smooth nonlinear function $f$ over a convex compact region. Based on this function approximation capability of fuzzy systems, adaptive fuzzy controller for affine nonlinear system with unknown functions is possible. Fuzzy basis function based fuzzy system is used to present those unknown nonlinear functions. The parameters of the fuzzy systems including membership functions characterizing linguistic terms in fuzzy rules are updated according to some laws which are based on Lyapunov stability theory (Anderson H. C, Lofti A and Tsou A.C, 1997, Boukezzola R, Galichet S and Foulloy L, 2004, Campos J and Lewis F. L, 1999) However, it should be noted that some kind of robust approaches have to be adopted for adaptive fuzzy control due to inherent approximation errors between the approximating fuzzy system and he original nonlinear functions, and most likely only semi global stabilization can be achieved if no supplementary control strategy is employed.

6. Takagi-Sugeno (T-S) model based fuzzy control
   T-S fuzzy model (Takagi T and Sugeno M, 1985) is in fact a fuzzy dynamic model (Cao S. G, Rees N. W and Feng G, 1995 and 1997). This model is based on using a set of fuzzy rules to describe a global nonlinear system in terms of a set of local linear models which are smoothly connected by fuzzy membership functions. The fuzzy modeling method offers an alternative approach to describing complex nonlinear systems (Fantuzzi C and Rovatti R, 1996, Tanaka T and Wang H. O, 2001, Yang H, 1993, Zeng K Zhang N. Y and Xu W. L, 2000) and drastically reduces the number of rules in modeling higher order nonlinear systems. Consequently, fuzzy models. More importantly, T-S fuzzy models provide a basis for development of systematic approach to stability and controller design of fuzzy control systems in view of powerful conventional control theory and techniques. Based on difference of design approaches, the methods for stability analysis and control design of T-S fuzzy system can be roughly classified into the following six categories:
   • Simple local controller design and stability checking
   • Stabilization with/without various performance indexes
   • such as $H_{\infty}$ and $H_2$ control based on a nominal linear model and a single quadratic Lyapunov function
   • Stabilization with/without various performance based on a common quadratic Lyapunov function
   • Stabilization with/without various performance on a piecewise quadratic Lyapunov function
   • Stabilization with/without various performance indexes on based on fuzzy quadratic Lyapunov function
   • Adaptive control when parameters of T-S fuzzy models are unknown

D. T-S Model and universal function approximation
   T-S fuzzy models or so called fuzzy dynamic models can be used to represent complex MIMO systems with both fuzzy inference rules and local analytic linear models as follows:(1)
The number of the input vector, some measurable variables of the system, is the grade of membership of the output (4)

\[ y(t) = C_i x(t) \]

Where: \( R^1 \) denotes the fuzzy inference rule, \( m \) the number of inference rules, \( F^i_j \) fuzzy sets, \( x(t) \) the state vector, \( u(t) \) the input vector, \( y(t) \) the output vector and \( A_i, a_i, c_i \) the matrices of the \( l \)th local model, and \( z_0 = [z_1, z_2, z_3, z_4] \) some measurable variables of the system, for example, the state variable. It is also assumed without loss of generality that the origin is the equilibrium of the T-S fuzzy. It is also noted that the local model in terms of \( \{z_1, z_2, z_3, z_4\} \) in (1) only represents the properties of the system in local region and thus is referred to as the fuzzy local model. By using a standard fuzzy inference method, that is, using a singleton fuzzifier, product fuzzy inference, and center average defuzzifier, the T-S fuzzy model in (1) can be written as (Tanaka K and Wang H. O. 2001):

\[
x(t + 1) = A_i u(t) + B_i y(t) + a_i
\]

\[
y(t) = C_i x(t)
\]

Where:

\[
a_i = \sum_{j=1}^{n_i} \mu_{i,j} A_j, \quad B_i = \sum_{j=1}^{n_i} \mu_{i,j} B_j
\]

\[
\mu_i = \frac{\xi_1(z)}{\sum_{j=1}^{n_i} \xi_1(z)}
\]

\[
\xi_1(z) = \prod_{i=1}^{n} F^i_j(z)
\]

\[
\mu_1 \geq 0 \quad \sum_{i=1}^{n} \mu_i = 1
\]

And \( F^i_j(z) \) is the grade of membership of \( z_j \) in the fuzzy set \( F^i_j \). It should be noted that the previous model is a nonlinear model in nature since the membership functions are nonlinear functions of the premise variables which contain some or all of the state variables in general. The previous T-S fuzzy model is in fact the state space fuzzy model. Similarly, the input-output fuzzy model can also be defined (Gao S. G., Rees N. W. And Feng G, 1996)

The TSK model structure strategy with linear function as consequent and a non-linear function estimator for local controllers was selected by fuzzy rules. The antecedents are similar to the Mamdani fuzzy system and the consequents can be any function describing a local controller with the fuzzy region. Fig. 1 shows a schematic representation of such a network with three inputs, one output and three rules. The rules are in the following form:

- **R1**: if \( x \) is \( A_1 \) and \( y \) is \( B_1 \) and \( z \) is \( C_1 \) then \( f_1 \)
- **R2**: if \( x \) is \( A_2 \) and \( y \) is \( B_2 \) and \( z \) is \( C_2 \) then \( f_2 \)
- **R3**: if \( x \) is \( A_3 \) and \( y \) is \( B_3 \) and \( z \) is \( C_3 \) then \( f_3 \)

where: \( (A_1, A_2, A_n, B_1, B_2, B_n, C_1, C_2, C_n) \) are the input fuzzy sets and \( (f_1, f_2, f_n) \) are the output fuzzy sets. The nodes in the first layer compute the membership degree of the inputs in the antecedent fuzzy sets. The product nodes \( \Pi \) in the second layer represent the antecedent conjunction operator. In the consequent part, the fuzzy mean operator is realized by the normalization node N and the summation operator. By using smooth antecedent membership functions, such as the Gaussian functions, the following relationship can be applied:

\[
uA_i(x; c_i, \sigma_i) = \exp \left( -\frac{(x - c_i)^2}{2\sigma_i^2} \right)
\]

The \( c_\) and \( \sigma_\) parameters can be adjusted by gradient-descent learning algorithms, such as back-propagation (Reynolds N. 2000). This allows for a fine-tuning of fuzzy model to the available data for optimisation and prediction accuracy.

![Fig. 13 : TSK - NF Structure](image-url)

The fuzzy output can be expressed as:

\[
f = \frac{\bar{w}_1 f_1 + \bar{w}_2 f_2 + \bar{w}_3 f_3}{w_1 + w_2 + w_3} = \bar{w}_1 f_1 + \bar{w}_2 f_2 + \bar{w}_3 f_3
\]

where \( f_1, f_2 \) and \( f_3 \) are the outputs of the three sub-models which in this particular case are the three local controllers of the air motor speed. Performances local controllers are as shown in Figs: 2, 3 and 4, depicting low speed controller (Mode 1), medium speed controller (Mode 2) and high speed controller (Mode 3) respectively.

Solar classroom heating T-S fuzzy modeling approach

In ANFIS, the membership functions are extracted from a data set that describes the system behavior. ANFIS is used to tune existing rule base with a learning algorithm based on a collection of training data. This allows the rule base to be adaptive. A hybrid method consisting of back propagation (a steepest descent method) for parameters associated with the input membership functions and least square estimation for the parameters associated with the output membership functions is used for ANFIS learning to update membership functions. As
a result, the training error decreases at least locally throughout the learning process. Therefore, with higher number of initial membership functions, it will be easier for the model parameter training to converge. Human expertise about the target system to be modeled may aid in setting these initial membership function parameter in fuzzy inference system (FIS) structure. The MATLAB toolbox implements ANFIS function to develop fuzzy model. The MATLAB toolbox function genfis1 generates an initial single output Sugeno type FIS for ANFIS training using a grid partition on data. From input-output data sets on which the trained was not presented. The statistical measures like root-mean square error (RMSE) and sample standard deviation (STD) maybe used to compare predicated and target values during model validation. The lower value of RMSE indicates better ANFIS model. The statistical measure is defined as:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{m=1}^{n} (y_{pred,m} - t_{mean,m})^2}
\]

\[
STD_{sample} = \sqrt{\frac{1}{n-1} \sum_{m=1}^{n} (y_{pred,m} - t_{mean,m})^2}
\]

Where \( n \) represents the number of data samples used in training/validation, \( y_{pred,m} \) indicates the predicted output, \( t_{mean,m} \) indicates the measured value of one data sample (i.e. target output). In order to obtain the optimal model parameters, the fuzzy rule architecture of the ANFIS model is constructed for different types and number of membership functions. Also, hybrid learning rule function is used to train model according to input-output data pairs, and the number of iterations set to a reasonable value say, 100. The overall production process, the control systems take care of several sub processes

IV. Conclusion
In this paper, a fresh air heating of a fuzzy model based system on fuzzy control has been successfully set up. It works with three different modes. The fuzzy controller design of the three different control rules was completed. The Mode 1 is taken an example to prove that the system is able to provide fresh air according to different setting temperature. The transition process of the Mode 2 to the Mode 3 is to prove that the system can adjust automatically according to the change of solar energy. Though the analysis of the experimental data, it is easy to verify that the system is own high accuracy in stability and able to resist interference. The fuzzy model predicted the outlet water temperature with a good level of accuracy. The qualitative and quantitative results indicated a one to one mapping between actual outlet water temperature and the predicated values. The said technique can successfully be used for estimation of the solar classroom heating system performance evaluation. Further investigation may be carried out to study the robustness of the fuzzy modeling approach in predicting outlet water temperature in variety of weather conditions. This study will be helpful for the intelligent design and control of solar heating appliances.

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