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DEVELOPMENT OF FUZZY LOGIC CONTROL SYSTEM

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ABSTRACT

Describes the architecture of the fuzzy logic controller (FLC) and its advantages in various industrial applications. A prototype of cooperative neural fuzzy controller, CONEFCON, has been developed to demonstrate the feasibility of FLC.

1.0 INTRODUCTION

Since the first introduction of "Fuzzy Set Theory" by Prof. L. A. Zadeh of University of California, Berkeley, 1965, there has been rapid development of the theory and application of fuzzy logic to control systems. Fuzzy logic controllers (FLC) are being increasingly applied in areas where system complexities, development time and costs are the major issues.

Classical controllers are designed by various techniques for a variety of control system applications and are modeled on the systems or process being controlled. Traditional control theory is applicable in situations where the analytical behaviour of the system to be controlled is known. However, in many situations, e.g., in space exploration, full knowledge is not available, yet control decisions still have to be made. In such situations, a reasonable idea is to find a human operator who is good in this kind of control, and translate his control experience into a precise formula. The control experience is usually formulated in terms of natural language rules like: if x is small, then control action must also be small. Fuzzy control is based on the human operator behaviour. The methodology of translating these rules into an actual control strategy is known as fuzzy control. The main idea of fuzzy control is to build a model of a human control expert who is capable of effecting control without the need to think in a complex mathematical model. These control rules are translated into the framework of fuzzy set theory providing a calculus which can simulate the behaviour of the control expert. Fuzzy control systems have been successfully applied to a wide variety of practical problems. It has been shown that these controllers may perform better than conventional model-based controllers especially when applied to nonlinear processes which are difficult to model, and where there is a significant heuristic knowledge from the human operator [1, 2].

This paper briefly presents the structure and operation of a fuzzy-based setpoint controller. In addition, to identify good practical ideas and evaluate the current FLC that handles uncertainties, existing industrial applications that incorporate FLC are presented. It will discuss the advantages of using FLC as an intelligent system, and its robustness in application that combine neural network and fuzzy logic controller concepts.

2.0 BASIC STRUCTURE OF THE FUZZY LOGIC CONTROLLER

The basic configuration of an FLC comprises four principle components [3, 4, 5]:

1. Fuzzification Interface
2. Rule Base
3. Inference Mechanism
4. Defuzzification Interface

Fuzzification

The fuzzification process can be expressed by: x = fuzzifier (x_o) , where x_o is a vector of crisp values of one input variable from the process; x is a vector of fuzzy sets defined for the variable; and fuzzifier is a fuzzification operator with the effect of mapping crisp data to fuzzy sets. In the application of process control, a fuzzy logic controller requires two input parameters: error and change of error. The crisp values of error and change of error are then converted into fuzzy terms such as [NB, NM, NS, ZE, PS, PM, PB], which can be understood by the fuzzy inference mechanism.

Rule Base

The rule base holds a set of "if - then" rules that are quantified via fuzzy logic and used to represent the knowledge that human experts may have about how to solve a problem in their domain of expertise. Each rule has the form of an IF-THEN statement. The IF side of a rule contains one or more conditions, called antecedents which hold degree-of-membership values calculated during fuzzification. The THEN side of a rule contains one or more actions, which correspond directly to variables, called fuzzy outputs.

Inference Mechanism
The inference mechanism has two basic tasks:

(1) determining the extent to which each rule is relevant to the current situation as characterized by the input u_i, $i=1,2,....,n$
(2) drawing conclusions using the current inputs u_i and the information in the rule base.

Often, more than one rule applies to the same action (fuzzy output), in which case the common practice is to use the rule that is most true, or has the greatest strength.

Defuzzification
Defuzzification can be expressed by: y_{ou}=defuzzifier(y), where y is the fuzzy control action, y_{ou} is the crisp control action; and the defuzzifier is the defuzzification operator. After taking the logical sum for all rules, the fuzzy inference engines come out with a final conclusion/action in fuzzy term. It has to be transformed into a deterministic control signal that can be used to drive the actuator/plant. The procedure to convert a fuzzy term into a deterministic value is called defuzzification.

3.0 INDUSTRIAL APPLICATIONS OF FUZZY LOGIC CONTROLLER

Today, the practical application of FLC has expanded rapidly due to its incredible flexibility and adaptability. Fuzzy logic is an innovative technology that enables the implementation of ‘intelligent’ functions in embedded systems. This section will focus on a few major industrial applications (automotive engineering, medical process, telecommunication, environmental control, chemical process control, autonomous robotics, etc.) which have incorporated the FLC to enhance control-engineering solutions.

3.1 Fuzzy Logic in Automotive Engineering

The growing interest in the automotive industry to implement FLC in automotive systems has produced several major automotive products such as anti-lock brake systems (ABS), anti-skid steering system, automatic transmissions and automatic gearbox control. Von Altrock [5] presents various automotive applications which have incorporated FLC to improve on the performance of the conventional systems.

He also presents how fuzzy logic and conventional systems can complement each other to improve the performance of the ABS irrespective of road and weather conditions [6]. Conventional ABS uses electronic sensors to measure the speed of every wheel and a microcontroller to control the fluid pressure for the brake cylinders. Even though the mathematical model for the braking system of a car does exist, the interaction of the braking system with the car and the road is too complex to model adequately. The fuzzy logic system uses input data such as the speed of the wheels, speed of the car and hydraulic pressure of the brake fluid that stems from the existing sensors of the ABS. The fuzzy logic system then evaluates the reaction of the car to the braking and estimates the current road surface. Experiments showed that a first prototype with just 6 fuzzy logic rules could improve performance significantly. In one test on tracks that alternate from snowy road to wet road, the fuzzy logic ABS detected the change even during braking. Von Altrock, also discusses the use of FLC as an enabling technology in the engine control system, automatic gearbox control and anti-skid steering systems (ASS).

Fuzzy logic is also incorporated in the truck speed limiter control [7]. The design of an algorithm for this control problem proved to be difficult, since the same speed limiter device is used in a variety of different trucks, which exhibit different behaviours. With a truck speed limiter, the operating point moves because of the different load situations, such as driving uphill or downhill as well as driving empty or with a full load. Conventional control algorithms, such as PID controls, assume a linear model of the process under control and hence do not offer a solution. Von Altrock also presents a speed limiter which integrates with a fuzzy logic algorithm using the software tool *fuzzy*TECH®. After optimization of the fuzzy logic rule strategy on different trucks and various load conditions, the FLC achieves a much smoother response. It does not show overshoot behaviour, and provides a higher accuracy of keeping the speed limit compared to a conventional controller.

3.2 FLC in Medicine

The control of oxygen delivery to mechanically ventilated newborn infants is a time intensive process that must balance adequate tissue oxygenation against toxic effects of oxygen over-exposure. Oxygen toxicity plays a role in the development of chronic lung disease in newborn infants. Yao, Kohane and Stark [8] emphasise that manual control of the oxygen concentration (FIO_2) may be delayed by human response times (i.e. a clinician may not be present to respond immediately). They have designed and implemented a microcomputer-based system to automatically and continuously control the FIO_2 delivered to mechanically ventilated newborn infants. The system utilises a fuzzy logic controller based on rules generated by neonatologists who routinely provide care for ventilated infants. In preliminary trials, FIO_2 fuzzy controller shows promising results to control patient oxygen saturation levels and reduce the overall oxygen exposure. Further clinical trials will test the actual clinical efficacy of this

FIO_2 controller, and additional patient data will allow more fine-tuning of the fuzzy control parameters. Current research also includes combining it with other techniques such as neural networks, genetic algorithms [9, 10], and adaptive fuzzy control [11].

Von Altrock [12] also presents a case study on the use of FLC to control the depth of the anaesthesia in a patient during an operation. From a control engineering view, the task for the anaesthetist is to keep the depth of the anaesthesia between the awakening threshold and exitus threshold. As a result of the operation itself and changes in the patient's condition, the actual anaesthesia depth fluctuates around its set point. The role of the FLC is to keep the fluctuations small, such that the set point of anaesthesia depth can be set higher, resulting in less strain on the patient. FLC with two inputs and one output had been developed and tested. The field study showed that "normal" operations are handled quite well by the FLC.

3.3 Fuzzy Control in Telecommunications

Hellendoorn [13] presents FLC as an excellent heuristic method to solve problems with various complexities in communication and computer networks. In one of the case studies, he developed a fuzzy system to calculate the shortest path from a given source node to any other node in the network [15]. The simulations show that using a fuzzy link evaluator [FLE] has an obvious influence on the shortest path routing strategies especially in the following areas:

(i) 'bad links' are better recognised by the fuzzy router
(ii) fuzzy system can easily handle more than just one input parameter
(iii) the design and tuning of a FLE can easily be done by a network expert
(iv) a fuzzy router can easily be adapted to changing conditions in a network.

Hellendoorn also present the use of fuzzy in Call Admission Control (CAC) and Usage Parameter Control (UPC). In the CAC, the fuzzy rule base has to decide whether the network has enough resources left to provide Quality of Service (QoS) requirements to a new connection without affecting the QoS that has been guaranteed to the existing connections. In UPC, FLC supervises the established connections by checking and punishing violating connections. More research on the application of FLC in the telecommunications industry is expected in future.

3.4 Fuzzy Logic in Environmental Control

Brubaker [16] presents the use of FLC in a precision temperature and humidity controller by Liebert Corporation of Columbus, Ohio. The design of a precision environmental control system is often a far greater challenge due to the nonlinearities caused by such system behaviour as air flow delay and dead times, uneven airflow distribution patterns, and duct work layouts. In addition, uncertainties in system parameters are often present, for example room size and shape, location of heat-producing equipment, thermal mass of equipment walls, and amount and timing of external air introduction. A fuzzy logic approach was investigated and ultimately implemented by Liebert in LogiCool Control System. Simulations conducted by Liebert engineers showed that LogiCool with 6 fuzzy inputs, 3 fuzzy outputs and 144 rules, fully met its operational requirements associated with precise control of the temperature and humidity in rooms with uncertain and nonlinear characteristics. Damper and compressor cycling times have been greatly reduced, thus the component life is increased and installation includes no tuning procedure.

3.5 Fuzzy Logic in Chemical Process Control

Von Altrock et. al. [17] describes a complicated process control in polyethylene production in which ethylene is converted to polyethylene by a polymerisation reaction. In the polymerisation, the ingredients, ethylene and a solvent, react using a catalyst. The quality of the final product depends on the purity of the ingredients, the reaction pressure and temperature, and the concentration of the substances. The measurement of these factors during the reaction is incomplete. Only by analysing the resulting polyethylene it is possible to reveal the quality of the final product. However, this analysis information is only available a few hours later.

To control the quality of the polyethylene produced during the reaction, Hoechst Corporation of Germany uses a fuzzy logic-supervising controller in its Munchsmunster plant. This controller estimates the quality of the current polyethylene production on the basis of the existing sensor signals. Every ten seconds, the fuzzy logic controller adjusts the set values of the process accordingly. The fuzzy logic system controls the catalyst feed using three input variables that stem from the online process sensors. The fuzzy logic system uses 75 rules and reduces the standard deviation by more than 40% since its first operation in 1990.

3.6 Fuzzy Logic in Autonomous Robotics

The goal of autonomous robotics is to build physical systems that accomplish useful task without human intervention in unmodified environments - that is, in environments that have not been specifically engineered for the robot. Safiotti [18] outlines some of the challenges posed by autonomous robotics, and discusses how some of the peculiar features of fuzzy logic can help in meeting the challenges. He discusses ten papers presented by researchers working in the field of autonomous robotics. He concludes that fuzzy logic can model different types of uncertainties and imprecisions; it allows to build robust controllers starting from heuristic and qualitative models; and it provides a natural framework to integrate logical reasoning and numerical computation. It is also noted that fuzzy technologies can address some problematic situations that are known for the non-fuzzy ones in these applications.

3.7 Other Application Areas

Other applications that incorporate fuzzy logic include: microwave ovens, washing machines, camcorders, video cameras, vacuum cleaners, elevator control, cruise-control for automobiles, optimised planning of bus time-tables, cancer diagnosis, subway control, prediction system for early recognition of earthquakes, positioning of wafer-steppers in the production of semiconductors, etc.

4.0 ADVANTAGES OF FUZZY LOGIC CONTROLLER

Generally speaking, FLC demonstrates the following major advantages over the conventional control system [19, 20, 21]:

1. FLC is very successful in handling systems with nonlinearities and various complexities, without having to develop their mathematical models in an explicit form using any integral, differential or complex mathematical equations.
2. As a rule-based approach, fuzzy controller design involves incorporating human expertise on how to control a system into a set of rules (a rule base).
3. Continuous variables may be represented by linguistic constructs that are easier to understand, making the controller easier to implement and modify. For instance, instead of using numeric values, temperature may be represented as "cold, cool, warm, or hot". Complex processes can often be controlled by relative few fuzzy rules, allowing a more understandable controller design and faster computation for real-time applications.

5.0 OPTIMIZATION OF FUZZY LOGIC CONTROLLER

Fuzzy rules for a FLC are obtained either from domain experts or by observing the people who are currently doing the control. The membership functions for the fuzzy sets will be derived from the information available from the domain experts and/or control actions [22]. But the translation of these into fuzzy set theory is not formalised and arbitrary choices concerning for example the shape of membership functions have to be made. The quality of the fuzzy controller can be drastically influenced by changing shapes of membership functions. The building of such rules and membership functions requires tuning. In order to provide fuzzy reasoning with learning function, various learning and optimization methods have been proposed [23]:

(i) combination of neural networks and fuzzy controllers,
(ii) a self-tuning method of fuzzy reasoning by using (a) genetic algorithm, (b) interior penalty method, or (c) descent method.

The following sections will describe different combinations of neural networks and fuzzy systems.

5.1 Combining Fuzzy Logic Controllers And Neural Networks

A combination of neural networks and fuzzy controllers offers the possibility of solving the tuning and design problem of fuzzy control. The combination of both approaches assembles the advantages of both and avoids their drawbacks [24]. There are several approaches to neural-fuzzy systems from which a designer can choose, and two generic approaches (i) Cooperative Neuro-Fuzzy Models and (ii) Hybrid Neuro-Fuzzy Models will be briefly described below.

5.1.1 Cooperative Neuro-Fuzzy Models

Nauck [25] describes Cooperative Neural Fuzzy Models as a system where a neural network is used to determine several parameters (rules, rule weights and/or fuzzy sets) of a fuzzy system. Cooperative models can be further divided [26]:

(a) The neural net derives the parameters of membership functions from training data. The fuzzy sets are learned offline, and are used with predefined fuzzy rules to implement a fuzzy controller.
(b) The neural net derives linguistic control rules from training data. The learning is done offline, and the fuzzy sets have to be defined in another way.
(c) The neural net adapts parameters of the fuzzy sets online, i.e. while the fuzzy controller operates. It is necessary to know the fuzzy rules, and initial fuzzy sets. In addition, an error measure has to be defined that guides the learning process.
(d) The neural net learns weight factors applied to the fuzzy rules in an online or offline mode. The weights are usually interpreted as the "importance" of a rule, and it modifies the output of a rule. Fuzzy rules and fuzzy sets have to be known in advance.

5.1.2 Hybrid Neuro-Fuzzy Models

A neural network, and a fuzzy system are combined into one homogeneous architecture. The system may be interpreted as a special neural network with fuzzy parameters, or as a fuzzy system implemented in a parallel distributed form [25]. The advantages of this model are the consistent architecture that makes the communication between two different models unnecessary. The fuzzy sets can be interpreted as weights, and the rules, input variables, and output variables can be represented as neurons. Hybrid neural fuzzy controllers learns in a supervised mode where a fixed learning task or a free learning task together with an external reinforcement signal is needed [26].

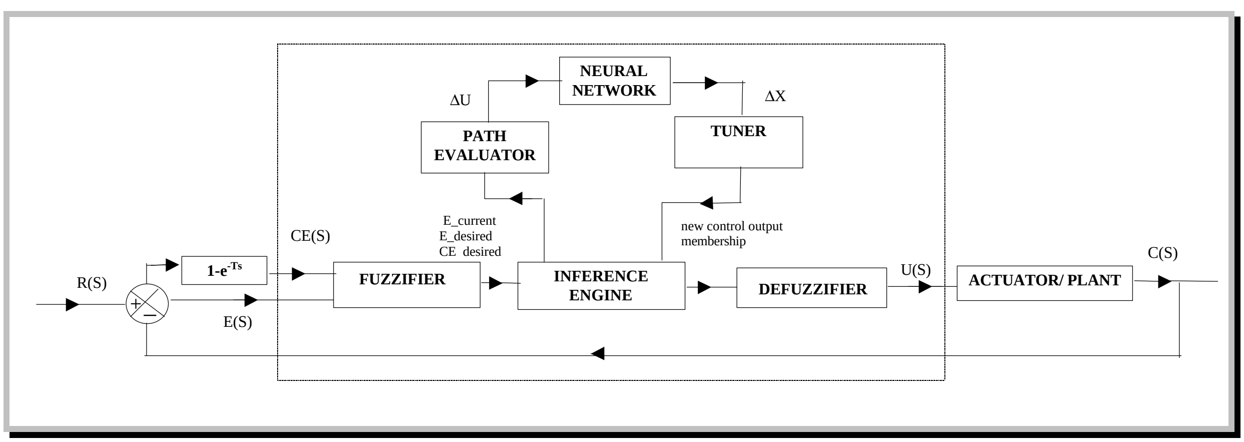
An approach that is capable of learning fuzzy sets and fuzzy rules is presented by the NEFCON model [27]. NEFCON is able to learn the fuzzy sets and the fuzzy rules of a neural fuzzy controller by backpropagating a fuzzy error measure through the NEFCON architecture. The learning of a rule base is done by deletion of rules, that means, the learning process can work online and does not need sample data such as the. clustering approaches [27]. Simulations of the controller used to balance an inverted pendulum have shown that the learning procedure improves the behaviour of the fuzzy controller and is able to handle extreme situations where the non-learning controller fails [14].

5.2 CONEFCON

To demonstrate the feasibility of fuzzy neural controller in various industrials applications, a prototype controller CONEFCON, have been developed by implementing cooperative neural fuzzy concept [4]. CONEFCON is developed using C++ and implemented in the form of graphical simulation environment. Fig. 1 shows the architecture of the system. Simulation results show that CONEFCON is capable of controlling various simulated industrial processes. Well-trained neural networks employed in CONEFCON were able to generate appropriate data to perform the membership function adjustment. In particular, the neural-fuzzy controller eliminates the drawback in the design of a conventional fuzzy controller whereby the engineer must tune the membership functions of the fuzzy sets by trial and error. As CONEFCON is implemented on the cooperative neural fuzzy concept, it combines the advantages of both approaches and avoids their drawbacks.

6.0 CONCLUSION

This paper reviews various practical application of FLC in real world products and industries. In all the applications discussed, FLC is an extremely successful means of controlling systems with nonlinearities and various complexities. To incorporating FLC in systems with various complexities is feasible, versatile and has many advantages. Combining neural networks and fuzzy controller to handle systems with various complexities further enhances the robustness of FLC; CONEFCON was developed based on this concept. More research is necessary to develop the general topology of fuzzy neural models, learning algorithms, approximation theory so that these models are made applicable in system modeling and control of complex systems.



R(s) = Reference Signal, E(s) = Error Signal, CE(s) = Change of Error Signal, U(s) = Control Action C(s) = Process or Output Variable, E_current = Error for current sampling interval, E_desired = Desired Error for next sampling interval, CE_desired = Desired Change in Error for next sampling interval, ΔU = small increment of control output proposed by path evaluator,
ΔX = percentage of displacement referring to the current control output membership function

Fig. 1: Architecture of CONEFCON

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