

# Fuzzy Logic Assisted Control of Inspired Oxygen in Ventilated Newborn Infants

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*The control of oxygen delivery to mechanically ventilated newborn infants is a time intensive process that must balance adequate tissue oxygenation against possible toxic effects of oxygen exposure. Investigation in computer assisted control of mechanical ventilation is increasing, although very few studies involve newborn infants. We have implemented a fuzzy controller for the adjustment of inspired oxygen concentration (FIO<sub>2</sub>) in ventilated newborns. The controller utilizes rules produced by neonatologists, and operates in real-time. A clinical trial of this controller is currently taking place in the neonatal intensive care unit (NICU) of Children's Hospital, Boston, MA.*

## INTRODUCTION

Oxygen toxicity plays a role in the development of chronic lung disease in newborn infants requiring mechanical ventilation. [1,2] In premature infants, inadequate maintenance of tissue oxygenation is implicated in the development of retinopathy of prematurity. [3] In order to avoid the effects of too much or too little oxygen, control of oxygen delivery to ventilated newborns has become a priority in neonatal intensive care.

Among the many ventilator parameters that affect patient respiratory status, the inspired oxygen concentration (FIO<sub>2</sub>) is most frequently manually adjusted on an acute basis to control oxygen delivery and maintain patient hemoglobin oxygen saturation levels. Manual control of the FIO<sub>2</sub>, however, may lag the clinical condition of the patient. That is, a patient may have an increased oxygen requirement as demonstrated by a lower oxygen saturation, but the manual increase of FIO<sub>2</sub> may be delayed by human response times (i.e. a clinician may not be present to respond immediately). Conversely, a patient may have a decreased oxygen requirement as clinical conditions improve, yet the amount of oxygen delivered may not be immediately decreased. The latter scenario may be more common because of the perception that a patient with high oxygen saturation is "doing well" and does not require immediate intervention.

We have designed a microcomputer based system to help control the FIO<sub>2</sub> delivered to mechanically ventilated newborn infants. This system utilizes a fuzzy logic controller based on "rules" generated by neonatologists who routinely provide care for

ventilated infants. The goal of this control system is to maintain patient oxygenation (measured by oxygen saturation using pulse oximetry) at a target level set by the physician.

Instead of controlling the ventilator directly, the system currently operates by displaying suggested FIO<sub>2</sub> changes to the physician, who then decides whether to execute the recommended change. This ensures medical safety until the system is fully tested for clinical efficacy. A clinical trial of the FIO<sub>2</sub> control system is currently taking place in the neonatal intensive care unit (NICU) of Children's Hospital, Boston, MA.

## BACKGROUND

### Computer Assisted Ventilation

Investigation into computer-controlled or computer-assisted mechanical ventilation is expanding. One form of computer assistance is an "expert system" designed to advise the clinicians about ventilator management. Some recent examples include: VentPlan, a ventilator management advisor that interprets patient physiologic data to predict the effect of proposed ventilator changes [4]; WeanPro, a program designed to help wean post-operative patients from ventilators [5]; and KUSIVAR, a program which describes a comprehensive system for respiratory management during all phases of pulmonary disease. [6] Although many such expert systems have been described, few have been tested in clinical patient care.

Other investigators have studied direct computer control of specialized aspects of ventilator management. In adults for example, studies of computer-controlled optimization of positive end-expiratory pressure, and computerized protocols for management of adult respiratory distress syndrome have been explored by East. [7] A computerized ventilator weaning system for post-operative patients has been tested by Strickland. [8]

Experience in computer controlled ventilation in infants, however, is limited. In one of few reports available in the literature, Morozoff and Evans showed that their computerized FIO<sub>2</sub> controller could maintain the hemoglobin oxygen saturation (SaO<sub>2</sub>) of a ventilated newborn infant for approximately 1 hour periods with results comparable to manual FIO<sub>2</sub> control. [9]

Morozoff and Evans describe their FIO<sub>2</sub> controller as a “differential-feedback” controller. Other investigators have described similar FIO<sub>2</sub> controllers for adults based on the “proportional-integral-derivative” (PID) design. [10] For best response, most PID controllers and feedback-loop controllers need to have their control parameters optimized for the system in which they are used. This may lead to degradation of performance if the system changes (e.g. if the patient’s physiologic status changes, or the controller is switched to a new patient). Yu addressed this problem in FIO<sub>2</sub> control by using multiple controllers that dynamically adapted by selectively utilizing the controller that best matched the system response at any given point in time. [11]

### **Fuzzy logic controllers**

Since Zadeh first published his seminal paper on fuzzy sets in 1965 [12], applications utilizing fuzzy logic have proliferated rapidly. Mamdani’s development of fuzzy controllers in 1974 [13] gave rise to the utilization of these controllers in ever expanding capacities, particularly in Japan where many industrial processes now employ fuzzy control. [14] In addition, fuzzy control techniques have recently been applied to various medical processes, such as pain control [15] and blood pressure control. [16]

When compared to classical control theory, a fuzzy logic approach to control offers the following advantages: [14,17]

- 1) It can be used in systems which cannot be easily modeled mathematically. In particular, systems with non-linear responses that are difficult to analyze may respond to a fuzzy control approach.
- 2) As a rule-based approach to control, fuzzy control can be used to efficiently represent an expert’s knowledge about a problem.
- 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”.
- 4) Fuzzy controllers may be less susceptible to system noise and parameter changes, thus making them more robust.
- 5) Complex processes can often be controlled by relatively few logic rules, allowing a more understandable controller design and faster computation for real-time applications.

In the context of FIO<sub>2</sub> control in the newborn infant, a fuzzy logic approach can simplify the many complex factors and interactions that determine patient oxygenation. For example, a ventilated infant may exhibit decreased oxygen levels in the blood (as

measured by SaO<sub>2</sub>) for many different reasons, including: failure to make respiratory effort, an obstructed endotracheal tube, or an increase in pulmonary shunting. Each cause may require differing changes in FIO<sub>2</sub> to maintain target SaO<sub>2</sub> levels, and many other factors may influence oxygenation. At different times, the same magnitude of change in FIO<sub>2</sub> may result in completely different oxygenation states, even within the same patient.

FIO<sub>2</sub> control in the newborn thus demonstrates some of the previously mentioned features which make classical control techniques difficult to apply: the system to be controlled is complex with many factors and interactions, it is very difficult to model mathematically, and system responses to FIO<sub>2</sub> changes are often non-linear and unpredictable.

## **SYSTEM DESCRIPTION**

### **FIO<sub>2</sub> Controller**

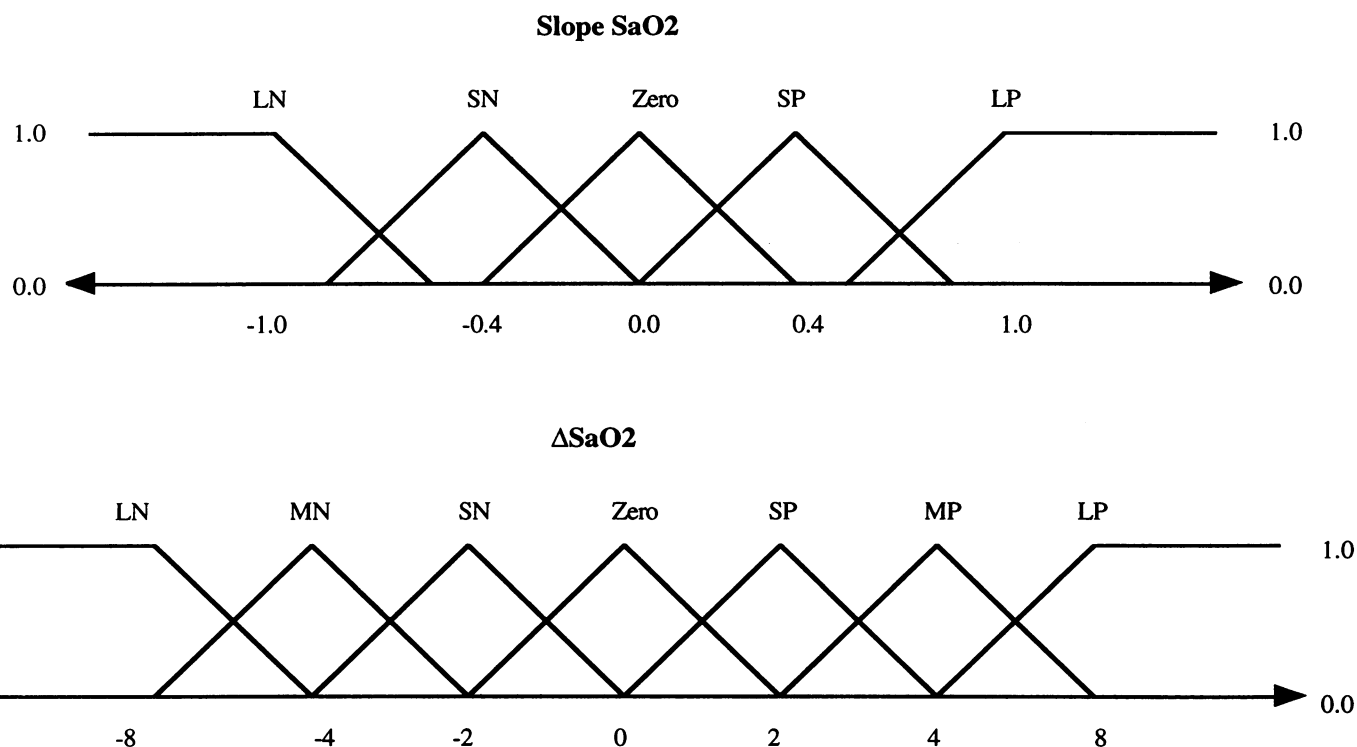
We chose SaO<sub>2</sub> as our measurement parameter and FIO<sub>2</sub> as our control parameter for the operational model of maintaining patient oxygenation.

SaO<sub>2</sub> as measured by pulse oximetry is a well established method of monitoring patient oxygenation status. Its advantages over direct measurement of blood oxygen levels include rapid equilibrium with changes in blood oxygen levels, continuous monitoring, and noninvasive sampling. We used the error between the patient’s SaO<sub>2</sub> and the target SaO<sub>2</sub> ( $\Delta$ SaO<sub>2</sub>), and the slope of SaO<sub>2</sub> (SaO<sub>2</sub>-slope) as the specific inputs to the fuzzy controller.

Although many ventilator parameters affect patient oxygenation (e.g. mean airway pressure, ventilatory rate, tidal volumes, etc.), the FIO<sub>2</sub> is used to maintain the desired oxygenation status when the patient’s overall respiratory status has been stabilized.

The design of the fuzzy controller then follows standard methods, with fuzzification of the input parameters, construction of fuzzy inference rules, and defuzzification or calculation of a “crisp” output value that represents the controller’s action.

To fuzzify the input parameters, the values of  $\Delta$ SaO<sub>2</sub> and SaO<sub>2</sub>-slope were divided into fuzzy regions, with 7 regions chosen for  $\Delta$ SaO<sub>2</sub> and 5 regions chosen for the SaO<sub>2</sub>-slope. Triangular membership functions were assigned to each region, as illustrated in Figure 1.



**Figure 1**  
**Membership Functions of Input Parameters**  
 LN: large negative, MN: medium negative, SN: small negative  
 SP: small positive, MP: medium positive, LP: large positive

Using the fuzzy input parameters, the inference rules that form the body of the controller were constructed in the standard declarative form: IF situation THEN action . The combination of 7  $\Delta\text{SaO}_2$  fuzzy regions and 5 SaO<sub>2</sub>-slope fuzzy regions yields 35 rules. The logic of these inference rules are based on the expert knowledge of the neonatologists. Some example rules follow:

- Rule: IF the  $\Delta\text{SaO}_2$  is small-negative AND the SaO<sub>2</sub>-slope is medium-negative (situation) THEN increase the FIO<sub>2</sub> by a medium-positive amount. (action)
- Rule: IF the  $\Delta\text{SaO}_2$  is large-negative AND the SaO<sub>2</sub>-slope is large-negative THEN increase the FIO<sub>2</sub> by an extremely-large-positive amount.
- Rule: IF the  $\Delta\text{SaO}_2$  is small-negative AND the SaO<sub>2</sub>-slope is small-positive THEN do nothing.

All 35 rules are summarized in Table 1.

For any pair of  $\Delta\text{SaO}_2$  and SaO<sub>2</sub>-slope inputs, we

apply each of the inference rules in turn. Each rule will yield an action value. The defuzzification step then involves choosing a method to combine all the action values into a final value (a “crisp” value) that represents the controller output. We used the weighted mean of all the rule outputs to produce a single output value, in this case a change in the FIO<sub>2</sub>. [18]

Although there are relatively few fuzzy inference rules, continuously calculating the crisp output in real-time may not always be feasible. To help minimize time-delays, we compiled the fuzzy inference rules into a look-up table at runtime. Thus, during actual fuzzy control operation, evaluating the inputs becomes a simple and fast table look-up producing the controller output.

The FIO<sub>2</sub> controller operates as follows:

- 1) SaO<sub>2</sub> values are obtained for the patient every 1-2 seconds.
- 2) Every 10 seconds, the  $\Delta\text{SaO}_2$  and the SaO<sub>2</sub>-slope are calculated.  

$$\Delta\text{SaO}_2 = (\text{ave. SaO}_2 \text{ values over last 10 seconds}) - \text{target SaO}_2$$

$$\text{SaO}_2\text{-slope} = \text{least squares regression of SaO}_2$$
- 3) The calculated  $\Delta\text{SaO}_2$  and SaO<sub>2</sub>-slope are used as

		SaO2-slope				
		LN	SN	ZERO	SP	LP
ΔSaO2	LP	0	0	↓↓↓	↓↓↓↓	↓↓↓↓↓
	MP	↑	0	↓↓↓	↓↓↓	↓↓↓
	SP	↑	0	↓	↓	↓↓
	ZERO	↑↑	↑	0	↓	↓↓
	SN	↑↑↑	↑↑	↑	0	0
	MN	↑↑↑↑	↑↑↑	↑↑	↑	0
	LN	↑↑↑↑↑	↑↑↑↑	↑↑↑	↑↑	0

**Table 1**  
Inference rules for FIO2 control, given fuzzified ΔSaO2 and SaO2-slope

indices for the compiled fuzzy controller look-up table. A suggested FIO2 change is returned as the controller output.

**System Components**

The FIO2 fuzzy control system is implemented on an Apple Macintosh and is programmed in Macintosh Common Lisp. The SaO2 data is obtained from a Nellcor N-200 pulse oximeter through a RS-232 serial port on the back of the oximeter.

**CLINICAL STUDY**

**Study Design**

In order to test the FIO2 control system in a medically safe manner, the computer did not directly control the ventilator oxygen delivery. Instead, suggestions for changes in FIO2 were displayed for the physician to execute according to his/her best medical judgment. The computer system was programmed to record automatically all recommended and actual FIO2 changes.

The clinical trial protocol was approved by the Clinical Investigations Committee of Children's Hospital, Boston, MA., and informed consent was obtained from the parents of patients entered into the study. Patients were eligible if they were newborn infants admitted to the NICU and required mechanical ventilation. Patients were excluded if they had demonstrated intracardiac shunting of blood from right to left, or if they required vasoactive pressor medications to maintain blood pressure.

Each infant was studied for a 6 hour period of time. The initial 2 hours served as a control period during which the computer system collected SaO2 and FIO2 data. No interventions were made during this time. For the subsequent 2 hour experimental period, the system made recommendations for FIO2 changes in addition to acquiring data. The investigator manually carried out the recommended FIO2 changes if they were consistent with his/her clinical judgment. Finally, another 2 hour control period of data gathering (without recommendations for FIO2 change) completed the study period for the patient.

All clinical care activities proceeded as usual, and the NICU medical and nursing staff were not prevented from manually adjusting the FIO2 at any time during the trial.

**Preliminary Study Results**

Patient #1: target SaO2 = 93%

	Ctrl-1		Expt		Ctrl-2	
	FIO2	SaO2	FIO2	SaO2	FIO2	SaO2
Ave:	26	96	25	94	26	94
SD:	0	1.6	6.0	1.9	2.6	3.0

Patient #2: target SaO2 = 95%

	Ctrl-1		Expt		Ctrl-2	
	FIO2	SaO2	FIO2	SaO2	FIO2	SaO2
Ave:	27	95	26	95	29	94
SD:	4.6	3.2	6.1	2.6	8.5	5.1

(Ctrl: control period, Expt: experimental period, Ave: average, SD: standard deviation)

## SUMMARY

Controlling oxygen exposure in newborn infants is a delicate balance. The infants must receive enough oxygen to ensure adequate tissue oxygenation and to prevent hypoxemia. Conversely, too much oxygen may produce toxic effects.

The FIO<sub>2</sub> fuzzy controller shows promise in the preliminary trials to control patient oxygen saturation levels, and was able to maintain a target SaO<sub>2</sub> better than routine manual control. Further clinical trials will test the actual clinical efficacy of this FIO<sub>2</sub> controller, and additional patient data will allow more fine tuning of the fuzzy control parameters (e.g. the shape of the membership functions and the choice of fuzzy regions).

The ease of implementing this fuzzy controller illustrates some of the advantages of this approach. No complex mathematical models were required, the simple rule-based nature of the controller is easy to understand and modify, expert knowledge about the problem is utilized, and the controller was easily designed for non-linear system responses.

Current research in fuzzy control include combining it with other techniques such as neural networks and genetic algorithms [19,20], and adaptive or self-modifying fuzzy control. [18,21] As more medical processes become candidates for computerized control, the numerous options offered by these approaches will enhance the ability to produce a safe and clinically efficacious control system.

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