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Neuro-Fuzzy Decision Support System for Optimization of the Indoor Air Quality in Operation Rooms

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ABSTRACT

In order to minimize surgical site infections, indoor air quality in hospital operating rooms is a major concern. A wide range of literature on the relevant issue has shown that air contamination diminution can be attained by applying a more efficient set of monitoring and controlling systems that improve and optimize the indoor air status level. This paper discusses a fuzzy inference system (FIS) and the integrated model neuro-fuzzy inference system (ANFIS) focusing on the control of contamination via proper airflow distribution in an operating room, which is essential to guarantee the accuracy of the surgical procedure. A deep learning estimation approach is proposed to predict incidence in the presence of airborne contamination. The project's goal is to reduce airborne contamination to improve the surgical environment and reduce the predicted incidence during surgeries. The neuro-fuzzy deep learning model was trained with a neural network structure and tested by considering 3 important parameters that affected the air quality introducing the specialization of the system to control the model's target. Finally, the proposed approach has been put into practice by making use of data collected by sensors placed within a real operating room in a hospital in Mashhad, Iran. The proposed model attains 97.3% and 95% validation accuracy for estimating the relative humidity and particles, respectively. The efficacy of the proposed neuro-fuzzy indicates that the system significantly lowers risk values and enhances indoor air quality.

Abbreviations

ANFIS	:	Neuro-Fuzzy Inference System
FIS	:	Fuzzy Inference System
OR	:	Operating Room
TSK	:	Takagi-Sugeno-Kang
NAP0	:	Normal air quality power level 0
LAP1	:	Low air quality power level 1
LAP2	:	Low air quality power level 2
LAP3	:	Low air quality power level 3
HAP4	:	High air quality power level 4
HAP5	:	High air quality power level 5
HAP6	:	High air quality power level 6
HAP7	:	High air quality power level 7
R_g	:	Power Level Range

1. Introduction

Operation rooms (ORs) equipment has an important role in diagnosis, treatment, and surgeries. The ORs' air conditioner has a significant impact on the indoor air quality of the surgical process and recovery. In the absence of acceptable assessment of ORs' air status level, hospitals suffer from technical deficiencies and lose their effectiveness, with a significant share of the costs of hospitals being allocated to the provision and repair of this equipment, resulting in large-scale scientific and economic damage to the health of patients [1][2]. In hospitals, airborne particles can be a serious threat to patients, as it is known that most opportunistic pathogens that cause hospital-acquired infections are at least partly dispersed in the air [3][4], especially in the OR [5]. Their presence could be a source of infections such as those of the surgical site [6]. To limit the onset of contamination, an OR is typically divided into progressively less contaminated areas, from the entrance to the operating theatres [7].

As the research on this issue has progressed, in the ORs' air quality situation, artificial intelligence techniques are frequently applied as a detector and controllers in ORs [8][9]. This will require a great deal of consideration for a variety of sensors and devices and reviewing existing streams that should be close to the given sources. The OR is a special unit requiring a clean environment with the fewest number of particles in the air [10]. In addition, during surgical procedures, the team and the surrounding environment release dust particles, textile fibers, and respiratory aerosols loaded with vital microorganisms [11]-[13] that can settle on surgical instruments or enter directly into the surgical site causing surgical site infections [14]. The heating, ventilation, and air conditioning systems significantly influence the operating room environment, including temperature, relative humidity, pressurization, particle counts, filtration, and ventilation rate [3].

Many studies have shown that the necessity of the right decision and proper assessment based on the patient's condition is an appropriate manner of constant monitoring and control of ORs. To diminish the airborne particles, they need to be monitored constantly. The essential key that affects the air conditioning, ventilation, and heating systems is maintaining the humidity and temperature in an optimal situation. A fuzzy model was presented by [8][15][16] to classify and monitor the patient's vital sign condition. The expert-fuzzy system is applied to support the surgeon's decision-making and evaluation of uncertain parameters [17]-[19]. A fuzzy logic controller to control the air quality in the hospital interior is shown in the literature [20][21]. In this paper, we consider input parameters consisting of the room size, air temperature, and particles and the heating power as an output to refresh air quality to optimal levels.

In this work, we propose an operating room air quality monitoring estimating system based on a deep-learning technique. Due to the unclear and fuzzy nature of ORs' data, as well as the relationships that exist in the decision support system models, the FIS and ANFIS are the most effective technique under deep learning-base systems [22]-[24] particularly used in the healthcare context [25][26]. According to the case study situation, the main challenge was the lack of integrity between input data due to the nature of data and the lack of a predetermined model to estimate the air condition and monitor the results during surgeries in the ORs. The goal of the proposed monitoring is to manage contamination in ORs efficiently. According to the capability of neural networks and the ambiguity of the available data, the neural fuzzy (FIS integrated by the ANFIS method) applying for modeling.

A FIS integrated by ANFIS allows prediction of the air quality in the operating room proposed that takes into account three parameters, the particle count in the operating room (ISO 5, ISO 7), temperature (relative humidity), and room size. Despite the variety of studies examining the issue of air quality, there are no studies in the literature applying FIS and ANFIS to estimate the air situation and monitor the result in ORs during the surgeries; for this reason, our study presents an innovative model to understanding the challenge of management in ORs through the support of AI techniques.

The main contribution of this work is proposing the Neural networks integrated by the Fuzzy model to estimate the air quality and monitor simultaneously to detect any incompatibility of environmental conditions by diminishing the constraints. On the other hand, the presented features have been collected in real-time through hi-tech devices and developed directly on the field through different phases by an interdisciplinary research team. The FIS, obtained by combining the potential of fuzzy logic and neuro-fuzzy systems, gives the possibility to monitor OR conditions by appropriately modeling input data and by reproducing the cognitive process of experts through inferential techniques.

2. Method

This study focuses on the air quality of ORs improvement and maintenance at the proper level, as well as the problem of instability environmental conditions and the presence of many unknown suspended particles in the air throughout the operation time, using modeling techniques based on artificial intelligence systems. This research tries to investigate whether air quality improvement may affect the quality of the surgery and recovery situation of the patients. Iranian care state hospitals were selected as a case study for this investigation. Our methodology is proposed in two phases. In the first phase, inputs and output data are collected from devices to train the model. The fuzzy model extracted rules based on the Mamdani model to estimate the output. After this phase terminates, the optimization phase starts. The proposed methodology is depicted in Fig. 1.

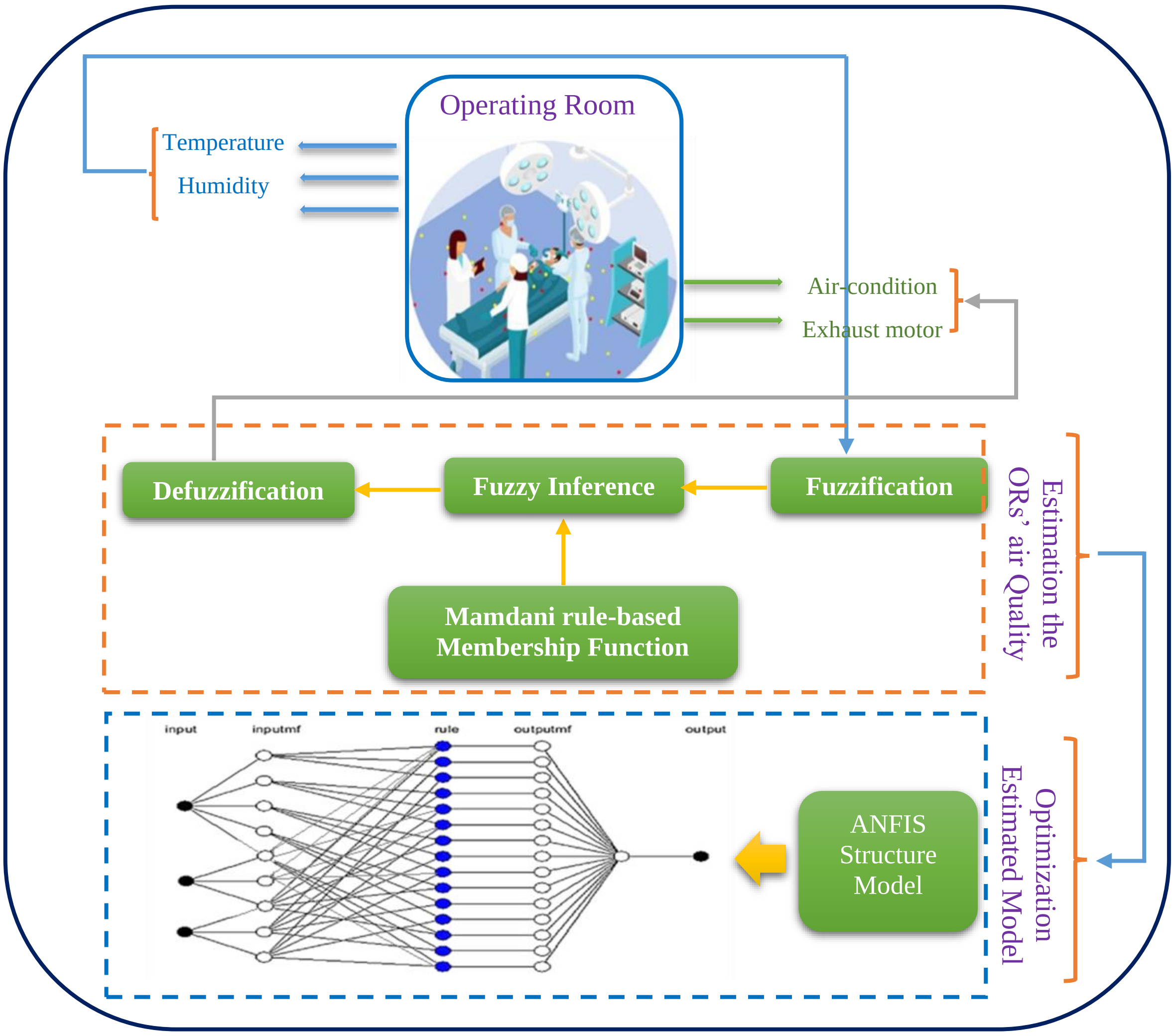

Fig. 1. Proposed methodology

In order to implement these phases, the complementation methodology is fully described step by step in the following subsections.

2.1. Data Collection

This study was performed on 12 ORs undergoing surgery admitted to Mashhad Hospital, Iran. The particle count data from up to 5 particle channels and the configurable recipe database can store up to 50 recipes for sampling and reports. The particle counters have been positioned in all operating rooms to collect data in different environmental conditions and to better understand all events that could alter the particles present in the various ORs. Finally, the last installed measurement device consists of a multi-parameter tool whose purpose is to monitor the climatic conditions of the operating room by measuring the relative humidity, differential temperature, and speed of the airflow in correspondence with the ventilation outlet. Table 1 represents the data model collected by each device reported. We determine the inputs and output of the model; inputs are room size (6m to 40m), temperature (-5 ºC to 35 ºC), particle count (0.5µm), and output is the Heater output Power (0 to 100). Table 1 shows the 2 inputs and outputs in ORs. The particle data collected by particle counter in the range of 55.250 particles/m^3.

Table 1. Data set collected by the high-tech device

No.	Room Size (m)	Temperature (ºC) Humidity	Heating Power
1	40	-5	100
2	18	-5	60
3	40	-5	100
4	18	-5	80
5	6	-4	60
6	12	-3	65
7	30	6	40
8	20	2	40
9	40	30	0
10	40	0	80
11	32	35	0
12	6	35	0

2.2. FIS Implementation

In this paper, we use FIS and ANFIS, which are a kind of deep learning based on the Takagi–Sugano fuzzy inference system to model automatic control of optimized air quality of OR using Neuro-Fuzzy to Improve Performance. At first FIS model was trained by a data set and proposed a model then ANFIS was trained and modeled to optimize the air quality of ORs.

We want to design a fuzzy system to control the air by controlling the particles and temperature of 12 of the hospital rooms, which gives the room a decent amount of heat, according to the size of the room. That is, if the air was very cold and the room was very large, the air handling unit would work with maximum power, or if the air was a bit cool and the room was in the middle, the medium temperature control unit would work.

Fuzzy systems can also utilize human knowledge, which is expressed in terms of rules-if-expressed, in their structure. This feature is specific to the fuzzy system, and artificial neural networks are deprived of this capability. One of the most effective and widely used methods in fuzzy-nerve systems is to reduce the number of basic rules and simplify modeling using clustering. It is also one of the ANFIS data structures. The design of the FIS can be summarized into 3 main stages: fuzzification, inference, and defuzzification [27]. All the designed clinical linguistic variables, membership functions, and rules have been included in a Mamdani FIS [28][29]. The goal of the FIS is to predict the different grades of severity related to operation rooms' air quality and, hence, synthesize them on a colored graph for ease of representation in Fig. 2.

The FIS system has three inputs and one output to train the system. The inputs are entered into the model and trained with output data. Because the system has three inputs and one output, in each line of the text file, there should be 4 numbers separated by a comma, and these numbers are saved in the text file. If the room was 40 meters and the air temperature was -5 (coldest), the particles count was then the maximum power output should be the maximum (i.e., 100), So we put these four values in the first line of the text file (40, -5, 4.110,100), which is the same as in the other row.

To determine the number of particle charges during the day, a particle counter and a multi-parameter unit allowed monitoring of the microclimatic parameters that have been positioned in 12 ORs under study. Based on the particle counter data collected particle count values, the four fuzzy sets are considered Normal0, High1, High2, and High3. The membership functions of the four fuzzy sets are considered to have a Gaussian shape. The membership functions and Gaussian fuzzy set of the particle count range are shown in Table 2. The data range is based on the ISO 14644-1 standard used by the FDA dictates the maximum concentrations of particles per square meter in cleanrooms.

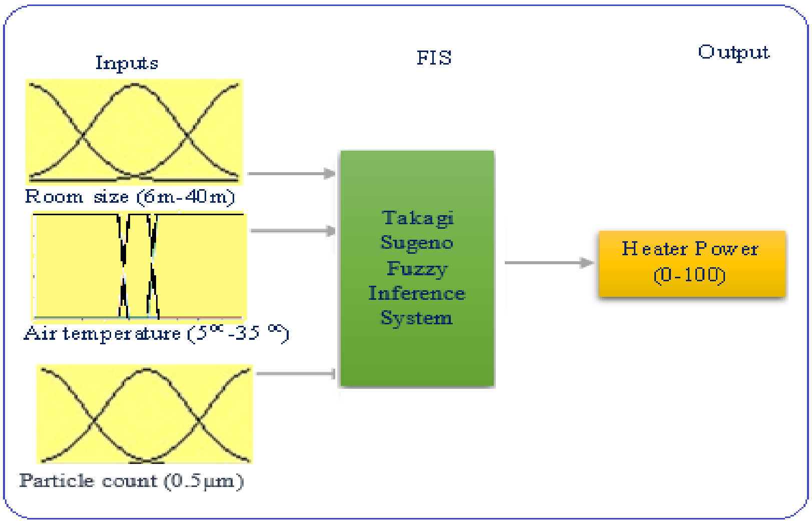

Fig. 2. The proposed FIS

Table 2. The Gaussian Fuzzy set and the particles count range (ISO 14644-1)

	Fuzzy Set	Range
Particles count	Normal0	< 3.530
	High1	3.525-3.600
	High2	3.580-3.700
	High3	>3.690

Operating room temperature for this input parameter, 3 fuzzy sets have been considered: Low1, Normal0, and High1. The membership functions of the 3 fuzzy sets will be trapezoidal. Following the same procedure for the definition of the ranges for the particle count, it is possible to create a similar Table 3, in which the temperature values for each fuzzy set can be displayed. Fig. 3 represents the overall membership function.

Table 3. The Triangular Fuzzy set and the temperature range

	Fuzzy Set	Range
Temperature (ºC)	Low1	<15
	Normal0	15-25
	High1	>25

2.3. ANFIS Implementation

The most common paradigms of intelligent systems include neural networks (NN), fuzzy logic (FL), and neuro-fuzzy. Appropriate integration of intelligent systems results in a sophisticated system that is capable of solving difficult problems. ANFIS is a rule-based system; its rules are developed during a training process. The Mamdani and Takagi-Sugeno-Kang (TSK) with two main types of FIS

[30] applied to estimate the model and shown in Fig. 2. In Table 4, the first number represents the number of states representing the size of the room or three modes in fuzzy, (i.e., small- medium-large), the second number is the temperature states (very cold- cold- medium- hot- very hot), and the third number indicates particles count. So, the number of MFs is 3 5 3 created a series of rules and training data. Fig. 4 represents the training data in ANFIS modeling. In the training phase, the error tolerance is set to 0.1, and each epoch is set as 100 iterations.

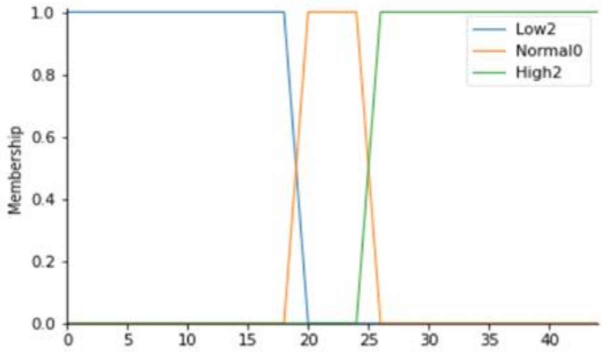

Fig. 3. The membership function of the FIS and ANFIS model

Table 4. Variables and the membership function of ANFIS

	Number of MFs	MF Type
Inputs	3 5 3	Trimf
Output	1	Constant

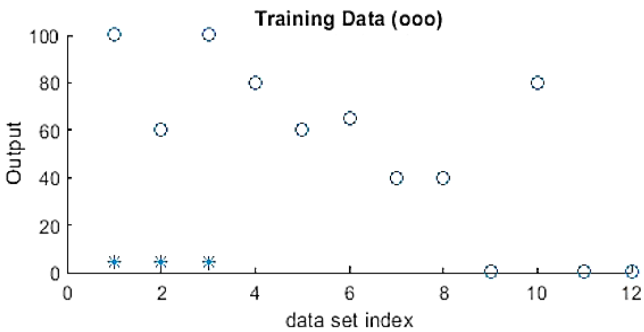

Fig. 4. Neuro-Fuzzy Designer Training Data

3. Results and Discussion

By using data collected by the devices installed in the operating room in a hospital in Mashhad, Iran, the proposed strategy was validated offline. The evaluation of the ANFIS attempted to test experimentally whether the same variation in output reflecting the input condition could be appreciated in response to a variation of the input reflecting the environmental conditions of the OR. To compute the estimation and accuracy of the air quality, model evaluations (1) and (2) are applied. The evaluation and implementation of the optimization model are shown in Table 5.

$$Precission = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TI_i} \quad (1)$$

$$Accuracy = \frac{\sum_{i=1}^{N} TP_i}{Total} \quad (2)$$

In order to identify and estimate the power level related to the air quality in the operating room to avoid surgical site infections, this study suggests a fuzzy inference method. The goal is to make the air conditioning room as efficient as possible to reduce contamination risk and avoid life-threatening situations for patients and clinicians the same as each other. Finally, the 8 fuzzy sets signed with the L (low) in the case of a low Air-Quality Power level, with the H (high) in the case of a high Air-Quality Power level: NAP0, LAP1, LAP2, LAP3, HAP4, HAP5, HAP6, and HAP7. Accordingly, triangular membership functions are considered appropriate for these membership functions. Table 6 and Fig. 5 represent the details of the range of power levels and relative fuzzy sets.

Table 5. The measurement test and ANFIS optimization model evaluation

Inputs	Accepted range	Accuracy	Error ratio
Temperature	0-100 (%RH)	97.3%	2.7% RH
Particles	0.2, 0.5, 2, 3, 7, 12 µm	95%	5%

Table 6. The power level and their fuzzy sets

Output	Range	Fuzzy Set
Air-Quality Power level	$0 < R_g < 0.25$	NAP0
	$0.25 < R_g < 1$	LAP1
	$1 < R_g < 2$	LAP2
	$2 < R_g < 3$	LAP3
	$3 < R_g < 4$	HAP4
	$4 < R_g < 5$	HAP5
	$5 < R_g < 6$	HAP6
	$6 < R_g < 7$	HAP7

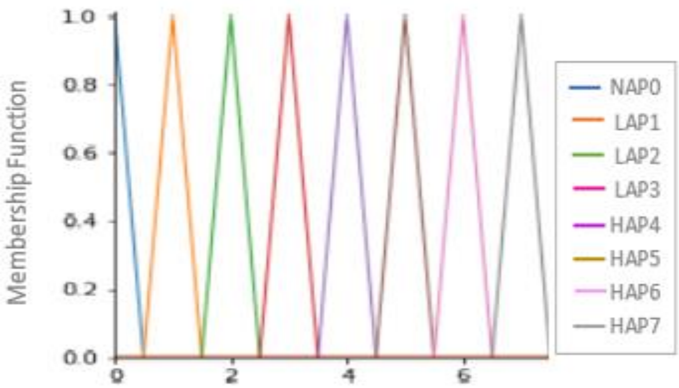

Fig. 5. The membership function of the fuzzy set

4. Conclusion

In this paper, we offer an optimization model based on a fuzzy inference system for monitoring the air quality in the operating room in order to preserve the surgical environment and optimize the ensuing managerial decisions. Real-world inputs collected at a hospital in Mashhad, Iran, were used to validate the developed ANFIS. Our system's results demonstrate that they provide a reliable evaluation of the OR's air quality situation. The limitation in terms of input type and number can be a very interesting starting point for future analyses to support risk management in the ORs. In future work, deep learning and meta-heuristic optimization algorithms can be improved indoor air quality by estimating more accurately. To acquire the effectiveness of the method and acceptable performance, using different Artificial intelligence estimation methods based on different variables can show intriguing results.

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