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A Power-Efficient Analog Hardware Type-2 Fuzzy Classifier Architecture for Water Potability

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Abstract. This work presents an ultra-low-power analog fuzzy classifier based on Gaussian membership functions, MIN/MAX rule evaluation, and OTA-based defuzzification, operating in the subthreshold region for energy-efficient real-time inference. The architecture is evaluated on a water quality assessment dataset with reduced feature complexity, achieving competitive accuracy of 85.98% compared to the software equivalent of 89.42% and demonstrating suitability for low-power edge applications with a total power consumption of 72nW.

1 Introduction

Environmental datasets, such as water quality measurements, are often characterized by noise, uncertainty, and overlapping feature distributions, leading to unclear class boundaries [1]. In such conditions, hard computing techniques may exhibit limited robustness and generalization performance [2]. To address these challenges, fuzzy systems provide an effective framework by associating each input with a degree of membership, enabling reliable decision-making under uncertainty.

Fuzzy Inference Systems (FIS) implement this reasoning through three main stages: fuzzification, rule evaluation, and defuzzification [3]. In this process, fuzzy if-then rules are applied and the output is obtained using defuzzification methods such as the Center of Gravity (COG).

Alongside these approaches, advances in Machine Learning (ML) have enhanced data-driven modeling capabilities. However, software and digital implementations may introduce increased computational cost and latency, especially in continuous monitoring systems. In contrast, analog implementations enable real-time inference with reduced power consumption, making them suitable for resource-constrained applications [4].

In this work, we present an ultra-low-power analog Type-2 Mamdani Fuzzy Inference System (FIS) for water quality classification. The proposed architecture employs Gaussian membership functions, MIN/MAX rule evaluation, and OTA-based defuzzification, providing a compact and energy-efficient solution for real-time environmental monitoring.

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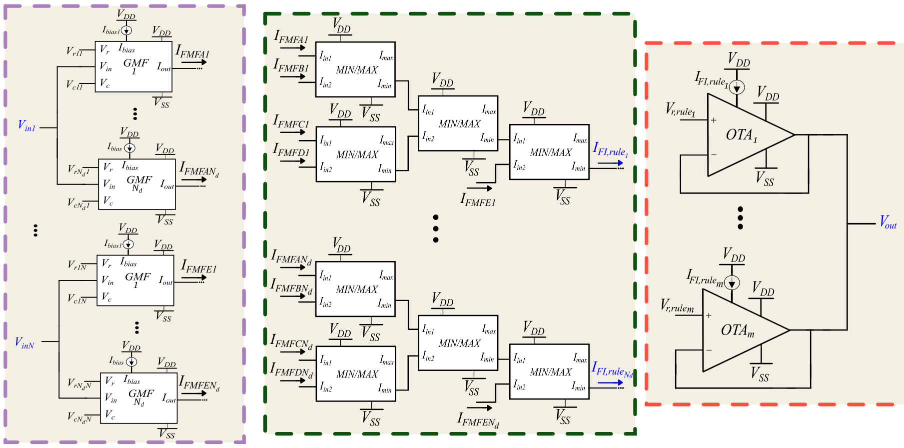

(a) (b) (c)

Figure 1: High-level architecture of the proposed FIS. (a) Fuzzification block. (b) Rule evaluation stage. (c) COG implementation.

2 Proposed Architecture

The proposed system is a fully analog Fuzzy Inference System (FIS) implemented in 65 nm CMOS technology, operating in the subthreshold region with ultra-low supply voltages ($V_{DD} = -V_{SS} = 0.3$ V). The architecture follows the standard fuzzy inference pipeline shown in Fig. 1, consisting of three main stages: fuzzification, rule evaluation, and defuzzification.

2.1 Fuzzification

In the fuzzification stage, input voltages are mapped to membership degrees using Gaussian Membership Functions (MFs), following the architecture in Fig. 1a. These functions are implemented through a modified bump circuit as illustrated in Fig. 2a, where the center, width, and amplitude are electronically controlled by V_r, V_c, and I_{bias}, respectively [5]. The output is a current-mode representation of the membership degree, which is forwarded to the next stage.

2.2 Rule Evaluation

The rule evaluation stage computes the firing strength of each rule using MIN/MAX current-mode circuits, implementing the fuzzy AND/OR operations. The proposed circuit [6] ,depicted in Fig. 2b, employs a cross-coupled PMOS structure combined with an adapted current mirror , enabling direct computation of:

$$I_{\text{max}} = \max(I_1, I_2), \quad I_{\text{min}} = \min(I_1, I_2). \tag{1}$$

2.3 Defuzzification

Defuzzification is performed using the Center of Gravity (COG) method:

$$\text{COG} = \frac{\sum_i I_{f_i} V_{r_i}}{\sum_i I_{f_i}}, \tag{2}$$

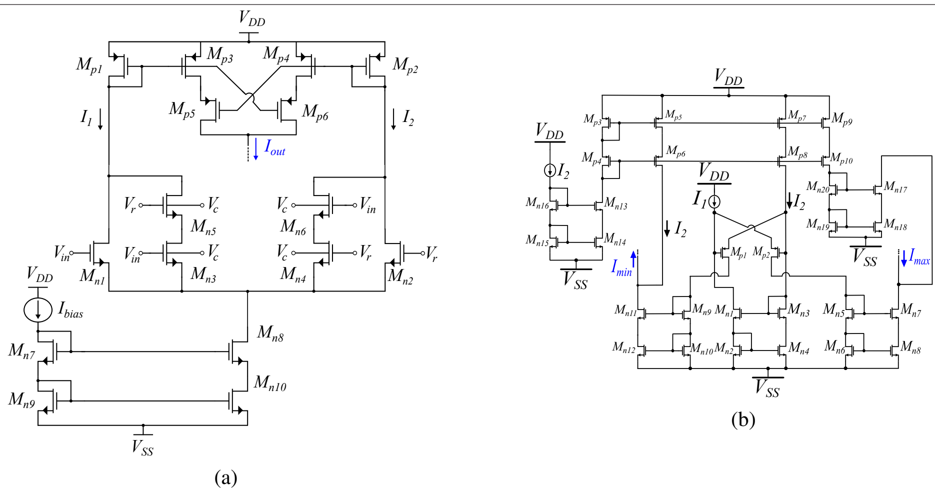

Figure 2: (a) Gaussian membership function circuit and (b) Current-mode MIN/MAX rule evaluation circuit.

where the firing strengths are represented as currents and the centroids as voltages. The implementation utilizes Operational Transconductance Amplifiers (OTAs) in a feedback configuration shown in Fig. 1c, with the OTA illustrated in Fig. 3a, providing a direct voltage output without additional conversion stages. The corresponding circuit analysis is based on the methodology presented in [7]. Overall, the proposed architecture enables efficient fuzzy

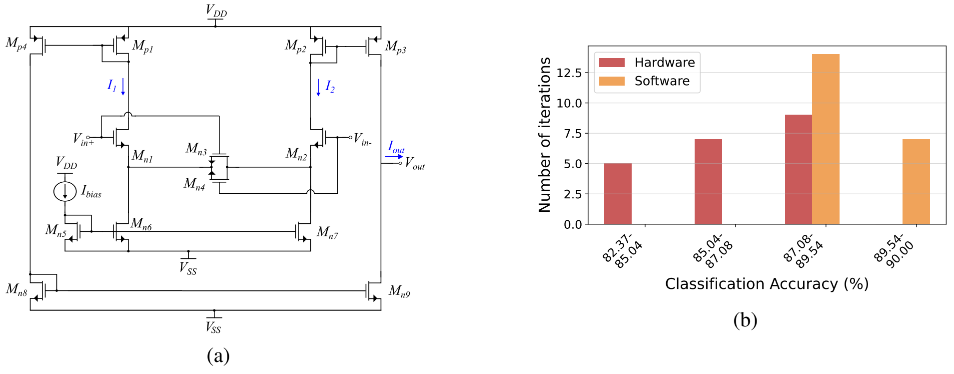

Figure 3: (a) Operational Transconductance Amplifier (OTA) and (b) Accuracy of the Software and Hardware implementations for 20 iterations.

inference through current-mode processing and subthreshold operation, achieving low power consumption and real-time performance suitable for edge applications.

3 Simulation Results and Data Analysis

The dataset employed in this work is a water quality dataset [8] consisting of multiple physicochemical parameters, such as heavy metals (e.g., arsenic, lead, mercury), chemical compounds (e.g., nitrates, chloramine), and biological indicators (e.g., bacteria, viruses). The classification task is formulated as a binary problem, where each sample is labeled as safe or non-safe for consumption.

Given the relatively high dimensionality of the dataset, a feature selection process is applied to extract a reduced set of five representative features, preserving the most relevant information while reducing data overlap and computational complexity.

Post-layout simulations of the proposed fuzzy classifier were carried out using the TSMC 65 nm CMOS process in Cadence Virtuoso. The evaluation includes multiple training iterations presenting the results in Fig. 3b.

The proposed classifier achieves classification accuracies ranging from 82.37% to 88.25%, with an average accuracy of 85.98%. A corresponding software-based implementation achieves a mean accuracy of 89.42%, indicating that the analog fuzzy classifier provides competitive performance while maintaining significantly lower power consumption and enabling real-time operation.

These results highlight the effectiveness of the proposed architecture for low-power environmental monitoring applications, where continuous and reliable water quality assessment is required.

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