The Use of GA and PSO Algorithms to Improve the Limitations of a Readout Circuit of an pH-ISFET Sensor

Abdelkhalak Harrak and Salah Eddine Naimi

Abstract A readout circuit described in this paper to enhance the temperature sensibility. An ISFET-based pH sensor type employed, with a temperature compensation had been improved and high linearity over a large range of pH changed from 1 to 12. In the beginning, the general optimization techniques used are the particle swarm algorithm and the genetic algorithm. Then a local optimization was applied to find a combination of geometry of the transistors for a good optimization result. With the optimization techniques used, the simulation results give a very low-temperature dependence of the circuit and good precision.

Keywords Evolutionary algorithm · pH-ISFET · Temperature insensitivity · Linearity

1 Introduction

In micro-nanoelectronics, we find a wide use of algorithms or of course artificial intelligence used to optimize the behavior of a circuit that constitutes from many transistors. The market need for sensors with high measurement accuracy requires good optimization of different physical quantities of circuits, hence the arrival of artificial intelligence [1]. Nowadays, the use of ISFETs chemical sensors is essential to confront the problems of detection of chemical and/or biological elements in several fields. Many of the devices are developed for the chemical and biological processing such as enzyme-substrate reaction, antigen-antibody bonding and protein-protein interaction. The adaptation and study of this circuit must have the implementation of optimization algorithms. Temperature is an important factor that affects the pH measurement. The working mechanism of a pH-ISFET is described by $I(V)$ equations similar to the MOS transistor. Studies that have been carried out

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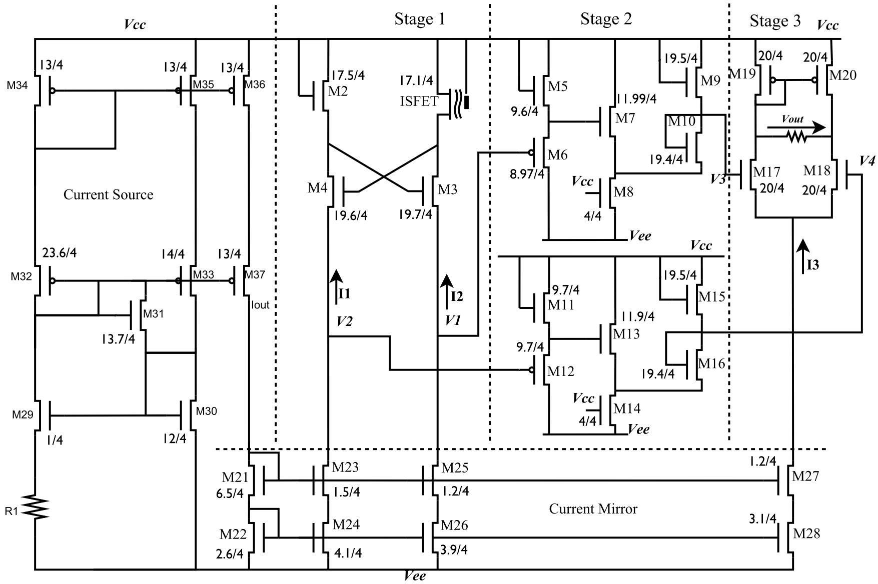
by some research show that pH-ISFET is very sensitive to temperature, which gives unreliable measurements. For this, it is very important to find good methods and techniques to study the temperature behavior of ISFET sensors in order to improve their temperature stability [2–4]. In this work, we will study the temperature sensitivity of the circuit and linearity by using the genetic algorithm and particle swarm optimization.

2 The Main Blocks of the Proposed Circuit

The readout circuit has been proposed to improve the linearity of the output signal and to compensate the effect of temperature of the circuit. This readout circuit operates in a differential mode, as shown by the circuit structure in Fig. 1. The readout circuit consists of three main stages, and also of two power supply stages, these



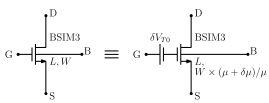


Fig. 1 **a** The proposed circuit: $R1 = 400\,\text{k}\Omega$, $R2 = 23.35\,\text{k}\Omega$ and $V_{cc} = -V_{ee} = 3\,\text{V}$ (the thermal coefficients of $R1$ are as: TC1 = 1.510e−3 and TC2 = 510-7). **b** Mismatch macro-model of MOSFET transistors

circuit's stages which contain the ISFET sensor, are designed, based on CMOS technology. In the first stage, which called Caprios quad, there are four transistors, the ISFET, M2, M3 and M4, which allow to extract a differential signal between $V1$ and $V2$, and this signal represents the threshold voltage variation of the pH-ISFET sensor. The second block is made of two attenuators, receive the two voltages $V1$ and $V2$, attenuate and shift them to be adapted to the inputs of the differential amplifier. The third stage is a differential amplifier, operates in weak inversion and allows the compensation of the temperature, of the difference of two signals $V3$ and $V4$, which are the outputs of the two attenuators.

2.1 The Mismatch Analysis

The sources of mismatch between devices are mainly limited by mathematical and experimental investigation into two, global and local variations (f_D and f_A, respectively).

$$\sigma^2(\Delta P) = f_L(W, L) + f_G(D) \approx \frac{A_P^2}{WL} + S_P^2 D^2 \tag{1}$$

where, $f_L(W, L)$ is the component depending on the transistor size. While $f_G(D)$ is associated with the dependence of the surface gradient (on the liquid) [5]. L and W are the geometry of the gate; D is the separation between the devices.

We had to think about how these changes affect the temperature sensitivity and linearity of the pH-ISFET readout circuit. Usually, the mismatch behavior modeled using two parameters, the mismatch of threshold voltage $\delta V_{T0} = V_{T01} - V_{T02}$, getting a standard deviation $\sigma_{V_{T0}}$, and the mismatch of current gain factor $\delta\beta/\beta = (\beta_1 - \beta_2)/\beta$ getting a standard deviation σ_β (with C_{ox} is the capacitance of gate, μ is the carrier mobility and $\beta = \mu C_{\mathrm{ox}}$). Each model of the transistor in the readout circuit implemented in Spice appears in Fig. 1b. Based on the dependent variables, a simple approach is used in this work, taking into consideration the total density of sites constant ($N_s = N_{\mathrm{sil}} + N_{\mathrm{nit}}$). Modeling the mismatch behavior of the sensitive membrane, generally requires an assumption of Gaussian PDF for the random part of the mismatch. The simulation was done with $\overline{N_{\mathrm{sil}}} = 4.5 \times 10^{18}\,\mathrm{cm}^{-2}$, $\sigma(N_{\mathrm{sil}}) = 5 \times 10^{17}\,\mathrm{cm}^{-2}$ and $N_s = 4.6 \times 10^{18}\,\mathrm{cm}^{-2}$. Even there is no experimental validation for the approach, so the simulation is not very precise, but in general, it gives an indication of its sensitivity to the variation of the process. The output distribution predicted by the method of Monte Carlo is performed by assigning the mobility variation $\delta\mu$ and the threshold voltage variation δV_{T0} as randomly generated:

$$\sigma(\delta V_{T0}) = \frac{A_{V_{T0}}}{\sqrt{2WL}}; \quad \sigma(\delta\mu) = \frac{A_\mu}{\sqrt{2WL}} \tag{2}$$

With, $A_\mu = 2.34 \times 10^{-4}\,\mathrm{cm}^3/\mathrm{V\,s}$ and $A_{V_{T0}} = 20.36 \times 10^{-9}\,\mathrm{V\,m}$, L and W being the size of the transistors.

3 Optimization Using Evolutionary Algorithms

3.1 The Genetic Algorithm

The change in temperature affects 37 transistors that make up the proposed read-out circuit. Not like most traditional search and optimization problems, the genetic algorithm works with a population of solutions [6]. An interval of the maximum and minimum width of the transistors defined, is chosen as an initial population. As in nature, the genetic algorithm evolves by selecting the best genes that can adapt to the existing environment, based on the principles of reproduction and mutation [7, 8]. The fixed population size was kept at 2000. The mutation rate was applied at 0.1, the crossover operator rate is 60%. At each production, 80% of promising individuals replace the population. As a general rule, we need to give the algorithm some stop criteria. Many criteria have been tested: the quality of the best result, the generation numbers and the population convergence. Generation number 500 gave us the results of this article. The simulation made in Xeon processor at @2.13 GHz in about 74 h. Three objectives define the cost minimization function:

- Minimize the quadratic error Δ_{T1} between the circuit output and the regression line of V_{out}, for a pH from 1 to 12 and at a temperature $T = 20\,^\circ\mathrm{C}$. The error Δ_{T1} is expressed by (3), where β_1 and β_2 are the parameter estimators of the linear regression at $T = 20\,^\circ\mathrm{C}$.
- The maximum residual error indicated in (4) must be minimized for a temperature range from 20 to 80 °C and a pH from 1 to 12.
- Minimize the quadratic error Δ_{T2} between the circuit output V_{out} at $T = 80\,^\circ\mathrm{C}$ and the regression line of V_{out}, for a pH range from 1 to 12 and at temperature $T = 20\,^\circ\mathrm{C}$. The error Δ_{T2} is expressed by Eq. (5).

$$\Delta_{T1} = \sqrt{\sum_{\mathrm{pH}=1}^{\mathrm{pH}=12} (V_{\mathrm{out}}(\mathrm{pH})_{T=20\,^\circ\mathrm{C}} - (\beta_1 \times \mathrm{pH} + \beta_2))^2} \tag{3}$$

$$\Delta_{\mathrm{Max}} = \max[V_{\mathrm{out}}(\mathrm{pH}) - (\beta_1 \times \mathrm{pH} + \beta_2)] \tag{4}$$

$$\Delta_{T2} = \sqrt{\sum_{\mathrm{pH}=1}^{\mathrm{pH}=12} (V_{\mathrm{out}}(\mathrm{pH})_{T=80\,^\circ\mathrm{C}} - (\beta_1 \times \mathrm{pH} + \beta_2))^2} \tag{5}$$

Let us define three objectives G_1, G_2 and G_3 for the above errors Δ_{T1}, Δ_{T2} and Δ_{Max}. A single error Δ to be reduced is as follow:

$$\Delta = \sqrt{w_1(\Delta_{T1} - G_1) + w_2(\Delta_{\text{Max}} - G_2) + w_3(\Delta_{T2} - G_3)} \quad (6)$$

The dimensions w_1, w_2 and w_3 are width coefficients which must be adapted manually to obtain the best optimization.

3.2 Particle Swarm Algorithm

The particle swarm optimization (PSO) algorithm is a heuristic method inspired by the attitude of fish or bird populations [9]. A set of parameters is associated with a particle (in our problem we have associated the sizes of the channel of the transistor). It needs a population of random solutions to initiate the search. The particles circulate through the problematic space following the current optimal particles. The PSO is different from the GA algorithm because it does not have scalable operators. The PSO algorithm has shown its performance in various difficult optimization situations [10]. However, due to its information sharing action, all particles can rapidly converge toward a local minimum. On the other hand, the low rate of convergence is one of the drawbacks of GA. The PSO algorithm uses the recently introduced cost function.

4 Discussion and Simulation Results

The proposed circuit has been simulated using a standard BSIM3v3 provided by the MOSIS AMI 1 μm CMOS process. As a result of some simulations, the channel width of the transistors takes an approximate upper and lower limit. The overall optimization of the widths of the transistors was carried out by the PSO and the GA algorithms; the transistors lengths were fixed at 4 μm. The transistors width obtained by the simulation are presented on the circuit Fig. 1. As expected, the PSO and GA algorithms give two different optimal dimensions to the circuit. Indeed, the temperature sensitivity was approximately 2.56×10^{-4} pH/°C with the PSO and 2.89×10^{-4} pH/°C with the GA. According to the local optimization and as shown by the sensitivity curve in Fig. 2, the highest temperature drift is fewer than 2.39×10^{-4} pH/°C, while the precision of the circuit is approximately 0.014 pH. At a temperature of 20 °C, the determination coefficient is approximately 99.99 and 99.98% at a temperature of 80 °C. A Monte Carlo simulation was executed for a single final optimized conception. The result of about 2000 Monte Carlo analysis demonstrate good circuit behavior, even when a mismatch between devices is taken into account as described in Table 1. Finally, the proposed readout circuit achieves an efficiency of 15.7% for a temperature sensitivity of 0.001 pH/°C and a resolution of 0.05. Based on these results, in the future, the yield may be improved.

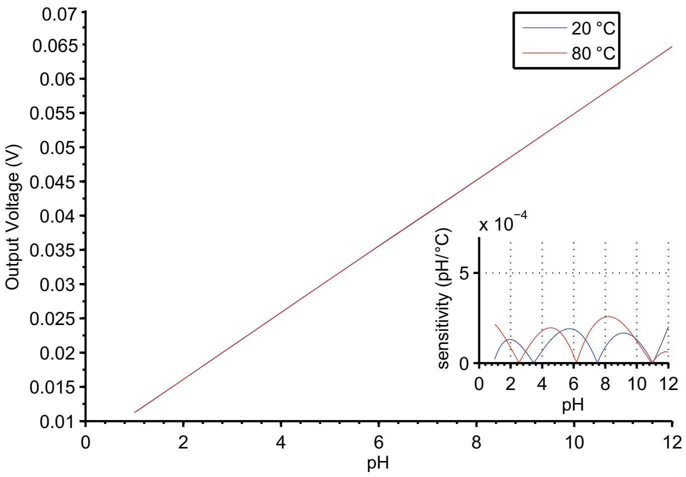


Fig. 2 The output of the proposed circuit as a function of the pH, at a temperature variation from 20 to 80 °C. In the bottom corner: the temperature sensitivity of the output pH/°C

Table 1 Efficiency of the readout circuit

Characteristics		2 point calibration (pH 2–4 or 7–10) (%)	3 point calibration (pH 4–7–10) (%)
Accuracy (pH)	Sensitivity (pH/°C)		
0.01	0.0005	1.1	1.1
0.05	0.0005	8.2	8.5
0.05	0.001	14.4	15.7
0.1	0.0005	8.5	8.5

5 Conclusions

A pH-ISFET sensor has been improved and linked with a simple and efficient circuit, compatible with standard CMOS technology. The temperature sensitivity of the sensor has been greatly improved. Through the use of site-binding theory, we modeled the temperature dependence of the sensitive membrane (SiO_2/Si_3N_4), and subsequently, we used the Veriloge-a language to implement it, while the BSIM3v3 model of AMI CMOS 1 µm supplied by MOSIS has been used for all transistors. Intensive simulation validates the robustness and the operating principle of the pH-ISFET readout circuit. In a wide range of temperature (from 20 to 80 °C) and pH (from 1 to 12), the circuit presents a good linearity, which has been proved by the coefficient of determination, was found around $R^2 = 0.9999$. Three isothermal zones were obtained at pH values (2.5, 6 and 11), with the temperature sensitivity equal to 2.4×10^{-4} pH/°C. The readout circuit accuracy was found to be 0.014pH. The temperature sensitivity was found to be less than 0.001 pH/°C for an unoptimized efficiency interval between 8.5 and 15.7%, indicating that the probability of circuit manufacturing failure will be low.

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