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Robust Optimization of Self-x Sensory Electronics in Presences of Environmental Variations for Industry 4.0

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Summary:
This paper introduces a new methodology to robustly optimize the re-configurable self-x ICs for industry 4.0 in the presence of environmental uncertainty (EU). For handling the EU, variance measure methodology has been selected due to its simplicity. The traditional particle swarm optimizer has been amended by adaptively adjusting its acceleration coefficients and expanding its selection procedure. The performance of the proposed modifications has been tested on two bench-marking functions. The extrinsic evaluation of the proposed algorithm has also been done on an instrumentation amplifier.

Keywords: Instrumentational amplifier, Sensory electronics, Self-x properties, Robust optimization, adaptive weight robust particle swarm optimizer.

Background, Motivation and Objective

The reliability, performance and accuracy of sensory electronics (SEs) are significantly improving with the introduction of self-x (self-calibration, self-healing, etc.) properties for industry 4.0. To introduce self-x properties in reconfigurable SEs, evolutionary and meta-heuristic algorithms have shown superiority and powerful capabilities in addressing the multi-objective optimization problems. A considerable amount of literature is available for the introduction of self-x properties in integrated electronics (ICs) [1]. However, the optimization of ICs in the presence of uncertainties is very rare [2]. In general, there are three different types of uncertainties in ICs, i.e., drift due to fabrication process (input uncertainty), uncertainty due to imperfect observer: (output uncertainty) and environmental uncertainty (EU). While in [2] authors have recently proposed the noise immune meta-heuristic algorithms for handling the input and output uncertainty of sensory electronics for industry 4.0, the primary objective of this paper is the robust optimization of reconfigurable ICs in the presence of EU.

Traditional particle swarm optimizer (PSO) is being elected as an optimizer for this research. Wide swing reconfigurable indirect current feedback instrumentational amplifier (CFIA) [3] which is an integral part of SEs is being chosen as a test vehicle for extrinsic evolution of the suggested optimizer. Transistors widths of CFIA are serving as a tuning knobs and system output is being analyzed by the robust optimizer for its online trimming as shown in Fig. 1. For tackling EU, variance measure has been adopted due to its simplicity [4]. The details of the output and input uncertainties can be found in [5].

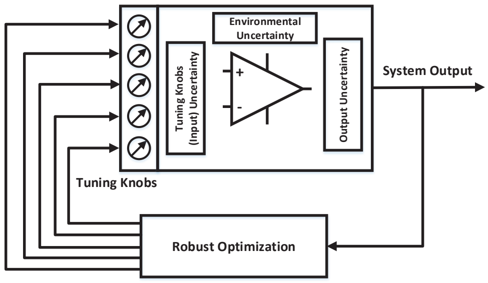

Fig. 1. Types of uncertainties in ICs.

Description of the Proposed Methodology

As already mentioned, PSO has been selected as an optimizer for this research. Due to objective space complexity of fully differential CFIA [6], a sigmoid-function-based weighting strategy [7] is being used to adaptively control the cognitive and social scaling factors, which indirectly optimize the exploitation and exploration while enhancing the convergence rate simultaneously. The basic structure of the proposed adaptive weight robust particle swarm optimizer (AWRPSO) is analogous to confidence-based robust optimization presented in [4], however, AWRPSO adaptively adjusts the acceleration coefficients along with taking EU into account.

AWRPSO begins with random initialization followed by the evolution of cost function. Then the variance measure will be evaluated to confirm the robustness of the solution. The particle's personal or global best is being amended in case of better fitness value. The cogni-

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tive c_1 and social c_2 scaling factors are being updated according to the following equations

$$c_1 = c_2 = F(D) = \frac{a}{1+e^{-c(D-d)}} + b$$

where $a = 0.5$, $b = 1.5$, $c = 0.000035 \times$ search range (distance between upper & lower bound of particle), $d = 0$ and $D = P_{p\,or\,g}(k) - x_i(k)$ which represent the distances of the particle i to its p_{best} or g_{best} at k_{th} iteration. After that, the particle's velocity and position are being updated, this procedure continues until maximum iterations. The details of the remaining AWRPSO parameters can be found in [2].

Results

For performance visualization of AWRPSO, further two different bench-marking functions (Schwefel & Griewank) from [2] are being opted [7]. To compare the exploitation and exploration capabilities of AWRPSO, three modifications of PSO are selected from the literature [8], i.e., linearly decreased inertia weight (PSO-LDIW), PSO with constriction factor (PSO-CK) and PSO with time-varying acceleration coefficients (PSO-TVAC). This experiment is performed using 30 particles and 750 iterations, while the convergence curve is computed by taking the mean of 100 runs which is depicted in Fig. 2. It is apparent that the convergence performance of the proposed AWRPSO is better than other.

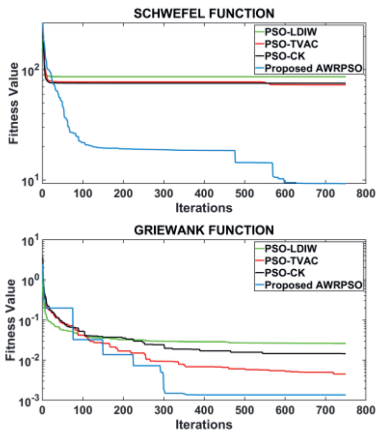

Fig. 2. Mean convergence curve comparison of AWRPSO and other state-of-art PSO.

AWRPSO is also employed on CFIA for its extrinsic evaluation. CFIA circuit is implemented by using AMS CMOS 0.35 µm technology. There are twenty-one tuning knobs (degree of freedom) and six objectives for this design test: bandwidth ≥ 40 MHz, gain ≥ 90 dB, phase margin ≥ 60°, power dissipation ≤ 2 mW, slew rate (SR) ≥ 50 V/µs and input common mode range (ICMR) [-1 V, 1 V]. Moreover, all transistors' length is kept constant to 1 µm and AWRPSO only alters the widths with step size of 1 µm. The detailed schematic diagram of CFIA can be found in [3]. For multi-objective optimization, an agglomerative approach is applied [2]. EU is modelled by varying the temperature from -40 °C to +85 °C and the performance deviation of CFIA is illustrated in Fig. 3. It can be seen that without considering EU, the performance of CFIA deviates significantly, while for the robust solution the performance deviation is only 1/8 in case of gain. Hence the proposed extrinsic optimization promises more efficient intrinsic optimization or dynamic reconfiguration. For the intrinsic evolution of AWRPSO, we are actively working on designing of the reconfigurable SE with self-x properties for industry 4.0.

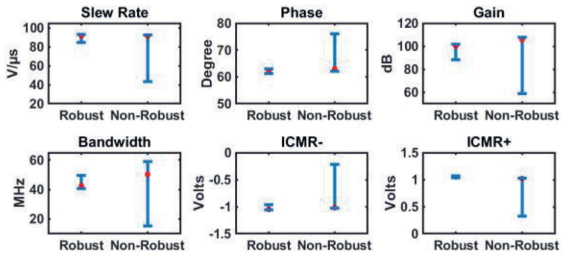

Fig. 3. Comparison of robust and non-robust solution.

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