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Self-x integrated sensor circuits immune to measurement noise in the presence of input perturbation by using robust optimization

Integrierte Sensorelektronik mit Self-x-Eigenschaften und verbesserter Immunität gegenüber Rauscheinflüssen bei der Messung und Störung der Eingangsgrößen durch ein robustes Optimierungsverfahren

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Abstract: This paper aims to propose a new technique to extend the performance of the reconfigurable self-x sensory system for industry 4.0 to efficiently obtain robust solution even in the presence of uncertainty both in the input and output stage. Variance measure is employed to handle the uncertainty in the input stage or search space. As far as measurement or objective space, uncertainty is concerned archive-based method applied, and it does not demand any additional computational resources. The traditional evolutionary algorithm, i.e., particle swarm optimizer (PSO), has been modified by expanding its selection process with the proposed solutions. The performance of the extended algorithm is undertaken to study on three benchmarking functions in the presence of uncertainties. The extrinsic evaluation of the proposed algorithm is also performed on the Miller operational amplifier, which is a fundamental part of sensory systems for industry 4.0. Drift due to fabrication process tolerances and aging effects of the transistors is modeled as input uncertainty of the operational amplifier, and imperfect observer (sensor or analog to digital converter) is modeled as output uncertainty. The application confirms the worthiness of proposed uncertainty handling algorithm for industry 4.0.

Keywords: Reconfigurable Miller operational amplifier, universal and self-x integrated sensor interface, noise immune robust particle swarm optimizer.

Zusammenfassung: Dieser Beitrag schlägt einen neuen Ansatz und Methode zur Verbesserung rekonfigurierbarer Systeme mit Self-x-Eigenschaften für Industrie 4.0

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vor. Dabei sollen robuste Lösungen auch bei Präsenz von Unsicherheit in Ein- und Ausgangsstufen des Systems erhalten werden. Ein Varianzmaß wird eingesetzt um die eingangsseitige Unsicherheit des Suchraums zu erfassen. Sofern die Unsicherheit des Mess- bzw. Zielraumes betrachtet wird, wird eine Archiv-basierte Methode verwendet, die keine zusätzlichen Rechnenresourcen benötigt. Ein bewährtes Optimierungsverfahren, das sogenannte Partikel-Schwarm-Optimierungsverfahren (PSO), wurde für die Ziele dieser Arbeit angepasst, indem der Selektionsprozess mit der hier vorgeschlagenen Verfahrensweise erweitert wurde. Die Tauglichkeit des erweiterten Verfahrens wurde für gegebene Unsicherheiten anhand von üblichen Benchmark-Problemen untersucht und bestätigt. Die vorgeschlagene Methode wurde dann an der extrinsischen Optimierierung bzw. Dimensionierung eines einfachen Miller-Operationsverstärkers demonstriert. Dabei wurde die Wirkung von Herstellungstoleranz und Alterung der Bauelemente als eingangseitige Unsicherheit modelliert, die durch nichtideale Beobachter (Sensor, ADC) verursachte als ausgangsseitige Unsicherheit. Die Ergebnisse dieser praxisnahen Anwendung bestätigten ebenfalls die Validität des verfolgten Ansatzes und der implementierten Methode.

Schlüsselwörter: Rekonfigurierbarer Miller Operationsverstärker, universelle integrierte Sensorschnittstelle mit Self-x-Eigenschaften, robuster störungsresistenter Schwarmoptimierer.

1 Introduction and survey

In the past few years, computational intelligence, artificial intelligence and machine learning have attracted enormous attention. Even though previously, the focus was the cloud intelligence and big data analysis, the current focus is the application of machine learning in the area of IoT and

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Industry 4.0 whose fundamental part is Sensors 4.0 [7]. With the introduction of artificial intelligence besides having the self-x (self-calibration, self-healing, etc.) features. these smart integrated systems will have much-enhanced uncertainty suppression capabilities. Although there is a considerable amount of literature [1, 9] about the introduction of self-x features in the integrated circuits: however deviation of calibration systems itself is never discussed. In [2] only one type of deviation, i.e., uncertainty at the input is considered, which leads to unacceptable system performance even after the calibration or optimization. The second type of uncertainty is due to variation in the operating or environmental conditions. While the third type of uncertainty that these smart systems have is the measurement uncertainty (observer uncertainty) due to uncertainty in sensor measurements or modelling error in case of indirect measurements. Because of imperfect observer (sensor or ADC) and it also experiences the same performance degradation as the main integrated circuit is facing. State-of-the-art solutions currently have no answer in which the context of observer uncertainty addressed for the smart chips while the search space and the objective space in the presences of noise become highly unpredictable. This measurement uncertainty can propagate easily in the optimization process and misleading the optimizer results. So, the primary goal of this research article is to design noise immune optimizer that can perform reliably even in the presence of uncertainty in the search and objective space for the self-x systems.

For such a scenario, the concept of robust optimization has the potential to address such problems [10, 12, 13]. As far as selection of optimizer is a concern for practical applications, the derivative-based optimization techniques cannot be utilized because the objective space is discontinuous [11, 12]. On the other hand, meta-heuristic optimization algorithms (MHOAs) perform extremely good even in the presence of discontinuous objective space. For this reason, particle swarm optimization (PSO) is used in this paper for robust optimization. Reconfigurable Miller operational amplifier (opamp) selected as a test vehicle for extrinsic evolution of proposed optimizer that is the integral part of sensory electronics 4.0. Whose transistors widths are serving as tuning knobs and uncertainty at the output is being analyzed by the robust optimizer for its online calibration as shown in figure 1. Currently, there is also ongoing research activity in our institute on the extension of USIX (universal and self-x integrated sensor interface) chip [6] for building the hardware platform for the intrinsic evolution of optimization algorithms.

For tackling the uncertainty of the tuning knobs (fabrication process tolerances and aging effects of the tran-

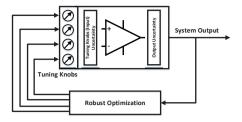


Fig. 1: Block diagram of the proposed system.

sistors), mostly two different methods are being used in the literature: Expectation and Variance Measure [3, 10]. These methods inspect the behaviour of neighbours in the objective space to endorse its robustness. The mathematical expression for expectation measure is given as

$$E(x) = \frac{1}{|B_{\delta}(x)|} \int f(y) dy \tag{1}$$

subject to: $x \in S$

where B_{δ} is the number of neighbor solutions around one possible solution x within the radius δ , S represents the hard constrained feasible region and f(y) is the objective function. In this method, expectation measure substituted the objective function and then the expectation value is optimized. On the other hand, variance measure can be express mathematically as

$$V(x) = \frac{|F(x) - f(x)|}{|f(x)|} \le \eta$$
 (2)

subject to: $x \in S$

where η represent the thresholds value which can be set manually or adaptively [12] and F(x) is worst result function among the selected solutions and f(x) is current objective function evaluation. In this method, if variance in the objective function is above the given threshold, then the objective function will be penalized to stop further agents to go into that region. It does not require any further computation.

For output uncertainty, normally archive-based or surrogate-based techniques are preferred because they do not require any additional measurement computations. While the surrogate-based technique introduces one more level of uncertainty so it is not the part of this article [3, 10, 14]. Archive-based noise suppression method works well for the meta-heuristic optimization algorithms due to enormous exploring capability of search particles during optimization process at the cost of additional memory resources. At the start, because exploitation of optimization is high, the optimizer might select wrong optimum solution due to presence of noise, but as exploration goes up, it quantifies its correctness with the help of archive.

Proposed solution

As already mentioned in the literature review, MHOAs are right candidate for the real-world optimization problems. Although the proposed noise immune optimization is implemented on PSO, but it is applicable for any metaheuristic optimization. The basic structure of the PSO is same as first time presented by Eberhart [5]. The flowchart for the proposed noise immune robust particle swarm optimizer (NIRPSO) is presented in the figure 2. The basic architecture of NIRPSO is similar to confidence-based robust optimization presented in [10], but NIRPSO also take into account the measurement uncertainty.

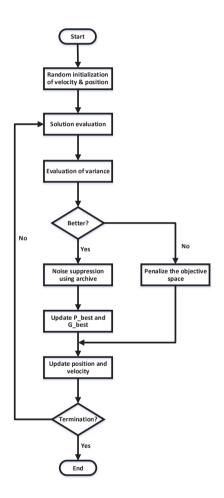


Fig. 2: Flow diagram of NIRPSO.

NIRPSO begins with random initialization of velocity and position of the particles. Then the evolution of cost function for each particle is performed. Variance of particles is being evaluated in order to confirm their robustness within the specified limits of input uncertainty. If the

variance measure is above the acceptable threshold, then the objective function is being penalized to stop further particles exploration in this region. While for the opposite scenario, the algorithm search in the archive for the similar solutions for the sake of uncertainty suppression. Due to explorative nature of MHOAs, archive-based uncertainty suppression is the most dominating candidate. In case of better fitness value of the particle than the particle's personal or global best, corresponding field is being updated. At the end, the particle's velocity and position value is being amended, and this process continues until the end of maximum iteration.

The value used for $c_1 = c_2 = 2$ after varying them within the specified intervals although it has no significant impact on the performance of the optimizer. The parameters of NIRPSO are as follows

- $c_1 = [0.5,2]$ (Cognitive scaling factor).
- $c_2 = [0.5,2]$ (Social scaling factor).
- $w = w_{\text{max}} \text{currentIteration} \left(\frac{w_{\text{max}} w_{\text{min}}}{\text{maxIteration}} \right)$ $w_{\text{max}} = 0.9$ and $w_{\text{min}} = 0.1$ (Inertia).
- Initial velocity = 0.
- Maximum velocity = 20 % of upper bond of particle position.
- Pbest is particles personal best.
- Gbest is Swarm's best-known position.

Results

In order to see the behavior of proposed NIRPSO three bench marking (BM) functions are selected from the literature [10]. This experiment was carried out using 30 particles and 150 iterations all other initialization parameters were kept the same as mentioned in the above section. In the figure 3 the first column shows the BM function while the second column shows the convergence curves. The convergence curve shows the degrading behavior over these BM functions. In case of BM3 it takes below 50 iterations while it takes above 50 iterations for other two functions. To achieve convergence takes considerable amount of time due to presence of uncertainty. NIRPSO becomes confident with the passage of iterations minimizing the uncertainty level for these BM functions from 10 % to approximately 1.8 % that can be improved further by increasing number of iterations.

NIRPSO is also applied on Miller opamp for its extrinsic design. The circuit of Miller opamp is implemented using CMOS 0.35 µm technology from Austriamicrosystems (AMS) and it is shown in figure 4. For this problem six main objectives: slew rate (SR) $\geq \frac{10 \text{ V}}{\text{usec}}$, input common

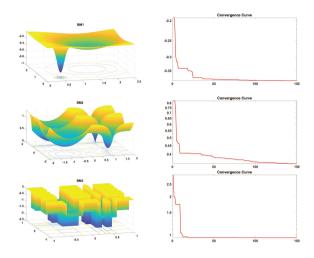


Fig. 3: Behaviour of NIRPSO on BM1, BM2, BM3.

mode range (ICMR) $[-1\,\mathrm{V},1\,\mathrm{V}]$, gain $\geq 80\,\mathrm{dB}$, bandwidth $\geq 10\,\mathrm{MHz}$, phase margin (PM) $\geq 60^\circ$ and power dissipation $\leq 2\,\mathrm{mW}$ are considered. An agglomerative approach is employed for the multi-objective optimization; details can be found in our institution's former research work [8]. For this experiment, the biasing current is supposed to be 30 μ A and biasing transistors Q_b is also assumed to be 3 μ m in order to provide stable biasing voltage. Furthermore, the length of all transistors are kept constant to 1 μ m for the sake of channel length modulation effects minimization and NIRPSO only varies the width which makes total seven parameters. The problem is formulated as follows:

suppose $\vec{x} = w_i, i = 1, 2,, 7$

$$f(\vec{x}) = \begin{cases} \frac{\text{out} - spec}{spec} & \text{for minimum search} \\ \frac{spec}{spec} & \text{for maximum search} \end{cases}$$
 (3)

while \vec{x} represents the width of transistor and $f(\vec{x})$ is objective function. More details about it can be found in [8] because the main focus of this article is the presence of uncertainty in search and objective space. Spread of deviation at the input level, i.e., in the widths of transistors is considered as 1 μ m.

From the transistors sizing as illustrated in the figure 4, the performance of non-robust is much better than the robust solution in terms of area and power dissipation. On the other hand, if there are any process variations at the input side (widths of transistors from -1 μm to 1 μm), then the performance of non-robust deviates considerably from the nominal value as specified in the table 1. These deviations are illustrated graphically as well in figure 5, where first column represents the robust solution, and second column represents the non-robust solution. The deviation

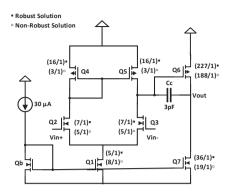


Fig. 4: The schematic of Miller opamp, ratios represent the width to the length of the transistors and all dimensional are in μ m.

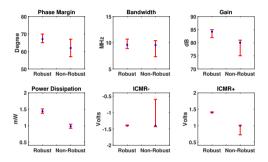


Fig. 5: Plot of error bars for robust and non-robust solution.

for ICMR- is almost 40 % below the acceptable limits while for gain-bandwidth product it is approximately 26 %. In case of robust solution, the magnitude of deviation is not too large, and it is always above the desired specifications except the gain-bandwidth product where deviation is approximately 8 % of the nominal value.

Table 1: Specification deviation of robust and non-robust solution

	$\frac{SR}{(\frac{V}{\mu sec})}$	Gain (dB)	Bandwidth (MHz)	PM (0)	Power (mW)	ICMR (V)
Without Perturbation	i					
Robust	15.0	84.1	9.9	67	1.45	[-1.40, 1.40]
Non-Robust	22.7	80.0	9.9	62	0.98	[-1.40, 1.10]
With Perturbation						
Robust (maximum)	18.0	85	10.7	70	1.51	[-1.41, 1.41]
Non-Robust (maximum)	25.2	81	10.4	67	1.0	[-1.43, 1.20]
Robust (minimum)	12.0	83	9.1	65	1.4	[-1.40, 1.40]
Non-Robust (minimum)	20.1	75	7.3	58	0.9	[-0.60, 0.70]

The NIRPSO also reduces the output root mean square error from 4.24 % to 0.56 % with the help of archive method. In order to illustrate measurement uncertainty suppression capabilities of NIRPSO the voltage response of Miller opamp in unity configuration for robust particles is also measured. Figure 6 shows the comparison

between the ideal output signal and the predicted output signal of NIRPSO along with the noisy output signal due to observer uncertainty with only five particles and 80 iterations. The NIRPSO recalibrate the self-x system even in the presence of uncertainty at the input and being able to reduce the uncertainty level of output and give us reliable solution. The performance of system can be improved further by increasing the number of iterations.

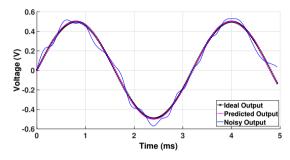


Fig. 6: Comparison of the ideal observer, the noisy observe, and NIRPSO predicted output.

4 Conclusions

In this article, two types of uncertainties and their solutions for reconfigurable self-x sensory systems of industry 4.0 are discussed. The proposed NIRPSO has the potential to work reliably even in the presence of the uncertainty at the input and the output. For input uncertainty variance measure is used to avoid non-robust solution while for output uncertainty, an archive-based method is utilized for minimizing the uncertainty level. Although the proposed scheme is implemented on PSO, it can be modified easily for any evolutionary algorithm. The performance of NIRPSO is evaluated with three different single objective BM functions. Finally, the extrinsic optimization of NIRPSO is evaluated on the Miller opamp circuit. The NIRPSO gave us reliable solution even in the presence of uncertainties besides that it also suppressed the uncertainty level at the output stage. In the future work, selection of a threshold for variance measure will be performed automatically. As far as intrinsic evolution of NIRPSO is concerned our institute is also working on an implementation of the reconfigurable sensory self-x system for industry 4.0. Lastly, the proposed NIRPSO will be modified by hybrid evolutionary algorithms for handling multi-objective problem without the need of agglomerative approach anymore [4].

References

- M. Andraud, H.-G. Stratigopoulos, and E. Simeu. Oneshot non-intrusive calibration against process variations for analog/rf circuits. IEEE Transactions on Circuits and Systems I: Regular Papers, 63(11):2022-2035, 2016.
- [2] M. J. Barragan, G. Leger, A. Gines, E. Peralias, and A. Rueda. On the limits of machine learning-based test: a calibrated mixed-signal system case study. In Proceedings of the Conference on Design, Automation & Test in Europe, pages 79-84. European Design and Automation Association, 2017.
- H.-G. Beyer and B. Sendhoff. Robust optimization—a compre-[3] hensive survey. Computer methods in applied mechanics and engineering, 196(33-34):3190-3218, 2007.
- M. Z. bin Mohd Zain, J. Kanesan, J. H. Chuah, S. Dhanapal, and G. Kendall. A multi-objective particle swarm optimization algorithm based on dynamic boundary search for constrained optimization. Applied Soft Computing, 70: 680-700. 2018.
- R. Eberhart and J. Kennedy. A new optimizer using particle swarm theory. In MHS'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science, pages 39-43. leee, 1995.
- R. Freier. Ein universelles und dynamisch rekonfigurierbares Interface für eingebettete und intelligente Multi-sensorsysteme mit self-x Eigenschaften. 2015.
- G.-B. Huang, E. Eleftheriou, D. Kudithipudi, J. Tapson, and H. Yu. Guest editorial: Special issue on new trends in smart chips and smart hardware. IEEE Transactions on Emerging Topics in Computational Intelligence, 3(1):1-3, 2019.
- A. C. Kammara, L. Palanichamy, and A. König. Multiobjective optimization and visualization for analog design automation. Complex & Intelligent Systems, 2(4):251-267, 2016
- S. Lee, C. Shi, J. Wang, A. Sanabria, H. Osman, J. Hu, and [9] E. Sánchez-Sinencio. A built-in self-test andin situanalog circuit optimization platform. IEEE Transactions on Circuits and Systems I: Regular Papers, 65(10):3445-3458, 2018.
- [10] S. Mirjalili, A. Lewis, and S. Mostaghim. Confidence measure: a novel metric for robust meta-heuristic optimisation algorithms. Information Sciences, 317:114-142, 2015.
- [11] P. Rakshit and A. Konar. Recent advances in evolutionary optimization in noisy environment—a comprehensive survey. In Principles in Noisy Optimization, pages 89-169. Springer, 2018.
- P. Rakshit, A. Konar, S. Das, L. C. Jain, and A. K. Nagar. Uncertainty management in differential evolution induced multiobjective optimization in presence of measurement noise. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 44(7):922-937, 2013.
- [13] P. Rakshit, A. Konar, and S. Das. Noisy evolutionary optimization algorithms-a comprehensive survey. Swarm and Evolutionary Computation, 33:18-45, 2017.
- [14] A. Schütze and N. Helwig. Sensorik und messtechnik für die industrie 4.0. tm-Technisches Messen, 84(5):310-319, 2017.