A Novel Solution based on Multi-Objective AI Techniques for Optimization of CMOS LC_VCOs

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***Abstract*— A method of optimizing components and transistors sizing for CMOS Cross-Coupled LC voltage controlled oscillators is presented in this paper. The design constrains of power consumption, phase noise, and the Figure of Merit (FoM) of LC_VCOs are applied on Multi-Objective AI techniques, simultaneously. The design parameters of LC_VCOs are obtained from the two strong algorithms, the Multi-Objective Inclined Planes system Optimization (MOIPO) and the Multi-Objective Particle Swarm Optimization (MOPSO). It was implemented in MATLAB, to the Pareto Optimal Front (POF) solutions, which have an amazingly trade-off between three objective functions. The LC_VCO circuits were simulated using this method in a 0.18µm-CMOS process by HSPICE RF environment. The results show that the size of components of the PMOS-only and NMOS-only integrated LC_VCOs and the optimal trade-off curve between minimum power and minimum phase noise.**

***Index Terms*— Artificial intelligence techniques, cross-coupled LC_VCOs, Multi-Objective Inclined Planes system Optimization (MOIPO), Multi-Objective Particle Swarm Optimization (MOPSO).**

I. INTRODUCTION

Optimization is a mature technology that has been studied extensively by researchers over the last half century [1]. Over the years, optimization methods have evolved considerably and many algorithms and implementations are now available and used in the engineering optimization community. Artificial Intelligence (AI) techniques, such as neural network models, fuzzy logic, expert systems, and heuristic and evolutionary algorithms, are expected to play important roles in solving complex engineering designs. The Voltage-Controlled Oscillator (VCO) is one of the most important blocks in RF communication systems. It is still a challenge to achieve a good performance with low phase noise, low power consumption and wide frequency tuning [2]. There has to be a trade-off among those key requirements and finally, the optimal FoM. VCOs are vital components of PLL circuits, which play an indispensable role in Radio Frequency (RF) Integrated Circuits (IC) for wireless communications like Bluetooth or Wireless Local Area Network (WLAN) [3].

In the design of oscillator circuits, designers often aim at both minimum phase noise and minimum power consumption for a given oscillation frequency. Since, these two objectives are contradictory, this tradeoff is reflected in the Figure-of-Merit (FoM) as follows, where ω_0 is the oscillation frequency, P is the DC power consumption, $\Delta\omega$ is the offset from the output frequency and $L(\Delta\omega)$ is the oscillator phase noise. Given by following equation, the original lesson's equation, where, Q is the loaded quality factor of the oscillator, k is the Boltzmann's constant, T is the absolute temperature, P_{sig} is the oscillation output power, F is the noise factor of the amplifier and $\Delta\omega_1/f_3$ is the corner frequency between ω_1/f_2 and ω_1/f_3 portion of the phase noise spectrum [3].

$$FoM = L(\Delta\omega) + 10\log\left[\frac{P}{1mW}\cdot\left(\frac{\Delta\omega}{\omega_0}\right)^2\right] \tag{1}$$

$$L(\Delta\omega) = 10\log\left\{\frac{2FkT}{P_{sig}}\left[1+\left(\frac{\Delta\omega}{2Q\Delta\omega}\right)^2\right]\cdot\left(1+\frac{\Delta\omega_1/f_3}{|\Delta\omega|}\right)\right\} \tag{2}$$

Different LC_VCO design methodologies have been proposed, either to achieve low phase noise [2], or low power [4], or targeting low FOM [5]. But as discussed in [6], there are several challenges in RFIC design in improving the important circuit parameters, i.e. power, noise, linearity, gain, power supply and frequency. In LC_VCOs there are only some imprecise formulas as the rule of thumb for calculation of phase noise and power consumption. Therefore, the design of an optimized LC_VCO needs many time-consuming, and perhaps blind, trials and errors. Utilizing Multi-Objective evolutionary techniques such as Inclined Planes system Optimization (MOIPO) and Particle Swarm Optimization (MOPSO) algorithm can turn these blind attempts into an organized series of iterations directed at obtaining power, phase noise, and FoM-optimized designs for LC_VCOs (e.g. NMOS-only and PMOS-only). The multi-objective algorithms MOIPO and MOPSO can produce pareto fronts and trade-off diagrams. Phase noise, power consumption, and FoM as the three major objectives are used in the form of a unique technique. HSPICE RF and HBOSC analysis are used for simulation. There are other optimization algorithms that were used to optimize RF circuit [2], [7]-[12]. Furthermore, in the three SA, IPO, and PSO, the objectives were merged into a unique objective using a weighting technique.

In the next section, the cross-coupled LC_VCOs that was chosen as an application example for the proposed technique is presented. Section 3 presents a case study of the proposed tool/technique and a brief description of the algorithms used. Section 4 details the constraints and performance/fitness functions models that were taken into account in the proposed optimization technique. Section 5 presents the simulation results and compares the performance of LC_VCOs. Finally, the conclusions are offered in section 6.

II. LC_VCO DESCRIPTION

During the design, two VCO architectures were taken into consideration (see Fig. 1). When dealing with high frequency applications, LC_VCO circuits are preferred to other proposed oscillator structures, such as the ring oscillators [7]. Different structures of LC oscillators have been already studied. In fact, the CMOS cross-coupled LC_VCO offers better rise- and fall-time symmetry, which results in a smaller $1/f^3$ noise corner. In addition, the VCO bias current must be doubled for the NMOS structure to obtain the same tank amplitude as in CMOS structure [7].

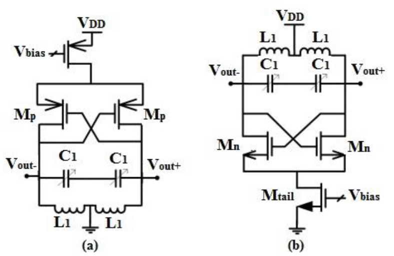

Figure 1: a) The PMOS-only cross coupled LC_VCO, b) NMOS-only cross coupled LC_VCO

III. ARTIFICIAL INTELLIGENCE TECHNIQUES FOR OPTIMIZATION OF CMOS LC_VCOS

In the past few decades, there has been a widespread interaction between researchers seeking for various AI methods to determine the best solutions for a given function. The AI techniques are developed by mimicking or simulating the processes found in nature.

A. Multi-Objective Optimization

Pareto Optimality: Multi-Objective Optimization problems consist of simultaneously optimizing several objective functions [13]. It considers, without the loss of generality, the minimization of the *n* components F_k , *k=1,…,n* of a vector function *F* of a vector variable *x* in a search space $\varphi \subseteq R^m$, with

$$F(X)=[F_1(x),\ldots,F_n(x)]^T \tag{3}$$

It is assumed that all the F_i take on real values so that ordering is possible. If the different objectives are competitive, there is no meaningful solution to this problem because it is not possible to evaluate the relevance of each objective with respect to the others. The most accepted concept of optimality for multi-objective problems is the pareto optimality which is defined as follows:

Pareto Optimality. A given $x^* \in \varphi$ is said to be pareto optimal or non-inferior if there is no other $x \in \varphi$ such that

$$\forall i \in \{1,\ldots,n\}, \tag{4}$$

$$F_i(x) \le F_i(x^*) \wedge \exists j \in \{1,\ldots,n\} | F_j(x) \le F_j(x^*) \tag{5}$$

For a given multi-objective problem, the pareto-optimal set *P* is the set of all the $x \in \varphi$ that are pareto-optimal and the pareto front P^f is the set of all the optimal vector function values [13].

B. Multi-Objective Particle Swarm Optimization (MOPSO) Algorithm

Particle Swarm Optimization (PSO) [14] is a stochastic meta-heuristic created to optimize nonlinear functions based on the movement of bird flocks looking for food. In this method, a swarm (population) of particles (solutions) moves across the search space (evolve) guided by personal and social leaders. To expand a PSO algorithm into a MOPSO, two main modifications are usually done: the creation of an external repository to store the non-dominated solutions, and the use of a leader selection method to select a global leader for the particles among a set of equally good solutions according to some criterion. When the external repository becomes full, an archiving strategy is needed to prune it and keep it on a predefined size, discarding some non-dominated solutions based on some criterion. This criterion has great impact in the quality of the solutions generated in the search, especially in many-objectives due to the large portion of the population that becomes non-dominated. There are many approaches in the literature to manage the repository, and a comparison among some of them is done in [15]. Additionally, two of the approaches that prune the repository and presented good results are the Ideal and Multilevel Grid Archiving (MGA) archives [15].

Since there is no single optimal solution in MOPs, a leader selection method is also needed, and this method has impact on the quality of the solutions as well. A comparison between some of the leader selection methods available in the literature is presented in [15], and three of them that had good results are the Crowding Distance (CD) and NWSum method [15]. Another aspect that has been observed in a MOPSO is that in some conditions the velocity of the particles can become too high, generating erratic movements towards the limits of the decision space. To avoid such situations, the Speed-constrained Multi-objective PSO (SMPSO) algorithm presents a velocity constriction mechanism based on a factor x that varies based on the values of the influence factor of the social (C_1) and personal (C_2) leaders. In SMPSO, the crowding distance metric is used in both, the leader selection method and the archiving strategy. Due to its good results in the literature, SMPSO is an algorithm frequently used as a reference [15].

C. Multi-Objective Inclined Planes system Optimization (MOIPO) Algorithm

The method of IPO is designed based on the dynamic of sliding motion along a frictionless inclined surface [16]. In this algorithm each agent, named “tiny ball” (similar to the particles in PSO) searching the problem space to find the optimum solution. In nature and on surface of the earth, when an object (here, tiny ball) is elevated, it loses potential energy and automatically goes to lower elevation levels. These phenomena in physic are named as the gravitational force which applies to any objects by the earth.

In IPO algorithm, each ball has 3 specifications: position (x), height (h) and angels (ϕ) in relation to the other balls. Ball's positions are feasible solutions for the problem and fitness function is used to calculate the height of each ball. For a clear explanation, we assume a system by N ball as the following:

$$x_i^{\min} \le x_i \le x_i^{\max}, \quad 1 \le i \le N_d \tag{6}$$

where x_i is a decision variable, i is the dimension and N_d is the number of dimension. An example of search space in IPO algorithm is shown in Fig. 2 with 3 balls. The purpose of IPO is to find the minimum of fitness function $f(x_1,x_2,\ldots,x_{Nd})$ which is defined on the problem space. The angle between the *i-th* ball and *j-th* one at interval t is calculated in the following equations where, $f_j(t)$ is the value of fitness function (height) for the *i-th* ball in time t.

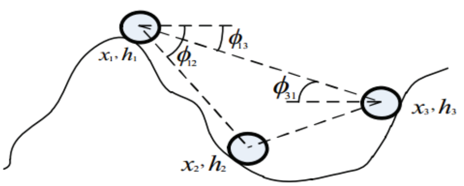

Figure 2: An example of search space with 3 balls (in IPO)

$$\phi_{ij}^d(t) = \left(\tan^{-1}\left(\frac{f_j(t) - f_i(t)}{x_i^d(t) - x_j^d(t)} \right) \right), \tag{7}$$

for d=1,…,n and i,j=1,2,…,N, i≠j

The acceleration amount and direction are calculated using the following equations:

$$a_i^d(t) = \sum_{j=1}^{N} U(f_j(t) - f_i(t)).\sin(\phi_{ij}^d(t)), \tag{8}$$

where $U(.)$ is the unit step function:

$$U(w) = \begin{cases} 1 & w > 0 \\ 0 & w \le \end{cases} \tag{9}$$

In each iteration of IPO algorithm, the position of each ball is updated by using the following equations, in which k_1 and k_2 are two changing constants with time, $rand_1$ and $rand_2$ are two random variables in the range [0 1] and $v_i^d(t)$ is *i-th* ball velocity in dimension d in time t. x_{best} is the best ball position until current iteration.

$$x_i^d(t+1) = k_1.rand_1.a_i^d(t).\Delta t^2 + k_2.rand_2.v_i^d(t).\Delta t + x_i^d(t), \tag{10}$$

$$v_i^d(t) = \frac{x_{best}^d(t) - x_i^d(t)}{\Delta t}, \tag{11}$$

$$k_1(t) = \frac{c_1}{(1 + \exp((t - shift_1) \times scale_1))}, \tag{12}$$

$$k_2(t) = \frac{c_2}{(1 + \exp((t - shift_2) \times scale_2))}, \tag{13}$$

In the above equations c_1, c_2, $shift_1$, $shift_2$, $scale_1$ and $scale_2$ are experimentally determined constants for each function [10], [16].

In MOIPO, the algorithm of pareto optimality method is used to identify non-dominant position and it uses an external repository for maintaining the positions [17]. The initial population is randomly generated according to the specified range, then the fitness of population is calculated and eventually the best balls in an external repository (Pareto Solutions) are maintained.

Next according to the IPO algorithm, the position of the ball for the next iteration of the algorithm is updated. This update includes putting all the balls that are not currently dominant in the tank. Simultaneously, each ball that has been dominated by the process of the tank can be removed. Each time the tank of limitations has passed, and considering that the storage capacity is limited, it is imputed proportional to the number of balls in each of hypercube to every possible hypercube and by the roulette wheel, hypercube selected and randomly surplus points will be removed. This process continues until the storage capacity reaches to a quorum [17].

IV. THE PROPOSED TECHNIQUE

Using the proposed optimization tool, several LC_VCOs with different f_{osc} were optimized and simulated. In this paper, we use two multi-objective meta heuristic called the MOPSO and MOIPO. These algorithms are based on a communication tool between the HSPICE/RF and MATLAB software. In short, this tool works as follows. After generating the circuit's netlist, the parameter's values are introduced in this netlist. Then, the MATLAB calls HSPICE/RF was used to check the constraints and evaluate the performances. These performances are then introduced in the optimization algorithm and 'new' parameter's values are generated, etc [17]. Next, each configuration of the LC_VCOs is optimized as depicted in Fig. 1. So, each one is designed for wide oscillation frequency in a 0.18µm-CMOS technology, in which the following conditions are satisfied while the phase noise, power consumption, and FoM, are used in the form of a unique technique, which are optimized simultaneously. The user-defined constraints are the size of transistors, inductors, bias voltage (V_{bias}), capacitors and quality factor of inductors. The design considerations can be stated as follows:

Optimize = *phase noise & power consumption & FoM*

The user-defined constrains are listed in Table 1.

Table 1
The User-Defined Constraints

Design Considerations	Parameter	Unit	Value
oscillation frequency	f_{osc}	GHz	1.1–2.3
width of transistors	$W_{n,p,tail}$	µm	10–100
length of transistors/technology	L	µm	0.1–0.2
bias voltage	V_{bias}	V	0.55–1
inductors	$L1$	nH	1–9
capacitors	$C1$	pF	1–7
quality factor of inductors	Q	–	7–13
power supply	V_{DD}	V	1.8

The proposed optimization tool optimized each structure and determined the value of design variables, transistors sizes, tank inductances and capacitances and bias voltage (V_{bias}) of tail transistor. For simplification of implementation, in circuit (Fig. 1) of any two sorts of cross-coupled LC_VCOs, inductors are connected to resistor as serial and Q inductors were considered with this resistor (Fig. 3). Capacitances were considered pure. MOSFETs were considered with capacitances and resistors parasitic using parasitic models in radio frequency.

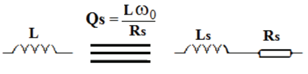

Figure 3: Inductance model

When MOIPO and MOPSO are applied as two optimizer core in MATLAB, any ball or particle is included with a value of design variables. Some parameters of MOIPO and MOPSO algorithms are shown in Table 2 and 3.

Table 2
Some Parameters of MOIPO Algorithm

MOIPO	Parameters						
	iter.	*balls*	*Nrep*	c_1	c_2	$scale_1$	$scale_2$
Value	20	17	100	6.3	2.3	0.71	0.93
MOIPO	*shift1*		*shift2*	*alpha*	*Ngrid*	*beta*	*gamma*
Value	10.1		14.1	0.1	10	4	2

Table 3
Some Parameters of MOPSO Algorithm

MOPSO	Parameters					
	iteration	*particles*	*Nrep*	*C1*	*C2*	*W*
Value	20	17	100	3	2	1
MOPSO	*Wdamp*	*alpha*		*Ngrid*	*beta*	*gamma*
Value	0.95	0.1		10	4	2

V. RESULTS

The design of two sorts of cross-coupled LC_VCOs is performed using of mathworks MATLAB R2013b. Simulation temperature was a default temperature, (i.e. 25C). Implementation is carried out with MSI CX41, Intel (R) Core (TM) i5-3230M CPU @ 2.60GHz processors, 6GB RAM. The fitness functions and the limitations are examined by HSPICE A-2010.03-SP1, simulation software. Using the introduced multi-objective evolutionary algorithms, the trade-off curves (Pareto Front) are shown in Figure 4 to 7 for each of the algorithms, for NMOS-only and PMOS-only LC_VCOs, are obtained. Note that only trade-off for both objectives phase noise and power have been drawn (due to the conflict between them).

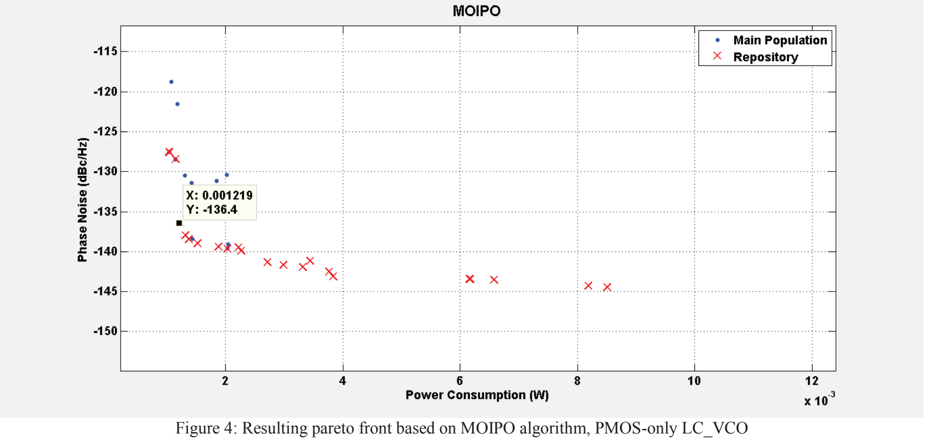

Figure 4: Resulting pareto front based on MOIPO algorithm, PMOS-only LC_VCO

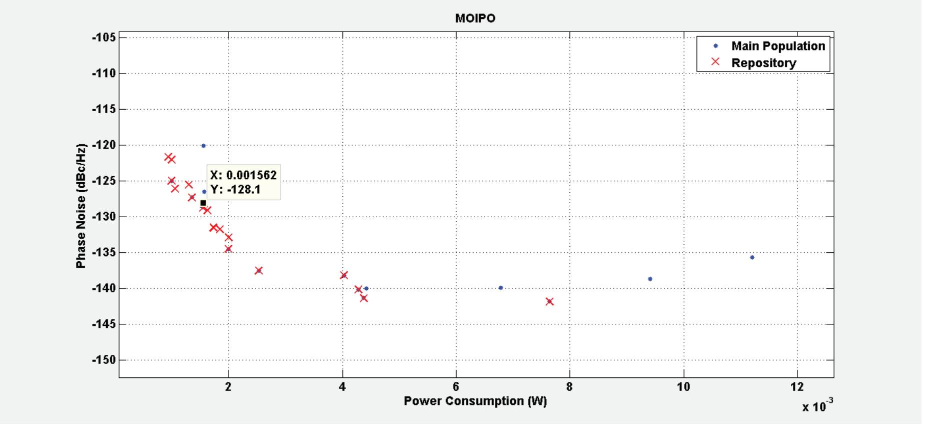

Figure 5: Resulting pareto front based on MOIPO algorithm, NMOS-only LC_VCO

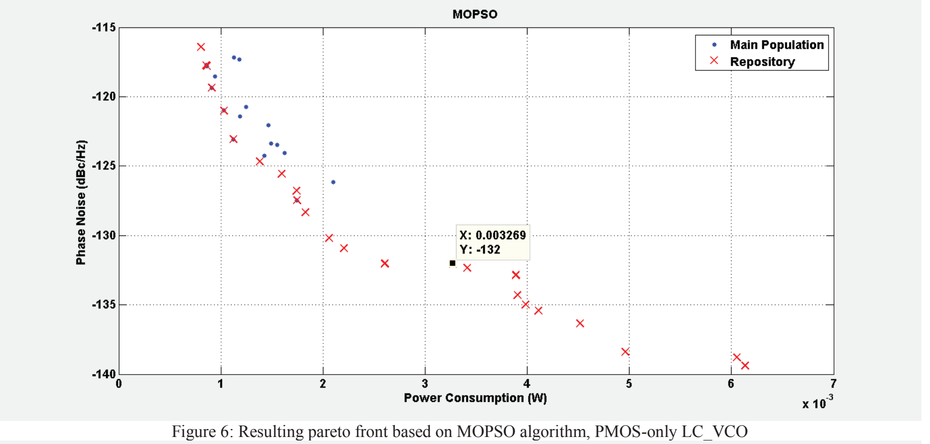

Figure 6: Resulting pareto front based on MOPSO algorithm, PMOS-only LC_VCO

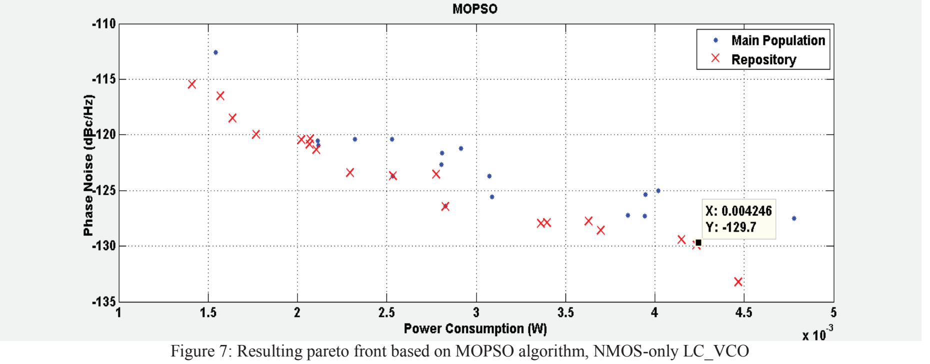

Figure 7: Resulting pareto front based on MOPSO algorithm, NMOS-only LC_VCO

The simulation results of phase noise using the HBOSC method with HSPICE RF are shown in Figure 8 to 11.

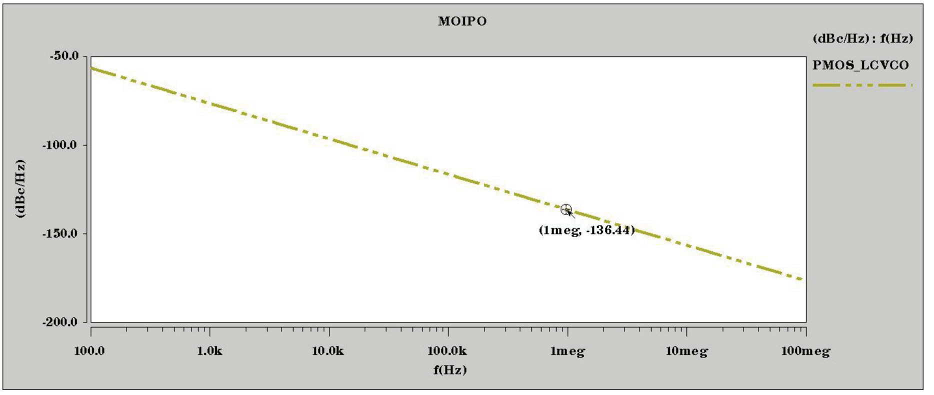

Figure 8: The simulated phase noise using the HBOSC method based on MOIPO algorithm, PMOS-only LC_VCO

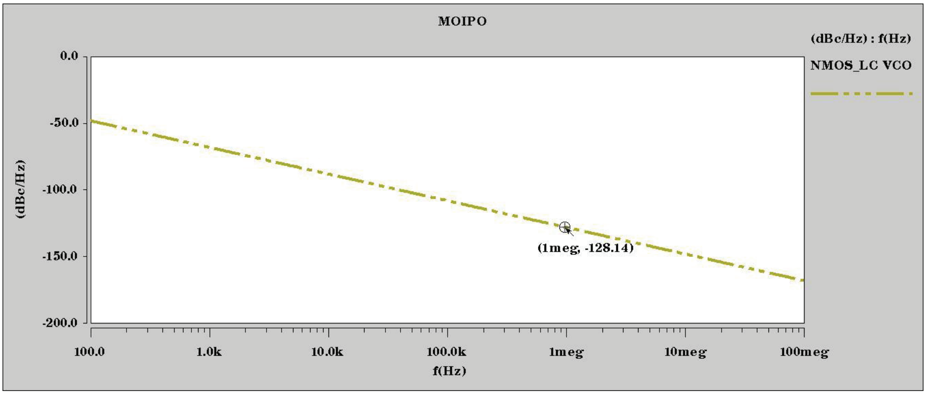

Figure 9: The simulated phase noise using the HBOSC method based on MOIPO algorithm, NMOS-only LC_VCO

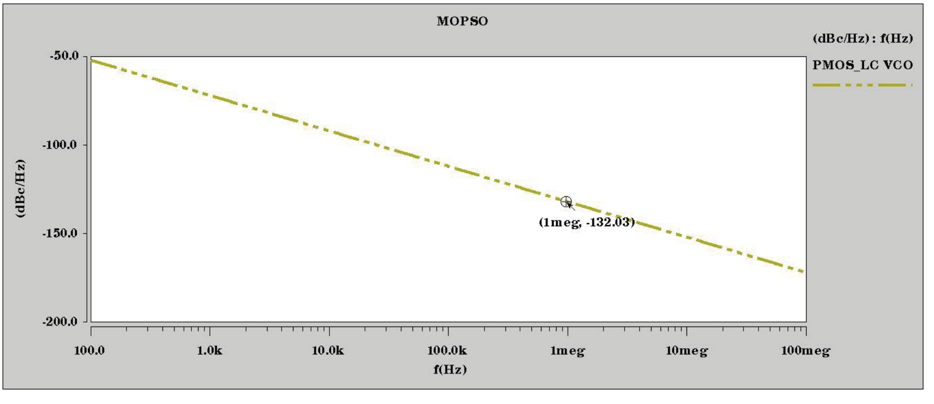

Figure 10: The simulated phase noise using the HBOSC method based on MOPSO algorithm, PMOS-only LC_VCO

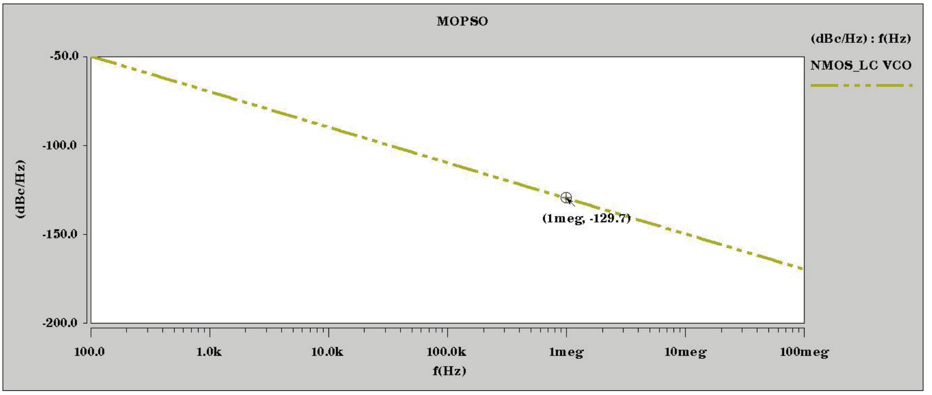

Figure 11: The simulated phase noise using the HBOSC method based on MOPSO algorithm, NMOS-only LC_VCO

Each point on pareto front presents an optimized design. Therefore, the designer can select each configuration, and extract the circuit parameters for his/her desirable design. The extracted data for each configuration are presented in Table 4 to 7.

Table 4
The Extracted Data for each Configuration (Pareto front Solutions) based on MOIPO Algorithm for NMOS-only LC_VCO

Pareto front Solutions↓	Parameters				
	$L_{n,tail}$ (μm)	W_n (μm)	W_{tail} (μm)	$L1$ (nH)	$C1$ (pF)
1	0.1528	52.59	20.94	4.129	10
2	0.1530	63.41	26.36	3.603	1.412
3	0.1786	60.55	26.35	3.555	1.753
4	0.1589	63.72	26.46	3.452	1.361
	V_{bias} (mV)	f_{osc} (GHz)	power (mW)	phase noise (dBc/Hz)	FoM (dBc/Hz)
1	650	2.16	1.3	-125.56	191.14
2	650	1.98	1.6	-129.11	192.94
3	650	1.83	1.4	-127.29	191.26
4	650	2.05	1.6	-128.14	192.4

Table 5
The Extracted Data for each Configuration (Pareto front Solutions) based on MOPSO Algorithm for NMOS-only LC_VCO

Pareto front Solutions↓	Parameters				
	$L_{n,tail}$ (μm)	W_n (μm)	W_{tail} (μm)	$L1$ (nH)	$C1$ (pF)
1	0.1	56.63	20.55	2.838	1.728
2	0.11	64.58	28.45	3.077	1.494
3	0.111	48.58	20	2.985	1.633
4	0.1	55.60	20	3.106	1.319
	V_{bias} (mV)	f_{osc} (GHz)	power (mW)	phase noise (dBc/Hz)	FoM (dBc/Hz)
1	745.44	2.105	3.6	-127.76	188.64
2	721.73	2.109	4.1	-129.44	189.75
3	783.36	2.114	4.2	-129.93	190.17
4	752.46	2.254	4.2	-129.70	190.37

Table 6
The Extracted Data for each Configuration (Pareto front Solutions) based on MOIPO Algorithm for PMOS-only LC_VCO

Pareto front Solutions↓	Parameters				
	$L_{p,tail}$ (μm)	W_p (μm)	W_{tail} (μm)	$L1$ (nH)	$C1$ (pF)
1	0.1797	10	19.88	4.972	1.875
2	0.1735	10	10	4.991	1
3	0.1794	10	10.02	4.969	1.218
4	0.1686	10	10.26	5	1
	V_{bias} (mV)	f_{osc} (GHz)	power (mW)	phase noise (dBc/Hz)	FoM (dBc/Hz)
1	749.13	1.62	2.3	-139.89	200.56
2	108.21	2.198	1.2	-136.44	202.42
3	758.46	2.009	1.2	-128.42	193.86
4	818.94	2.204	1	-127.54	194.22

Table 7
The Extracted Data for each Configuration (Pareto front Solutions) based on MOPSO Algorithm for PMOS-only LC_VCO

Pareto front Solutions↓	Parameters				
	$L_{p,tail}$ (μm)	W_p (μm)	W_{tail} (μm)	$L1$ (nH)	$C1$ (pF)
1	0.159	51.15	44.93	2.327	2.426
2	0.157	56.53	43.10	2.038	2.346
3	0.149	59.75	42.86	2.415	2.750
4	0.156	54.90	44.96	1.930	2.345
	V_{bias} (mV)	f_{osc} (GHz)	power (mW)	phase noise (dBc/Hz)	FoM (dBc/Hz)
1	870.99	2.02	4	-134.99	195.1
2	900	2.18	3.4	-132.32	193.8
3	863.45	2.25	3.9	-132.85	194.0
4	880.97	2.32	3.3	-132.03	194.2

The results of the comparison between performances obtained from using the proposed technique are presented in Figure 4 to 11 and Tables 4 to 7, and some of the published papers [3], [10], [12], [18]-[20]. It is obviously clear that new

MOIPO algorithm and MOPSO algorithm could reach to the optimum results for the design of cross-coupled LC_VCOs. Furthermore, the new MOIPO algorithm shows better results than the PSO algorithm in optimization of two sorts Cross-Coupled LC_VCOs. Therefore, by using an appropriate multi-objective approach, the global minimal is explored and shown to the designer. They represent a significant design trade-off between the phase noise and power consumption with values of power consumption ranging from 1 to 4.2 mW, phase noise from -139.89 to -125.56 dBc/Hz and FoM from 188.64 to 202.42 dBc/Hz, which are a value well within the wireless applications.

VI. CONCLUSION

In this paper, an optimization tool based on two multi-objective evolutionary algorithms, Multi-Objective Inclined Planes system Optimization (MOIPO) and Multi-Objective Particle Swarm Optimization (MOPSO), were presented and applied to the design and optimization of two sorts cross-coupled LC_VCOs in which, the power, phase noise and Figure of Merit (FoM) of the LC_VCOs are minimized simultaneously. The optimized results include a center frequency within 2.1GHz, the medium 2.6mW power consumption, the medium -130.7dBc/Hz phase noise at 1MHz offset, and medium 193.4dBc/Hz FoM. The comparison of results show a promising potential of the proposed tool for wireless and RF applications due to their capability to generate multiple solutions along the Pareto Optimal Front (POF) as well as their efficiency in parallel execution. For future work, the robustness of the proposed algorithm could be tested with transistors in different process corners and then further analysed the performance with statistical analysis.

REFERENCES

[1] Y. S. Ong, "Artificial intelligence technologies in complex engineering design." University of Southampton, 2002.

[2] L. Jia, J. G. Ma, K. S. Yeo, and M. A. Do, "A novel methodology for the design of LC tank VCO with low phase noise," Proceedings - IEEE International Symposium on Circuits and Systems, vol. 10, no. 1, pp. 376–379, 2005.

[3] R. Povoa, R. Lourenco, N. Lourenco, A. Canelas, R. Martins, and N. Horta, "LC-VCO automatic synthesis using multi-objective evolutionary techniques," in Circuits and Systems (ISCAS), 2014 IEEE International Symposium on, 2014, pp. 293–296.

[4] H. Lee and S. Mohammadi, "A subthreshold low phase noise CMOS LC VCO for ultra low power applications," IEEE Microwave and Wireless Components Letters, vol. 17, no. 11, pp. 796–798, 2007.

[5] P. K. Rout, U. K. Nanda, D. P. Acharya, and G. Panda, "Design of LC VCO for optimal figure of merit performance using CMODE," 2012 1st International Conference on Recent Advances in Information Technology, RAIT-2012, pp. 761–764, 2012.

[6] B. Razavi and R. Behzad, RF microelectronics, vol. 1. Prentice Hall New Jersey, 1998.

[7] I. Krout, H. Mnif, M. Fakhfakh, and M. Loulou, "Optimizing LC VCO performances through a heuristic," Wseas Transactions on Electronics, vol. 5, no. 6, pp. 274–281, 2008.

[8] D. J. Allstot, K. Choi, and J. Park, Parasitic-aware optimization of CMOS RF circuits. Springer Science & Business Media, 2003.

[9] J. P. J. Park, K. C. K. Choi, and D. J. Allstot, "Parasitic-aware design and optimization of a fully integrated CMOS wideband amplifier," Proceedings of the ASP-DAC Asia and South Pacific Design Automation Conference, 2003., pp. 904–907, 2003.

[10] M. R. Vakili and S. H. Zahiri, "Parasitic-aware Optimization of a 2.4 GHz Cross-Coupled LC VCO using IPO compared to PSO," in Computer and Knowledge Engineering (ICCKE), 2013 3th International eConference on, 2013, pp. 35–39.

[11] E. Ebrahimi and S. Naseh, "Investigating the performance of cross-coupled CMOS LC-VCOs using genetic algorithm," Proceedings of 21st International Conference Radioelektronika 2011, no. c, pp. 1–4, Apr. 2011.

[12] A. Sallem, P. Pereira, M. Fakhfakh, and H. Fino, "A Multi-objective Simulation Based Tool: Application to the Design of High Performance LC-VCOs," in Technological Innovation for the Internet of Things, Springer, 2013, pp. 459–468.

[13] S. a Ghoreishi, M. a Nekoui, S. Partovi, and S. O. Basiri, "Application of genetic algorithm for solving multi-objective optimization problems in robust control of distillation column," International Journal, vol. 3, no. 1, pp. 32–43, 2011.

[14] J. Kennedy and R. Eberhart, "Particle swarm optimization," Neural Networks, 1995. Proceedings., IEEE International Conference on, vol. 4, pp. 1942–1948 vol.4, 1995.

[15] O. R. Castro and A. Pozo, "A MOPSO based on hyper-heuristic to optimize many-objective problems," in Swarm Intelligence (SIS), 2014 IEEE Symposium on, 2014, pp. 1–8.

[16] M. M. H. Mozaffari, H. Abdy, and S. S. H. Zahiri, "Application of inclined planes system optimization on data clustering," in Pattern Recognition and Image Analysis (PRIA), 2013 First Iranian Conference on, 2013, pp. 1–3.

[17] N. Sayadi and seyed hamid Zahiri, "MOIPO, A New Approach for Multi-Objective Optimization in Information technology," in National Conference on Computer Engineering and IT Management, 2014, p. 10.

[18] M.-T. Hsu, W.-J. Li, and C.-T. Chiu, "Design of low phase noise and low power modified current-reused VCOs for 10GHz applications," Microelectronics Journal, vol. 44, no. 2, pp. 145–151, 2013.

[19] B. S. Sreeja, "Low-power CMOS LC QVCO using zero-biased transistor coupling of MWCNT network-based VCO structure," Microelectronics Journal, vol. 45, no. 2, pp. 196–204, 2014.

[20] H. R. Sadr and M. Dousti, "Purification of inductors and improvement of phase noise in monolithic differential LC-VCOs," AEU - International Journal of Electronics and Communications, vol. 66, no. 2, pp. 128–132, 2012.