Addressing the 5G Cell Switch-off Problem with a Multi-objective Cellular Genetic Algorithm

Francisco Luna, Rafael M. Luque-Baena, Jesús Martínez
Dept. of Languages and Computer Science
Universidad de Málaga
Málaga, Spain
Email: {flv,rmluque,jmcruz}@lcc.uma.es

Juan F. Valenzuela-Valdés, Pablo Padilla
Dept. Signal Theory, Telematics and Communications
Universidad de Granada
Granada, Spain
Email: {juanvalenzuela,pablopadilla}@ugr.es

***Abstract*—The power consumption foreseen for 5G networks is expected to be substantially greater than that of 4G systems, mainly because of the ultra-dense deployments required to meet the upcoming traffic demands. This paper deals with a multi-objective formulation of the Cell Switch-Off (CSO) problem, a well-known and effective approach to save energy in such dense scenarios, which is addressed with an accurate, yet rather unknown multi-objective metaheuristic called MOCell (multi-objective cellular genetic algorithm). It has been evaluated over a different set of networks of increasing densification levels. The results have shown that MOCell is able to reach major energy savings when compared to a widely used multi-objective algorithm.**

***Index Terms*—Energy saving, cell switch-off, multi-objective optimization, metaheuristics, cellular genetic algorithm.**

I. Introduction

The demands of data traffic in cellular networks has grown steadily since the very beginning of the first telecommunication systems, and it will continuing doing so in the future. Indeed, a recent report from Ericsson states that "Total mobile data traffic is expected to rise at a compound annual growth rate (CAGR) of 42 percent" [1], being smartphones the source of 90% this traffic. In order to accommodate such a traffic demands, vendors and operators are currently developing the next generation of mobile networks, the fifth (5G). A widely recognized key enabler technology of 5G systems is network densification, i.e., the deployment of a large number of small-scale base stations (BSs) of different types (Heterogeneous Networks or HetNets) [2]. Ultra Dense Network (UDN) [3] deployments allows for a major spectrum reuse, thus enhancing the system capacity.

The point is that a major energy efficiency issue raises in UDN deployments in low traffic periods, in which the entire system is fully operating, but underutilized. A promising approach proposed recently to reduce this waste of power consumption lies in switching off a subset of the base stations of the network [4], [5]. This combinatorial optimization problem, called the Cell Switch-Off (CSO) problem, is known to be NP-complete [6], as the search space grows exponentially with the number of BSs. Given the expected sizes of the envisioned UDNs, addressing this problem with exact optimization algorithms is discarded due to the time required to compute the optimal solution. Our approach here is to rely on metaheuristics [7]. In particular, the problem has been formulated as a multi-objective optimization problem as two conflicting quality criteria are optimized at the same time and, as a consequence, multi-objective metaheuristics have been considered. Several quality criteria have been proposed in the literature for addressing the CSO problem [8] and, among them, we have used the minimization of the number of BSs switched on and the maximization of the total capacity the network is capable of providing to the User Equipments (UEs). This problem has been addressed with two multi-objective evolutionary algorithms, NSGA-II [9] and MOCell [10]. The former is the *de facto* standard in the multi-objective domain, and already used for solving the CSO problem. It will serve as the baseline algorithm in this study. To the best of our knowledge, MOCell has never been used before in the context of the CSO problem. The two algorithms have been evaluated over different UDN scenarios with increasing densities of both BSs and UEs. The results have shown that MOCell is able to outperform NSGA-II, specially in highly dense UDNs. Therefore, the contributions of this work are:

1) As to the system model, we have modelled the service area with a set of regions that have different propagation conditions and four types of cells with fairly different propagation features (macrocells, microcells, picocells, and femtocells).
2) We have addressed the CSO problem with MOCell for the very first time, showing it is able to outperform NSGA-II, a well known algorithm already used for this problem.
3) The reported results shows that, in the studied scenarios, it is possible to keep only a small subset of the BS switched on (below 15% of the total BSs deployed) to provide maximum capacity to the UEs present in the network, thus making the UDNs highly sustainable in terms of power consumption.

The rest of the paper is organized as follows. The next section details how the UDN has been modeled. Section III frames the experiments conducted, briefly describing the algorithms used, the methodology, and a discussion of the results obtained. Finally, the main conclusions drawn as well as the lines for future research are given in Sect. IV.

TABLE I: Model parameters for cells and users

Cell	Parameter	LL	LM	LH	ML	MM	MH	HL	HM	HH
macro	G_{tx}	14								
	f	2 GHz (BW = 100 MHz)								
micro1	G_{tx}	12								
	f	3.5 GHz (BW = 175 MHz)								
	λ_P^{micro1} $[BS/km^2]$	100	100	100	200	200	200	300	300	300
micro2	G_{tx}	10								
	f	5 GHz (BW = 250 MHz)								
	λ_P^{micro2} $[BS/km^2]$	100	100	100	200	200	200	300	300	300
pico1	G_{tx}	5								
	f	10 GHz (BW = 500 MHz)								
	λ_P^{pico1} $[BS/km^2]$	500	500	500	600	600	600	700	700	700
pico2	G_{tx}	7								
	f	14 GHz (BW = 700 MHz)								
	λ_P^{pico2} $[BS/km^2]$	500	500	500	600	600	600	700	700	700
femto1	G_{tx}	4								
	f	28 GHz (BW = 1400 MHz)								
	λ_P^{femto1} $[BS/km^2]$	1000	1000	1000	2000	2000	2000	3000	3000	3000
femto2	G_{tx}	3								
	f	66 GHz (BW = 3300 MHz)								
	λ_P^{femto2} $[BS/km^2]$	1000	1000	1000	2000	2000	2000	3000	3000	3000
UEs	λ_P^{UE} $[UE/km^2]$	1000	1000	1000	2000	2000	2000	3000	3000	3000

II. System model

This section is devoted to detailing the UDN model used. We have a target service area of 500×500 square meters, which has been discretized using a grid of 100×100 points (also called "pixels" or area elements), each covering 25 m^2 where signal power is assumed to be constant. Ten different regions have been defined with different propagation conditions. In order to compute the received power at each point, $P_{rx}[dBm]$, the following model has been used:

$$P_{rx}[dBm] = P_{tx}[dBm] + PLoss[dB] \tag{1}$$

where, P_{rx} is the received power in dBm, P_{tx} is the transmitted power in dBm, and $PLoss$ are the global signal losses, which depend on the given propagation region, and are computed as:

$$PLoss[dB] = GA + PA \tag{2}$$

where GA are the total gain of both antennas, and PA are the transmission losses in space, computed as:

$$PA[dB] = \left(\frac{\lambda}{2 * \pi * d}\right)^K \tag{3}$$

where d is the Euclidean distance to the BS, K is the exponent loss, which ranges randomly in $[2.0, 4.0]$ for each of the 10 different regions. The signal to interference plus noise ratio (SINR) for UE k, is computed as:

$$SINR_k = \frac{P_{rx,j,k}[mW]}{\sum_{i=1}^{M} P_{rx,i,k}[mW] - P_{rx,j,k}[mW] + P_n[mW]} \tag{4}$$

where $P_{rx,j,k}$ is the received power by UE k from BS j, the summation is the total received power by UE k from all the BSs operating at the same frequency that j, and P_n is the noise power, computed as:

$$P_n = -174 + 10\log_{10} BW_j \tag{5}$$

being BW_j the bandwidth of BS j, defined as 5% of the BS operating frequency (see Table I below). Finally, the capacity of the UE k is:

$$C_k[bps] = BW_k^j[Hz] * \log_2(1 + SINR_k) \tag{6}$$

where BW_k^j is the bandwidth assigned to UE k when connected to BS j, assuming a round robin scheduling, that is:

$$BW_k^j = \frac{BW_j}{N_j} \tag{7}$$

where N_j is the number of UEs connected to BS j, and UEs are connected to the BS with the highest SINR, regardless of its type.

In order to model a HetNet, four different types of cells of decreasing size are considered: femtocells, picocells, microcells, and macrocells. Two subtypes of femto, pico and microcells are also defined, summing up 7 cell types. Their serving BSs all have a $P_{tx} = 750mW$, so their actual coverage is defined by their operating frequencies and the subsequent losses they induce when computing the SINR. The BSs are deployed using independent Poisson Point Processes (PPP) with different densities (defined by λ_P^{BS}). UEs are also deployed using a PPP (defined by λ_P^{UE}), but using social attractors (SAs), following the procedure defined in [11]. This deployment scheme uses two factors, α and μ_β, that indicates how strong BSs attract SAs and how SAs attract UEs. They have been set to $\alpha = \mu_\beta = 0.25$.

The detailed parametrization of the nine scenarios addressed is included in Table I. The names in the last nine columns, XY, stand for the deployment densities of BSs and UEs, respectively, so that X = {L,M,H}, meaning either low, medium, or high density deployments (λ_P^{BS} parameter of the PPP), and Y = {L,M,H}, indicates a low, medium, or high density of deployed UEs (λ_P^{UE} parameter of the PPP), in the last row of the table. The parameters G_{tx} and f of each type of cell refers to the transmission gain and the operating frequency (and its available bandwidth) of the antenna, respectively.

In this context, the way of computing the problem objectives is as follows. The number of BSs switched on (first objective) consists of just summing up the active BSs in the candidate solution proposed by the metaheuristics. In order to compute total capacity of the system, the UEs are first assigned to the BSs that provides the highest SINR, the available BW of the BSs is then shared between the users connected (if any) and, finally, the capacity is computed (Eq 6) and aggregated.

III. Experimentation

This section elaborates on the experimentation conducted to show the performance of both NSGA-II and MOCell when addressing the nine UDN scenarios detailed above. First, a brief description of the algorithms is included; second, the methodology used in the experiments is presented; and, finally, we undertake the analysis of the results obtained.

A. Algorithms

The Non-dominated Sorting Genetic Algorithm II, NSGA-II, was proposed by Deb *et al.* [9]. It is a genetic algorithm based on generating a new population from the original one by applying the typical genetic operators (selection, crossover, and mutation); then, the individuals in the new and old population are sorted according to their rank, and the best solutions are chosen to create a new population. In case of having to select some individuals with the same rank, a density estimation based on measuring the crowding distance to the surrounding individuals belonging to the same rank is used to get the most promising solutions.

The Multi-Objective Cellular Genetic Algorithm, MOCell, is a cellular genetic algorithm (cGA) [10]. Like many multi-objective metaheuristics, it includes an external archive to store the nondominated solutions found so far. The archive is bounded and uses the crowding distance of NSGA-II to keep diversity in the Pareto Front. The selection is based on taking an individual from the neighborhood of the current solution and another one randomly chosen from the archive. After applying the crossover and mutation operators, the new offspring is compared to the current one, replacing it if better; if the solutions are nondominated, the worst individual in the neighborhood is replaced by the current one. In these two cases, the new individual is added to the archive.

The BSs of the UDNs are numbered, what allows both NSGA-II and MOCell to use a binary string representation in which each bit i indicates whether BS i is either activated or deactivated. The two algorithms share the same representation and the genetic operators, specifically, Two Point Crossover with a crossover rate of 0.9, and Bit Flip mutation with a mutation rate of 1/L, where L is the number of BSs of the UDN. Binary tournament is the selection operator and the stopping condition is to compute 100000 function evaluations.

B. Methodology

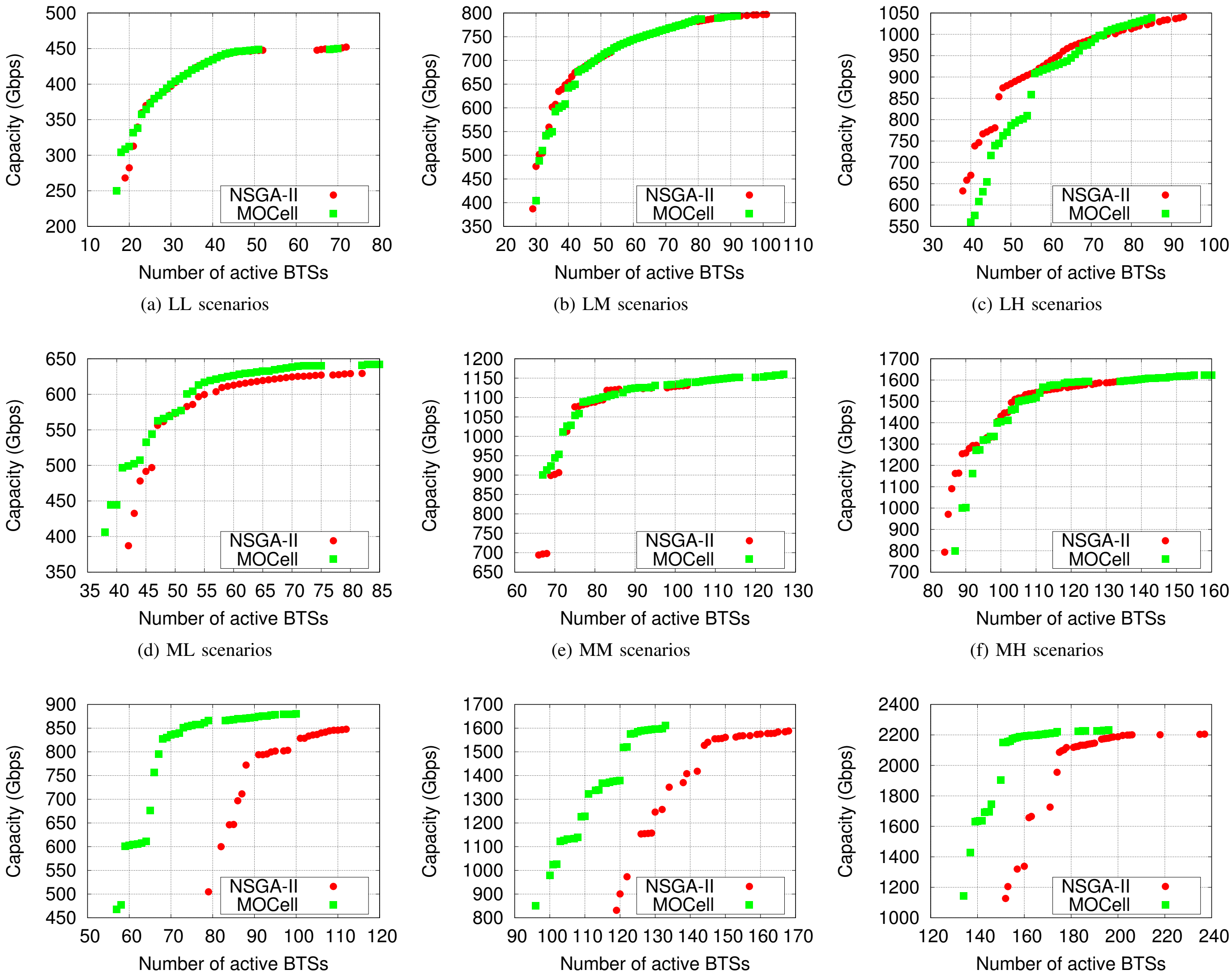
As metaheuristics are stochastic algorithms, 30 independent runs for each algorithm and each UDN scenario have been performed. Each run addresses a random instance, that is, the scenarios are randomly generate for each run, but with the same 30 seeds, so as to guarantee that the two algorithms tackled the same random instances. In order to measure the performance of NSGA-II and MOCell, two indicators have been used: the hypervolume (HV) [12] and the attainment surfaces [13].

The HV is considered as one of the more suitable indicators in the multi-objective community. Higher values of this metric are better. Since this indicator is not free from an arbitrary scaling of the objectives, we have built up a reference Pareto front (RPF) for each problem composed of all the nondominated solutions found for each problem instance by all the algorithms. Then, the RPF is used to normalize each approximation prior to compute the HV value.

While the HV allows one to numerically compare different algorithms, from the point of view of a decision maker, it gives no information about the shape of the front. The empirical attainment function (EAF) [13] has been defined to do so. EAF graphically displays the expected performance and its variability over multiple runs of a multi-objective algorithm. Informally, the 50%-attainment surface in the multi-objective domain, which is the chosen here, is analogous to the median value in the single-objective one.

C. Results

Let us start by analyzing the results of shown by the attainment surfaces, which are displayed in Fig. 1. There is one plot for each of the nine UDN scenarios, and each of the three rows corresponds to the three densities of BSs of Table I (i.e., L, M and H), with an increasing UEs density within each row. There are common findings to all the figures. First, the higher the number of UEs, the higher the total capacity delivered by the UDN. This is a clear consequence of densification, as a large number of BSs are available in the UDN, and the algorithms then just explore solutions that switch on more of them. Second, in all the scenarios, a number of active BSs exists for which the capacity hardly increases. This value strongly depends on the position of UEs, the UEs-to-BS association scheme used (i.e., best SINR), and the round robin policy at BSs that shares the bandwidth equally between the connected UEs. And, third, as to the comparison between NSGA-II and MOCell, it can be observed that the differences are very tight in the easier instances, that is, those networks with a low number of BSs and a low number of UEs, but they become remarkable in the more dense UDNs (Figs. 1g to 1i). It can be seen that the attained points of MOCell clearly dominates those of NSGA-II (i.e., minimize the number of active BSs and maximize the capacity at the same time). Their solutions are, therefore, more efficient both in power consumption and spectrum reuse. This is precisely the target UDNs that are expected to be deployed in 5G systems [2], so we consider that the results are very relevant.



(a) LL scenarios (b) LM scenarios (c) LH scenarios

(d) ML scenarios (e) MM scenarios (f) MH scenarios

(g) HL scenarios (h) HM scenarios (i) HH scenarios

Fig. 1: Attaiment surfaces of NSGA-II and MOCell for the nine different UDN scenarios

Elaborating a bit more on the results obtained, we would like to recall that the average number of BSs deployed for each of the L, M, and H scenarios are, respectively, 800, 1400 and 2000, i.e., the sum of all the λ_P values of each cell type, divided by four, as these values are given in $[BS/km^2]$. In this context, it can be seen in the attainment surfaces that the algorithms are able to switch off, on average, around 90% of the BSs, i.e., 700, 1260, and 1800, respectively, while providing full capacity to the UEs. This will make 5G systems sustainable and clearly establishes the activation/deactivation of BSs as a key strategy to save energy and match the defined requirements for 5G.

In order to corroborate the visual inspection of attainment surfaces, Table II includes the average HV values of the 30 approximated Pareto fronts reached by NSGA-II and MOCell. The grey colored background in the table indicates a better (higher) value of the indicator. The conclusions drawn with the data shown are clear: MOCell outperforms NSGA-II in six out of the nine scenarios, specially in all the UDNs with

TABLE II: Results of the HV indicator

UDN	NSGA-II	MOCell
LL	0.4172	0.4307
LM	0.4662	0.4592
LH	0.4435	0.4260
ML	0.2791	0.3036
MM	0.3586	0.3641
MH	0.3062	0.2949
HL	0.0769	0.2298
HM	0.0608	0.1587
HH	0.1474	0.2172

the more dense BS deployments (H{L,M,H} settings). In these later cases, the improvements of MOCell are very significant (recall that the approximated fronts are normalized before HV is computed), while those of NSGA-II are, in general, very tight.

Finally, it is worth noting that, as the algorithms share all the genetic operators, the difference in the solutions reached comes from the different search engines that explore the search space in a fairly different way. As a consequence, MOCell seems to be a promising approach for solving the CSO problem, specially when handling highly dimensional problems.

IV. Conclusion

This work addresses the problem of switching off cells in the context of the upcoming 5G ultradense network deployments, with the aim of reducing the power consumption of the entire system while providing the UEs with maximum capacity. The problem has been formulated as a multi-objective optimization problem with these two objectives (minimizing the number of active BSs and maximizing the aggregated capacity of all the UEs). It has been addressed with two multi-objective metaheuristics, a classical well-known one, NSGA-II, used previously in similar formulations of the problem, and a rather novel, yet accurate (but not that well known) proposal called MOCell. The two algorithms have been evaluated over a set of nine different UDN scenarios, which incorporates different density levels of both BSs and UEs. The results have shown that MOCell is able to ouperform NSGA-II in six out of these nines scenarios, specially in those with the more dense deployments. The two algorithms have been configured so that they share all the underlying search operators, so the differences in the results are provoked by the different ways of exploring of the search space of the CSO problem.

As future works, we are working on the line of enhancing the problem modeling, by considering a power control strategy in the BSs to increase the SINR and, thus, the overall capacity of the network, as well as using different UEs-to-BS assignment policies. On the algorithmic side, we are devising new search operators and evaluating recent multi-objective metaheuristics for the CSO problem.

Acknowledgement

This work has been supported by the UNGR15-CE-3311 and TIN2016-75097-P projects of the Spanish National Program of Research, Development and Innovation. Francisco Luna, Rafael M. Luque-Baena and Jesús Martínez also acknowledge support from Universidad de Málaga.

References

[1] Ericsson, "Mobility Report," *White Paper*, no. June, 2017. [Online]. Available: https://www.ericsson.com/assets/local/mobility-report/documents/2017/ericsson-mobility-report-june-2017.pdf

[2] D. Lopez-Perez, M. Ding, H. Claussen, and A. H. Jafari, "Towards 1 Gbps/UE in Cellular Systems: Understanding Ultra-Dense Small Cell Deployments," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2078–2101, 2015.

[3] X. Ge, S. Tu, G. Mao, C.-X. Wang, and T. Han, "5G Ultra-Dense Cellular Networks," *IEEE Wireless Communications*, vol. 23, no. 1, pp. 72–79, feb 2016.

[4] Q.-N. Le-The, T. Beitelmal, F. Lagum, S. S. Szyszkowicz, and H. Yanikomeroglu, "Cell Switch-Off Algorithms for Spatially Irregular Base Station Deployments," *IEEE Wireless Communications Letters*, vol. 6, no. 3, pp. 354–357, jun 2017.

[5] F. Lagum, Q.-N. Le-The, T. Beitelmal, S. S. Szyszkowicz, and H. Yanikomeroglu, "Cell Switch-Off for Networks Deployed With Variable Spatial Regularity," *IEEE Wireless Communications Letters*, vol. 6, no. 2, pp. 234–237, apr 2017.

[6] D. Gonzalez G., J. Hamalainen, H. Yanikomeroglu, M. Garcia-Lozano, and G. Senarath, "A Novel Multiobjective Cell Switch-Off Framework for Cellular Networks," *IEEE Access*, vol. 4, pp. 7883–7898, 2016.

[7] C. Blum and A. Roli, "Metaheuristics in combinatorial optimization: Overview and conceptual comparison," *ACM Computing Surveys*, vol. 35, no. 3, pp. 268–308, 2003.

[8] D. González González, E. Mutafungwa, B. Haile, J. Hämäläinen, and H. Poveda, "A Planning and Optimization Framework for Ultra Dense Cellular Deployments," *Mobile Information Systems*, vol. 2017, pp. 1–17, 2017.

[9] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182 – 197, 2002.

[10] A. J. Nebro, J. J. Durillo, F. Luna, B. Dorronsoro, and E. Alba, "Mocell: A cellular genetic algorithm for multiobjective optimization," *Int. J. of Intelligent Systems*, vol. 24, no. 7, pp. 723 – 725, 2009.

[11] M. Mirahsan, R. Schoenen, and H. Yanikomeroglu, "HetHetNets: Heterogeneous Traffic Distribution in Heterogeneous Wireless Cellular Networks," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 10, pp. 2252–2265, 2015.

[12] E. Zitzler and L. Thiele, "Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach," *IEEE Trans. Evolutionary Computation*, vol. 3, no. 4, pp. 257–271, 1999.

[13] J. Knowles, "A summary-attainment-surface plotting method for visualizing the performance of stochastic multiobjective optimizers," in *5th International Conference on Intelligent Systems Design and Applications (ISDA'05)*, 2005, pp. 552 – 557.