On Pareto-Koopmans Efficiency for Performance-Driven Optimisation in Self-Organising Networks

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Abstract

In this paper, a novel Multi-Objective Optimisation (MOO) method has been introduced for Self-Organising Networks (SONs). Meta-heuristic algorithms based on Simulated Annealing (SA) are used to evaluate the Pareto Frontier (PF) of UE throughput vs. fairness index in a simulation of Coverage & Capacity Optimisation (CCO) use-case in SON-LTE. We have evaluated the performance optimisation methods through the final optimal set of solutions. The boundaries of the optimal sets are evaluated as PF and compared with the results of the conventional method of Multi-Objective Simulated Annealing (MOSA). We have detected a Pareto improvement for the estimated PF of the proposed method, which outperforms that of MOSA.

1 Introduction

Wireless networks have become increasingly complex. This complexity is known to be the most limiting factor for future developments and this is why the current situation is believed to be a *complexity crisis* [1]. The self-organisation concept, originally introduced by Ashby [2], has proved to be able to tackle this problem and reduce costs while increasing efficiency. The self-organisation concept was further nourished by mathematical methods regarding complexity. The Self-Organising Network (SON) has been identified as a powerful platform for the implementation of these methods in wireless communication networks [3].

In this paper, a method based on the Pareto-Koopmans efficiency [4] for performance optimisation in SON is introduced. To clarify which application in SON is aimed at, we need to introduce the terms used in this article. The term of *optimisation* has widely been used for various applications. However, optimisation in SON can specifically be based on three different approaches [5]: capacity-driven, coverage-driven, and performance-driven. A performance-driven optimisation process is to improve User Equipment (UE) perceived performance, such as throughput, fairness, desired Key Performance Indicator (KPI) or Quality of Service (QoS) parameters. In this paper we particularly focus on performance-driven optimisation in SON. On the other hand, the Pareto-Koopmans efficiency of systems is said to be accomplished when it would be impossible for a node to be better off without another node to be worse off. This definition of efficiency leads us to a set of optimal points, which is known as Pareto Frontier (PF) [6]. PF is well known in realms of economy, social sciences and numerous branches of engineering for Multi-Objective Optimisation (MOO) problems. The main goal of a MOO is to find the *optimum* solutions, which corresponds to the optimal values of multiple objectives. PF is a notion for applications of MOO when the input parameters are also deeply coupled, which is referred to as *coupling* or *conflict* problem. Surveying literature, in [7] authors introduced SON and its use-cases in wireless networks. The problem of coupling was also identified in some use-cases. Amongst them, Coverage & Capacity Optimisation (CCO) use-case has been discussed in several studies [8, 9]. It well established that in a cellular network, the coverage, capacity and quality of service are deeply coupled to each other. Though there are plenty of works in literature that attempt at jointly optimising these coupled objectives, it is worth pointing out that many alternative optimisation tools suitable for this problem have not yet been fully explored. More specifically most of the previous works focus on network level while assuming same settings for all cells. This paper addresses the problem of coupling within self-optimisation function of SON, which is rolled out in a modern cellular networks infrastructure, such as Long-Term Evolution (LTE) and LTE-Advanced.

Though the coupling problem within SON has been addressed in literature, however, the state of the art is far from mature. The coupling problem happens in SON when one objective function is desired, but, optimising the desired objective worsens other performance indicators, e.g. targeting higher capacity *can take toll on* coverage or energy efficiency. To solve such a problem that have mutually coupled multiple objectives, MOO is usually applied. However, classic MOO suffers from a draw back that it may reach one of many optimal points in the state-space of an underlying system. This shortcoming is compromised by considering a PF consisting of a set of optimal solutions to a Decision-Making (D-M) module in SON that in turn can choose a best desired solution [10]. While the classic MOO addresses the complexity arising from the coupling among the multiple objectives in SON, it may not address the presences multiple resources or parameters [11]. In contrast, in this paper we consider Multi-Resources Multi-Objectives (MRMO) optimisation. In this approach all objective functions are optimised in parallel there by providing a set of alternative optima, which offers flexibility to the D-M. To this end, we generally require a population-based algorithm, e.g. meta-heuristic, to produce the optimal set. Rest of the paper is organised as follows: we present a literature review in Section 2 including related works regarding MOO. In Section 3, the system model is explained which introduces the algorithm of Enhanced Adaptive Simulated Annealing (EASA), applying it to performance optimisation in a SON/CCO use-case. Finally, in Section 4 we present the simulation results and later in the conclusion we discuss the outcome.

2 Survey and Related Works

As a part of SON, self-optimisation has been viewed as a broad and open area, not yet well studied. One of the main reasons has been as the complexity of optimisation functions and the large number of parameters for optimisation [7]. The main motivation is to find how to solve coupling problem within self-optimisation module of SON and how to access the set of optimal points while an optimisation process of MOO is running. Studies based on MOO have focused on access to such set. In Pareto-Koopmans efficiency, this final set will appear as a PF. On the other hand, as the PF for the underlying problem introduces the upper bound for an optimal set, i.e. a boundary for the optimisation process, any improvement in this frontier, which is a *Pareto improvement*, is desired. It is interesting to know self-organisation as the evolution of system states along a PF. The coupling problem in wireless networks has been observed in even earlier work [12], which introduces a trade-off between coverage and capacity without Pareto notion. The approach in [12] is based on a customised relation between coverage and capacity, which is not in line with the Pareto-Koopmans efficiency and self-optimisation of SON. Recent studies have introduced parametric methods to handle the coupling problem such as controlling α-fairness against bit rate in [13] which introduces an impact of α-fairness that can trade between efficiency and fairness. Another methods for Pareto improvement have been studied in [14], where the game-theoretic Pareto improvement with Max-Min optimisation is introduced, which characterises the PF based on rate in a cell-optimisation process.

2.1 Fundamental Theorems

An interesting mathematical theorem has been studied in [15] that proves that performances of all Single-Objective Optimisation (SOO) algorithms, including deterministic, stochastic and heuristic algorithms, across the set of all underlying problems are the same, unless the algorithm is tailored to exploit the specific structure of a problem. However, this does not imply that any algorithm is capable of finding the solution for all optimisation problems. To clarify, if $\Pr\,(S_u|f,u,A_1)$ indicates the probability of performance for algorithm A_1 simulated u times on sample set S_u and f as the objective function, then:

$$\sum_f \Pr\,(S_u|f,u,A_1) = \sum_f \Pr\,(S_u|f,u,A_2) \tag{1}$$

where A_2 is the second algorithm simulated u times on the same function f and the sample set being the same. Then, all optimisation algorithms will indicate the same performance in terms of overall average, with a given set of observations, i.e. performance is *independent* of SOO algorithms. This theorem, namely No Free Lunch (NFL), states that the universally best SOO algorithm does not exist. Nonetheless, it has recently become known that MOO using some algorithms does not comply with the NFL [16], including algorithms those do not depend on a priori information, i.e. heuristic or meta-heuristic with less dependency. So these theorems pave the way to new methods, which are able to enhance the final performance with achieving a better set of optimal solutions. This also, leads us to the concept of Pareto improvement, which concerns the improvement of the PF for the underlying problem. In the next section, this improvement in derived PF will be shown.

2.2 Multi-Objective Optimisation

In the following, we introduce MOO algorithms, also called as Vector, Multi-Criteria or Multi-Performance Optimisation [4], which have been considered in this study. Some studies have exploited certain methods to convert the MOO problem into a SOO problem by weighted-sum, ε-constraint or similar aggregation or scalarising methods. Though this conversion can be used for convex optimisation problems, most optimisation problems in SON are non-convex. So these methods may not be suitable unless necessary convexity conditions are provided. However, meta-heuristic algorithms are considered for broader MOO problems in the field as they do not need to convexity conditions. The use of weighted-sum has been confronted by many contradictions in literature because the general solution for setting the weights is still an open topic, which may not satisfy the D-M, particularly, for complex system as the desired application in this study. The weighted sum has been utilised for self-optimisation of pilot power in SON [17] and the study of joint optimisation of Energy Efficiency (EE) and Spectral Efficiency (SE) in [18]. Though, a comprehensive comparison between the weighted sum and heuristic methods has not yet been conducted [19], however, converting the MOO problems into a SOO should produce sub-optimal solutions. The weighted sum can be found amongst the first studies in this field from the 1980's. However, with such techniques the advantage of MOO can be lost as the implicit trade-off within MOO provides much more flexibility to the D-M and the provided PF reveals trade-off boundaries to the D-M.

2.2.1 Methods and Algorithms for MOO

There are several heuristic optimisation algorithms, originally introduced for SOO problems; amongst them SA has been known because of its potential to be easily extended to MOO problems. Also, mixing different heuristic algorithms in MOO problems has been studied in [20]. Authors apply Genetic Algorithm (GA) strategy for a sample population of interacting solutions while a scalarising function is used in their approach. As in this study, we focus on Pareto optimal set, the multi-objective version is utilised, i.e. Multi-Objective Simulated Annealing (MOSA), introduced in [21], that is an extension of SA. We will compare the proposed algorithms with the results of MOSA for the considered case in this study. Authors in [22] have presented a method based on archiving in MOSA. This method is basically stores all non-dominated solutions and then determines the acceptance probability for each objective function based on the stored data. This method does not use a scalarised objective function. In fact, the methodology is based on a concept of Tabu search into SA, which creates the archiving process as a memory for the optimisation process. A self-similar extension to SA was offered in [23] for MOSA. In this approach, improvement or deterioration with respect to the objective functions are accepted based on probabilities for each move. So deterioration to all objective functions is also possible with a random probability (this is similar to the deterioration probability in SA for SOO problems). An interesting adaptation of the Pareto optimal set into MOSA was proposed in [22] which adapts the acceptance criterion in MOSA algorithm based on Pareto-domination

2.2.2 Pareto Frontier

With this study, a PF is provided. To find the PF, we have to notice that every optimal point, which was found by one run of the optimisation algorithm, should not be a part of the PF unless there is no more optimal point, which satisfies the Pareto-Koopmans efficiency condition. So in this sense the MOSA algorithms were run for several times to find the optimal points which can shape parts of the PF. However, this should not provide the exact PF as it needs to search all state-space, which is impossible in limited-time and with given convergence conditions. So various points, which may shape the region of the PF, can be found via this approach. This region is called Pareto optimal set.

3 System Model

Numerous approaches have been developed in the literature with the aim of determining the Pareto optimal. However, SA-based algorithms have been identified amongst the best meta-heuristic algorithms for MOO problems with many advantages over conventional methods [16], comparable with Multiobjective Optimisation with Genetic Algorithm (MOGA) [24]. We have chosen MOSA for the optimisation task in this study to compare with the multi-objective algorithm of EASA [25].

The pseudo-code for the EASA is shown in the figure 1. We used the scenario of CCO use-case as recommended by 3GPP, which aims at enhancing the coverage and capacity in SON. In the CCO use-case, the ultimate technical functionalities concern the increase of both capacity and coverage in a cellular network, which is subject to the coupling problem. As we have already explained in Section 1, to measure the performance we have to exploit indicators for a comparison study. To this end, we exploited throughput and also Jain's Fairness Index (JFI), in order to be able to compare the result with the other studies. Figure 2 shows the scenario in SON with CCO use-case, which we have considered in this study.

begin procedure
  define objective functions $\boldsymbol{f}_n(\boldsymbol{\zeta})$, $\boldsymbol{\zeta}=(\zeta_1, \zeta_2, ...)^T$ *;n=1,2,...*
  define the Pareto optimal set
  begin initialisation
    initialise initial Temperature T_0,
    initialise initial guess $\boldsymbol{\zeta}^{(0)}$
    set final Temperature T_f
    determine max(Iteration)
  end initialisation
  determine S:= Similarity Measure
  define cooling schedule $T \rightarrow \alpha(S).T$; $0<\alpha<1$
    while $(T>T_f)$ *and* $(m<M)$ *and* $(n<N)$
      new random locations: $\boldsymbol{\zeta}_{m+1}$
      calculate $\delta_n=\boldsymbol{f}_n(\boldsymbol{\zeta}_{m+1})-\boldsymbol{f}_n(\boldsymbol{\zeta}_m)$
      accept the new solution if all f_n *is better*
        if ***not*** *improved*
          calculate $\beta_n=exp(-\delta_n/(KT(S,t)))$
        generate rand
          if all $\beta_n>rand$
            accept the new solution
          endif
        endif
      update the best $\boldsymbol{\zeta}^*$, $\boldsymbol{f}^*$
    end while
end procedure

Figure 1. Pseudo-Code for EASA

In this scenario, we aim at maximising performance for desired users in a cell. SON parameters are considered for the performance evaluation.

3.1 Performance Evaluation

The following procedure was designed to evaluate the adaptive optimisation process. We aim for:

$$\max\{f_n(p_1, p_2, \ldots, p_j)\} \quad ; n \in N,\ j \in K \qquad (2)$$

where K is the number of cells, p is the performance measure and f_n is the n^{th} objective function, N is the number of objective functions, so the optimal SON parameters can be formulated as:

$$\{\hat{\zeta}_1, \hat{\zeta}_2, \ldots, \hat{\zeta}_j\} = \underset{\zeta_1, \zeta_2, \ldots, \zeta_j}{\arg\max}\{f_n(.)\} \qquad (3)$$

which is any combination of $\zeta_1, \zeta_2, \ldots, \zeta_j$ network parameters within K cells. In this study, the performance measure is defined based on similarity between measured KPIs and desired (target) KPIs. KPIs from all involved cells are considered, as:

$$\{KPI_{ij}\} \quad ; i^{th}\ KPI\ in\ j^{th}\ cell \qquad (4)$$

As the network operator may consider different patterns of KPIs for different cells, a measure, using all parameters is considered. If the target and measured KPIs are denoted by $KPI^{(t)}$, $KPI^{(m)}$ respectively,

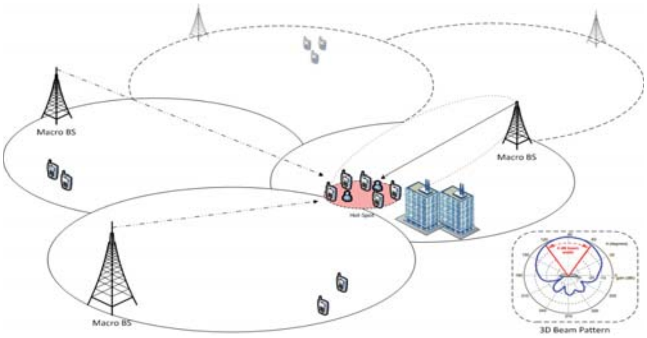

Figure 2: SON with CCO use-case and Antenna Beam Pattern

$$p_j = \sum_i w_{ij} \left\| KPI_{ij}^{(m)}, KPI_{ij}^{(t)} \right\| \quad (5)$$

is the general form of performance measure in this approach and w_{ij} is weight for the i^{th} KPI in the j^{th} cell (||.|| denotes a measure). In this case, each cell may have its own performance: in the first step the overall performance measure of p_j is considered for cell *j*. We evaluate each step of the optimisation by measuring the similarity between the measured and targeted KPIs.

A scenario was set up in SON, to develop an analytical model for downlink (DL). The shadowing of log-normal distribution is utilised with correlations amongst users who are served by the same eNodeB and with their distances being less than a pre-defined value (100m in the simulation). Path loss, penetration loss, and thermal noise are added to the final model. Fairness index and throughput are formulated as the objective functions, which are used in the optimisation process (detail in the next section). The Physical Resource Block (PRB) bandwidth (*W*=180 KHz) of each user in the j^{th} cell was applied, and ρ is the bandwidth efficiency parameter. Input parameters including both antenna parameters (tilt and azimuth), also multi-objective algorithm of EASA are considered, and a complete set of measurements and indicators are considered for all cells as well as traffic loads information. A pair of input parameters is considered for each cell as:

$$\boldsymbol{\zeta}=\{(\theta_1, \Phi_1,), (\theta_2, \Phi_2)\ldots(\theta_j, \Phi_j)\} \quad ; j \in K \qquad (6)$$

where θ is tilt angle and Φ is azimuth orientation angle, with slight variations in inputs, we will have:

$$\boldsymbol{\zeta}'=\{(\theta_1', \Phi_1'), (\theta_2', \Phi_2')\ldots(\theta_j', \Phi_j')\} \quad ; j \in K \qquad (7)$$

To accept the changes, an evaluation based on optimisation is carried out. Suppose β is the acceptance probability for the n^{th} objective function in EASA and then we will have:

$$\beta_n = \exp(-\delta_n/KT(S,t)) \; ;\delta_n=f_n(\boldsymbol{\zeta})\text{-}f_n(\boldsymbol{\zeta}') \; ;n \in N \qquad (8)$$

S is the similarity measure, *K* is the Boltzmann constant and *T(S,t)* is the annealing function in EASA with *t* as time. This algorithm for self-optimisation function in SON is used to adaptively update pair parameters of all cells, i.e. θ, Φ.

3.2 SON-LTE Scenario

With the formulation of the problem in the previous section, a scenario based in SON-LTE was considered. In this section, a description of the considered scenario is explained. We assume the transmit power is 30dBm and the noise power is -114dBm per PRB. An antenna pattern having a relative gain of 10dBi is modelled as:

$$B(\theta) = -\left\{\frac{12(\theta - \Theta)^2}{\Delta\theta^2}\right\} \;, B(\varphi) = -\left\{\frac{12(\varphi - \Phi)^2}{\Delta\varphi^2}\right\} \quad (9)$$

where $B(\theta), B(\varphi)$ are the antenna beam patterns, Θ, Φ are the central reference angles for the tilt and azimuth, respectively (ref. Table 1). Therefore, the 3D model of the antenna pattern can be numerically obtained as a joint model of $B(\theta), B(\varphi)$. Also, it is assumed that all cells have the same resource of bandwidth and a fixed number of PRBs. The diameter of each cell in the initial conditions is equal to 1Km. In addition, there is no scheduling for PRBs. Values for parameters of the shadowing and path loss are based on 3GPP recommendation as for the shadowing effect user correlations were considered (Table A.2.1.1-3 in [26]).

The path loss model is based on *Okumura-Hata*, which is initialised for LTE in this simulation (penetration loss is 20dB). The height difference between antenna and UE is supposed to be 50m (3GPP recommendation: 20-70m). To conduct an accurate shadowing model, two-dimensional shadowing is exploited in the simulation. Also, standard deviation is 8dB, $\mu=0$ for a log-normal distribution with spatial dependency. Detail of initial setting for the network parameters is shown in table 1. For coverage, the corner of each cell must receive at least a power greater than or equal to the threshold from one of three neighbours as when a cell outage happens in other scenario in SON and the self-healing function of SON is enabled to recover the problem. Finally, the two objective functions are considered using throughput and JFI, which are:

$$\begin{aligned} f_{1,i} &= \rho\, W\log(1 + SINR_i) \\ f_{2,j} &= JFI_j \qquad ; j \in K \end{aligned} \qquad (10)$$

where ρ is the efficiency parameter for the Bandwidth (*W*), and SINR is calculated based on the received signal, noise powers and interferences in DL. f_1, f_2 are throughput and fairness functions, respectively. $f_{1,i}$ is the throughput for the i^{th} UE and $f_{2,j}$ is the JFI of UE throughputs for the j^{th} cell, as well. Also for consistency, we use 10%-top UE throughputs as the benchmark.

Table 1: Set-Up Parameters in SON-LTE Scenario

Thermal Noise	-114dB/PRB
Height Difference (UE,eNodeB)	50m
Noise Figure	9 dB
PRB (W)	180KHz
Antenna Gain	10dBi
eNodeB Tx Power	30dBm
Cell Radius	1 Km
Bandwidth Efficiency Coeff. ($\boldsymbol{\rho}$)	0.9
Max Number of UE in Cell	50
Vertical half power Beam-width ($\Delta\theta$)	10°
Horizontal half power Beam-width ($\Delta\boldsymbol{\varphi}$)	60°
Penetration Loss [26]	20dB

4 Simulation Results Analysis

To implement the objective functions, we consider the *inverse* of throughput and JFI for cell one as the energy of states in both methods of MOSA and EASA to compare the results. Figure 3 shows 10%-top UE throughput in cell No. 1 for both methods as both methods are converged into the final optimal point. In order to implement in a self-optimisation function of SON, the final parameters based on D-M will be derived to adjust the network parameters, e.g. antenna tilt and azimuth. Regarding the 10%-top benchmark, it is based on reports that 1% of users use about 50% of bandwidth and 10% of users use about 90% of bandwidth. This means that with a 10%-top UE throughput we are managing about 90% of cell traffic. To this end, we choose the 10%-top UE throughputs for comparison purposes.

Figure 4 shows the JFI for the same process of optimisation. However, we can see in these two figures that the point-to-point optimum results outperform in EASA. The convergence region specifies the optimum solution provided by optimisation process. With the process of Section 2.2.2, we construct the PF for both optimisation processes, which leads to an optimal set (ref. Section 3 for system model) for each method as plotted in figure 5. Exploiting SA, MOSA as well as EASA are able to recognise the non-dominated Pareto optimal set. Usually meta-heuristic optimisation methods do not need priori information; however, in some variations of MOSA such as modified ranking with goal information [4] a priori information is needed. Also, in the case of EASA, we need target KPI that is a part of the proposed method in section-3. In figure 5, each point is related to one optimisation process, which satisfies the Pareto-Koopmans efficiency condition.

In figure 5, we note that the Pareto optimal set is a set of points, which do not resemble a boundary. Yet, as we have explained in Section 2, this would be the final MOO results in a time-constraint approach as even with meta-heuristic algorithms a whole search in state-space is not feasible. Nonetheless, with the same approach, we compare the Pareto optimal set for each method. To this end, the estimated boundaries ($\widehat{\mathrm{PF}}$) for two methods are shown in figure 6. It can be seen that $\widehat{\mathrm{PF}}_{\mathrm{EASA}}$ outperforms $\widehat{\mathrm{PF}}_{\mathrm{MOSA}}$. In this figure, the enhancement of estimated PFs can be seen which is a Pareto improvement as previously explained in Section 2.

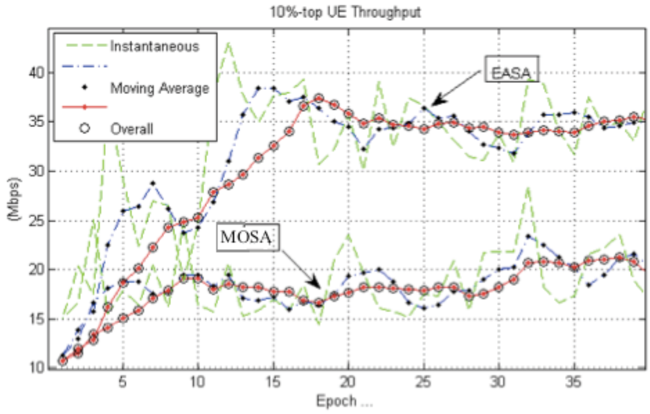

Figure 3: UE Throughput in SON-LTE Scenario of CCO

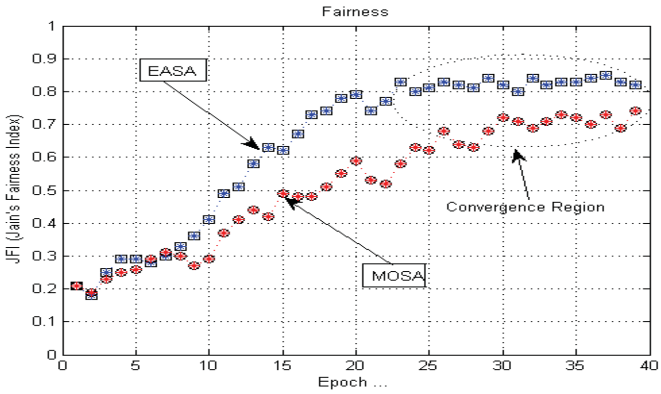

Figure 4: Multi-Objective Optimisation of Fairness Index

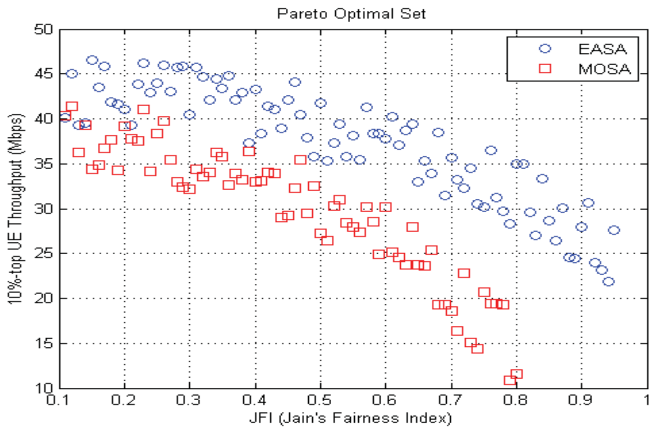

Figure 5: Pareto Optimal Sets for Throughput vs. JFI

5 Conclusion

In this paper, we introduced a method based on SA for MOO in SON-LTE and compared the results with the ones obtained from conventional method of MOSA for a scenario in CCO use-case. In this scenario, the problem of coupling was addressed which is recognised between UE throughput and Jain's fairness index in this study. The optimisation process was carried out with a parameter setting of LTE based on 3GPP recommendations. As the input parameters of SON, we chose the antenna parameters of tilt and azimuth to investigate the performance optimisation methods.

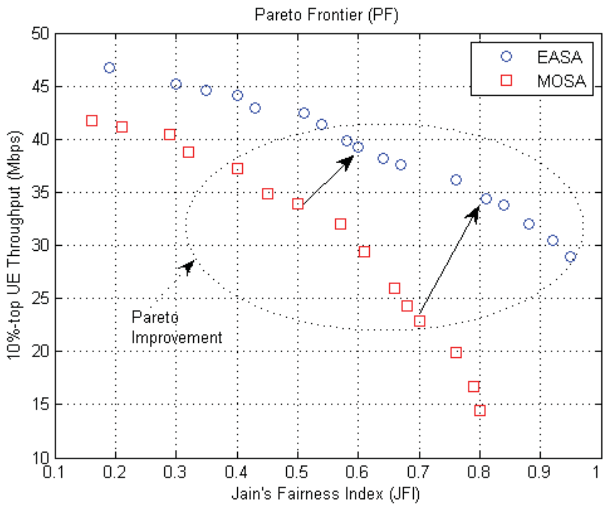

Figure 6: Pareto Frontiers ($\widehat{PF}$) for MOSA and EASA

To this end, a Pareto Frontier was estimated based on an optimal set in Pareto-Koopmans efficiency regime, which has been achieved and compared with the conventional method of MOSA. We can conclude that EASA outperforms MOSA as a Pareto improvement was detected between their frontiers. For future research, the influence of other parameters of SON such as coding rate and resource block on the Pareto Frontier will be investigated.

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