

Landscape-Enabled Algorithmic Design for the Cell Switch-Off Problem in 5G Ultra-Dense Networks

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Abstract

The rapid evolution of mobile communications, remarkably the fifth generation (5G) and research-stage sixth (6G), highlights the need for numerous heterogeneous base stations to meet high demands. However, the deployment of many base stations entails a high energy cost, which contradicts the concept of green networks promoted by next-generation networks. The Cell Switch-Off (CSO) problem addresses this by aiming to reduce energy consumption in ultra-dense networks without compromising service quality. This article explores the CSO problem from a multi-objective optimization perspective, focusing on how spatial network demand heterogeneity affects the multi-objective landscape of the problem. In addition to the deep

landscape understanding, it introduces a local search operator designed to exploit these landscape characteristics, improving the multi-objective efficiency of metaheuristics. The results indicate that increasing heterogeneity simplifies the exploration of the problem space, with the operator achieving closer approximations to the Pareto front, particularly in minimizing network power consumption.

Keywords: exploratory landscape analysis, multi-objective optimization, metaheuristics, energy efficiency, 5G

List of Abbreviations

5G	5th Generation of Mobile Communications
6G	6th Generation of Mobile Communications
BW	Bandwidth
CSO	Cell Switch-Off
EAF	Empirical Attainment Function
ELA	Exploratory Landscape Analysis
HetNet	Heterogeneous wireless cellular network
HV	Hypervolume
ICT	Information and Communication Technologies
KPI	Key Performance Indicator
MIMO	Multiple-Input Multiple-Output
MOEA	Multi-Objective Evolutionary Algorithm
MOP	Multi-Objective Problem
NSGA-II	Non-Sorting Genetic Algorithm II
PC	Power Consumption
PLO	Pareto Local Optima
PPP	Poisson Point Process
QoS	Quality of Service
RPF	Reference Pareto Front
SA	Social Attractor
SINR	Signal-to-Interference-plus-Noise Ratio
SNR	Signal-to-Noise Ratio
SBS	Small Base Station
UE	User Equipment
UDN	Ultra-Dense Network

1 Introduction

Wireless communication technologies are under constant evolution motivated by use cases and application scenarios that require ever-increasing performance. From the first generation to the fifth (5G) [1], these technologies have operated at higher frequency bands, larger bandwidths, and higher data rates, providing users with enhanced quality of experience. Indeed, even before the first 5G networks were commercialized in 2019 and also coinciding with the 5G standardization [2], industry, academia, and standards organizations have begun to research the sixth generation (6G) of wireless communication systems [3, 4]. Among the key enabling technologies already established for 5G [5], the deployment of a large number of heterogeneous small base stations (SBSs) to increase the spatial reuse of the spectrum is key to improving the network capacity to meet the expected system performance [6]. These are known as ultra-dense networks (UDNs) [7, 8], and are still one of the key development trends for 6G [9, 3].

In this context, both environmental sustainability and operational expenditures are two major issues in Information and Communication Technologies (ICT) [10] in general, and in 5G/6G UDNs in particular [11, 12], as base stations account for 60% to 80% of the power consumption of the cellular network [13] and more than 1000 BS/km² are expected to be deployed [7, 6]. This is especially critical in periods of low or no traffic demands, when most of the SBSs are not serving any user. In these scenarios, either switching off or entering SBSs into sleep mode has been proposed as a useful strategy to enhance energy efficiency [14], which has even been included in the releases of standard bodies [15, 2]. The decision task of selecting which SBSs have to be deactivated has been approached in the literature from different perspectives such as clustering [16, 17], game theory [18] or, more recently, machine learning techniques [19, 20, 21]. This decision problem has also been formulated as a combinatorial optimization problem, named Cell Switch Off (CSO) [22], which is known to be NP-complete [23]. All different flavors of the CSO problem, in either their static [24] or dynamic [25] versions, must consider not only reducing the UDN energy consumption (trivially solved by deactivating all SBSs) but also any key performance indicator (KPI) of the user Quality of Service (QoS). The CSO problem has been addressed with exact [26, 27], heuristic [28, 29] and metaheuristic techniques [30], using single [31, 32] *vs.* multi-objective [33] approaches. This work falls into the latter research domain, where compromise solutions

between energy consumption and network capacity are sought [34, 35, 36], but aims to deepen the characterization of the multi-objective landscape of the CSO problem to obtain a fundamental understanding of its difficulty and design improved search strategies. Given the nature of CSO, it can be considered as a large-scale sparse multi-objective combinatorial optimization problem [37] because many SBSs can be deactivated when traffic demand is low.

This work has its roots in the seminal work on multi-objective combinatorial landscape analysis by Liefvooghe *et al.* [38], extending the study from multi-objective NK-landscapes to the CSO problem. It aims at gaining insights into how two major problem descriptors, namely the spatial distribution of both the network infrastructure (i.e., SBSs) and the traffic demand (i.e., user equipments, UEs), impact the problem landscape and, hence, the difficulty for multi-objective metaheuristics to address it properly. To the best of our knowledge, this is the first time a study of the CSO problem has been undertaken. Other features considered to characterize the CSO landscape are a set of several black-box local measures that have been estimated from a sample of solutions [39] and computed over the smallest instances tackled in previous works, which have more than 1000 decision variables (the LL scenarios in [36]). As this work pursues realistic settings, global measures have been avoided because they require a full enumeration of the solution space, such as the proportion of Pareto optimal solutions [38], which is not computationally affordable in the context of this optimization problem.

Experiments were conducted over a set of 800 instances with different levels of network densification (i.e., the number of SBSs and UEs per km²) and different degrees of non-uniformity in the SBSs and UE locations throughout the wireless network (i.e., heterogeneity in spatial traffic demand) [40]. We have been able to provide empirical evidence indicating that, according to the exploratory landscape analysis, as long as SBSs and UEs get closer among them (higher non-uniform spatial distribution), the CSO problem becomes easier to solve. On the basis of these results, a novel local search operator that takes advantage of this severity in the heterogeneity of traffic demands has been devised. In order to show its effectiveness, we have generated a new set of instances in which the network is partitioned into several regions, each with different levels of traffic heterogeneity (see Figure 1). In summary, the main contributions of this work are as follows:

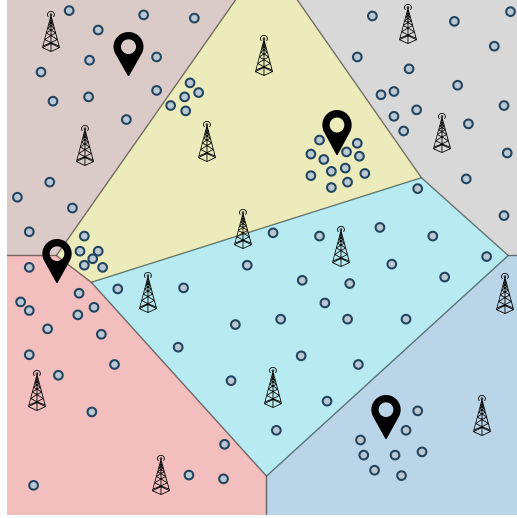


Figure 1: A wireless network with several regions, each one having a different level of non-uniformity in the spatial distribution of the traffic demands. The grey point $\bullet$ represents users of the network, the icon $\blacklozenge$ denotes social attractors, and the $\blacktriangle$ denotes an SBS that includes sectors and cells.

- This is the very first time in which a multi-objective exploratory landscape analysis on a realistic problem like the CSO is carried out. This has required a huge amount of computational effort as realistic instances have been considered for the landscape sampling to capture the inherent problem characteristics.
- A novel landscape-aware local search operator has been engineered to capitalize on previous findings.
- Extensive experiments have been carried out to show empirical evidence of the effectiveness of the newly developed operator.

The rest of the paper is organized as follows. Section 2 outlines the background of this work, defining the CSO problem and the tools used for landscape characterization. Section 3 delves deeply into the analysis of the exploratory landscape analysis of the CSO problem. Then, Section 4 defines the landscape-aware local search operator proposed. Section 5 presents the findings on landscape explorability with respect to heterogeneity and the landscape-aware operator. Finally, Section 6 summarizes the conclusions reached and outlines some future research directions.

2 Background

2.1 The CSO Problem

This section provides the reader with the background related to this work. First, the CSO problem is described, beginning with the modeling of the ultra-dense 5G network, the strategy for user and base station deployment, and the formulation of the problem objectives. Then, the characterization of multi-objective landscapes is outlined.

2.1.1 Network Modeling

The foundation of network modeling is based on the one used in previous research (see Section 3 of [36]). For this reason, we have decided to move the complete modeling to Appendix A of this article, limiting ourselves to describing the modifications made in this section.

Regarding the UE-cell association, two modifications have been made to the modeling. First, in previous work, the association was based on the highest SINR (Signal-to-Interference-plus-Noise Ratio) received by the UE. Since interferences are largely mitigated and can be disregarded due to intelligent frequency reuse [41, 42], this article opts instead for the use of the SNR (Signal-to-Noise Ratio). Therefore, the SNR in UE k is defined as follows:

$$SNR_k[dB] = P_{rx,j,k}[dBm] - P_n[dBm] \quad (1)$$

where $P_{rx,j,k}$ represents the signal power received by UE k from cell j , and P_n denotes the noise power (equation (A.5)).

Second, the allocation mechanism adapted in this work is based on the theoretical maximum capacity that can be offered to the UE, assuming that the cell has no associated UEs and can dedicate its entire bandwidth to the UE. This mechanism encourages the association of UEs with smaller cells and higher working frequencies, which in turn provide greater capacity while inducing lower consumption.

2.1.2 Deployment Strategy

It is common to find scientific literature where Poisson Point Processes (PPP) are used for the deployment of BSs and/or UEs in mobile networks. This is because PPPs provide a simple mathematical model to represent the random

and spatial distribution in deployments. Additionally, they are useful because the locations of both BSs and UEs in the real world can be quite random and scattered. The PPP model can be extended or modified to accommodate additional network features, such as UEs clustering or spatial correlations, providing a good balance between accuracy and complexity.

In this sense, Mirahsan *et al.* [40] proposed to overcome the limitations of PPPs through a heterogeneous spatial model that allows statistical adjustments. The model tweaks two statistical parameters related to the distribution of UEs: the coefficient of variation of a distance measure between UEs and the correlation coefficient between the locations of UEs and BSs. This model is suggested for heterogeneous wireless cellular networks (HetNets) to demonstrate the impact of heterogeneous and correlated traffic with BSs on network performance.

Based on this model, the deployment process used is described as follows.

1. *Deployment of BSs and UEs.* First, the deployment of BSs and UEs is carried out following a PPP.
2. *Deployment of social attractors (SAs).* Subsequently, SAs are deployed randomly in the scenario. These SAs represent real-world points of interest for UEs, such as central streets, shopping centers, etc.
3. *Adjustment of the location of SAs.* Each SA is moved towards its nearest BS in terms of received power, by a factor of $\alpha \in [0, 1]$. Therefore, the new location of the i^{th} SA is as follows:

$$SA_i^{new} = \alpha BS_{SA_i} + (1 - \alpha) SA_i^{old} \quad (2)$$

where SA_i^{new} is the new location of the SA, SA_i^{old} is the initial location, and BS_{SA_i} is the BS from which SA receives the highest power.

4. *Adjustment of the locations of the UEs.* With the SAs relocated, each UE is moved towards its nearest SA in terms of Euclidean distance, by a factor β . Consequently, the new location of i^{th} UE is:

$$UE_i^{new} = \beta SA_{UE_i} + (1 - \beta) UE_i^{old} \quad (3)$$

where UE_i^{new} is the new location of the UE, UE_i^{old} the initial location, and SA_{UE_i} is the closest SA. This approach of UEs moving towards

SAs can lead to some areas of the network becoming devoid of UEs. This implies that the distribution of UEs does not change; it simply contracts towards the SAs. To address this problem, the authors of [40] modified the value of β , shifting from a fixed value to modeling it as a random variable $\beta \sim \mathcal{N}(\mu_\beta, \sigma_\beta)$, where μ_β is the mean of β and σ_β is defined as $\sigma_\beta = (0.5 - |\mu_\beta - 0.5|)/3$ to minimize the probability that β falls outside $[0, 1]$. Thus, instead of moving all UEs towards the SAs by a fixed value, the amount of movement is varied according to a normal distribution, which aids in maintaining a more uniform distribution of UEs across the scenario and preventing areas without UEs.

Consequently, by modifying the factors α and β , the spatial distribution of the UEs can be altered in the scenario. This distribution alteration is visible in Figure 2. The figure illustrates the deployments for combinations of α and β that arise from all combinations of values $[0.0, 0.3, 0.6, 0.9]$. Moving to the right implies an increase in the value of β , while moving down indicates an increase in α . Furthermore, each combination of α and β entails limits on the maximum values of the two problem objectives, since a higher concentration of UEs near SBSs will concentrate allocations in a smaller number of cells, thereby resulting in lower consumption, since more cells can be switched off, and lower capacity such as bandwidth is shared among more UEs.

2.1.3 Problem Objectives

Let $\mathcal{B}$ be the set of SBSs deployed by a PPP and $\mathcal{C}_b$ the set of cells in SBS b , for every $b \in \mathcal{B}$. A CSO solution is represented as a bitstring s , where s_c^b indicates whether the cell c in SBS b is active or not. The first objective, minimizing Power Consumption (PC), is achieved as follows:

$$\min f_{PC}(s) = \sum_{b \in \mathcal{B}} P_b \sum_{c \in \mathcal{C}_b} s_c^b \quad (4)$$

where P_b represents the power consumption of SBS b (as detailed in Eq. A.8). It is important to note that P_b includes both the transmission power of each cell c within $\mathcal{C}_b$ and the maintenance power.

Next, to calculate the total capacity of the system, the UEs initially associate themselves with the active cell, providing them with the highest theoretical capacity. Let $\mathcal{U}$ be the set of UEs, also deployed by a PPP, $\mathcal{C}$ the complete set of cells within $\mathcal{B}$, and $\mathcal{A}(s) \in (0, 1)^{|\mathcal{U}| \times |\mathcal{C}|}$ the matrix where

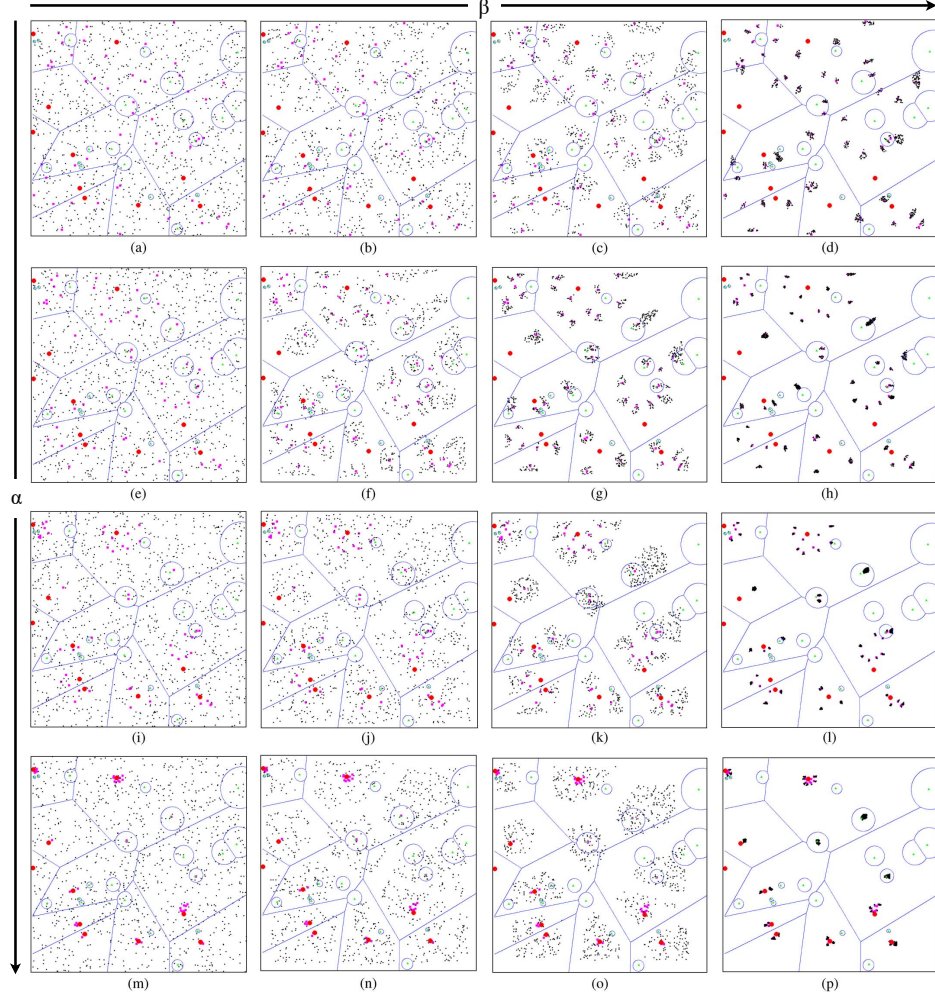


Figure 2: Deployments of UEs and SBSs for combinations of α and β resulting from combining the values 0.0, 0.3, 0.6, and 0.9 for each parameter. In the matrix, moving down the rows indicates an increase in α , while moving to the right in the columns implies an increase in β [40].

$a_{ij} = 1$ if $s_j = 1$ and cell j serves the UE i with the highest theoretical capacity, and $a_{ij} = 0$, otherwise. The second objective, which is to maximize the total capacity (Cap) provided to all UEs, is calculated as follows:

$$\max f_{Cap}(s) = \sum_{c \in C} \min(C_c^{cumulative}(s), C_c^{max}) \quad (5)$$

$$C_c^{cumulative}(s) = \sum_{i=1}^{|\mathcal{U}|} \sum_{j=1}^{|\mathcal{C}|} s_j \cdot a_{ij} \cdot C_i^j \quad (6)$$

where $C_c^{cumulative}(s)$ is the cumulative capacity that cell $c \in \mathcal{C}$ provides to the UEs in the scenario. C_c^{max} represents the maximum capacity that cell c can offer, calculated assuming an $SNR = 25 \text{ dB}$. C_i^j denotes the capacity that cell j provides to UE i (as detailed in Eq. (A.6)). The term $\min(C_c^{cumulative}(s), C_c^{max})$ ensures that capacities that exceed the maximum capacity threshold set in cells are not added to the capacity objective. It is crucial to note that the two objectives of the problem are conflicting: turning off cells leads to reduced network consumption but also affects the capacity provided to UEs. This conflict occurs because the switching off of cells increases the UE-cell distance (leading to higher propagation losses) and decreases the available bandwidth for serving the UEs.

It is also crucial to note the assumption that there is always a macrocell on in the scenario to prevent UEs from losing service. This macro cell is not included in the calculations of the objectives of the problem because the goal is to optimize the ultra-dense heterogeneous network. This provision ensures that, despite efforts to conserve energy by switching off certain cells, the fundamental service provision of the network (its capacity to connect UEs) is preserved, aligning with the core objective of balancing energy efficiency with service quality in ultra-dense network environments.

2.2 Multi-Objective Landscape Characterization

This section briefly describes the multi-objective landscape features that are the basis of this work, which can be categorized into global and local features, as defined in [38], and how they are measured. On the one hand, global features require enumerating the entire search space to be computed. They include, for example, the proportion of Pareto optimal solutions, the distance among them, their connectedness, etc. Given the context of our problem, set within a realistic scenario where the smallest instance of interest contains over 1000 binary decision variables, these characteristics become impractical. On the other hand, local features are computed from the neighborhood of a sample of solutions and make the numerical effort affordable.

Before going into the details of the particular measures used, it is important to describe how sampling is performed. As defined in the previous section, a

solution to the CSO problem is a binary string, and for such a representation, we have used a neighborhood structure at a Hamming distance of 1. Therefore, sampling is a walk over such an induced landscape, defined as an ordered sequence of solutions $(x_0, x_1, \dots, x_l)$, such that x_t is neighbor of x_{t-1} [43]. Walks can be either random when neighbors are selected randomly at each step, or adaptive when an improved neighbor is required for the walk to continue. Random walks enable the computation of the first autocorrelation coefficient, which is a measure that characterizes the ruggedness of the landscape (the larger, the smoother) [43, 44]. This autocorrelation measure does not make sense in adaptive walks, as the solutions are better at each step. Finally, while the length of a random walk, l , is defined in advance, for adaptive walks, this measure is the number of steps until the walk gets trapped in a local optimum.

3 Landscape Analysis of the CSO Problem

This section outlines the landscape features and descriptors of the CSO problem used in this study, as well as the experimental setup that includes the preliminary studies and the correlations obtained.

3.1 Landscape Features

Before describing the experimental setup, it is crucial to thoroughly understand each of the landscape features used in this study and the descriptors of the CSO problem. Table 2 contains the nomenclature for each feature or descriptor, a brief description, and, where applicable, the reference to the work from which it was derived.

Regarding the problem descriptors, two proximity factors can be shown. As detailed in Section 2.1.2, the first is the proximity factor of each SA to the closest SBS, denoted as α , and the second is the proximity factor of each UE to its closest SA, denoted as β . These descriptors are fundamental for the subsequent discussion of the correlations and the design of the landscape-aware local search operator.

Following the problem descriptors in Table 2, we can show the local landscape features classified into three types: those related to the hypervolume indicator (HV) [45], Pareto dominance, and the solutions. The first two types are based on the work of Liefooghe *et al.* [38], while the last type is

predominantly a contribution of this study. It is important to note that, as detailed in Section 2.2, obtaining the correlation between the objectives and the autocorrelation coefficients is not useful for adaptive walks. HV is a Pareto-compliant quality indicator widely used in the multi-objective community because it is able to gather information about the convergence and diversity of non-dominated solutions among the approximations to the Pareto front in one scalar value. It is computed by summing up the volume in the objective space enclosed by a given set of the non-dominated solutions. The higher the HV, the better.

Regarding the HV, three features are identified: `hv_avg`, `hvd_avg`, and `nhv_avg`. The first feature provides information on the average HV of the solutions in the walk, the second gives the average HV difference between the solutions of the walk and those of each neighborhood, and the last indicates the average HV of each neighborhood. Moreover, from random walks, we can also obtain the first autocorrelation coefficients (named `r1`) for these three features (`hv_r1`, `hvd_r1`, and `nhv_r1`). As explained in Section 2.2, the first autocorrelation coefficient of features related to HV provides information on the ruggedness of the landscape. In particular, a strong correlation with `hv_r1` indicates that local improvements are easily achievable through neighborhood exploration. This information is crucial for the local improvement strategy proposed in this article for the CSO problem.

Furthermore, features related to the dominance among the solutions of the walk and their neighborhoods can be derived, in addition to those associated with HV. In this sense, we find the proportion of dominated neighbors (`#inf_avg`), dominating neighbors (`#sup_avg`), and incomparable neighbors (`#inc_avg`). We also obtain the first autocorrelation coefficients for these features to observe trends in dominance throughout the random walks.

Among the other features of the solution, some define proportions (starting with `#`) and are identified by the type of cell (micro, pico, or femto) and the type of support structure (SBS, sector, or cell). In this context, some features define the average proportion of active structures for microcells (`#micro_sbs_on_avg`, `#micro_sector_on_avg`, and `#micro_cell_on_avg`), picocells (`#pico_sbs_on_avg`, `#pico_sector_on_avg`, and `#pico_cell_on_avg`), and femtocells (`#femto_sbs_on_avg`, `#femto_sector_on_avg`, and `#femto_cell_on_avg`). An SBS and a sector are considered active if at least one of their cells is active. Furthermore, the average proportion of UEs allocated to each type of cell is defined as a descriptor (`#micro_ue_avg`, `#pico_ue_avg`, and `#femto_ue_avg`).

Furthermore, another defined descriptor is the average distance from each UE to the nearest cell of each type (`micro_dist_avg`, `pico_dist_avg`, and `femto_dist_avg`). The features related to the objectives of the problem are also defined: first, there is an estimation of the correlation between the objective values obtained from random walks (`f_cor`); second, we obtain the average values of the objectives from the walk (`obj1_avg` and `obj2_avg`) along with their correlation coefficients (`obj1_r1` and `obj2_r1`). Finally, from adaptive walks, we can obtain the walk length (`walk_length`) to know the number of steps needed to reach a Pareto local optima (PLO).

Problem descriptors		
α	Closeness factor of the SA to the nearest SBS	Eq. 2
β	Closeness factor of the UE to the nearest SA	Eq. 3
Local landscape features related to the HV indicator		
<code>hv_avg</code>	Average single solution's HV value	[38]
<code>hv_r1</code>	First autocorrelation coefficient of single solution's HV value (from random walks)	[46]
<code>hvd_avg</code>	Average single solution's HV difference value	[38]
<code>hvd_r1</code>	First autocorrelation coefficient of single solution's HV difference value (from random walks)	[46]
<code>nhv_avg</code>	Average neighborhood's HV value	[38]
<code>nhv_r1</code>	First autocorrelation coefficient of neighborhood's HV value (from random walks)	[38]
Local landscape features related to the Pareto dominance		
<code>#inf_avg</code>	Average proportion of neighbors dominated by the current solution	[38]
<code>#inf_r1</code>	First autocorrelation coefficient of the proportion of neighbors dominated by the current solution (from random walks)	[38]
<code>#sup_avg</code>	Average proportion of neighbors dominating the current solution	[38]
<code>#sup_r1</code>	First autocorrelation coefficient of the proportion of neighbors dominating the current solution (from random walks)	[38]
<code>#inc_avg</code>	Average proportion of neighbors incomparable to the current solution	[38]
<code>#inc_r1</code>	First autocorrelation coefficient of the proportion of neighbors incomparable to the current solution (from random walks)	[38]
Features of the solutions		
<code>#micro_sbs_on_avg</code>	Average proportion of active micro-SBS	
<code>#micro_sector_on_avg</code>	Average proportion of active micro-sectors	
<code>#micro_cell_on_avg</code>	Average proportion of active microcells	
<code>#pico_sbs_on_avg</code>	Average proportion of active micro-SBS	
<code>#pico_sector_on_avg</code>	Average proportion of active micro-sectors	
<code>#pico_cell_on_avg</code>	Average proportion of active microcells	
<code>#femto_sbs_on_avg</code>	Average proportion of active micro-SBS	
<code>#femto_sector_on_avg</code>	Average proportion of active micro-sectors	
<code>#femto_cell_on_avg</code>	Average proportion of active microcells	
<code>#micro_ue_avg</code>	Average proportion of UEs allocated with microcells	
<code>#pico_ue_avg</code>	Average proportion of UEs allocated with picocells	
<code>#femto_ue_avg</code>	Average proportion of UEs allocated with femtocells	
<code>micro_dist_avg</code>	Average distance from the nearest microcell to the UEs	
<code>pico_dist_avg</code>	Average distance from the nearest picocell to the UEs	
<code>femto_dist_avg</code>	Average distance from the nearest femtocell to the UEs	
<code>f_cor</code>	Estimated correlation between the objective values (from random walks)	[38]
<code>obj1_avg</code>	Average single solution's value of the first objective	Eq. 4
<code>obj1_r1</code>	First autocorrelation coefficient of the single solution's value of the first objective (from random walks)	
<code>obj2_avg</code>	Average single solution's value of the second objective	Eq. 5
<code>obj2_r1</code>	First autocorrelation coefficient of the single solution's value of the second objective (from random walks)	
<code>walk_length</code>	Average length of adaptive walks	[47]

Table 2: Problem descriptors, multi-objective landscape features, and characteristics of the solutions considered in this article.

3.2 Experimental Setup

3.2.1 Preliminary Studies

Given that the CSO problem is a real-world telecommunication challenge, the computational costs (both memory and computational time) are considerable. For this reason, before performing the walks, collecting landscape features and problem descriptors, as well as calculating correlations, we conducted preliminary studies to improve efficiency without losing landscape information on the problem.

As described in Appendix A, we define 9 types of scenarios with different densities of SBSs and UEs for the problem. Additionally, we used 50 different random seeds to generate 50 similar instances of the scenario, each consistent in terms of the densities of SBSs and UEs. Consequently, we dealt with a total of 450 instances. Therefore, before beginning the exploratory landscape analysis, we performed consistency tests of the features across the different density scenarios. This approach allowed us to focus on working with the 50 seeds of the lower-density scenario (that is, the one requiring the smaller computational resources) so that the conclusions drawn could be extrapolated to the rest of the 9 scenarios. Following this preliminary study, we concluded that there were no significant differences in the correlations found across the nine scenarios. Hence, we decided to focus on the lower-density scenario for exploratory landscape analysis in this work.

Then, another study was conducted to determine the maximum length of the random walks. To be consistent with previous works where we used 100000 evaluations as the stopping condition of the algorithms, we decided to set the walk size to the same number. However, we faced a significant time challenge: exploring the entire neighborhood at each step of the walk. As mentioned above, our analysis focused on the lower-density instance, meaning fewer decision variables. However, considering the landscape analysis required to evaluate the entire neighborhood at each step of the walk, we would need to perform roughly about 120 million evaluations per walk, which is infeasible for a real-world problem. Consequently, we decided to evaluate if, instead of exploring the entire neighborhood, we could explore just a portion of it, which resulted in that we can limit our exploration to 5% of the neighborhood without losing information in the correlations while achieving a significant gain in computational time. The selection of which neighbors are explored is carried out through a random sampling of the complete neighborhood.

3.2.2 Correlations

In the analysis of landscape characteristics in multi-objective problems, understanding the interdependencies between different variables is crucial. For this purpose, the Kendall rank correlation coefficient [48], τ , which is a robust and nonparametric statistical measure, is used to quantify the association between two variables. The coefficient τ is calculated based on the number of concordant and discordant pairs in the dataset. A data pair is considered concordant if the observations in both variables maintain the same order; that is, if one observation is greater than another in one variable, it is also greater in the other. Conversely, a pair is deemed discordant when the order of observations in the two variables is opposite. The coefficient τ is calculated using the formula $\tau = \frac{N_c - N_d}{\sqrt{(N_0 - N_1)(N_0 - N_2)}}$, where N_c and N_d represent the number of concordant and discordant pairs, respectively. Here, $N_0 = \frac{n(n-1)}{2}$ is the total number of possible pairs in the dataset, with n being the number of observations. The terms $N_1 = \sum t_i(t_i - 1)/2$ and $N_2 = \sum u_i(u_i - 1)/2$ adjust the calculation of the ties within each of the variables, where t_i and u_i are the numbers of ties at the i^{th} observation of each variable, respectively. A value of τ close to 1 indicates a strong positive correlation, while a value close to -1 implies a strong negative correlation. A value around 0 implies no correlation. This coefficient is particularly useful in our study as it does not assume a linear relationship between the variables and is resilient to the presence of outliers.

To visually display the correlations between different features and descriptors, we have generated correlation boards for samples from adaptive walks and random walks, which are interpreted similarly to a correlation matrix. Blue circles indicate a positive correlation, while red circles indicate a negative correlation. The intensity of the color and the size of the circle are proportional to the strength of the correlation. Additionally, to provide an alternative visualization of the relationship between features, we have generated dendrograms using Ward’s hierarchical agglomerative clustering method [49]. This method allows us to separate clusters of features based on their dissimilarity, offering another layer of information about the landscapes and the justification of the correlations visualized in the boards.

Taking into account the wide range of features to be analyzed, this article focuses on three distinct subgroups: dominance, HV, and solution features, with a special emphasis on the problem descriptors α and β . Additionally,

the analysis of data collected through adaptive walks and random walks is conducted separately. This approach provides a comprehensive understanding of their respective behaviors within the solution space of the problem. Therefore, the correlations obtained through adaptive walks are represented on the correlation board in Figure 3, and in the dendrogram in Figure 4. Meanwhile, those obtained by random walks are shown in Figure 5, and the corresponding dendrogram in Figure 6.

Dominance-related features for adaptive walks From Figures 3 and 4, there is one main finding that can be drawn about the landscape and complexity of the problem, taking into account these features and the problem descriptors α and β . There is a strong correlation with `walk_length`, which suggests that, as long as SBSs and UEs are closer to each other (a higher level of clustering and, equivalently, a higher level of spatial heterogeneity in traffic demand), the landscape becomes easier to explore. Indeed, the number of steps of the adaptive walk increases, i.e., it is easier to find an improving solution. The positive correlation with `obj1_avg`, `obj2_avg`, `hv_avg` and `nhv_avg` corroborates this fact: the higher the values of α and β , the better the objectives of the problem, and thus the better the HV of the solutions and the neighborhood. A more clear trend can be seen in Table 3, where the data collected over the different β values is aggregated for different landscape features. It can be seen that the proportion of non-dominated solutions (`#inc_avg`) decreases with β , whereas the proportion of worse/dominated (`#inf_avg`) and better/dominating `#sup_avg` solutions increases. That is, on the one hand, the landscape is more informative (fewer non-dominated solutions, thus reducing the existence of plateaus), and, on the other hand, the probability of moving to an improving neighbor increases. Further experimentation conducted in Section 5 will support this claim.

β	hv_avg	#inc_avg	#inf_avg	#sup_avg
0.0	0.5735	0.2010	0.5951	0.2017
0.3	0.5667	0.1864	0.6063	0.2051
0.6	0.5642	0.1460	0.6373	0.2147
0.9	0.6137	0.0718	0.6936	0.2328

Table 3: Dominance-related landscape features aggregated over different values of β .

HV-related features for adaptive walks Apart from the correlations with `hv_avg` and `nhv_avg` discussed earlier, the negative correlation of α and β with `hvd_avg` suggests that a higher level of clustering implies greater variability in the HV of solutions compared to their neighborhoods. This indicates that as the spatial heterogeneity of traffic demands increases, the differences in HV between a solution and its surrounding solutions become less pronounced, reflecting a more uniform landscape. Therefore, higher values for α and β result in landscapes that are easier to explore.

Solution-related features for adaptive walks The spatial heterogeneity generated by α and β also has effects on the features of the solution traversed by the adaptive walk. Specifically, greater heterogeneity tends to produce solutions with a higher proportion of UEs associated with femtocells (positive correlation with `#femto_ue_avg`) and lower with microcells (negative correlation with `#micro_ue_avg`). Given that `hv_avg` and `nhv_avg` correlate positively with `#femto_ue_avg`, it can be observed that the associations of solutions that improve the objectives of the problem and the HV are primarily made with femtocells. This hypothesis is reinforced by the positive correlation of `#sup_avg` and slightly negative correlation of `#inf_avg` with `#femto_cell_on`, indicating that cell activation favors neighborhoods with a higher proportion of non-dominated solutions. Furthermore, the negative correlation of `#femto_ue_avg` with `hvd_avg` suggests that the difference in HV is smaller with a higher proportion of such associations. From this, it can be inferred that the ruggedness of the landscape is smoother in areas of high HV.

Dominance-related features for random walks Regarding the dominance features from random walks, a clear conclusion can be drawn with α and β : greater clustering results in neighborhoods with higher proportions of both dominated (strong positive correlation with `#inf_avg`) and non-dominated (strong positive correlation with `#sup_avg`) solutions compared to incomparable ones. This reinforces the hypothesis that a higher concentration of UEs towards SBSs makes the landscape easier to explore.

HV-related features for random walks The strong positive correlations of the problem descriptors with `hv_avg` and `nhv_avg` indicate that the solutions tend to be of higher quality in random samplings, corroborating the hypothesis



Figure 3: Correlation board for the features obtained through adaptive walks. Blue color indicates a positive correlation, while red color implies a negative correlation. Moreover, the intensity of the color and the size of the circle are proportional to the strength of the correlation.

that the landscape becomes easier to explore.

Solution-related features for random walks The correlations between the characteristics that define the proportion of active microcells and, to a lesser extent, picocells, with `#inc_avg` indicate that the highest proportion

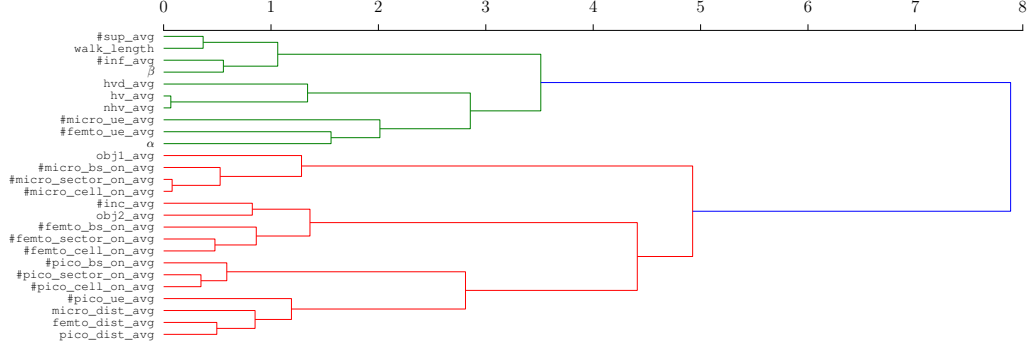


Figure 4: Ward's dissimilarity measure among the features obtained through adaptive walks.

of incomparable solutions is found when many microcells are active and, therefore, when there is a higher `hvd_avg`. This suggests that the ruggedness of the landscape is greater, making it more difficult to explore. Additionally, `#inf_avg` and `#sup_avg` have a very positive correlation with cells operating at higher frequencies, particularly femtocells. Therefore, having a higher proportion of active femtocells, and to a lesser extent picocells, results in a higher proportion of both dominated and non-dominated solutions and a landscape easier to explore due to the higher uniformity of the landscape, that is, less ruggedness. Consequently, it can be concluded that femtocells are key in guiding the search toward more promising areas of the landscape, while microcells present greater challenges. Regarding `hv_r1`, a negative correlation is observed with `#micro_cell_on_avg`, indicating that activating microcells leads to greater variability in HV throughout the walk. Furthermore, the strong positive correlation with `#femto_ue_avg` and negative with `#micro_ue_avg` suggest that favoring the use of femtocells tends to result in solutions with more similar HV values during the walk.

Finally, combining each analysis, two key conclusions can be drawn: a greater spatial heterogeneity in traffic demands results in a landscape that is easier to explore, and femtocells are of great importance for improving problem objectives and HV values. A previous paper [36] already elaborated on the line of this latter conclusion, in which the working hypothesis was that the activation of femtocells can improve the search process. This was demonstrated by devising problem-specific operators. Meanwhile, the first conclusion is further developed in this article through the design of a local

search operator that leverages the information obtained with spatial traffic heterogeneity.

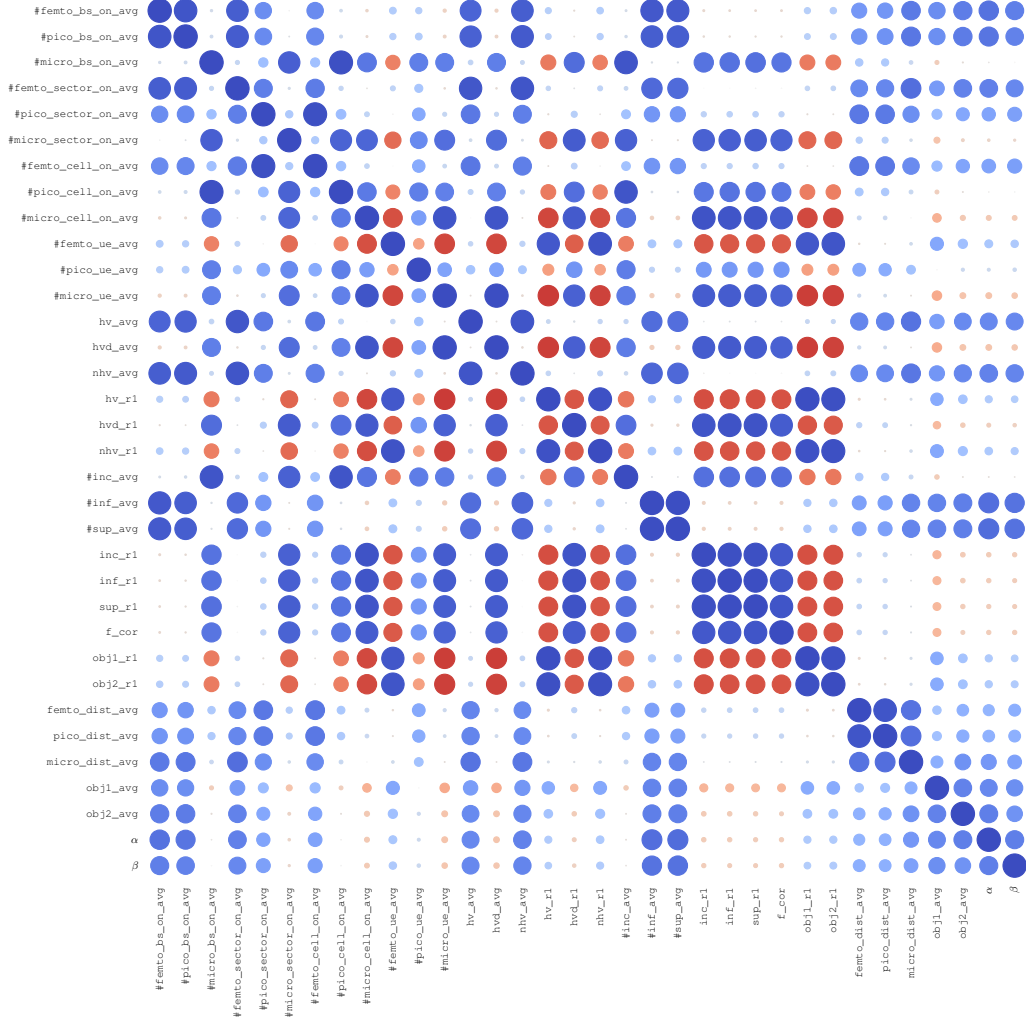


Figure 5: Correlation board for the features obtained through random walks.

4 Landscape-Aware Local Search

This section is devoted to describing a design of a local search operator that capitalizes on the knowledge acquired about the landscape characteristics

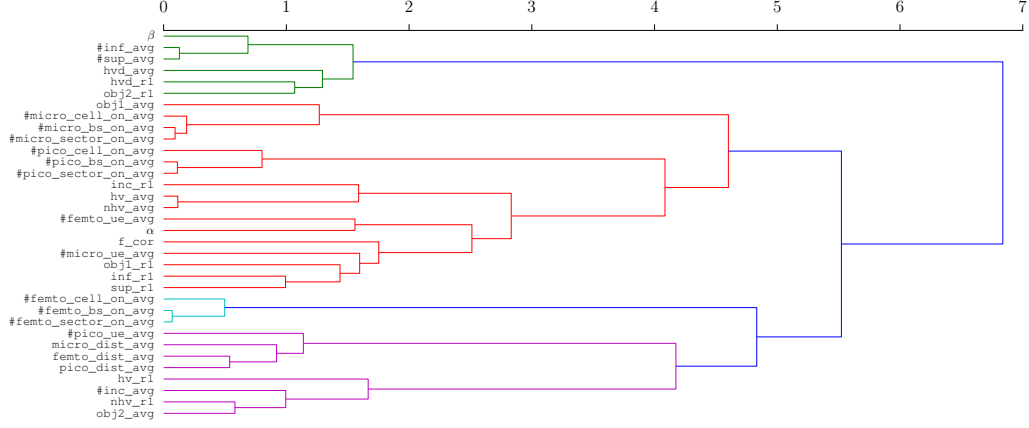


Figure 6: Ward's dissimilarity measure among the features obtained through random walks.

detailed in the previous section. One of the key insights from the landscape analysis of the CSO problem is that greater spatial traffic heterogeneity makes local exploration of the search space easier. This is due to the proximity of UEs to SBSs, which makes higher-frequency cells (femtocells and, to a lesser extent, picocells) crucial for the optimization process. These types of cells have a low energy consumption and a high capacity, thus meeting the demands in small, highly-density areas. On the contrary, their size (i.e., the area they can serve) is small, thus UEs have to be close enough to establish a high-quality wireless link.

Algorithm 1 outlines the designed local search operator, which is based on performing a tailored adaptive walk (see Section 2.2) starting from a given solution chosen with a given rate, and that ends in a Pareto local optimum. The strategy of the operator is similar to that of a multi-objective hill climber. Still, the key aspect of the operator is the utilization of landscape information in the determination of how the neighborhood of each solution is explored. In the standard case, the neighborhood just consists of all solutions at a Hamming distance of 1 from the solution that is explored randomly (one randomly chosen neighbor at each time, moving only towards an improving one). The newly devised strategy uses the landscape information so that the neighborhood is biased according to the value of the proximity factor β . This is achieved by the way the neighborhood is explored, so that those cells located in areas where the spatial heterogeneity of the traffic demands is

low (i.e., those in which β is known to be low and thus with more difficult landscape) are visited first, to identify the improvement neighbors in that area. Specifically, a Hamming neighbor would become part of the neighborhood with a probability of $1 - \beta$ (as detailed in lines 4-5 of Algorithm 2).

Algorithm 1 Landscape-aware local search operator

```

1: procedure LOCALSEARCHOPERATOR(solution, rate)
2:   if RANDOM() < rate then
3:     current  $\leftarrow$  COPY(solution)
4:     last  $\leftarrow$  COPY(solution)
5:     EVALUATE(current)
6:     plo  $\leftarrow$  false
7:     while  $\neg$ plo do
8:       current  $\leftarrow$  GETDOMINANTNEIGHBOR(current)
9:       if current is null then
10:        plo  $\leftarrow$  true
11:       else
12:        last  $\leftarrow$  COPY(current)
13:       end if
14:     end while
15:   end if
16:   return last
17: end procedure

```

5 Results

This section presents a brief experimentation to validate the effectiveness of the local search operator that incorporates landscape information. First, the methodology is outlined, and then, two experiments are conducted to, on the one hand, validate the hypothesis that increased spatial heterogeneity of traffic makes an easier landscape to explore and, on the other hand, to undertake a preliminary comparison between the newly devised aware operator and a standard multi-objective hill climber to show that our proposal can effectively profit from the landscape information.

Algorithm 2 Get a dominant solution of the landscape-aware Hamming neighborhood

```

1: procedure GETDOMINANTNEIGHBOR(current)
2:   neighborhood  $\leftarrow$  [ ]
3:   for  $i \leftarrow 0$  to GETNUMBEROFCELLS(solution) do
4:     probability  $\leftarrow 1 - \text{GETBETA}(\text{solution.GetCell}(i))$ 
5:     if random  $\leq$  probability then
6:       neighbor  $\leftarrow \text{COPY}(\text{solution})$ 
7:       neighbor.FlipBit(i)
8:       neighborhood  $\leftarrow$  neighborhood + [neighbor]
9:     end if
10:  end for
11:  neighborhoodSize  $\leftarrow \text{SIZEOF}(\text{neighborhood})$ 
12:  permutation  $\leftarrow \text{GETINTEGERPERMUTATION}(\text{neighborhoodSize})$ 
13:  for each  $i$  in permutation do
14:    neighbor  $\leftarrow$  neighborhood.GetNeighbor(i)
15:    EVALUATE(neighbor)
16:    if DOMINATES(neighbor, current) then
17:      return neighbor
18:    end if
19:  end for
20:  return null
21: end procedure

```

5.1 Experimental Methodology

NSGA-II [50] has been used as the baseline multi-objective solver in all the experiments. It has been configured to use a binary string representation with binary tournament selection, two-point crossover with a probability of 0.9, and bit flip mutation with a probability of $1/L$, where L is the total number of cells in the scenario. Furthermore, 100,000 evaluations have been used as the stopping condition. This metaheuristic configuration is inherited from [36].

NSGA-II has been hybridized by applying the local search operator right after the application of the crossover and mutation operators. The local search then starts from a given solution and continues until it converges to a Pareto local optimum, and at this point, it is inserted back into the

population. The evaluations of the objective functions consumed during the search are also counted towards reaching the stopping condition for a fair comparison, which means that, if the local search is applied with higher probabilities, the number of NSGA-II iterations is reduced, thus limiting the evolutionary process. Regarding the probability of application of the operator, the experiments were conducted with values of 0.001, 0.010, and 0.100.

5.2 Analysis of the Spatial Heterogeneity Impact on Landscape Explorability

For this exploratory analysis, the hybrid NSGA-II has been tested in 7200 different instances of the CSO problem, which is the result of performing an execution for each of the 50 different random seeds across the 9 density scenarios described in Appendix A and the 16 different heterogeneity factors devised in Figure 2 of Section 2.1.2. Considering the application of the three rates of the operator and the runs of the canonical metaheuristic, that is, without the local search operator, a total of 28,000 runs have been carried out.

In Figure 7, the difference in the HV values between the runs with the application of the multi-objective hill climber and the canonical metaheuristic is displayed (the raw HV values can be found in Appendix C). For this, the HV values have been averaged across all scenarios and seeds, in addition to the values of α , as β is the factor that shows more significant differences, as discussed in Section 3. This experiment aims to show that the HV difference tends to decrease with a higher value of β and, as a consequence, the exploration of the search space of the canonical NSGA-II with any intensification mechanism such as the multi-objective hill climber is able to reach much closer approximations to the Pareto fronts than those computed by the hybrid version of the algorithm. It can be concluded that the landscape can be easily explored when β is higher, that is, when traffic demands (UEs) are more clustered around the SBSs (cells).

The fact that the difference slightly increases for medium heterogeneity values, especially for the application ratio of 0.010, may be because an increase in β for a higher α does not strictly indicate lower heterogeneity in some cases. In Figure 2 of Section 3.2, it is observed that in deployment (k), with a higher α , there is greater heterogeneity than in (g), although the factor is lower. This issue could be responsible for the values observed for medium

heterogeneity.

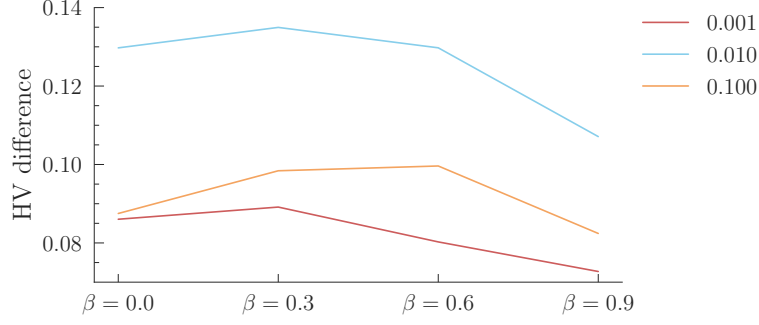


Figure 7: Average differences between the various application rates and the metaheuristic without local search.

To visually illustrate these differences, Figure 8 includes the attainment surfaces [51] for the HH scenario, the one with the highest density of UEs and SBSs. The empirical attainment function (EAF) [51] facilitates a graphical examination of the approximated Pareto fronts. Specifically, the EAF visually represents the expected performance and its variability of the Pareto fronts approximated by the multi-objective algorithm across several iterations. To put it simply, within the context of multi-objective optimization, the 50%-attainment surface serves a role similar to the median in single-objective optimization scenarios. The rest of the scenarios can be consulted in Appendix B. Therefore, in Figure 8 it can be observed that as the values of α and β increase, the difference between the Pareto front approximations with and without the application of the search operator decreases to the point of being very similar fronts. This corroborates that greater heterogeneity eases the search, and the metaheuristic does not require local search operators to achieve similar results. On the contrary, lower heterogeneity creates a landscape more amenable to the local search operator, particularly for improving the power energy consumption objective of the network.

5.3 Comparative Analysis of Local Search Operators Performance

To verify the effectiveness of the landscape-aware operator and validate the findings drawn from the feature correlations in Section 3.2, the hybrid NSGA-II

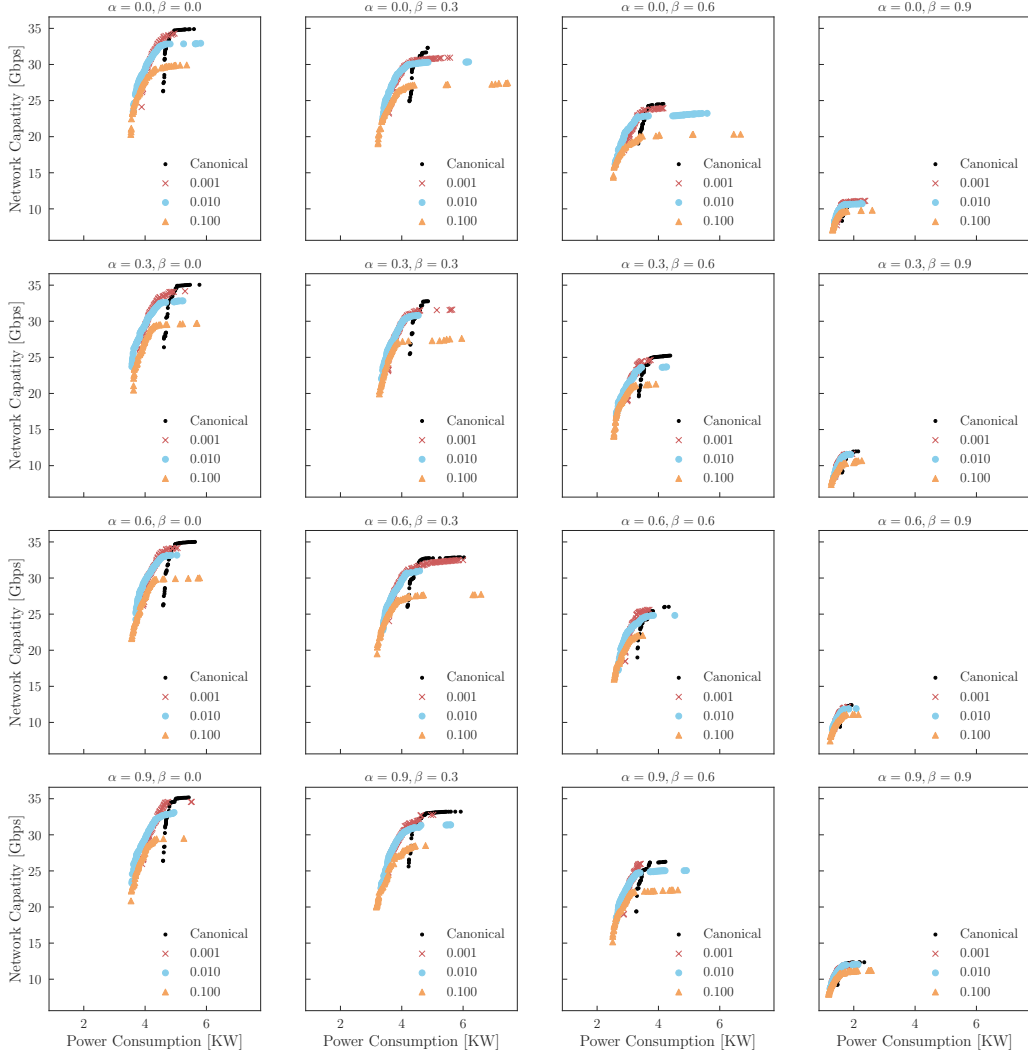


Figure 8: Approximations to the Pareto front for the different rates of application of the multi-objective hill climber in the HH scenario.

has been tested against 450 different instances. The spatial heterogeneity of traffic is divided into quadrants, with three of them exhibiting high heterogeneity ($\alpha = \beta = 0.9$), and one with low heterogeneity ($\alpha = \beta = 0.0$). Consequently, the landscape-aware operator will focus on improving the three quadrants with lower heterogeneity, which are inherently more challenging to explore, rather than concentrating efforts on the more navigable area of the

landscape, i.e., the network area with higher heterogeneity. In contrast, the multi-objective hill climber does not differentiate between areas, performing searches regardless of heterogeneity (i.e., the neighbors to be explored are chosen in a randomly uniform manner).

Figure 9 displays the HV gain achieved by the landscape-aware operator compared to the multi-objective hill climber for three different application rates: 0.001, 0.01, and 0.1. The application rate of 0.1 consistently provides the highest gain across all nine density scenarios. The 0.001 rate shows improvements in the majority of scenarios, seven out of nine, but these are quite marginal. The 0.01 rate achieves the least gains, outperforming the operator in only three of the nine scenarios. Nevertheless, for all rates, there is a discernible trend in scenarios of higher density, and it is more advantageous to apply the landscape-aware operator.

The results lead to the finding that landscape information, particularly regarding the spatial heterogeneity of network traffic, enables the enhancement of the outcomes of the metaheuristic. Conducting local searches targeted at more complex areas of the landscape allows the metaheuristic to achieve better approximations to the Pareto front, using the same stopping condition.

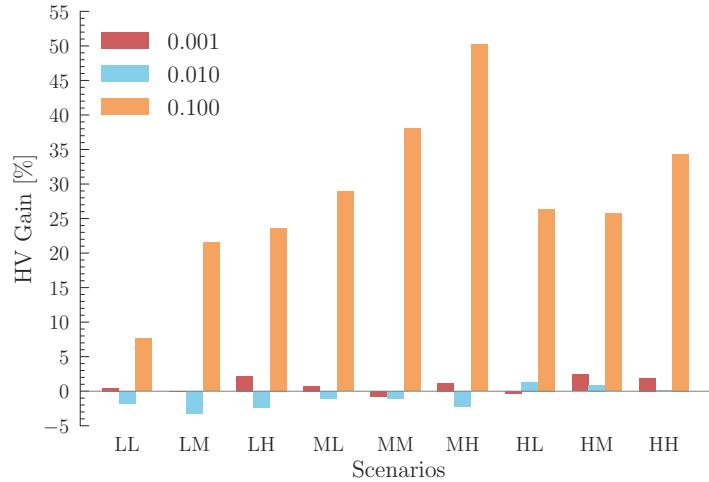


Figure 9: HV gain achieved by the landscape-aware operator compared to the multi-objective hill climber for three different application rates.

6 Conclusions and Future Work

After an in-depth analysis of the landscape of the CSO problem and after the examination of correlations between various features, this study has shown that an increase in the spatial heterogeneity of network traffic significantly smoothens the landscape, thus facilitating its exploration. To leverage this understanding, a novel search operator has been developed specifically to enhance multi-objective metaheuristics. This operator is designed to navigate the complexities of the landscape effectively, focusing on areas of the network characterized by lower heterogeneity. These regions, typically more challenging due to their uniformity, present unique opportunities for optimization that had previously been untapped. By strategically exploiting the information gleaned from the landscape analysis, the operator guides the search process towards more promising regions of the solution space. The empirical evidence presented confirms the efficacy of the operator, showcasing its ability to achieve better approximations to the Pareto front compared to traditional methods.

For future work, several directions are proposed that continue with the analysis of the problem landscape. First, an analysis of other problem descriptors, such as the association between UEs and cells, will be carried out. Second, we aim to continue the study of proposals for landscape-aware operators and genetic operators capable of operating with the information obtained from the landscape. Third, a study will be conducted on the problem-specific operators proposed in previous works to examine how the shape of the landscape, influenced by heterogeneity, affects the effectiveness of the operators. Fourth, due to the sparse nature of the CSO problem, where optimal solutions often involve a minimal number of active cells, there is a compelling interest in further investigating the landscape for sparse solutions.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

Disclosure Statement

No potential competing interest was reported by the authors.

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A Network Modeling

In this study, a service area measuring 500×500 meters is considered, within which ten distinct regions are defined, each with different propagation conditions. To calculate the received power, P_{rx} in dBm , at any given location within this area, the following model has been employed:

$$P_{rx}[dBm] = P_{tx}[dBm] + P_{loss}[dB] \quad (A.1)$$

where P_{rx} denotes the received power in dBm , P_{tx} represents the transmitted power in dBm , and P_{loss} refers to the global signal losses. These losses are contingent upon the specific propagation region and are computed as follows:

$$P_{loss}[dB] = GA + PA \quad (A.2)$$

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

$$PA[dB] = \left(\frac{\lambda}{4 \cdot \pi \cdot d} \right)^K \quad (A.3)$$

where d is the Euclidean distance to the corresponding sector in the SBS, K denotes the exponent loss, which randomly ranges in $[2.0, 4.0]$ for each of the 10 different regions. The Signal-to-Noise Ratio (SNR) for UE k , is computed as:

$$SNR_k = \frac{P_{rx,j,k}[mW]}{P_n[mW]} \quad (A.4)$$

where $P_{rx,j,k}$ is the received power by UE k from the cell j , and P_n is the noise power, computed as:

$$P_n[dBm] = -174 + 10 \cdot \log_{10} BW_j \quad (A.5)$$

being BW_j the bandwidth of cell j , defined as 10% of the operating frequency of SBS, which is the same for all cells it deploys (see Table 4).

In the final analysis, the UE capacity is determined based on the Multiple Input Multiple Output (MIMO) model as described in [52]. It is assumed that the transmission power from each antenna is P_{tx}/n_{tx} , with n_{tx} representing the number of transmitting antennas. When considering the subchannels as

uncoupled, their capacities can be summarized. Therefore, the total channel capacity for UE k is estimated using the Shannon capacity formula as follows:

$$C_k^j[bps] = BW_k^j[Hz] \cdot \sum_{i=1}^r \log_2 \left(1 + \frac{SNR_k \cdot \lambda_i}{n_{tx}} \right) \quad (\text{A.6})$$

where $\sqrt{\lambda_i}$ represents the singular value of the channel matrix $\mathbf{H}$, which has dimensions $n_{rx} \times n_{tx}$, indicating the number of receiving antennas times the number of transmitting antennas. The values of both n_{rx} and n_{tx} are contingent upon the type of cell, as detailed in Table 4. The term BW_k^j denotes the bandwidth allocated to UE k when it is connected to cell j , under the assumption of round-robin scheduling, which implies:

$$BW_k^j = \frac{BW_j}{N_j} \quad (\text{A.7})$$

where N_j denotes the number of UEs connected to a cell j .

To build a heterogeneous network, three types of cells are considered, varying in size and frequency: femtocells, picocells, and microcells. These cells originate from antennas within a sector of a SBS. Figure 10 illustrates the configurations used in our model. The first row shows three SBSs, each with three sectors and all cells in operation, represented by binary strings with all genes set to 1. The second row presents several solutions where a subset of cells are switched off, reflected in the binary strings with genes set to 0. Remarkably, the number of transmitting antennas for each cell type increases with frequency: 8 for microcells, 64 for picocells, and 256 for femtocells. Similarly, high-capacity UEs, likely to connect to smaller cells (picocells and femtocells), are assumed to have a larger number of receiving antennas, with 4 and 8 antennas for picocells and femtocells, respectively.

The deployment of cells in this system is achieved by placing SBSs within the work area, each having a random rotation angle for its sectors. This angle determines the orientation of the cell beams. Both SBSs and UEs are deployed using independent Poisson Point Processes (PPP) with different densities, denoted by λ_P^{Cells} for cells and λ_P^{UE} for UEs. Our software framework incorporates a discretization method that uses a grid comprising 100×100 points, also called “pixels” or area elements, each covering 25 m^2 where the signal power is considered uniform. Furthermore, vertical densification is addressed by considering 3 vertical area elements, equivalent to 25 meters of

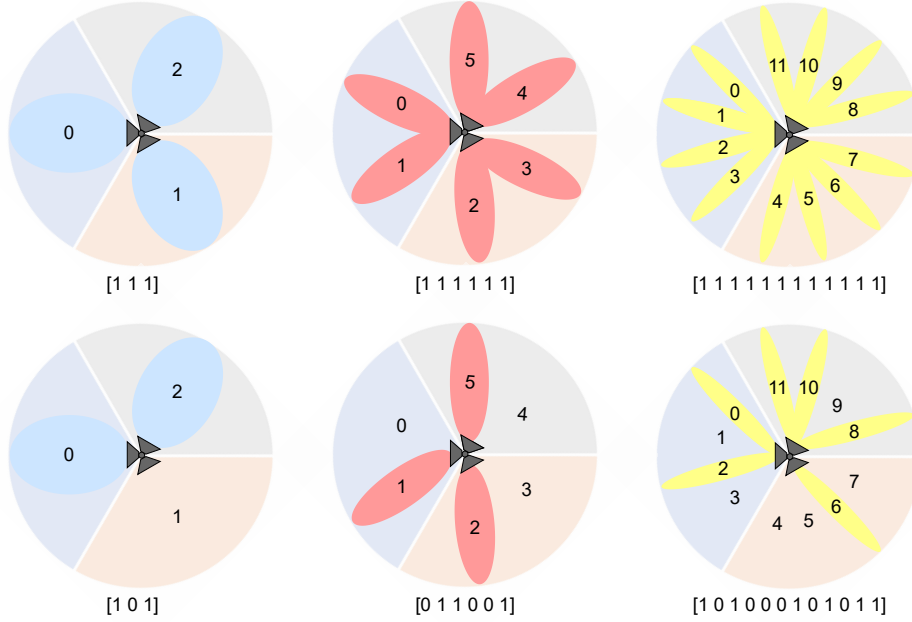


Figure 10: Configuration of the SBSs, sectors, and cells used in this work, along with their mapping into a binary encoded representation.

height. This approach is designed to reduce the computational cost of the SNR values.

The power consumption of a transmitter is computed using the model outlined in [53], which assumes the device transmits over fiber backhauling. Consequently, the standard power consumption of cell j , denoted as P_j , is expressed as follows:

$$P_j = \alpha \cdot P + \beta + \delta \cdot S_j + \rho \quad (\text{A.8})$$

where P denotes the transmitted or radiated power of the transmitter, the coefficient α represents the efficiency of the transmission power produced in the radio frequency amplifier and feeder losses. The term β refers to the power dissipated due to signal processing and site cooling, and δ indicates the dynamic power consumption per unit of data, with S being the actual traffic demand served by the cell. The power consumption of the transmitting device itself is denoted by the coefficient ρ . However, for a more accurate power

consumption model, the power consumed by air conditioning and the SBS power supply is also considered [54]. This aspect, referred to as maintenance power, is set to 2W per SBS, applicable for any SBS with at least one active cell.

The parameterization of the scenarios addressed in this study is detailed in Table 4. This table links the parameter to its corresponding equation in the formulation described above. The names in the last nine columns, XY, represent the deployment densities of SBSs and UEs, respectively, so that $X = \{L, M, H\}$, meaning either low, medium, or high-density deployments (λ_P^{Cell} 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 for each type of cell refer to the transmission gain and the operating frequency (including the available bandwidth) of the antenna, with n_{tx} and n_{rx} representing the number of transmit and receive antennas. Finally, the parameters of the power consumption model described previously are also included in the table. Therefore, nine different scenarios have been used in this work.

Cell	Parameter	Eq.	LL	LM	LH	ML	MM	MH	HL	HM	HH
Micro	G_{tx}	(A.2)	12								
	f	(A.5)	5 GHz (BW = 500 MHz)								
	α	(A.8)	15								
	β	(A.8)	10000								
	δ	(A.8)	1								
	$\rho[W]$	(A.8)	1								
	n_{tx}		8								
	n_{rx}		2								
	$\lambda_P^{micro} [Cells/km^2]$		300	300	300	600	600	600	900	900	900
Pico	G_{tx}	(A.2)	20								
	f	(A.5)	20 GHz (BW = 2000 MHz)								
	α	(A.8)	9								
	β	(A.8)	6800								
	δ	(A.8)	0.5								
	$\rho[W]$	(A.8)	1								
	n_{tx}		64								
	n_{rx}		4								
	$\lambda_P^{pico} [Cells/km^2]$		1500	1500	1500	1800	1800	1800	2100	2100	2100
Femto	G_{tx}	(A.2)	28								
	f	(A.5)	68 GHz (BW = 6800 MHz)								
	α	(A.8)	5.5								
	β	(A.8)	4800								
	δ	(A.8)	0.2								
	$\rho[W]$	(A.8)	1								
	n_{tx}		256								
	n_{rx}		8								
	$\lambda_P^{femto} [Cells/km^2]$		3000	3000	3000	6000	6000	6000	9000	9000	9000
UEs	$\lambda_P^{UE} [UE/km^2]$		1000	2000	3000	1000	2000	3000	1000	2000	3000

Table 4: Model parameters for UEs and SBSs.

B Approximations to the Pareto Front

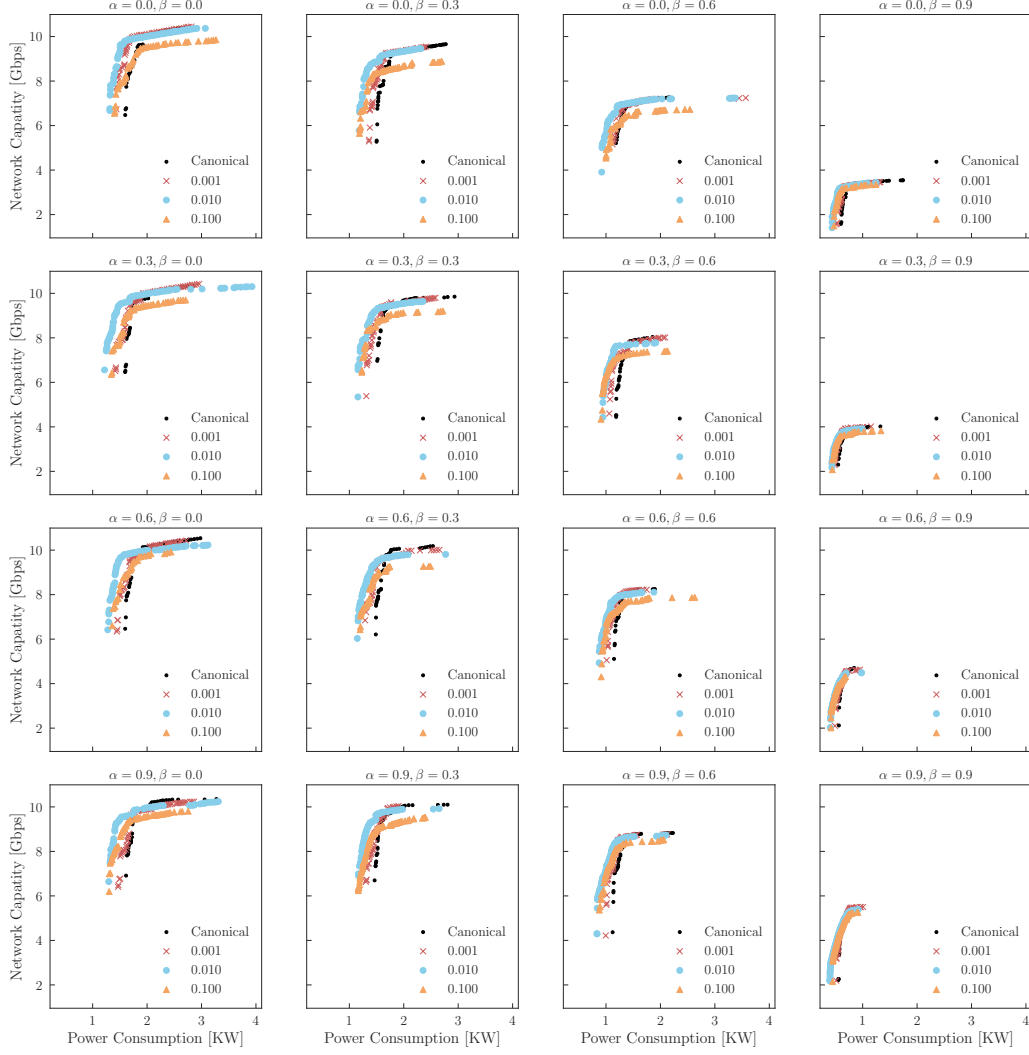


Figure 11: Approximations of the Pareto front for the different rates of application of the landscape-aware local search operator in the LL scenario.

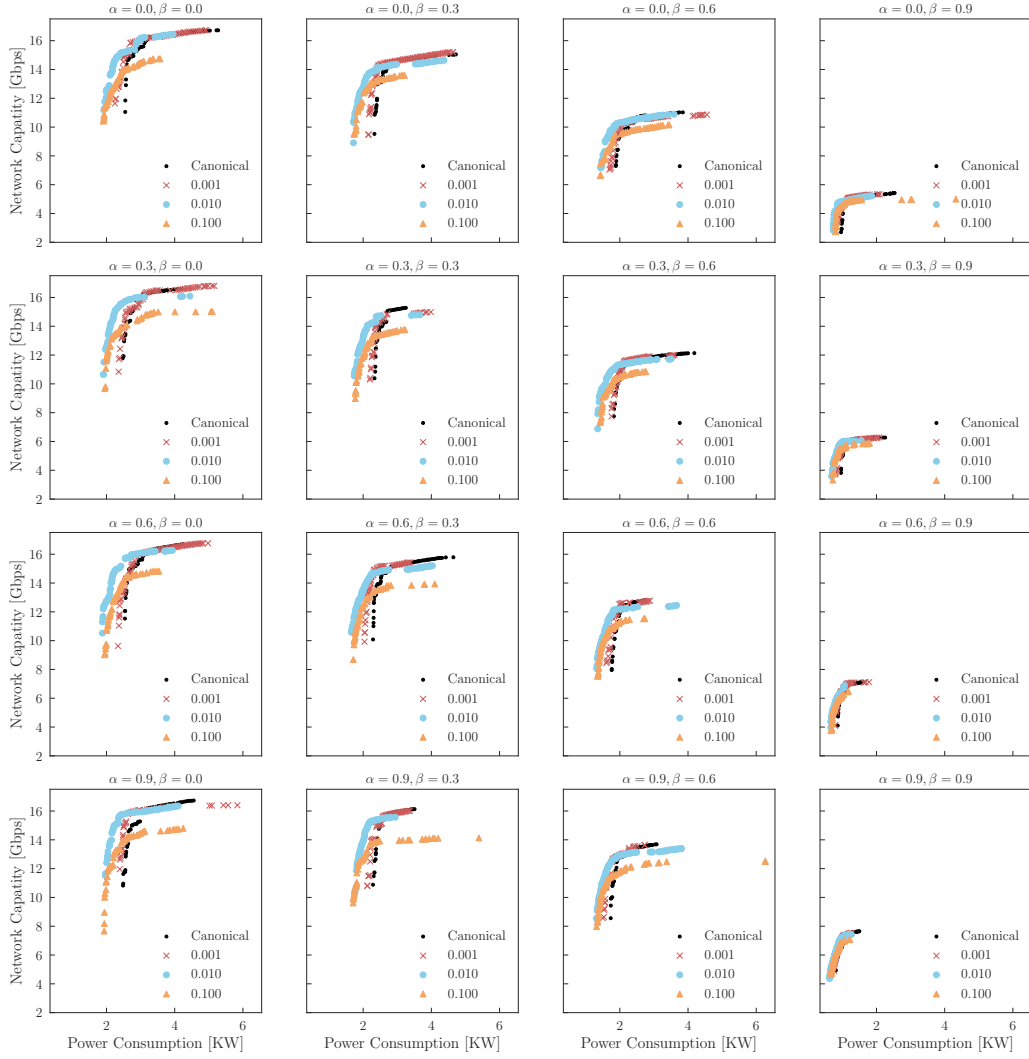


Figure 12: Approximations of the Pareto front for the different rates of application of the landscape-aware local search operator in the LM scenario.

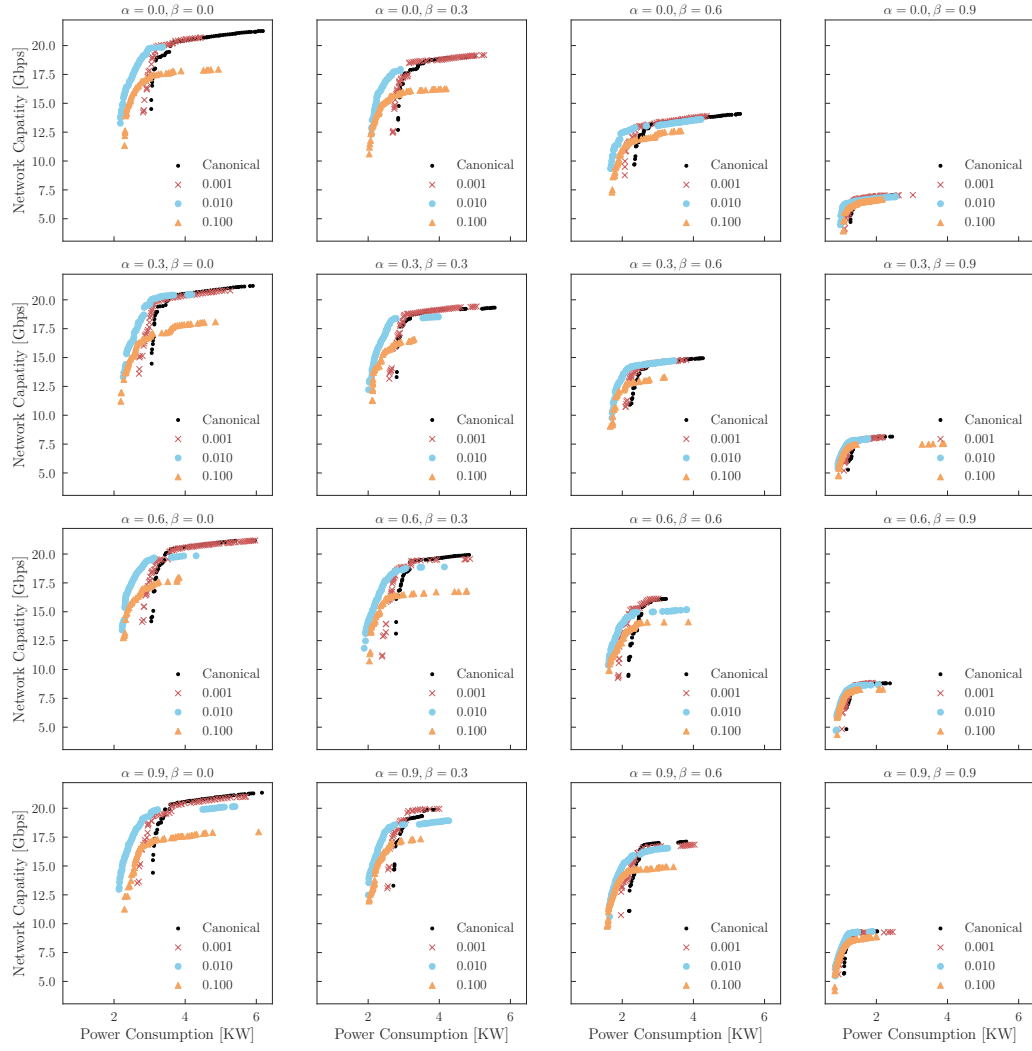


Figure 13: Approximations of the Pareto front for the different rates of application of the landscape-aware local search operator in the LH scenario.

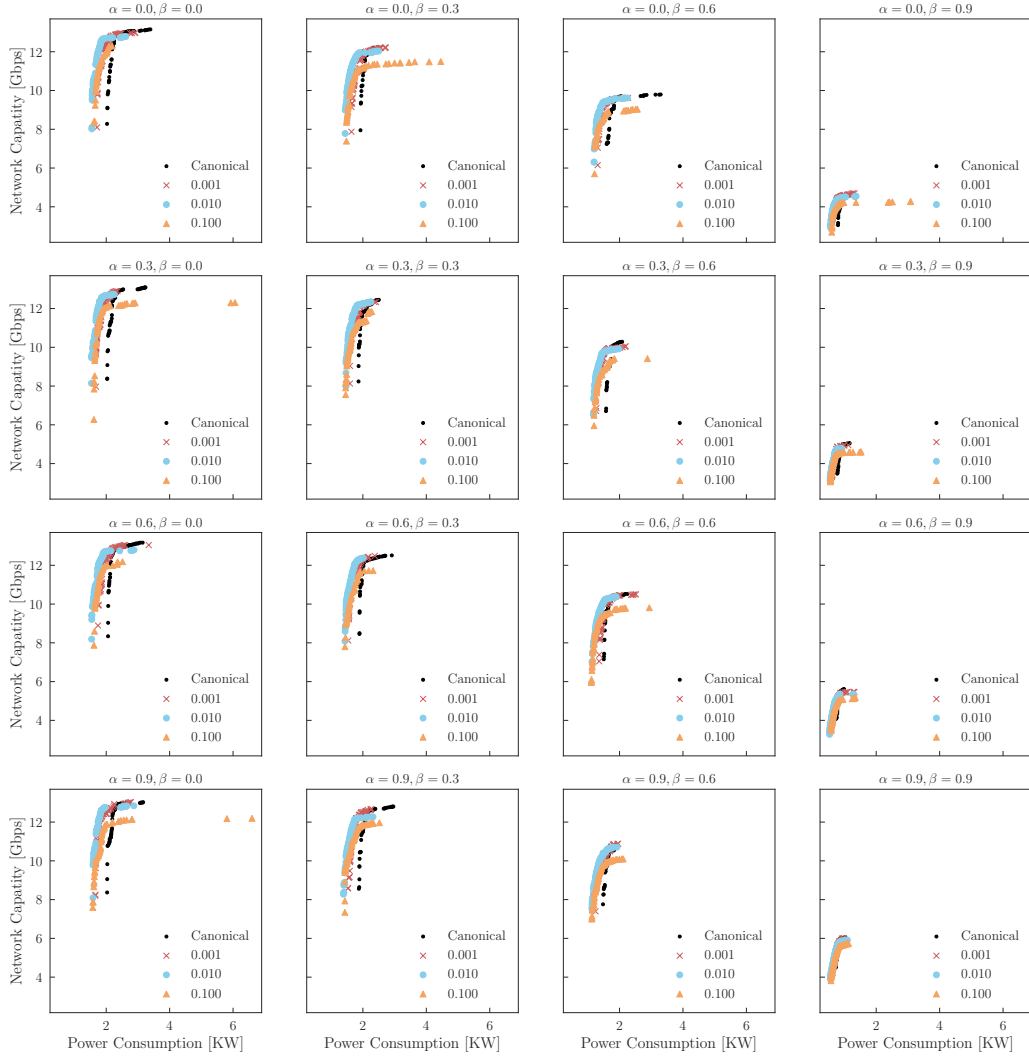


Figure 14: Approximations of the Pareto front for the different rates of application of the landscape-aware local search operator in the ML scenario.

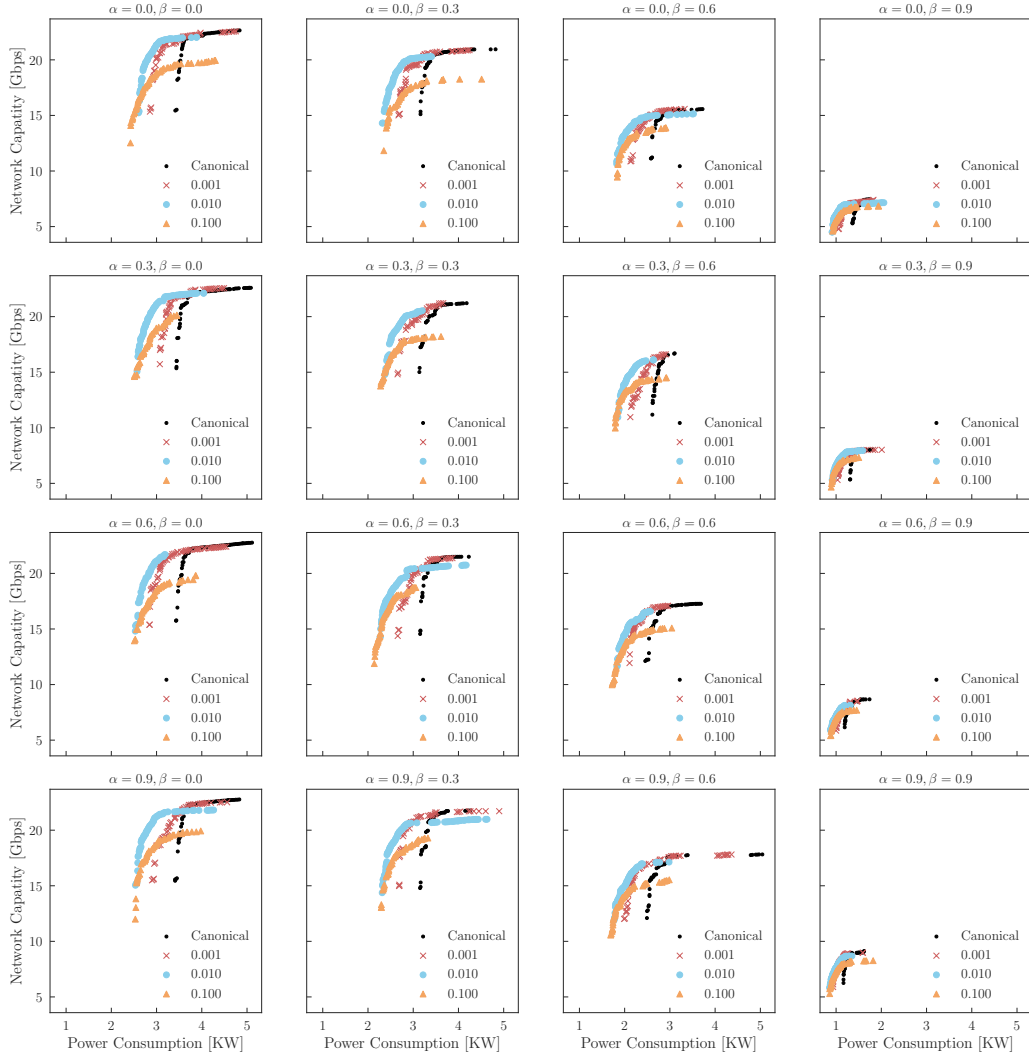


Figure 15: Approximations of the Pareto front for the different rates of application of the landscape-aware local search operator in the MM scenario.

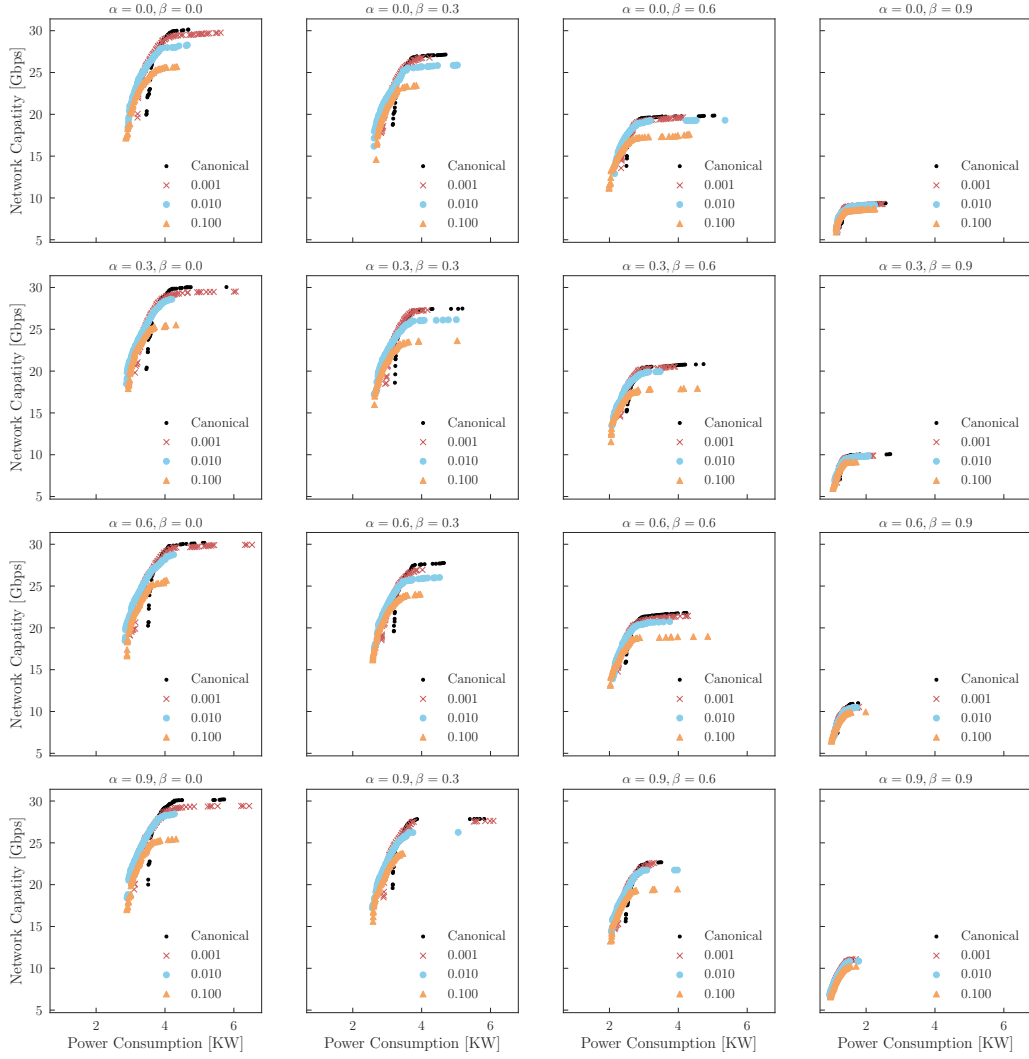


Figure 16: Approximations of the Pareto front for the different rates of application of the landscape-aware local search operator in the MH scenario.

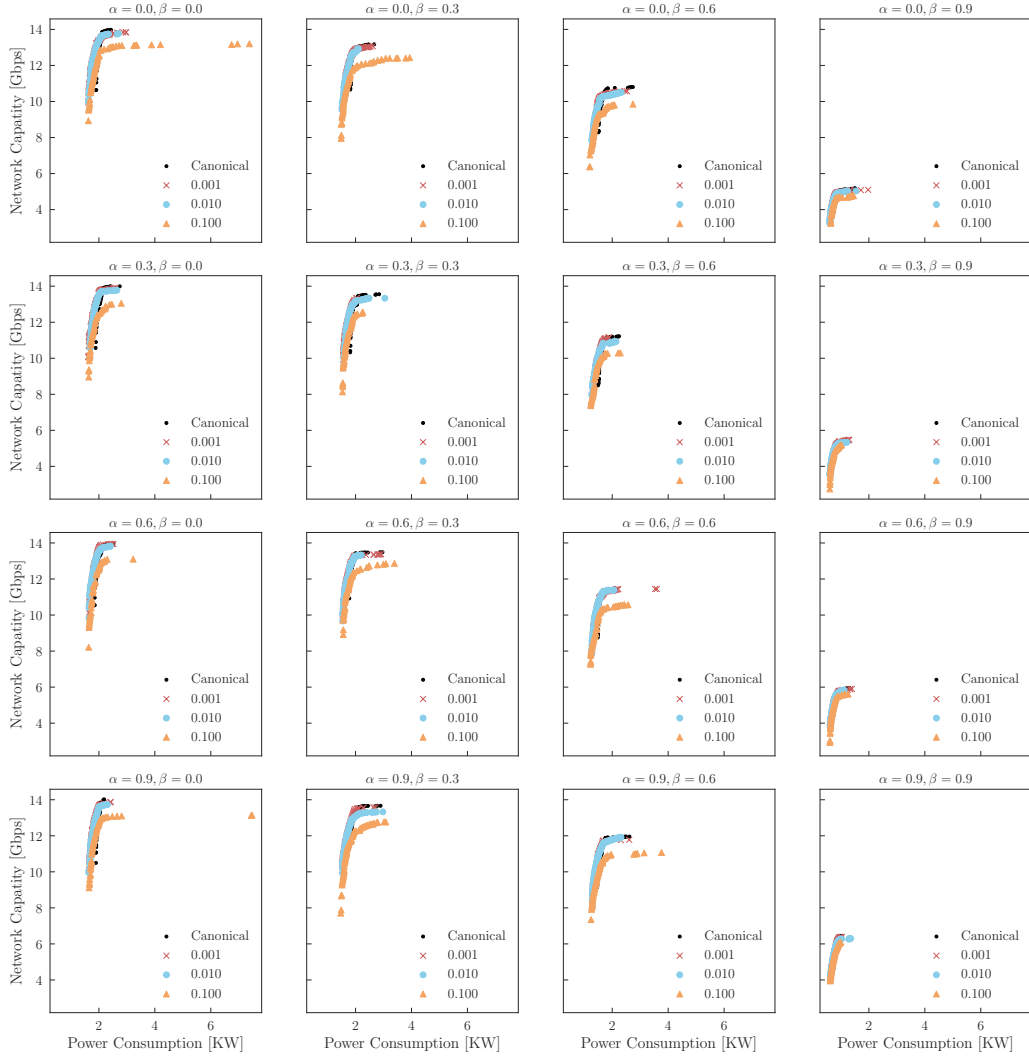


Figure 17: Approximations of the Pareto front for the different rates of application of the landscape-aware local search operator in the HL scenario.

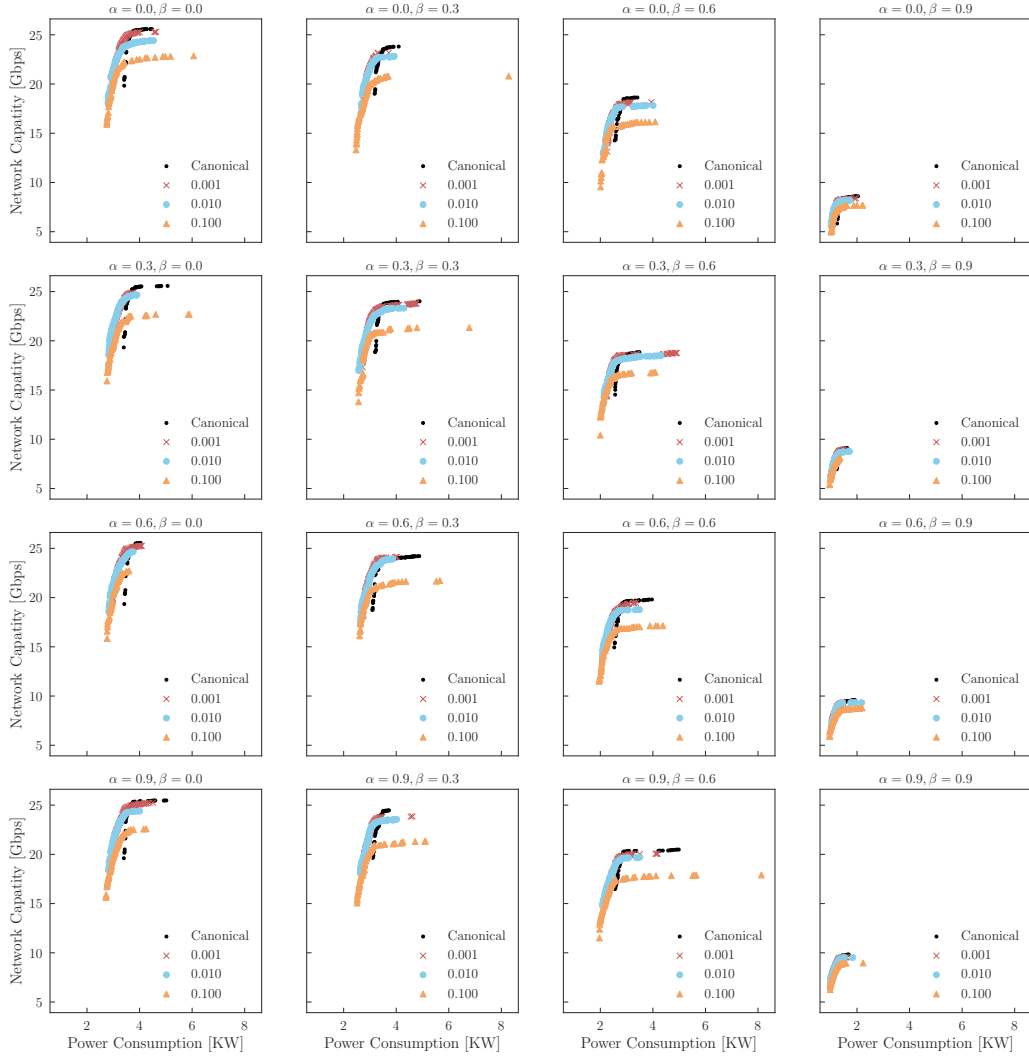


Figure 18: Approximations of the Pareto front for the different rates of application of the landscape-aware local search operator in the HM scenario.

C HV Values

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.3679	0.4240	0.4561	0.3926
0.0, 0.3	0.3585	0.4015	0.4519	0.4127
0.0, 0.6	0.3716	0.3974	0.4518	0.3979
0.0, 0.9	0.3582	0.4032	0.4349	0.4002
0.3, 0.0	0.3710	0.4102	0.4580	0.4023
0.3, 0.3	0.3525	0.4081	0.4496	0.4028
0.3, 0.6	0.3453	0.3859	0.4358	0.4119
0.3, 0.9	0.3444	0.3991	0.4303	0.4053
0.6, 0.0	0.3787	0.4081	0.4582	0.4098
0.6, 0.3	0.3546	0.4017	0.4497	0.3920
0.6, 0.6	0.3361	0.3894	0.4429	0.4064
0.6, 0.9	0.3184	0.3696	0.4141	0.3970
0.9, 0.0	0.3749	0.3990	0.4534	0.4204
0.9, 0.3	0.3518	0.3916	0.4483	0.4103
0.9, 0.6	0.3284	0.3761	0.4410	0.4034
0.9, 0.9	0.2944	0.3173	0.3997	0.3683

Table 5: LL

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.3396	0.3813	0.4365	0.4032
0.0, 0.3	0.3348	0.3770	0.4442	0.3992
0.0, 0.6	0.3512	0.3830	0.4424	0.3933
0.0, 0.9	0.3721	0.4119	0.4405	0.4078
0.3, 0.0	0.3406	0.3754	0.4452	0.3902
0.3, 0.3	0.3430	0.3767	0.4439	0.4033
0.3, 0.6	0.3365	0.3663	0.4436	0.4027
0.3, 0.9	0.3365	0.3918	0.4433	0.4079
0.6, 0.0	0.3390	0.3827	0.4463	0.3959
0.6, 0.3	0.3237	0.3876	0.4357	0.3916
0.6, 0.6	0.3197	0.3597	0.4387	0.3934
0.6, 0.9	0.3142	0.3708	0.4304	0.3960
0.9, 0.0	0.3383	0.3816	0.4436	0.3895
0.9, 0.3	0.3306	0.3606	0.4414	0.3894
0.9, 0.6	0.3116	0.3704	0.4289	0.3936
0.9, 0.9	0.3043	0.3457	0.4220	0.3839

Table 6: LM

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.3353	0.3721	0.4394	0.3824
0.0, 0.3	0.3209	0.3634	0.4348	0.3951
0.0, 0.6	0.3355	0.3895	0.4446	0.3940
0.0, 0.9	0.3603	0.4057	0.4371	0.3949
0.3, 0.0	0.3313	0.3815	0.4313	0.3865
0.3, 0.3	0.3288	0.3637	0.4394	0.3838
0.3, 0.6	0.3198	0.3611	0.4355	0.3915
0.3, 0.9	0.3361	0.3787	0.4393	0.4066
0.6, 0.0	0.3325	0.3689	0.4359	0.3783
0.6, 0.3	0.3173	0.3698	0.4403	0.3792
0.6, 0.6	0.3104	0.3703	0.4355	0.3882
0.6, 0.9	0.3204	0.3591	0.3281	0.3992
0.9, 0.0	0.3240	0.3712	0.4397	0.3778
0.9, 0.3	0.3235	0.3687	0.4371	0.3843
0.9, 0.6	0.3027	0.3565	0.4242	0.3957
0.9, 0.9	0.2850	0.3523	0.4063	0.3781

Table 7: LH

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.2800	0.3959	0.4512	0.4087
0.0, 0.3	0.2654	0.3665	0.4504	0.4011
0.0, 0.6	0.2780	0.3986	0.4463	0.4108
0.0, 0.9	0.2847	0.4104	0.4353	0.3985
0.3, 0.0	0.2746	0.4062	0.4520	0.4094
0.3, 0.3	0.2795	0.3822	0.4477	0.4047
0.3, 0.6	0.2526	0.3891	0.4360	0.4000
0.3, 0.9	0.2581	0.3805	0.4222	0.3832
0.6, 0.0	0.2853	0.3826	0.4514	0.4057
0.6, 0.3	0.2557	0.3901	0.4460	0.4041
0.6, 0.6	0.2520	0.3313	0.4318	0.4008
0.6, 0.9	0.2508	0.3637	0.4192	0.3731
0.9, 0.0	0.2783	0.4098	0.4469	0.4068
0.9, 0.3	0.2438	0.3888	0.4476	0.3986
0.9, 0.6	0.2366	0.3489	0.4239	0.3877
0.9, 0.9	0.2499	0.3365	0.3998	0.3579

Table 8: ML

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.2579	0.3715	0.4381	0.4026
0.0, 0.3	0.2568	0.3693	0.4379	0.3814
0.0, 0.6	0.2599	0.3647	0.4331	0.3953
0.0, 0.9	0.2604	0.3748	0.4309	0.3992
0.3, 0.0	0.2542	0.3438	0.4368	0.3979
0.3, 0.3	0.2430	0.3533	0.4302	0.3963
0.3, 0.6	0.2389	0.3515	0.4311	0.3934
0.3, 0.9	0.2497	0.3599	0.4265	0.4038
0.6, 0.0	0.2612	0.3735	0.4394	0.3901
0.6, 0.3	0.2259	0.3337	0.4232	0.3990
0.6, 0.6	0.2183	0.3421	0.4130	0.3940
0.6, 0.9	0.2118	0.3258	0.4138	0.3901
0.9, 0.0	0.2524	0.3558	0.4460	0.3907
0.9, 0.3	0.2346	0.3436	0.4330	0.3960
0.9, 0.6	0.2120	0.3497	0.4192	0.3984
0.9, 0.9	0.2337	0.3574	0.4116	0.3814

Table 9: MM

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.3418	0.3897	0.4182	0.3841
0.0, 0.3	0.3390	0.3974	0.4164	0.3798
0.0, 0.6	0.3599	0.3966	0.4163	0.3987
0.0, 0.9	0.3842	0.4148	0.4206	0.4065
0.3, 0.0	0.3312	0.3851	0.4161	0.3785
0.3, 0.3	0.3274	0.3749	0.4161	0.3798
0.3, 0.6	0.3413	0.3797	0.4149	0.3890
0.3, 0.9	0.3683	0.4055	0.4105	0.4060
0.6, 0.0	0.3375	0.3976	0.4256	0.3806
0.6, 0.3	0.3235	0.3829	0.4158	0.3843
0.6, 0.6	0.3332	0.3802	0.4120	0.3876
0.6, 0.9	0.3535	0.3875	0.4016	0.3946
0.9, 0.0	0.3456	0.3976	0.4261	0.3847
0.9, 0.3	0.3250	0.3774	0.4157	0.3830
0.9, 0.6	0.3349	0.3839	0.4094	0.3852
0.9, 0.9	0.3497	0.3815	0.4073	0.3771

Table 10: MH

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.3231	0.4389	0.4298	0.3928
0.0, 0.3	0.3182	0.4174	0.4218	0.3999
0.0, 0.6	0.3095	0.4044	0.4183	0.3883
0.0, 0.9	0.3569	0.4291	0.4268	0.3948
0.3, 0.0	0.3292	0.4374	0.4275	0.3949
0.3, 0.3	0.3176	0.4284	0.4151	0.4008
0.3, 0.6	0.3149	0.4067	0.4152	0.3975
0.3, 0.9	0.3535	0.4101	0.4187	0.3974
0.6, 0.0	0.3368	0.4274	0.4314	0.3972
0.6, 0.3	0.3171	0.4331	0.4283	0.3817
0.6, 0.6	0.3081	0.4046	0.4132	0.3871
0.6, 0.9	0.3352	0.3936	0.4934	0.3899
0.9, 0.0	0.3251	0.4368	0.4285	0.3929
0.9, 0.3	0.3039	0.4237	0.4188	0.3906
0.9, 0.6	0.3120	0.4082	0.4189	0.3872
0.9, 0.9	0.3184	0.3941	0.3996	0.3764

Table 11: HL

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.2576	0.3895	0.4200	0.3876
0.0, 0.3	0.2564	0.3901	0.4004	0.3874
0.0, 0.6	0.2869	0.3940	0.4168	0.3917
0.0, 0.9	0.3179	0.4075	0.4155	0.3837
0.3, 0.0	0.2763	0.4097	0.4235	0.3926
0.3, 0.3	0.2648	0.3998	0.4173	0.3912
0.3, 0.6	0.2771	0.3764	0.4030	0.3926
0.3, 0.9	0.3031	0.3969	0.4065	0.3878
0.6, 0.0	0.2651	0.3962	0.4248	0.3971
0.6, 0.3	0.2631	0.3849	0.4128	0.3855
0.6, 0.6	0.2498	0.3620	0.3967	0.3852
0.6, 0.9	0.2972	0.3840	0.3907	0.3869
0.9, 0.0	0.2661	0.3840	0.4211	0.3901
0.9, 0.3	0.2455	0.3847	0.3925	0.3857
0.9, 0.6	0.2577	0.3704	0.4036	0.3832
0.9, 0.9	0.2991	0.3858	0.3952	0.3858

Table 12: HM

α, β	Application rate			
	0.000	0.001	0.010	0.100
0.0, 0.0	0.2272	0.3698	0.4049	0.3687
0.0, 0.3	0.2360	0.3701	0.4033	0.3812
0.0, 0.6	0.2579	0.3584	0.4098	0.3807
0.0, 0.9	0.3117	0.3938	0.4118	0.4003
0.3, 0.0	0.2346	0.3904	0.4207	0.3798
0.3, 0.3	0.2318	0.3750	0.4101	0.3828
0.3, 0.6	0.2459	0.3511	0.4023	0.3880
0.3, 0.9	0.2775	0.3801	0.3944	0.3842
0.6, 0.0	0.2371	0.3724	0.4163	0.3879
0.6, 0.3	0.2176	0.3642	0.3955	0.3813
0.6, 0.6	0.2344	0.3512	0.3958	0.3867
0.6, 0.9	0.2742	0.3822	0.3906	0.3896
0.9, 0.0	0.2359	0.3670	0.4173	0.3869
0.9, 0.3	0.2257	0.3646	0.4029	0.3798
0.9, 0.6	0.2364	0.3572	0.4027	0.3824
0.9, 0.9	0.2786	0.3794	0.4002	0.3956

Table 13: HH