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Multi-objective Optimization Approach to Power Allocation in Multibeam Systems

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Current satellite systems employ multi-beam technology that allows for the dynamic allocation of the system resources (i.e. bandwidth and power), based on changing traffic distribution to provide substantial capacity gains. Often such an allocation tends to utilize the maximum DC power available, whereas a minimization of the same is desirable. This paper deals with the power allocation with respect to two seemingly conflicting objectives, namely the maximization of the available system throughput and the minimization of the system power consumption. A multi-objective

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optimization approach is proposed for power allocation to handle the aforementioned objectives. A state-of-the-art multi-objective genetic algorithm (MOGA), i.e. the non-dominated sorting genetic algorithm II (NSGA-II), is used as optimization approach. The set of obtained solutions is presented in the form of a Pareto front, which provides complete information to the user concerning the trade-off between the traffic demand and power requirements.

Nomenclature

N	=	number of beams
N_c	=	number of carriers
B_{TOT}	=	total bandwidth
P_{TOT}	=	total power
P_b	=	beam power
$P_{b,c}$	=	carrier power
B	=	carrier bandwidth
$P_{b,con}$	=	beam power constraint
$R_{b,req}$	=	bit rate requested by user in beam b
$R_{b,off}$	=	offered cumulative bit rate of all N_c carriers in beam b

I. Introduction

THE advent of new applications, including fixed and mobile multimedia interactive services, necessitate that satellite systems become more flexible. Design flexibility is essential to ensure that satellite systems can deal with emerging traffic requirements and unexpected market changes or the change in orbital location during the lifespan of the spacecraft. Flexibility could be viewed in four aspects with regard to coverage, power, frequency planning and higher layer functionalities (e.g. routing, switching)[1]. In exploiting these degrees of flexibility, multibeam satellites can play a key role since their design can easily be extended to support reconfigurability of power and frequency plans as well as routing and switching functionalities. This feature of multibeam systems along with the recent advances in Multi-Port Amplifier (MPA) and flexible Traveling Wave Tube Amplifier (TWTA) technology allow for efficient beam power allocation in response to the spatiotemporal variations of traffic demand.

In some previous work, optimization routine to efficiently apportion power across the beams to match the traffic demand has been considered.[5] Such an optimization is considered to be subject to a maximum RF power constraint, which, in turn, assumes a maximum DC power consumption. Since DC power consumption is a critical factor, the possibility of minimizing DC power is also warranted. However efforts toward modifying the DC/ RF power consumption have not been explored in detail in literature. Therefore, the present paper explores the power allocation problem with respect to both seemingly conflicting objectives: maximization of the available system throughput and minimization of the system power consumption, subject to the aforementioned constraints.

In order to handle these objectives, the appropriate cost (or objective) functions to quantify the performance of each objective have to be selected. In the case of the system power consumption this function is just the overall system power consumption, but in the case of the available system throughput four different cost functions are found in literature, namely the differential and unmet system capacities[7], satisfaction factor[8] and aggregate fitness. For the identification of the most suitable cost function a preliminary study, a comparison of the four functions is conducted. Following the results of Ref. 5, where a systematic study of the appropriate optimization techniques for the maximization of the available throughput is performed, a Genetic Algorithm (GA)[3] is adopted in the preliminary study. The results of the four cost functions employing the GA are then presented and compared and the best performing cost function is selected. Then, in order to enhance the system utilization, this cost function is used together with

the minimization of the overall system power consumption as cost functions of a multi-objective optimization problem (MOP).

A MOP deals with the optimization of multiple conflicting objective functions. In such MOPs the order relation between solutions relies on the concept of dominance. A solution dominates another if it is strictly better in one objective and better or equal with regard to all other objectives. The optimal solution then, is not a single solution like in single-objective optimization problems, but a set of non-dominated solutions defined as *Pareto optimal solutions*. This set of solutions represents the compromise between the conflicting objectives and allow for the selection of the best solution, according to the preferences of the decision maker and the priority of each objective.

Subsequently a state-of-the-art multi-objective genetic algorithm (MOGA), the non-dominated sorting genetic algorithm II (NSGA-II)[3] is employed for the resolution of this MOP. The set of solutions obtained is then presented in the form of a Pareto front (i.e. the image of the Pareto solutions in the objective space), providing complete information concerning the trade-off between the traffic demand and power requirements. The results are then analysed, demonstrating the potential benefits that arise from the use of the multi-objective approach.

The remainder of this paper is organized as follows. Section 2 presents the formulation of the resource optimization problem for multibeam architecture as a MOP. In the same section the optimization techniques applied to the problem in previous studies are presented and compared with the approach proposed in the present paper. Then the considered optimization techniques (GA for the preliminary study and NSGA-II for the multi-objective optimization) are described in section 3. The preliminary study and the experimental results using the proposed multi-objective approach are presented and analysed in section 4. Finally section 5 contains our conclusions and perspectives.

II. Resource Optimization in Multibeam Architecture

Multibeam Architecture and System Resources

Assume a multibeam satellite system with $b = 1,…,N$ beams, employing a typical four colour reuse pattern (for e.g., two colours in frequency and two in polarization), where the available total downlink bandwidth of the system B_{TOT} is equally distributed among the four colours. It is further assumed that the available bandwidth reused over the different colours is equally divided into the beams of each colour and each of these beams accommodates four carriers. A carrier represents the elementary system entity for conveying different streams of information and the bandwidth of each beam is equally divided among its carriers. The described layout could be visualized in Fig. 1, where the beam layout adopted for this paper's simulations is depicted.

Having allocated B_{TOT} equally among the carriers, the resource allocation pertains to the appropriate allocation of the total available system power P_{TOT}. P_{TOT} is a function of the platform total DC power on board the satellite, and must be allocated appropriately to each beam, so that the offered beam bit rate meets the user requirements in the same beam. The power allocated to each beam P_b, will then be equally divided among the N_c carriers of the beam $P_{b,c} = P_b / N_c$. Furthermore minimizing the overall power consumption while allocating the available P_{TOT} is also warranted.

B. Resource Optimization

Following this analysis the resource optimization problem is formulated as a MOP. The target of this optimization is to determine the beam power P_b, for which:
1. The system capacity is maximized (cost function f_1).
2. The overall power consumption is minimized (cost function f_2).
   Subject to:
   ➢ The power constrains of the system
   ➢ The power constrains of each beam

For the system capacity maximization the following four candidate cost functions have been employed in past studies:
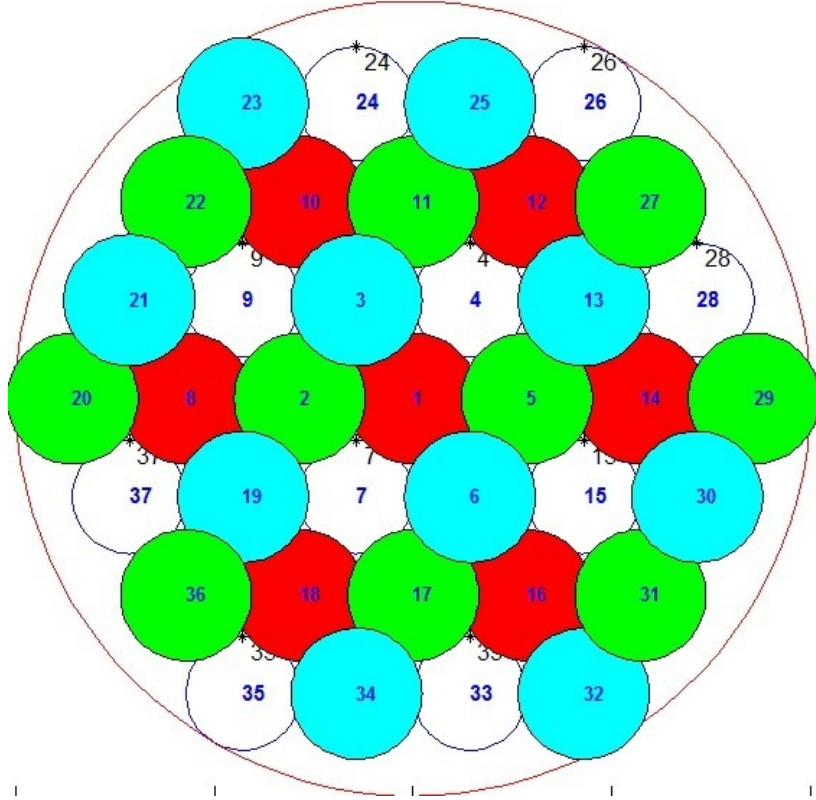
Figure. 1 Four colour reuse pattern, for a 37 circular beam layout

Differential System Capacity (DSC)

$$\text{Min } f_1 = \sum_{b=1}^{N} \text{abs}\left[R_{b,req} - R_{b,off}\right] \tag{1}$$

According to Eq. (1), offered beam capacities exceeding or being less than the required beam capacities, both contribute to the figure of merit and drive the optimization closer to the requirements.

Unmet System Capacity (USC)

$$\text{Min } f_1 = \sum_{b=1}^{N} \max\left[R_{b,req} - R_{b,off}, 0\right], \tag{2}$$

In Eq. (2), offered beam capacities exceeding the required do not contribute to the figure of merit and do not affect the optimization.

Satisfaction Factor (SF)

$$\text{Max } f_1 = \frac{\sum_{b=1}^{N} \min\left[R_{b,req}, R_{b,off}\right]}{\sum_{b=1}^{N} R_{b,req,}} \tag{3}$$

The offered beam capacities exceeding the required capacity do not contribute to the figure of merit defined in Eq. (3). But in this case the recessive beam capacities are scaled by the cumulative required capacity.

Aggregate Fitness (AF)

$$\text{Max } f_1 = \sum_{b=1}^{N} \frac{1}{1+\text{abs}\left[R_{b,req} - R_{b,off}\right]} \tag{4}$$

According to Eq. (4), offered beam capacities exceeding or being less than the required beam capacities, both contribute to the figure of merit, like in the case of the DSC, but these results are scaled down on a beam bases and the optimization is driven according to the sum of the individual beam fitness.

For the power consumption minimization the cost function employed is the following:

$$\text{Min } f_2 = \sum_{b=1}^{N}[P_b] \tag{5}$$

And the optimization is subject to the following constrains:

System power constraint

$$\sum_{b=1}^{N}[P_b] \leq P_{TOT} \tag{6}$$

Beam power constraints:

$$P_b \leq P_{b,con} \tag{7}$$

The offered, bit rate $R_{b,off}$ is calculated as follows:

$$R_{b,off} = \sum_{c=1}^{N_c} B \times f_{DVB-S2}(SNIR_c) \tag{8}$$

The function $f_{DVB-S2}(SNIR_c)$ quantifies the spectral efficiency of the various modulation and coding schemes employed by DVB-S2 as a function of the $SNIR_c$ of carrier c.

1. SNIR Calculation

The $SNIR_c$ of each carrier c, transmitted with power $P_{b,c}$ and bandwidth B is calculated as follows[4]:

$$SNIR_c = \frac{a_b^2 P_{b,c}(OBO)}{N_0(a_b)B + \sum_{q\in\Phi} \alpha_q^2 P_{q,c}(OBO) + I_{adj_{ch}}(B,XPD) + I_{adj_{sat}} + I_{inter}(OBO,C_b,Mod)} \tag{9}$$

Φ: is the set of co-channel beams in the coverage area with active carriers overlapping with the bandwidth of the intended carrier c (co-channel interference into intended beam b)

a_q: is a gain factor encompassing the effect of: satellite antenna beam q, terminal receive antenna gain, free space loss, clear sky attenuation and rain attenuation

N_0: is the noise power spectral density which is a function of a_b because of the increase in noise temperature under rain fading conditions

I_{adj_ch}: accounts for adjacent channel interference due to filter imperfections (function of B), including spillover from the beams in orthogonal polarization if both polarizations are employed (function of XPD)

I_{adj_sat}: Inter-system interference caused by adjacent satellites

I_{inter}: Intermodulation interference

The notation $P_{b,c}(OBO)$ denotes the dependence on the appropriate OBO according to the modulation scheme employed

C. Single-objective Transformation of the Considered MOP

An early approach in the direction of modifying the DC/RF power consumption along with the available system throughput is proposed in Ref. 6. In this approach a number of cost functions to quantify the satisfaction of the traffic demand are proposed. These cost functions include a DC consumption parameter, in order to take the power consumption into account, while maximizing the available throughput of the system. This technique known as *scalar approach* is transforming a MOP into a single-objective problem, by combining different objective functions (i.e. the traffic demand satisfaction and the DC consumption minimization) into a single-objective function in a linear way.

This type of approach however, requires a priori knowledge on the considered problem, in order to find the appropriate weights for the linear representation of the different objective functions. That is because the Pareto optimal solution is the node of the objective space hyperplane, defined by the weight vector and the feasible space of the problem. Thus the Pareto border has to be known in order to select the corresponding weights to obtain the desirable optimal solution.

A common misconception, is that the weights selected for the linearization of the MOP are representative of the relative importance of the different objectives. In these cases the objective space hyperplane defined by these weights, could intersect randomly with the feasible space of the problem, providing undesirable solutions.

Alternatively multiple weights can be used, that will be optimized in parallel along with the problem. However the computational cost of this process is significant and even this process cannot guarantee to provide all Pareto optimal solutions, since these are limited to the convex hull of the Pareto front (i.e. solutions in concave regions of the Pareto front cannot be found).

Furthermore the provided optimal solution of these scalar approaches is a single solution unlike the set of Pareto solutions, provided by the dominance based approaches, depriving the decision maker of the alternative solutions, suppressing useful information regarding the system's objective space.

The considered problem however is not known a priori. Hence, the present paper explores the power allocation problem as a strictly multi-objective problem (MOP) and not as a linear function of the various objectives. Formulation of the problem in a dominance based multi-objective setting seems to be novel in literature and in this course a state-of-the-art multi-objective genetic algorithm (MOGA), the non-dominated sorting genetic algorithm II (NSGA-II)[3],presented next, is employed for its resolution.

III.   Optimization Techniques

A. Genetic Algorithm (GA)

The GA adopted in the preliminary study of the paper, is a population based metaheuristic, where the search for a "good" solution starts from an initial population of acceptable solutions. This technique is based on the Darwinian evolutionary model, which consists in the following iterative process. Two parents are first selected from the whole population with a given selection criterion. Then two genetic operators are sequentially applied with some probability, namely recombination (or crossover) that exchanges portions of the parents solution vectors, and mutation that randomly modifies the individual. Finally the generated offsprings are evaluated and inserted back into the population following a given criterion.

B. Non-dominated Sorting Genetic Algorithm II (NSGA II)

NSGA-II is the most popular and referenced dominance based multi-objective algorithm in literature. It is a GA with a non-structured population, that is used to obtain the new population after applying the typical genetic operators (i.e. selection, crossover, mutation). As a GA belongs to the metaheuristic techniques, and since metaheuristics do not guarantee the optimality of the obtained solution the goal of this technique is to provide an approximation of the Pareto optimal set with two necessary properties: convergence to the Pareto optimal solutions and uniform diversity (i.e. a good distribution of the obtained solutions around the Pareto optimal front).

In this course, all individuals of the initial population are ranked with respect to both convergence and diversity. All non-dominated solutions are assigned to the rank 1 and are subsequently removed from the population in order to assign the current non-dominated solutions to the rank 2. This process is iterated for all individuals and then individuals within the same rank are ranked according to the distance from their surrounding individuals. Individuals with higher distances (i.e. good distribution) are ranked higher than others.

The individuals are then sorted according to their rank and the typical genetic operators are applied iteratively.

IV.   Experimental Results

For the simulations presented herein, the 37-beam system described in Fig. 1 has been simulated, where the antenna pattern is approximated by employing the Bessel function and the link budget is calculated assuming one user per beam, located at the beam edge (worst case position). The parameters of the link budget, are presented in Table 1.

Table 1 Link Budget Parameters

Link Budget Parameters For Capacity Results	
Parameter	Value
Frequency Band	Ku
User Link Bandwidth $\mathbf{B_u}$	46.875 MHz
HPA saturation Power $\mathbf{P_\tau}$	80 W
Max satellite antenna gain $\mathbf{G_T}$	52 dBi
Output Back Off **OBO**	5 dB
Satellite **EIRP**	66 dBW
Free Space Loss **L**	212 dB
Terminal Antenna Gain $\mathbf{G_R}$	41.7 dBW
Terminal noise Temperature **T**	207 K
Receive **C/N**	20.2 dB
External $\mathbf{(C/I)_{EXT}}$	30.0 dB

A. Problem Instance Setup

Simulating the above system, the cost functions defined in Section 2 are compared, based on their performance concerning the maximization of the available system throughput. The technique employed for the comparison of the cost functions is the most appropriate technique out of the standard metaheuristics techniques compared in Ref. 5, namely the GA. The solutions are encoded as 37-dimensional vectors, where each dimension represents the R/F power of the respective beam. The optimization parameters selected for the simulations are shown in Table. 2.

Table 2. GA Optimization Parameters

Parameter	Value
Population Initialisation	Random
Population Size	5856
Crossover Function	Uniform
Crossover Rate	0.95
Mutation Function	Uniform
Mutation Rate	0.05
Selection Function	Tournament
Elite Individuals	30
Fitness Evaluations	234240

B. Single Objective Results (Preliminary Study)

The performance assessment of the different cost functions is shown in Table. 3. The results reported involve averaging over 15 independent runs, as the computational time needed for 234240 evaluations did not allow the use of a bigger sample. The statistical confidence in the comparisons is assessed by performing the Wilcoxon test[2], with standard confidence level (0.95).

Table 3. Cost Function Performance Assessment

Cost Function	Capacity [Gbps]			Power [W]
	(Average of 15 runs)			
	Required	Offered	Unmet	
DSC	24.155	23.588	0.801	1758.2
USC	24.155	25.605	0.746	2145.7
SF	24.155	23.946	0.748	2010.4
AF	24.155	23.547	0.842	1752.5

	(Overall Best over 15 runs)			
DSC	24.155	23.593	0.778	1743.9
USC	24.155	24.879	0.709	2030.3
SF	24.155	24.879	0.709	2030.3
AF	24.155	23.588	0.802	1777.9

The numerical results presented above demonstrate the suitability of the USC as a cost function, since the USC provides the lower unmet capacity of all. This result is not surprising since USC focuses on the minimization of the unmet capacity, ignoring the impact of the exceeding beam capacities on the optimization. Therefore the performance of the SF, which also ignores the impact of the exceeding beam capacities is similar, with that of USC, obtaining also the same overall best solution. The performance of the best USC result in the satisfaction of the traffic demand is depicted in Fig. 2.
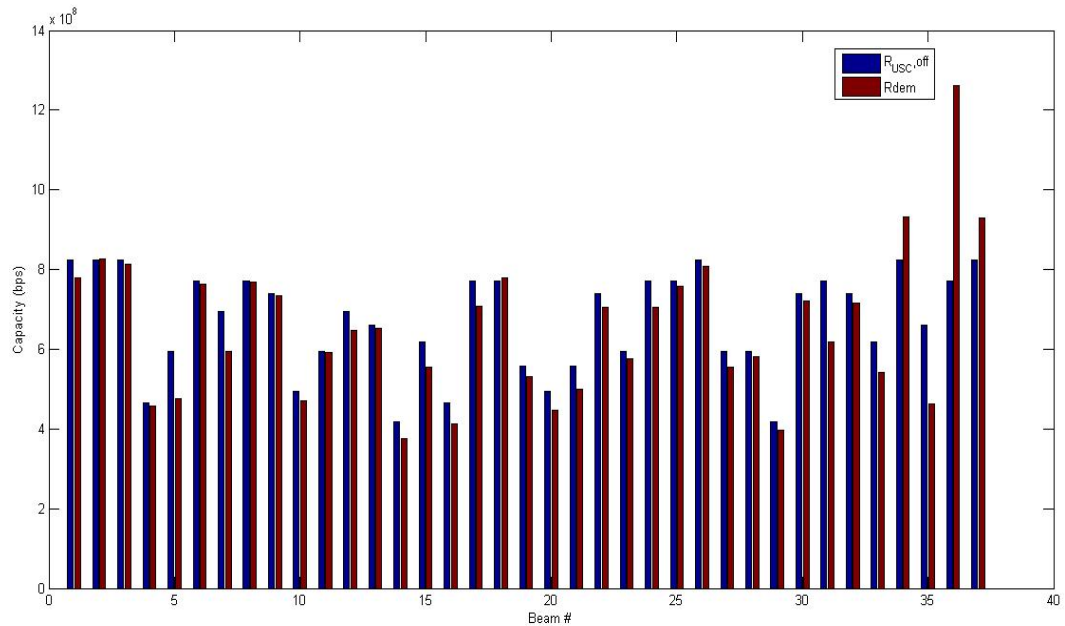

Figure.2   Single objective optimization performance (USC)

C. Multi-objective optimization results

The result presented in Fig.2 is the best result provided for the maximization of the system throughput. This can be used as initial seed for the multi-objective approach ensuring that the result providing the best performance in terms of the capacity maximization will be included in the Pareto optimal set of solutions and possibly will be further enhanced.

Subsequently the obtained solution is used with the same encoding described above as an individual of the initial population of the NSGA-II. The target of the optimization employing the NSGA-II is to determine the power P_b for which the Eq. (2) and (5), are minimized. The results reported from this optimization involve averaging of 15 independent runs and the optimization parameters selected are shown in Table. 4.

Table.4 NSGA-II Optimization Parameters

Parameter	Value
Population Initialisation	Random
Population Size	6000
Crossover Function	Uniform
Crossover Rate	0.9

Mutation Function	Uniform
Mutation Rate	0.05
Selection Function	Tournament
Fitness Evaluations	240000

The Pareto front obtained from the 15 runs is depicted in Fig. 3 providing complete information concerning the trade-off between offered capacity and power requirements, whereas the initial population provided by the single-objective approach is further enhanced.
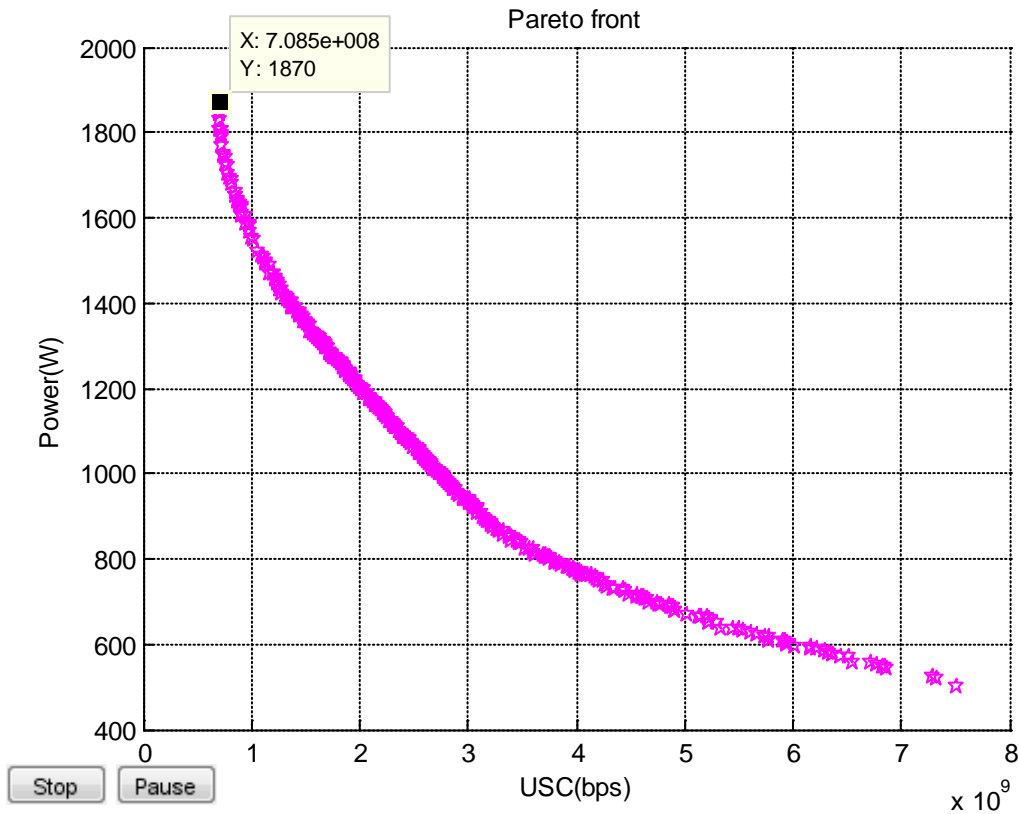

Figure. 3. Pareto front encompassing the enhanced result of the single-objective optimization.

From the above figure, it appears that the obtained Pareto front provides a large number of non-dominated solutions as well as a very good diversity. It is also evident that the result of the single-objective optimization, shown in Table 3 has improved significantly in terms of Power. In particular the allocation obtained by the single-objective approach, consuming 2030.3W for an USC of 0.709Gbps dropped to a power consumption of 1870W for the same USC. In other words the multi-objective approach allows for the system to perform the same in terms of satisfying the traffic demand while saving 7,9% power.

Furthermore the slope of the left part of the Pareto front is steep enough, to allow for even more significant power savings, in case the user is willing to let the USC deteriorate by little. Fig. 4 shows the left part of the Pareto front, demonstrating the trade-off between the satisfaction of the traffic demand and the power requirements. In this case the user can save up to 12% power by decreasing the USC by 2.7%. It is evident that the Pareto front obtained provides complete information regarding the trade-off between the two objectives, enabling the decision maker (in this point of view, the satellite operator) to adjust to the emerging traffic requirements according to the priority of the two objectives.

V. Conclusion

The present paper demonstrates how current multibeam satellite systems can benefit from the use of multi-objective approaches for the allocation of their resources, which is novel approach in literature. The interesting aspect is that the two objectives are seemingly conflicting: maximization of the available system throughput and the minimization of the system power consumption due to their relation to the power and yet the proposed technique can improve one objective by 7,9%, without deteriorating the other. Moreover complete information to the satellite operator regarding the trade-off of the different objectives is provided, enabling a full exploitation of the available flexibility of the system yielding significant capacity gains and power efficiency, which results to the prolongation of the spacecraft's life expectancy.
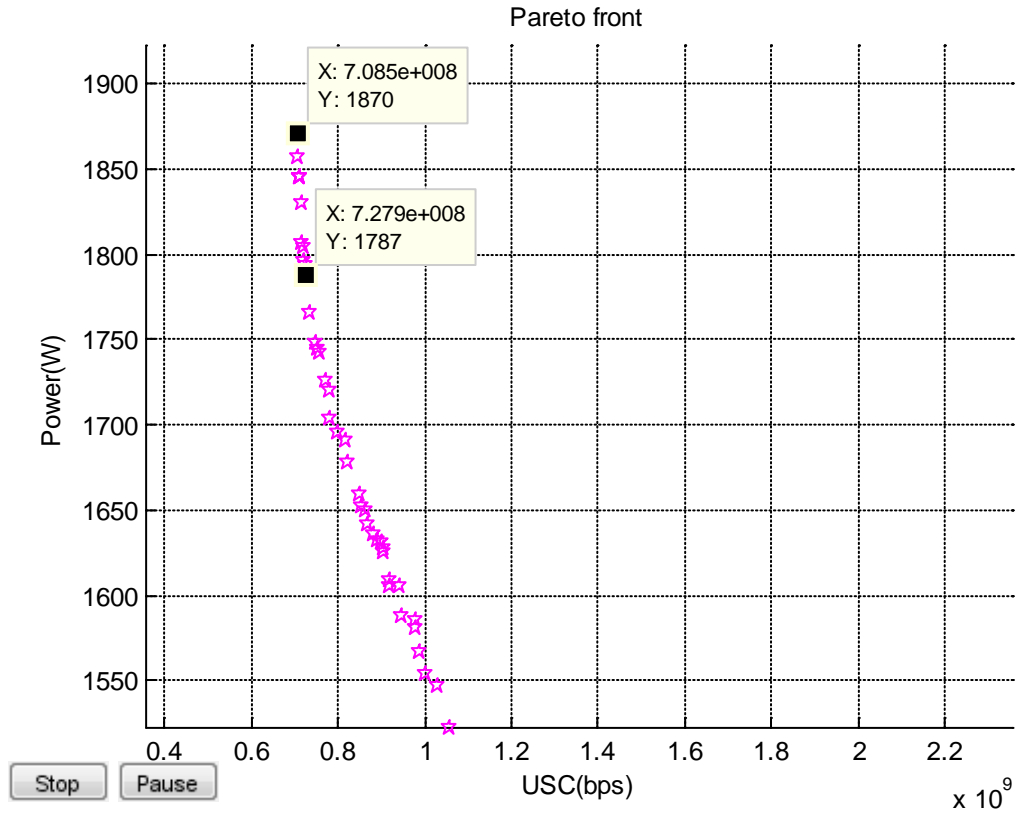

Figure.4 Pareto front, zoom in

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