Bi-objective Exact Optimization of Satellite Payload Power Configuration

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Abstract— **Communications satellites are designed to provide services by forwarding signals to customers. Uplink signals are filtered and amplified to ensure signal output quality. This is ensured by the payload part of the satellite. Reconfigurable hardware components like switches are embedded in the payload to route signals through the satellite. By setting switch positions, satellite engineers are able to connect, restore or reconfigure channels. However, to follow the increasing demands, satellite payloads embed more and more components. As a consequence, their manual management is becoming time-consuming and error-prone. Power transmission optimization has then a crucial role to decrease costs while keeping a maximum quality of service. In this aim, satellite operators would like to minimize the power of the signals sent from Earth while keeping a maximum amplification. In this work, we tackle for the first time this new bi-objective problem of optimizing input and output power. Exact methods have been considered to propose efficient alternatives to the satellite operators.**

Keywords: Multi-objective optimization, adaptive ϵ-constraint, satellite payload optimization

I. Introduction

Today, communication satellites have become essential for our communication systems. Since their birth in the 1960s, the satellite industry, and more precisely satellite services, have witnessed an exponential growth. Communication satellites have an expected lifetime of nearly 15 years and have to be reliable. Therefore, redundant systems are integrated to prevent failures and ensure flexibility.

A communication satellite is mainly composed of two distinct modules. The first module is the payload which receives uplink signals from Earth stations, filters, amplifies, and finally forwards the modified signals back to Earth. Components embedded in the payload are multiplexers, switches and amplifiers. The second module, called platform, embeds all subsystems required for the functioning of the satellite in space, regardless of the satellite's mission. Such sub-systems include power provisioning and propulsion. This work is focused on the payload module, which contains some reconfigurable components, i.e. switches. Indeed, engineers are able to remotely modify the position of the switches, which allows to connect or disconnect channels. Designing such payloads is an optimization problem for the satellite manufacturer point of view [1] in which the best network topology must be found while minimizing the number of components, due to their high cost. This work is focusing on a later stage, when the satellite operator faces configuration and reconfiguration problems during the lifetime of such satellites. The problem can be divided in three main categories:

- *The initialization problem* where no channels are pre-connected. Its goal is to configure the payload for the first time. This is the hardest and most sensitive task because the initial configuration determines the future reconfigurations.
- *The reconfiguration problem* where a pre-defined set of channels is already connected and new channels have to be added without interrupting the pre-connected channels.
- *The restoration problem* where component failures may appear and paths need to be reconnected.

For each of these previous problem categories, different objectives can be defined. For example, Stathakis et al. [2] minimized the number of switch changes for the reconfiguration problem. In this work, the problem of optimizing input/output power has been tackled to guarantee a maximum power efficiency. Indeed to reach the satellite, signals need a specific power to cross the atmosphere. Then to be optimally amplified, the signal power entering into an amplifier must reach a certain threshold. Furthermore the attenuations induced by the different passive components have to be taken into account. All these characteristics motivate the development and usage of efficient optimization procedures to ensure the satellite operator that choices are the closest to the optimal ones. The corresponding problem aims at optimizing the input signals power before amplification while keeping a maximal output power after amplification. The objective is to find efficient alternatives representing optimal power paths since these two objectives are conflicting.

This paper is organized as follows. The next section presents some related works about the payload optimization problem in general. Then, the input and output power optimization problem is described in more details. Section 4 introduces the corresponding bi-objective problem based on an integer linear program designed by [2]. This model allows us to apply the ϵ-constraint and its adaptive version [3] in order to produce optimal Pareto fronts. Section 5 and 6 depict our experimental setup and results. Finally, the last section presents our conclusions and perspectives.

II. Related work

Communication satellites are essential to communicate through long distances. For nearly 50 years, they have become more complex and keep embedding more components. Indeed, the increasing demands of the market request more flexibility and redundancy to ensure that signals are reliably forwarded to customers [4]. The market competition motivates satellite operators to request more power, longer lifetime and reliability. This is crucial to ensure quality of service (QoS). Until recent years, engineers were using their own experience and computerized schematics to configure satellites. Configuring a satellite implies modifying large switch matrices located in the payload in order to route channels. With the increasing size of payloads, this task has become time-consuming. Moreover, quality of services requirements are always more restrictive making fast (re-)configuration error-prone. That is the reason why satellite operators require efficient methods to solve (re)-configuration problems in a more efficient and optimal way. Some commercial softwares like [5], [6] explicitly explore the decision space. However, they act like black-box and their lack of flexibility does not allow satellite operators to take new objectives into account. On the academic side, a bread-first-search was proposed to optimally connect channels but this approach is unsuitable for large payloads [5], [6].

Implicit exploration was proposed by Stathakis et al. [2] with an integer linear program (ILP) based on flows problems. This model allows to solve various objectives. Those include the minimization of the longest length path, the number of switches changes and the number of channels interruptions. It can also be easily updated to add new ones. Stathakis et al. [7] also applied genetic algorithms to minimize the longest path length. Cellular genetic algorithms (cGA) [8] have shown that they are more efficient than the standard ones. Different exact-approximate hybridization schemes were also designed using the ILP and cGAs [9]. The first hybridization uses the best solution obtained by the cGA to speed up the branch and cut method. The second one consists in fixing some variables to reduce the ILP size. This reduction was performed according to the connected channels obtained in a first step by the cGA. Finally, they applied bi-objective exact methods to solve the problem of minimizing the longest path length while keeping a minimum number of switch changes [10].

In this work, a novel variant of the satellite payload problem is proposed where the input/output power are to be minimized. Indeed, it is a crucial one which could help satellite operator to reach a maximum power efficiency.

III. Problem description

The main task of a communication satellite payload is to filter and amplify signals coming from the Earth in order to be forwarded to customers. Before reaching the satellite, signals have to cross the atmosphere which induces power attenuation. Since signals are composed of different frequencies (channels) and amplifiers are dedicated to a single frequency, signals have to be routed in the payload to the adequate amplifier. This is done by configuring switches which are the only dynamic components of a payload. Figure 1 represents a simplified payload with 24 switches, 4 amplifiers and 8 channels. Switch positions can be modified in order to route channels. The number of positions a switch may have depends on its type. In figure 2, switch positions are described for each switch type. Switches and connectors are passive components and each of them induces some specific power attenuation. Therefore, satellite engineers must take these power losses into account before affecting channels to amplifiers. This is due to the saturation point of each amplifier. Indeed an optimal amplification can only be performed if channels have a required input power. The relation between the power entering into and going out the amplifier is a non linear function where the peek is located at saturation. Satellite operators therefore want to minimize the required power sent to the satellite by finding minimum attenuation paths with amplifiers having a low saturation point. This objective only concerns the input part of the payload which is located before amplifiers. On the contrary, in the output part of the payload, satellite operators require a maximum power after amplification. This means that channels have to use high gain amplifiers and paths to antenna having a minimum power attenuation. Both objectives are negatively correlated which means that an improvement of one of them implies a degradation for the other.

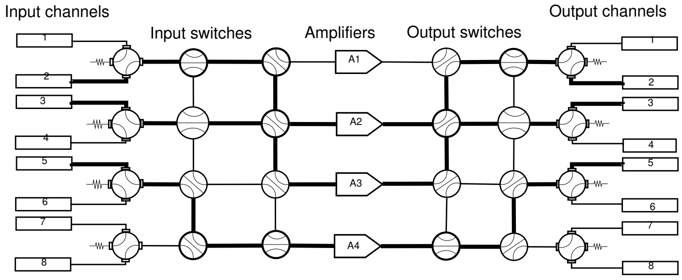

Fig. 1. Simplified payload

The corresponding bi-objective optimization problem for the satellite payload power problem is the following. The payload can be represented as an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ is the set of vertices representing all components and $\mathcal{E}$ is the set of edges representing all the existing links between components. Each switch position defines how incoming and outgoing links are connected. Thus, each switch s is a function $\mathcal{F} : \{1, ..., p\} \longrightarrow N_s$ where p is the number of positions a switch can have and N_s represents the set of all pairwise connections a switch can establish. This definition implies that vertices representing switches can dynamically change their neighborhood. The satellite payload optimization problem can be seen as a special case of the *k* edge-disjoint shortest paths

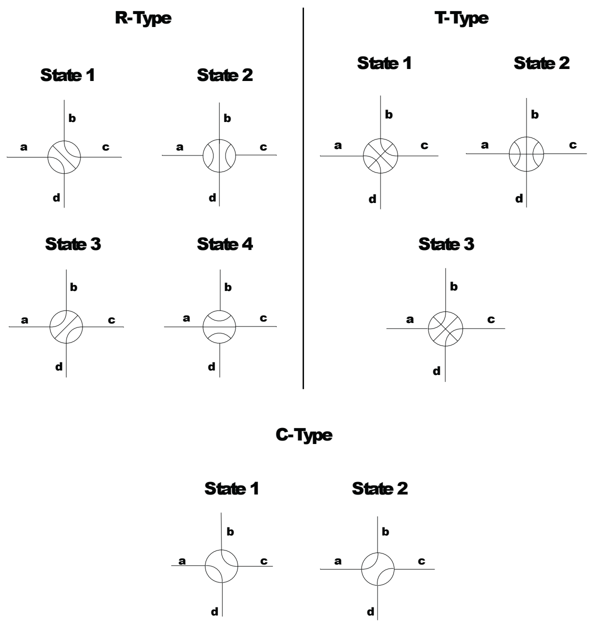

Fig. 2. R-switch positions

problem [11] which belongs to flows problem. Indeed, channels can never share the same link. A switch can be crossed by at most 2 channels depending on its position. Furthermore, every signal entering into a switch must necessarily leave this switch such that flow conservation properties can be applied. Obviously incoming channels (input channels) and outgoing channels (output channels) can be respectively represented as sources and sink. The next two formulations describe the input and the output problem separately.

Input Optimization problem

INSTANCE:

- a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ and k distinct pairs $(s_1, p_1), ..., (s_k, p_k)$ of vertices where the first element of each pair is an input channel and the second one the output channel.
- Each vertex posses a label $c(v) : v \in \mathcal{V}$ defining either:
  - an attenuation value if the component is passive,
  - an input power to saturation if the component is an amplifier.

OBJECTIVE: minimize $IPS = \sum_{v \in \mathcal{A}_m} c(v) + \sum_{v \in \mathcal{S}_{in}} c(v)$ where

- the set $\mathcal{A}_m \subseteq \mathcal{V}$ is the set of amplifiers used to amplify the k signals
- $\mathcal{S}_{in} \subseteq \mathcal{V}$ is the set of crossed switches located in the input part of the payload

QUESTION: Find whether there exists k edge-disjoint paths between $(s_i, p_i) \quad \forall 1 \leq i \leq k$ according to the objective.

Output Optimization problem

INSTANCE:

- a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ and k distinct pairs $(s_1, p_1), ..., (s_k, p_k)$ of vertices where the first element of each pair is an input channel and the second one the output channel.
- Each vertex posses a label $c(v) : v \in \mathcal{V}$ defining either:
  - an attenuation value if the component is passive,
  - an output power to saturation if the component is an amplifier.

OBJECTIVE: maximize $SOP = \sum_{v \in \mathcal{A}_m} c(v) - \sum_{v \in \mathcal{S}_{out}} c(v)$ where

- the set $\mathcal{A}_m \subseteq \mathcal{V}$ is the set of amplifiers used to amplify the k signals
- $\mathcal{S}_{out} \subseteq \mathcal{V}$ is the set of crossed switches located in the output part of the payload

QUESTION: Find whether there exists k edge-disjoint paths between $(s_i, p_i) \quad \forall 1 \leq i \leq k$ according to the objective.

This bi-objective input/ouput power optimization, tackled for the first time in this work, aims at finding the best alternatives, i.e. the set of non-dominated solutions.

IV. Bi-objective exact optimization

This bi-objective problem is tackled with scalarization techniques, which rely on a new variant of the integer linear program developed in [2]. This program is based on a multi-commodities flow model where every integer flow is affected to a channel to connect. It was originally designed in [2] to minimize the longest path length, the number of switches changes and the number of interruptions. This model has been updated because in the single objective case, only binary variables, indicating whether or not a flow value uses a connector, were defined. All coefficients were uniform and set to one. In the input/output power optimization case, switches and amplifiers must be in the objective. Power data are measured in decibel (dB) and are continuous values, which means that solutions values will be continuous as well. Each connected channel can be represented as a path with an input and an output power. A solution is a set of connected paths and the solution value will be the sum of the input power for the first objective and the sum of the output power for the second objective for each path. Due to space restrictions the full model is not described in this article but the interested reader can refer to [2].

In order to remain consistent with the original model from [2], the opposite of the input power has been maximized in order to keep the same optimization direction for both objectives (see Table I). This model is an integer flow one where the variable $flow_{l,c} \in \{0; 1\}$ indicates if the link l is used by the channel c. The constraint $\sum_{c \in Conn} flow_{l,c} \leq 1 \quad \forall l \in L$ ensures that a link can only be used at most by 1 channel. The flow amount crossing the link l is thus $\sum_{c_k \in Conn} k * flow_{l,c_k} \leq 1 \quad \forall l \in L$ where k is the integer flow value affected to the channel c_k. To model switch positions, a binary variable $b_{s,p} \in \{0; 1\} \quad \forall s \in S, \forall p \in P$ takes the value 1 if the switch s is in position p. In order to link switch position variables and flow variables, flow conservation constraints are defined as : $flow_{l1} + b_{s,p} * q - q \leq$

TABLE I
OBJECTIVES, PARAMETER AND DECISION VARIABLES

$ObjectiveFunctions:$	
$Max \sum_{c \in C_{conn}} -ips\_path_c$	(input power objective)
$Max \sum_{c \in C_{conn}} sop\_path_c$	(output power objective)
$Parameters:$	
$att_{l,c}$	$\forall l \in L, \forall c \in C$
att_s	$\forall s \in S$
$ip_{t,c}$	$\forall t \in T, \forall c \in C$
$op_{t,c}$	$\forall t \in T, \forall c \in C$
$Variables:$	
$z \in \mathbb{R}$	
$pos_s \in \mathbb{Z}$	$\forall s \in S$
$flow_l \in \mathbb{Z}$	$\forall l \in L \cup \{l_o\}$
$b_{s,p} \in \{0;1\}$	$\forall s \in S, \forall p \in P$
$twused_t \in \{0;1\}$	$\forall t \in T$
$twused_{t,c} \in \{0;1\}$	$\forall t \in T, \forall c \in C_{conn}$
$flow_{l,c} \in \{0;1\}$	$\forall l \in L, \forall c \in C_{conn}$
$used\_sw_{s,c} \in \{0;1\}$	$\forall s \in S, \forall c \in C_{conn}$
$path_c \in \mathbb{R}$	$\forall c \in C_{conn}$

TABLE II
CONSTRAINTS

$Constraints:$	
$flow_{l_i,i} = 1$	$\forall l_i \in CL_{conn}$
$flow_{l_i} = 0$	$\forall l_i \in \{\{CL_{in}\} - \{CL_{conn}\}\}$
$flow_{l1} + b_{s,p} * q - q \leq flow_{l2} \leq flow_{l1} - b_{s,p} * q + q$	$\forall s \in S$, $\forall p \in P$, $\forall (l_1, l_2) \in (L \cup \{l_0\})^2$, s.t. $m_{s,p,l_1,l_2} = 1$.
$\sum_{p \in P} b_{s,p} = 1$	$\forall s \in S$
$pos_s = \sum_{p \in P} p * b_{s,p}$	$\forall s \in S$
$twused_t * q \geq flow_{tl_{in_t}}$	$\forall t \in T$
$\sum_{t \in T} twused_t = q$	
$4 * used\_sw_{s,c} \geq \sum_{l \in L_s} flow_{l,c}$	$\forall s \in S, \forall c \in C_{conn}$
$used\_sw_{s,c} \leq \sum_{l \in L_s} flow_{l,c}$	$\forall s \in S, \forall c \in C_{conn}$
$\sum_{c \in C_{conn}} flow_{l,c} \leq 1$	$\forall l \in L$
$flow_l = \sum_{c_k \in C_{conn}} k * flow_{l,c_k}$	$\forall l \in L$
$twused_{t,c} \geq flow_{tlin_{t,c}}$	$\forall t \in T$
$flow_{l_0} = 0$	
$twused_t = \sum_{c \in C_{conn}} twused_{t,c}$	$\forall t \in T$
$ips\_path_c = \sum_{l \in L_{in}} att_{l,c} * flow_{l,c} + \sum_{s \in S_{in}} att_s * used\_sw_{s,c} + \sum_{t \in T} ip_{t,c} * twused_{t,c}$	$\forall c \in C_{conn}$
$sop\_path_c = -\sum_{l \in L_{out}} att_{l,c} * flow_{l,c} - \sum_{s \in S_{out}} att_s * used\_sw_{s,c} + \sum_{t \in T} op_{t,c} * twused_{t,c}$	$\forall c \in C_{conn}$

$flow_{l2} \leq flow_{l1} - b_{s,p} * q + q$ $\forall s \in S$, $\forall p \in P$, $\forall (l_1, l_2) \in (L \cup \{l_0\})^2$, subject to $m_{s,p,l_1,l_2} = 1$ (see Table II). m_{s,p,l_1,l_2} indicates whether or not links l_1 and l_2 are connected when switch s is in position p. The link l_0 is a special link for cases where a signal can not be propagated. $twused_{t,c} \in \{0;1\}$ $\forall t \in T, \forall c \in C_{conn}$ shows whether or not amplifier t is crossed by channel c. Besides $used\_sw_{s,c} \in \{0;1\}$ $\forall s \in S, \forall c \in C_{conn}$ is equal to 1 if channel c goes through switch s. Concerning the coefficients of the two objectives (see Table I):

- $att_{l,c}$ $\forall l \in L, \forall c \in C$ represents the power attenuation induced by channel c when it crosses link l.
- att_s $\forall s \in S$ represents the power attenuation induced by switch s.
- $ip_{t,c}$ $\forall t \in T, \forall c \in C$ is the required input power to saturate the amplifier t used by channel c.
- $op_{t,c}$ $\forall t \in T, \forall c \in C$ is the output power when amplifier t is saturated by channel c.

Algorithm 1 Bi-objective input/output ϵ-constraint(δ)

1: Pareto $\leftarrow \emptyset$
2: P $\leftarrow$ opt($\max OP(s) : s \in \mathcal{S}$)
3: $\epsilon \leftarrow$ P.input_power + δ
4: **while** P.hasSolution **do**
5:     P $\leftarrow$ opt($\max OP(s) : s \in \mathcal{S} \quad IP(s) \geq \epsilon$)
6:     Pareto $\cup$ {P.objectives}
7:     $\epsilon \leftarrow \epsilon + \delta$
8: **end while**
9: return Pareto

As scalarization techniques, the well-know ϵ-constraint method [12] and the adaptive version developed by Laumanns in [3] have been considered.

The ϵ-constraint method consists in optimizing one objective while the others are added to the set of constraints. For the bi-objective case, the input power is used as a constraint and the output power is optimized. The constraint problem can be expressed as follows: $\max OP(s) : s \in \mathcal{S} \quad IP(s) \geq \epsilon$ with $\mathcal{S}$ the set of all feasible solutions, $IP(s)$ is the input power for solution s and $OP(s)$ is the output power of solution s. First of all, one extreme is computed without the added constraint (algorithm 1 line 2). In our case, the problem is solved to obtain a maximal power output. Since the opposite of the input power is considered, the solution provides a minimal value. Then, ϵ is set to this minimal value and the corresponding constraint is added. The model is iteratively solved and ϵ is increased with δ (algorithm 1 lines 5-7) until no feasible solution is found. In this approach, δ must not be chosen too large in order to discover all Pareto solutions but if δ is chosen too small, time is wasted by finding duplicated solutions.

The adaptive version dynamically splits the objective space contrary to the standard version. This eliminates the duplicated solutions due to a too small splitting and ensures that no Pareto solutions are missing. For the bi-objective case, the method is straightforward, i.e. ϵ is not iteratively increased but is set with the input power value (see algorithm 2 line 5-7) found by solving the previous single objective run.

V. EXPERIMENTAL SETUP

Experiments have been conducted on the High Performance Computing (HPC) platform of the University of Luxembourg [13]. The IBM ILOG CPLEX 12.4 solver has been used on a

Algorithm 2 Bi-objective input/output adpative ϵ-constraint()

Pareto $\leftarrow \emptyset$
P $\leftarrow$ opt($\max OP(s) : s \in \mathcal{S}$)
$\epsilon \leftarrow$ P.input_power
while P.hasSolution **do**
    P $\leftarrow$ opt($\max OP(s) : s \in \mathcal{S} \quad IP(s) > \epsilon$)
    Pareto $\cup$ {P.objectives}
    $\epsilon \leftarrow$ P.input_power
end while
return Pareto

single Intel Xeon L5640 CPU core at 2.26GHz with 2Gb or RAM. Due to confidentiality reasons, payload specifications cannot be provided. Instances composed of 5, 10 and 15 channels to connect were considered. Contrary to [2], all instances have been solved on a payload embedding 3 different types of switches:

- T-Switches which possess 3 positions. These switches are more flexible because two channels can cross them in each position but they have a high attenuation power.
- C-Switches which only possess 2 positions. Only one channel can be forwarded by this kind of switch in every position.
- R-Switches which possess 4 positions. These switches have the lowest attenuation power. Despite the fact that they induce a lower attenuation than T-Switches, they are harder to configure because the number of channels crossing them depends on their position. Only one channel can cross these switches in position 2 and 4. Positions 1 and 3 allows two channels.

δ has been set to 1 for the standard ϵ-constraint. For these experiments, a total of 90 instances have been chosen: 30 instances for 5, 10 and 15 channels to connect. No time limit was set. Hit rate corresponds to the percentage of instances solved exactly. Only instances which cause an excess of memory have not been solved.

VI. Experimental results

Experimental results for both algorithms on the three problem sizes are presented in the following three tables. The best result for each instance is shaded in dark grey. Table III provides the average number of Pareto solutions as well as the standard deviation. Table IV shows the average processing time in seconds and the standard deviation. Finally the hit rate is considered in Table V.

As can be seen in Table III, the average number of Pareto solutions obtained by the adaptive ϵ-constraint is always greater than the one found by the standard version. Thus, some efficient solutions are missing and $\delta = 1$ for the standard algorithm has been defined too large.

The average time processing for both algorithms in Table IV indicates that the standard algorithm is slower. One could believe that missing some solutions would speed up the resolution. Nevertheless, this could be explained because the standard version wasted time in empty areas showing that

	ϵ-constraint	adaptive ϵ-constraint
5 channels	$4.53_{\pm 2.19}$	$6.91_{\pm 3.31}$
10 channels	$5.96_{\pm 2.50}$	$12.90_{\pm 7.85}$
15 channels	$6_{\pm 2.23}$	$13.48_{\pm 7.78}$

TABLE III
Average number of Pareto solutions

	ϵ-constraint	adaptive ϵ-constraint
5 channels	$2349.37_{\pm 1483.89}$	$450.74_{\pm 981.61}$
10 channels	$17142.60_{\pm 13362.72}$	$1509.60_{\pm 2636.28}$
15 channels	$18135.50_{\pm 15296.15}$	$4956.33_{\pm 7980.35}$

TABLE IV
Average time in seconds

	ϵ-constraint	adaptive ϵ-constraint
5 channels	100	100
10 channels	100	100
15 channels	30	90

TABLE V
Hite rate in %

a static δ is not appropriated for such fronts. Furthermore, the standard deviation proves that the complexity depends not only on instance size but also on which channels have to be connected.

Finally the hit rate (in percent) provides us a limit for the exact methods as presented in Table V. Indeed, every 5 and 10 channel instances have been successfully and optimally solved. However, the set of 15 channel instances have not been completely solved due to excess of memory usage for some instances. Therefore, instances with more than 10 channels start to be unsuitable for a exact bi-objective methods.

Finally, figure 3 is an example of optimal front obtained with the adaptive version. It clearly appears that efficient solutions are not uniformly distributed and the use of a dynamical ϵ like the one used in the adaptive version is here justified. Priority has to be given to algorithms which divide dynamically the objective space.

VII. Conclusion

In this work, a novel satellite payload optimization problem has been introduced and tackled using exact approaches, i.e. the bi-objective problem which consists in optimizing input and output power. For these first experiments on these new objectives, scalarization methods have been applied to study the distribution of the efficient solutions. The obtained optimal Pareto fronts are non uniform and efficient solutions are highly dispersed, forming some isolated dense areas. Besides the processing time and thus the complexity depend not only on the instance size but also on which channels have to be connected. Empirical demonstration of the unsuitability of scalarization techniques for very large instances has been provided. Future works will therefore consider the decomposition of the problem in sub-problems and their resolution with dedicated methods. The bottleneck problem could be also

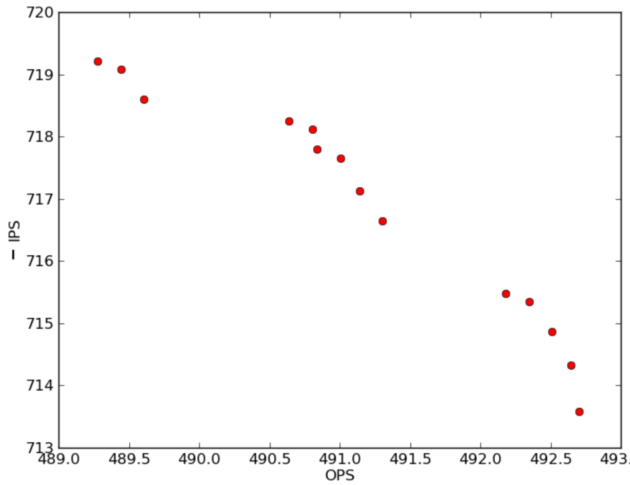

Fig. 3. A non uniform Pareto front

considered as a problem involving robustness because focusing on the worst power channel ensures the satellite operator that none of the other channels will have a lower power value.

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