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Resource optimisation for geostationary communication satellites

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Abstract: We study the dynamic allocation of limited resources in Geostationary Earth Orbit (GEO) communication satellites, where we optimise the placement of each beam, assign users to beams, and assign frequencies to beams. To serve the heterogeneous user demands on a wide geographical distribution, uniform power and bandwidth allocation across beams can be very inefficient. Each beam should be tailored to the allocated user demands to avoid overload or under-utilisation. Our proposed methodology comprises three stages: Stage I creates an initial beam laydown plan (BLP) constructed by Weighted k-Means clustering, and is followed by an improve and repair local search to ensure beam feasibility. Stage II allocates frequencies to beams (referred as beam colouring in the context of this paper) through Constraint Programming; if the BLP cannot meet the frequency (colour) requirement, a Binary Linear Programming model is applied to minimise the total assigned load that needs be removed. Stage III re-allocates any beams freed during Stages I and II, using our custom heuristic—Exhaustive Moving Centroid Heuristic Algorithm (e-MoCHA).

The purpose of our research is two-fold. 1) We are interested in how different satellite system designs and user characteristics impact the speed and performance of our proposed optimisation methodology; and 2) the solutions obtained by our algorithm can be used as an assessment tool to evaluate the best satellite system setup in order to meet the desired outcome. From the experimental results, we find that the total number of users is the main factor that affects on the algorithm processing time, followed by the number of available satellites, beam sizes, and user density. Modulation and Coding (MODCOD) scheme granularity and number of beams per satellite, on the other hand, have very little impact. In terms of outcomes, increasing the number of available satellites significantly improved the total user demands served.

Keywords: *Hybrid optimisation, resource allocation, system design analysis*

1 INTRODUCTION

We explore the problem of satellite resource allocation for Geostationary Earth Orbit (GEO) communication satellites and consider optimal placement of the spot beams (i.e., the location of the centre of the beams and the width of each beam), the user-beam allocation (which users are served by each beam), and beam-colour allocation (allocating frequency bandwidth to beams to avoid neighbouring beam interference).

GEO satellites provides reliable, beyond line of sight communications for a variety of applications including television broadcast, remote area connectivity and maritime and aeronautical broadband services. To provide these services, the satellite operator must allocate satellite resources to meet user demands. A large number of users have to share limited resources such as power and bandwidth. This forces satellite operators to utilise a frequency reuse strategy for efficient spectrum usage while minimising inter-beam and adjacent-beam interference.

Typically, GEO satellites utilise uniform power and bandwidth allocation across beams. This is an inefficient way to serve drastically different user demands across different geographical locations. This technique is more problematic for modern GEO satellites that are equipped with many tens to hundreds of spot beams as uniform allocation can result in user demand exceeding beam capacity and under-utilised beams. Advanced flexible resource allocation schemes that consider user demands and priorities are essential for satellites with a large number of dynamic beams.

We present an experimental analysis of SATCOM resource allocation through performance simulation of a representative SATCOM system with a custom optimisation algorithm. A structured design process has been followed in the development of the model and simulation methodology. This process considers four broad steps; define the experimental objectives, analyse model variables and factors, select experimental design and results analyses.

2 LITERATURE REVIEW

A vast body of literature is available on dynamic resource allocation for fixed-beam systems where the location and size of the spot beams are fixed. Some recent publications have considered satellite systems with flexible beams. Kisseleff et al. [2019] presents a model that optimises the number of beams, beam width, power and bandwidth allocation, but not beam shape and positions. Takahashi et al. [2020] considers multi-spot beams in a straight line using Digital Beamforming (DBF) and studies the effect of geographic distances between spot beams in the same frequency band and the geographic distances between adjacent spot beams in different frequency bands on the overall system throughput, however, it does not discuss flexibility in beam size and beam position.

Honnaiah et al. [2021] first groups users based on their demands to create clusters with evenly distributed total system demand, then assigns a beam to serve each cluster. These clusters are transformed into Vornoi polygons to form a tessellation. The Vornoi polygons are then converted to elliptical beams. Camino et al. [2021] builds on earlier works of Camino et al. [2014] and Camino et al. [2016], and proposes a Mathematical Programming formulation that simultaneously allocates users (stations) and reflectors to beams, and produces the beam laydown plan. The work uses Euclidean distance instead of the Haversine distance. Recently, Gaudry et al. [n.d.] proposes three integer programming-based algorithms that are solved by different hybrids of integer programming, constraint programming, and custom heuristics.

2.1 Contributions and outline of the paper

The main contributions of this work are: 1) a novel hybrid optimisation engine for flexible satellite resource allocation using weighted k-Means, custom heuristic e-MoCHA Gaudry et al. [n.d.], constraint programming, and integer programming; 2) a structured experimental design for satellite system parameter analysis and factor selection; and 3) investigation of how operational and system parameters impact the relative performance of the proposed optimisation methodology.

The rest of the paper is organised as follows. In Section 3, we present the satellite communication architecture and link and environment model. In Section 4, we present the parameter analysis, factor selection, and experimental design. In Section 5, we explain the different elements of our hybrid optimisation framework. In Section 6, we present numerical results and, finally, we summarise our findings in Sections 7.

3 MODEL DEVELOPMENT

3.1 Satellite Communication Architecture

The purpose of the model is to investigate how satellite system design impacts the optimisation algorithm, therefore communication link parameters and availability are not required. We consider forward link from a gateway hub to ground user terminals. It is assumed that the gateway has sufficient power and gain for forward uplink, therefore the optimisation algorithm only have to consider the forward downlink from the satellite to the users. The satellite is modelled as a multi-beam high throughput satellite (HTS), where the beam locations, size and frequency assignment are controllable.

Beam projections are modelled in accordance with Spies and Haakinson [1980] under the limiting assumptions defined in Gaudry et al. [n.d.]. Radiation patterns are simulated based on a simplified parabolic reflector, with the beam size defined as the edge of the half-power beamwidth (HPBW). Radiation patterns beyond HPBW are based on ITU design guidelines with co-channel interference assumed negligible at angles equating to -25db gain reduction.

3.2 Link and Environment Model

The satellite link parameters are similar to the generic Ka-band satellite used in Pratt and Allnutt [2019], with a downlink frequency between 19.7-20.2 GHz, utilising two channels with dual polarisation for a four colour (frequency) reuse scheme. Atmospheric interactions, propagation losses, pointing errors and miscellaneous system losses follow recommendations in Ippolito [2017]. It is assumed that all Earth terminals are stationary, have unobstructed line of site and a negligible altitude. The required throughput for communication links have been generated randomly between representative values for user services.

Required energy per bit to noise power spectral density ratio (E_b/N_o) values are selected based on the ability to establish a quasi-error free (frame error rate of 10^{-5}) link at the desired data throughput values and selected modulation and coding. It is assumed that modems allow for adaptive coding and modulation up to the standards of the DVB-S2X waveform, with roll-off and output-back off values selected from the DVB-S2X guidelines [ETSI].

The static environmental model considers clear sky day time operations over the Australian geographic region. Radio noise and antenna noise contributions are based on nominal design parameters of user terminals and recommendations for nominal natural induced noise sources detailed in Ippolito [2017].

4 EXPERIMENTAL DESIGN

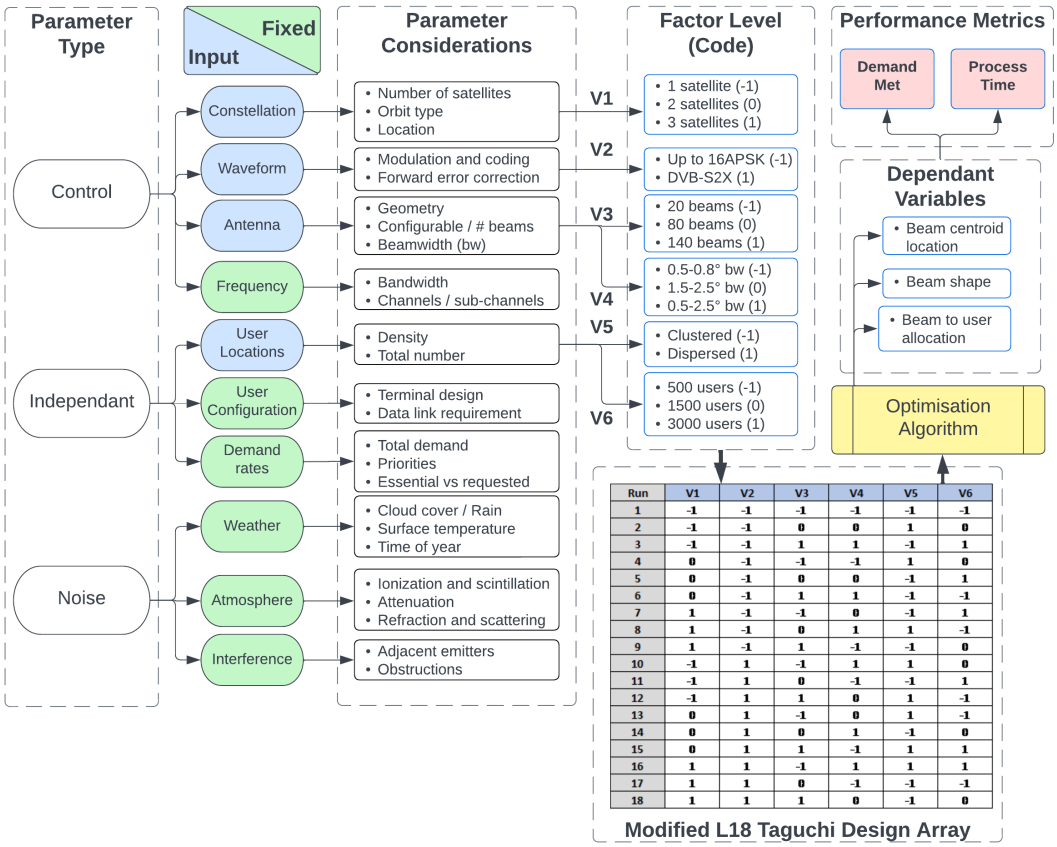
4.1 Objective

The experimental analysis considers variations in satellite system design, operating profiles and environments. A static optimisation algorithm will be applied to model system output behaviour and assess relative impact of system design changes through screening of the main effects. Additionally, simulations will assess robustness of coupled optimisation and design methodologies.

4.2 Parameter Analysis and Factor Selection

The parameter analysis characterises parameters by type (independent, noise, control and dependent) to assess cause and effect relationships within the system model. This drives an assessment on the probable system response to changing parameter settings, guiding the selection of fixed and variable parameters during simulations. As seen in Figure 1, each parameter is considered at different levels of abstraction based on the required model inputs. Known user satisfaction criteria directly related to identified dependant variables define the performance metrics used within the simulation. The coupled model and optimisation algorithm performance will be assessed by the run time across relative size complexity problem instances.

The input parameters to the simulation framework are called factors. Discrete levels are defined to represent the range of values a factor can be assigned. Increasing the number of levels representing a continuous factor improves model accuracy but requires an increased number of runs to analyse the main effects. The trade-off between reducing runs while improving the main effects analysis is driven by the experiment objectives. As seen in Figure 1, a combination of two-level and three-level factor representations is determined as sufficient to screen the model main effects.



Run	V1	V2	V3	V4	V5	V6
1	-1	-1	-1	-1	-1	-1
2	-1	-1	0	0	1	0
3	-1	-1	1	1	-1	1
4	0	-1	-1	-1	1	0
5	0	-1	0	0	-1	1
6	0	-1	1	1	-1	-1
7	1	-1	-1	0	-1	1
8	1	-1	0	1	1	-1
9	1	-1	1	-1	-1	0
10	-1	1	-1	1	1	0
11	-1	1	0	-1	-1	1
12	-1	1	1	0	1	-1
13	0	1	-1	0	1	-1
14	0	1	0	1	-1	0
15	0	1	1	-1	1	1
16	1	1	-1	1	1	1
17	1	1	0	-1	-1	-1
18	1	1	1	0	-1	0

Figure 1. Input / output experiment flowchart and parameter analysis

4.3 Experimental Design Selection

Complete enumeration of factor levels requires 324 test runs to screen a single optimisation algorithm. The orthogonality of selected factors allows for implementation of a structured experiment design using a limited set of combinations. From Figure 1, each factor is coded to represent a level to be used in an experimental run. The required number of experimental runs is reduced to 18 by implementing a modified Taguchi L_{18} design matrix with randomised selection of additional values for two-level factors and reduction of the design matrix size to accommodate 6 factors.

5 Optimisation Methodology

Stage I–Initial beam laydown. A BLP is the placement of the beams, i.e., the centre and the widths of the beams. The general steps are as follows:

1. **Initial BLP** The weighted k-Means clustering algorithm (Kerdprasop et al. [2005]) is used to produce the initial user clusters. The user demands are used as weights, (the centroid of each cluster is more likely to be closer to users with relatively larger demands). Once the initial BLP is completed, a beam will be placed on each cluster centered on the cluster centroid.
2. **Set beam width** Starting with the smallest beam width, increase iteratively until all users in the cluster are covered.
3. **Feasibility check** for load and coverage feasibility (all users must be within half-power beam width (HPBW) for coverage feasibility).
4. **Removing infeasibility** If an infeasibility exists, iteratively remove the furthest point from the centroid until the user cluster becomes load and coverage feasible for a beam. Lastly, assign unallocated

users to a neighbouring cluster without exceeding load and coverage limitations.

5. **Free beams (Optional)** Iteratively move users in overlapped beams to larger beams (larger in terms of number of users allocated to the beams) as long as it is feasible with the current coverage and load. The intention of this procedure is to create beams with no assigned users (creating free beams to be re-assigned).
6. **Reallocate beams (Optional)** If any beams are freed in Step 5, they will be greedily reallocated using a custom heuristic called e-MoCHA developed in Gaudry et al. [n.d.] to serve the unallocated users.

Stage II–Beam colouring. To minimize interference, no neighbouring beams can be given the same colour. Consider $\omega = 1.58 * beamwidth$ as the scope of influence of a beam, using a -25dB mask with ITU design guidelines for gain pattern beyond the beam radius, which is about 1.58 times larger than the beam footprint. We call this the Beam Planning Region (BPR) of a beam. Now, if the BPR of two beams overlap and that there exists a user in this overlap, then we say that the two beams are neighbouring each other.

We use Constraint Programming (CP) to check whether the current BLP can be coloured with 4 colours. If no feasible solutions can be found, the following procedure will be carried out.

Removing excess beams. Our strategy is to minimise the total assigned load that needs to be removed. This can be done by using the Binary Linear Programming model presented below. Let $\mathcal{B} = \{1, \ldots, N_B\}$ be the index set of beams and $\mathcal{C}$ be the set of cliques. A clique is a set of beams that are all neighbouring each other and therefore a colour can only be used at most once in a clique. Let $\mathcal{B}_c$ be the set of beams in Clique c. Let $\mathcal{L}_b$ be the total load assigned to Beam b, $\mathcal{R}$ be the set of available colours, and $\rho_{b,r}$ be a binary decision variable with $\rho_{b,r} = 1$ indicating Beam b is coloured with Colour r, and $\rho_{b,r} = 0$ otherwise. We introduce a "dummy colour" D and allocate it to all excess beams. Let $\mathcal{R}^* = \mathcal{R} \cup D$. The model is given as below. The objective function minimises the total load covered by colour D that will be removed

$$\min \sum_{b \in \mathcal{B}} \mathcal{L}_b \rho_{b,D}$$

with the constraints that ensures each beam is given exactly one colour

$$\sum_{r \in \mathcal{R}^*} \rho_{b,r} \; = \; 1, \quad \forall b \in \mathcal{B}$$

and ensures that no neighbouring beams will be colour with same real colour

$$\sum_{b \in \mathcal{B}_c} \rho_{b,r} \leq 1 \qquad \forall r \in \mathcal{R}, \forall c \in \mathcal{C}$$

Stage III–Reallocate freed beams. If there are beams freed during Stages I & II, we apply our heuristic algorithm e-MoCHA (Gaudry et al. [n.d.]) to generate a set of candidate beams to serve the unallocated users. The candidate beams are considered one by one in a descending order of beam load, each time with colour-feasiblility checked by CP. If the inclusion of the new beam makes the new BLP colour-feasible, it will be included, otherwise, it will be discarded, and the procedure will iterate to the next beam in the list.

Implementation details. As the weighted k-Means algorithm is stochastic, we may get a different initial BLP in different runs, which has an impact on the quality of the solution. For this reason, we tested the parameters "max_iter" (maximum number of iteration of k-Means for a single run) and "n_init" (number of times the k-Means is run with different centroid seeds). From the results of our experiments, it appears that setting max_iter = 1000 and n_init = 1000 can in general produce a reasonably-good initial BLP in a reasonable amount of time.

6 Results

From Figure 2, we can see that the total number of users is a dominating factor of algorithm processing time. With more users, the number of decision variables increases, and thus the size of the optimization problem increases as well. However, even though increasing the number of beams also increases the number of decision variables, the impact on computation time is much smaller.

On the other hand, number of satellites, beam-width, and user density also induced noticeable differences in the processing time of the optimization algorithm, but not to the same extent when compared to that of the number of users. Number of beams per satellite and MODCOD granularity have mild impacts on the processing time.

For experiments with inputs indicating more users per beam (due to clustered distribution, larger beamwidths, or just more users in the system), the results show a near linear increase in processing time but a decrease in demand met. The largest processing time is recorded for the scenario with two satellites, 80 beams each, a reduced MODCOD granularity, large beamwidths, and serving 3000 clustered users – this indicates strongly that the dominating effect of coupled inputs are related to an increased number of users per beam.

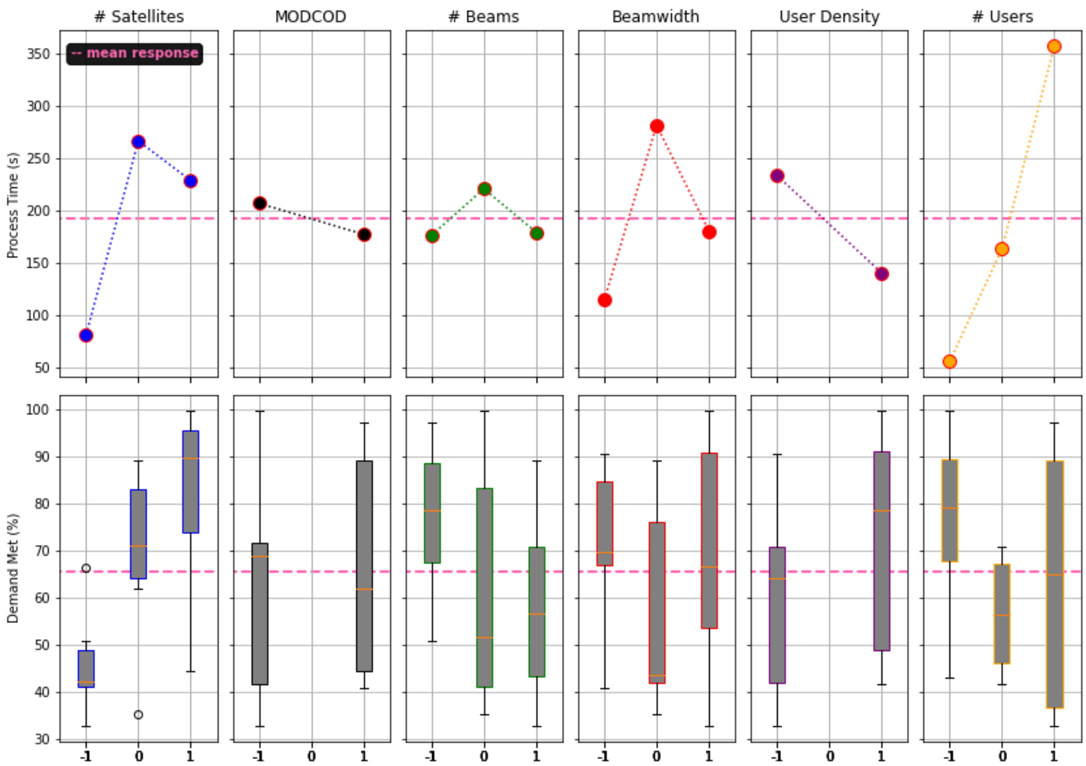


Figure 2. Main effects scatter plot and response box plot for processing time and demand met respectively

The wide distribution of demand met responses seen in Figure 2 indicates a strong coupling between optimal system setup and the operational scenario. Increasing the number of available satellites increases the demand met while other factors displayed weak effects when compared to the mean response. This is an intuitive result as the additional satellites are modelled to provide increased coverage without interference. Additionally, the optimisation method implemented additional satellites sequentially, explaining the notable increase in processing time. We assessed the total number of beams used in the optimized solution in order to evaluate the processing time and demand met for the two and three satellite scenarios. For the three satellite scenarios, from the the number of beams needed in the final solution, only one out of 6 runs in the experiments require the use of three satellites. As for the two satellite scenarios, three out of 6 runs require both satellites, which means that for the other runs, one satellite is enough to meet the user demands. Even though the number of satellites has a big impact in terms of percentage of demand met, the high launch costs and limited GEO slot availability significantly limit the feasibility of operating multi-satellite constellations. These findings highlight the fact that optimum system design is coupled to the operational scenario.

7 Conclusions and Recommendations

The system model and operational scenarios were developed to show how operational and system parameters impact the relative performance of the proposed solution methodology. It is rather clear that parameter selection for optimised system performance is dependant on the operational scenario, therefore having an adaptable system allows for improved coupling between performance and operational contexts. Increasing the number of decision variables and constraints in the optimisation algorithm directly increases the processing time (e.g., due to an increase in number of users). However, increased system flexibility did not have as large an impact on overall processing time. The results were dominated by coupled factors with increased user densities per beam. We recommend that for future simulation analysis, these coupled effects should be blocked by way of experimental design for better evaluation of the main effects of SATCOM system design parameters. The results from our experiments shows strongly the fact that our solution methodology, a hybrid optimization approach, is well suited for user distributions that reflects realistic operational scenarios. However, edge cases with dense users or scenarios resulting in a mismatch between beam capacity and requested demand has a negative impact on the performance of the algorithm.

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