Bi-objective Optimization of Satellite Payload Power Configuration

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1 Introduction

Communications satellites are sent to space to provide telecommunications services. They aim at forwarding signals coming from satellite operators to customers. These signals are made up of different channels representing a panel of frequencies. After receiving uplink signals, satellites apply noise filtering, frequency conversion and amplification before retransmission. All of these steps are conducted by the payload. The payload embeds different hardware components including reconfigurable switches. In order to set up or modify the payload configuration, engineers mostly used computerized schematics. However, the increasing demands of the market impose more flexibility and more larger payloads. Therefore, manual management is becoming error-prone and time-consuming. Some commercial softwares [1, 2] exist but they explicitly enumerate all feasible solutions to find the best one which is unsuitable for large instances. Moreover, those softwares act more like black box than decision aid methods. As a solution, an integer linear program has been proposed in [3] to solve different single objective payload optimization problems. Very large payload instances have been also tackled by using cellular genetic algorithms[4]. To the best of our knowledge, only [5] applied exact bi-objective methods while commercial softwares never considered multi-objective problems. Power transmission optimization is an important aspect that satellite operators have to take into account. The first consists of minimizing the required power to send to the satellite. The second one consists of maximizing the outgoing power from the satellite to the customers. In this article, we apply and compare multi-objective evolutionary algorithms to propose to the satellite operator a set of efficient power configurations.

2 Input/Ouput power optimization problem

In order to be correctly forwarded, signals have to be amplified due to the power losses induced by the atmosphere and the payload crossing (see example payload in Fig. 1). For this purpose, channels are forwarded to appropriate amplifiers. Before reaching the corresponding amplifier, a channel goes through different passive components which induce different attenuation characteristics. Among them, switches have a crucial role in the payload since they are the only dynamic components allowing engineers to change the payload configuration. There are various types of switches and each of them have different power attenuations which do not depend on the channel. Contrary to switches, connectors attenuation is related to the channel. Therefore, the satellite operator would prefer to define paths using the least possible connectors with high attenuation. However in order to be correctly amplified, incoming signals must also have a required power to saturate the amplifier so that amplification reaches its maximal value. This is due to the non linear relation between the input power to saturation(IPS) and the saturated output power(SOP). By taking these power data into consideration, satellite operators define the input power as the power to send to the satellite minus the different losses in order that channels saturate their amplifiers. Minimizing this objective corresponds to finding for every needed channel, a path with minimal losses going through amplifiers with a minimal required power to saturate them. The output power is defined as the power after amplification minus the different losses. Maximizing the output power is to find a path with minimal losses going through amplifiers having a maximal output power. Obviously, both objectives are negatively correlated which means that an improvement of one of them implies a degradation for the other. Satellite operators would like to minimize the power amount to sent to the satellite while keeping a maximum level of amplification. For this hard bi-objective problem, we decided to use multi-objective evolutionnary approaches.

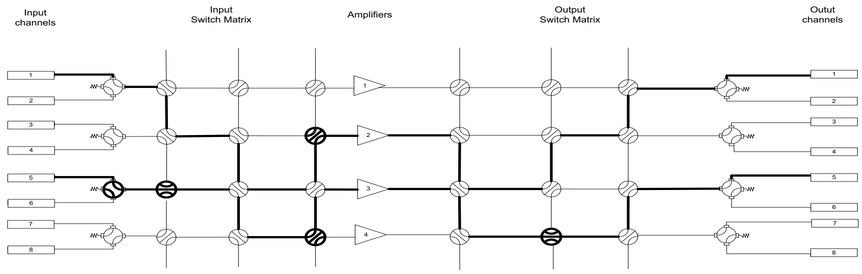

Fig. 1: Payload representation concept

3 Multi-objective evolutionnary approaches

We chose for our experiments to compare the performance of NSGAII [6], SPEA2 [7] and MOCell [8]. We performed these experiments on instances composed of 5, 10 and 15 channels to connect. To compare the results, we used the hypervolume, the generational distance and the spread indicator. The payload can be configured by modifying the switch matrix. Contrary to [4] which uses a binary encoding, we use an integer encoding to ensure that solutions stay consistent after applying evolutionary operators. First results have shown the difficulty for each algorithm to find feasible solutions. Most of the crossovers generate non feasible solutions. When a feasible solution is found, it starts to fill the population so that algorithms end with only a unique solution. In order to cope with this problem, we add a local search procedure which aims at completing the solution to obtain a feasible solution. In our case, feasible means that each input channels to connect reaches its corresponding output channel and goes trough only one amplifier. When a solution is not feasible, the local search will explore the solution to find the last component able to connect correctly the channel. We use a tree search algorithm to find the last available sub-path to ensure solution feasibility. This local search allows us to generate enough diversity by keeping a certain feasibility threshold. Results after integration of this local search shows that algorithms are now able to more fully explore the decision space. Indeed, hypervolume have increased and spread is become closer to zero. Indicators show that the best results are provided by MOCell.

4 Conclusion

We tackled for the first time the bi-objective problem of optimizing input/output power in communication satellites. Experiments have shown the difficulty to obtain a reasonable number of feasible solutions to get enough diversity. A local search algorithm has been added to multi-objective evolutionary algorithms to preserve diversity. Our results show that we can use non feasible solutions by correcting them in order to produce more diversity. MOCell stands out by its lower time processing and higher diversity. Future work will consider different encodings, such as indirect ones.

References

1. TRECS. Transponder reconfiguration system [online]. http://www.integ.com/TRECS.html.
2. J.P. Chaumon, J.C. Gil, T.W. Beech, and G. Garcia. Smartrings: advanced tool for communications satellite payload reconfiguration. page 11 pp., 2006.
3. A. Stathakis, G. Danoy, T. Veneziano, J. Schleich, P. Bouvry, and G. Morelli. Optimising satellite payload reconfiguration: An ILP approach for minimising channel interruptions. In *Proceedings of 2nd ESA Workshop on Advanced Flexible Telecom Payloads, Noordwijk, The Netherlands*, 2012.
4. A.Stathakis, G.Danoy, J.Schleich, P.Bouvry, and G.Morelli. Minimising longest path length in communication satellite payloads via metaheuristics. In *GECCO*, pages 1365–1372, 2013.
5. A. Stathakis, G. Danoy, T. Veneziano, P. Bouvry, and G. Morelli. Bi-objective optimisation of satellite payload configuration. 2012(to appear).
6. K.Deb A.Pratap S.Agarwal T.Meyarivan. A fast and elitist multiobjective genetic algorithm:nsga-ii. *IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION*, 6(2), 2002.
7. E.Zitzler, M.Laumanns, and L.Thiele. Spea2: Improving the strength pareto evolutionary algorithm. 2001.
8. A.Nebro, J.Durillo, F.Luna, and B.Dorronsoro. Mocell: A cellular genetic algorithm for multiobjective optimization. *International Journal Of Intelligent Systems*, 24:726–746, 2009.