Approximate Solutions in Space Mission Design

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Abstract. In this paper, we address multi-objective space mission design problems. We argue that it makes sense from the practical point of view to consider in addition to the 'optimal' trajectories (in the Pareto sense) also approximate or nearly optimal solutions since this can lead to a significant larger variety for the decision maker. For this, we suggest a novel MOEA which is a modification of the well-known NSGA-II algorithm equipped with a recently proposed archiving strategy which aims for the storage of the set of approximate solution of a given MOP. Using this algorithm we will examine several space missions and demonstrate the benefit of the novel approach.

1 Introduction

In a variety of applications in industry and finance a problem arises that several objective functions have to be optimized concurrently leading to *multi-objective optimization problems* (MOPs). For instance, in space mission design, which we address here, there are two crucial aims for the realization of a transfer: minimization of flight time and fuel consumption of the spacecraft ([2], [13], [11], [10]). The scope of this paper is (a) to show that it makes sense to consider in addition to the 'optimal' trajectories also approximate solutions since by this the decision maker (DM) is offered a much larger variety of possibilities, and (b) to present one way to compute this enlarged set of interest with reasonable effort. As a motivating example for (a) we consider the MOP in Section 4.2 which is a model for the transfer from Earth to Mercury, and the following two points x_i with images $F(x_i), i = 1, 2$:

$$\begin{aligned} x_1 &= (782,\, 1288,\, 1788)\ , & F(x_1) &= (0.462,\, 1001.7) \\ x_2 &= (1222,\, 1642,\, 2224), & F(x_2) &= (0.463,\, 1005{,}3) \end{aligned}$$

The two objectives are the propellant mass fraction—i.e., the portion of the vehicle's mass which does not reach the destination—and the flight time (in days). In the domain, the first parameter is of particular interest: it determines the departure time from the Earth (in days after 01.01.2000). $F(x_1)$ is less than $F(x_2)$ in both components, and thus, x_1 can be considered to be 'better' than x_2. However, note that the difference in image space is small: the mass fraction of the two solutions differs by 0.001 which makes 0.1% of the total mass, and the flight time differs by four days for a transfer which takes almost three years. In case the DM is willing to accept this deterioration, it will offer him/her a second choice in addition to x_1 for the realization of the transfer: while the two solutions offer 'similar' characteristics in image space this is not the case in the design space since the starting times for the two transfers differ by 440 days.

The identification of the two solutions would be a fundamental requirement during the preliminary design of a space mission. In fact, in order to increase the reliability of the design, the mission analysts would need to identify one or more back-up solutions, possibly with identical cost, for each baseline solution. Furthermore, for each mission opportunity (i.e. each launch date) rather than an optimal solution, it is generally required to identify a set of nearly optimal ones, possibly all with similar cost. Such a set would represent a so called *launch window*, since for each solution in the set a launch would be possible. Designing for the suboptimal points further increases the reliability of the mission since it gives the freedom to deviate from the chosen design point with little or no penalty. This holds true also for Pareto optimal solutions. It is therefore desirable to have a whole range of nearly Pareto optimal solutions for each Pareto point.

The field of evolutionary multi-objective optimization is well-studied and MOEAs have been successfully applied in a number of domains, most notably engineering applications ([1]). Approximate solutions in multi-objective optimization have been studied by many researchers so far (e.g., [7], [14], [6]). A first attempt to investigate the benefit of considering approximate solutions in space mission design has been done in ([12]), albeit for the single-objective case.

The additional consideration of (all) approximate solutions in multi-objective space mission design problems is new and will be addressed in this paper. Crucial for this approach is the efficient computation of the enlarged set of 'optimal' points since in many cases the 'classical' multi-objective approach is a challenge itself. For this, we will propose an algorithm which is based on the well-known NSGA-II ([3]) but equipped with an archiving strategy which was designed for the current purpose. Note that 'classical' archiving/selection strategies—e.g., the ones in [4], [9], [6], [5], or the one NSGA-II uses—store sets of mutually non-dominating points (which means that e.g. the points x_1 and x_2 in the above example will never be stored *jointly*). That is, these selection mechanisms—though they accomplish an excellent job in approximating the efficient set—can not be taken for our purpose.

The remainder of this paper is organized as follows: in Section 2, we give the required background which includes the statement of the space mission design problem under consideration. In Section 3, we propose a new genetic algorithm for the computation of the set of approximate solutions and present further on in Section 4 some numerical results. Finally, we conclude in Section 5.

2 Background

2.1 Multi-Objective Optimization

In the following we consider continuous multi-objective optimization problems

$$\min_{x\in Q}\{F(x)\}, \tag{MOP}$$

where $Q \subset \mathbb{R}^n$ is compact and F is defined as the vector of the objective functions $F : Q \to \mathbb{R}^k, \quad F(x) = (f_1(x), \dots, f_k(x))$, with $f_i : Q \to \mathbb{R}$.

Definition 1. *Let $v, w \in Q$. Then the vector v is* less than *w ($v <_p w$), if $v_i < w_i$ for all $i \in \{1, \dots, k\}$. The relation $\leq_p$ is defined analogously. $y \in Q$ is* dominated *by a point $x \in Q$ ($x \prec y$) with respect to (MOP) if $F(x) \leq_p F(y)$ and $F(x) \neq F(y)$. $x \in Q$ is called a* Pareto optimal point *or* Pareto point *if there is no $y \in Q$ which dominates x.*

The set of all Pareto optimal solutions is called the *Pareto set* (denoted by P_Q). The image of the Pareto set is called the *Pareto front*. We now define another notion of dominance which we use to define approximate solutions and the set of interest:

Definition 2. *Let $\epsilon = (\epsilon_1, \dots, \epsilon_k) \in \mathbb{R}^k_+$ and $x, y \in Q$. x is said to ϵ-dominate y ($x \prec_\epsilon y$) with respect to (MOP) if $F(x) - \epsilon \leq_p F(y)$ and $F(x) - \epsilon \neq F(y)$. x is said to $-\epsilon$-dominate y ($x \prec_{-\epsilon} y$) with respect to (MOP) if $F(x) + \epsilon \leq_p F(y)$ and $F(x) + \epsilon \neq F(y)$.*

Definition 3. *Denote by $P_{Q,\epsilon}$ the set of points in $Q \subset \mathbb{R}^n$ which are not $-\epsilon$-dominated by any other point in Q, i.e., $P_{Q,\epsilon} := \{x \in Q \mid \nexists y \in Q : y \prec_{-\epsilon} x\}$.*

The set $P_{Q,\epsilon}$ contains all ϵ-efficient solutions, i.e., solutions which are optimal up to a given (small) value of ϵ. Fig. 1 gives two examples.

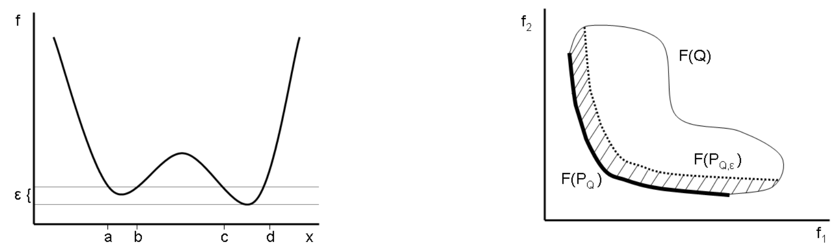


Fig. 1. Two different examples for sets $P_{Q,\epsilon}$. Left for $k = 1$ and in parameter space with $P_{Q,\epsilon} = [a, b] \cup [c, d]$. Right an example for $k = 2$ in image space.

Alg. 1 gives an archiving strategy which aims for the approximation of $P_{Q,\epsilon}$, where A_0 is a given archive, p a candidate solution, $\Delta \in \mathbb{R}^k_+$ the discretization parameter, and $B(y, \Delta) := \{x \in \mathbb{R}^k : |x_i - y_i| \leq \Delta_i,\ i = 1, .., k\}$. See [10] for the related discussion.

Algorithm 1 $A := ArchiveUpdateP_{Q,\epsilon}\ (p, A_0, \Delta)$

Require: population P, archive A_0, $\Delta \in \mathbb{R}_+$, $\Delta^* \in (0, \Delta)$
Ensure: updated archive A

$A := A_0$
if $\nexists a_1 \in A :\ a_2 \prec_{-\epsilon} p$ and $\nexists a_2 \in A :\ F(p) \in B(F(a_2), \Delta^*)$ **then**
  $A := A \cup \{p\}$
  for all $a \in A$ **do**
    if $p \prec_{-(\epsilon+\Delta)} a$ **then**
      $A := A \backslash \{a\}$
    end if
  end for
end if

2.2 The Design Problem

The examples we analyze are taken from two classes of typical problems in space trajectory design: a bi-impulsive transfer from the Earth to the asteroid Apophis, and a low-thrust multi-gravity assist transfer.

Bi-impulse Problem For the bi-impulsive case, the propellant consumption is a function of the velocity change, or Δv, required to depart from the Earth and to rendezvous with a given celestial body. Both the Earth and the target celestial body are point masses with the only source of gravity attraction being the Sun. Therefore, the spacecraft is assumed to be initially at the Earth, flying along its orbit. The first velocity change, or Δv_1, is used to leave the orbit of the Earth and put the spacecraft into a transfer orbit to the target. The second change in velocity, or Δv_2, is then used to inject the spacecraft into target's orbit. The two Δv's are a function of the positions of the Earth and the target celestial body at the time of departure t_0 and at the time of arrival $t_f = t_0 + T$, where T is the time of flight. Thus, the MOP under consideration has two objective functions $f_1(x) = \Delta v_1 + \Delta v_2$ and $f_2(x) = T$, with the solution vector $x = [t_0, T]^T$.

MLTGA Problem It is here proposed to use a particular model for multiple gravity assist low-thrust trajectories (MLTGA). Low-thrust arcs are modeled through a shaping approach based on the exponential sinusoid proposed in [8]. The spacecraft is assumed to be moving in a plane subject to the gravity attraction of the Sun and to the control acceleration of a low-thrust propulsion engine[13]. Gravity manoeuvres are modeled through a powered swing-bys approximation[13]: a pair of low-thrust arcs are linked through a Δv manoeuvre when the gravity of the swing-by planet is not strong enough to gain the required change in velocity. As for the bi-impulsive case, we are interested in the minimization of two objectives: the propellant mass fraction and the flight time. The first objective is $f_1(x) = 1 - e^{-(\frac{\Delta V_{GA}+\Delta V_0}{g_0 I_{sp1}} + \frac{\Delta V_{LT}}{g_0 I_{sp2}})}$ with the solution vector[11] $x = [t_0, T_1, k_{2,1}, n_1, ..., T_i, k_{2,i}, n_i, ..., T_N, k_{2,N}, n_N]^T$. Where ΔV_{GA} is the sum of all the ΔVs (variation in velocity) required to correct every gravity assist manoeuvre, ΔV_0 is the departure manoeuvre, while ΔV_{LT} is the sum of the total ΔV of each low-thrust leg. Then, $k_{2,i}$ is the $i-th$ shaping parameter for the exponential sinusoid and n_i the number of revolutions around the Sun, t_0 is the departure time and T_i the transfer time from planet i to planet $i+1$. The two specific impulses I_{sp1} and I_{sp2} are respectively for a chemical engine and for a low-thrust engine and g_0 is the gravity acceleration on the surface of the Earth. For the tests in this paper, we used $I_{sp1} = 315$s and $I_{sp2} = 2500$s. The second objective function is $f_2(x) = t_N - t_0$ with t_N the time of arrival at destination.

3 A Genetic Algorithm for the Computation of $P_{Q,\epsilon}$

In this section we propose a MOEA which aims for the computation of the set of approximate solutions, $P_{Q,\epsilon}$-NSGA-II, which is a hybrid of NSGA-II ([3]) and the archiver $ArchiveUpdateP_{Q,\epsilon}$. Further, in order to be able to compare the obtained solutions with another strategy, we introduce a performance metric.

The Algorithm The algorithm we propose in the following is based on NSGA-II. We have decided to take this one as our baseline algorithm for two reasons. First, this algorithm is well-known and has been found to be very efficient. Second, we think that the elements which constitute NSGA-II fit nicely to our context: a (finite) archive A containing points which are mutually non-$(-\epsilon)$-dominating can be viewed as a set of Pareto fronts with different ranks, and also in the current setting the first front (i.e., the non-dominated front) should be given the priority since (i) improvement of the current set is clearly an objective and—in case the solutions are already near to P_Q—a local search around P_Q (e.g., mutation) is a search within $P_{Q,\epsilon}$. Thus, we have decided to adopt the ranking from NSGA-II, as well as the crowding distance in order to maintain diversity, and the genetic operators since they are proven to be well-suited for continuous problems.
The algorithm $P_{Q,\epsilon}$-NSGA-II reads as follows: the initial offspring $\mathcal{O} \subset Q$ is chosen at random, and the first archiver is set to $\mathcal{A}_0 := ArchiveUpdateP_{Q,\epsilon}(\emptyset, \mathcal{O}_0, \Delta)$. Alg. 2 describes how to obtain the subsequent archives $\mathcal{A}_{l+1}$ from $\mathcal{A}_l$. Hereby the function $Select()$ picks $n_p/2$ elements from $\mathcal{A}$ at random, if $|\mathcal{A}| \leq n_p/2$ then $\mathcal{C} := \mathcal{A}$ is chosen (n_p denotes the population size). The next three operators are as in NSGA-II: $DominationSort()$ assigns rank and crowding distance to $\mathcal{C}$, $TournamentSelection()$ performs the tournament selection, and $GeneticOperator()$ performs simulated binary crossover and polynomial mutation on $\mathcal{P}$. Finally, the archive $\mathcal{A}_l$ is updated by $\mathcal{O}$ using $ArchiveUpdateP_{Q,\epsilon}$ leading to the new archive $\mathcal{A}_{l+1}$.
The new algorithm is in fact very close to NSGA-II, merely the selection strategy to keep the 'promising' points of the search has changed (by adding an archive to

NSGA-II). Recall that the motivation for the storage of approximate solutions is to obtain in addition to the 'optimal' points also points which are close to these points in image space but which differ significantly in parameter space. Thus, it is desired to maintain a certain diversity in parameter space, and that is why the chromosomes $\mathcal{C}$ are chosen randomly from the current archive by $Select()$.

Algorithm 2 Iteration step of $P_{Q,\epsilon}$-NSGA-II

Require: archive $\mathcal{A}_l$, $\Delta \in \mathbb{R}_+$, population size n_p
Ensure: updated archive $\mathcal{A}_{l+1}$
1: $\mathcal{C} := Select(\mathcal{A}_l, n_p/2)$
2: $\mathcal{C}' := DominationSort(\mathcal{C})$
3: $\mathcal{P} := TournamentSelection(\mathcal{C}')$
4: $\mathcal{O} := GeneticOperator(\mathcal{P})$
5: $\mathcal{A}_{l+1} := ArchiveUpdateP_{Q,\epsilon}(\mathcal{A}_l, \mathcal{O}, \Delta)$

Performance Metric In order to be able to compare the results of different algorithms, or just two sets A and B, we propose to use the following metric:

$$\mathcal{C}_{-\epsilon}(A, B) := |\{b \in B \;:\; \exists a \in A : a \prec_{-\epsilon} b\}|/|B|, \tag{1}$$

which is a straightforward extension of the *set coverage metric* suggested in [15]. Analogue to the original metric, $\mathcal{C}_{-\epsilon}(A, B)$ is an unsymmetric operator which aims to get an idea of the relative coverage of the two solution sets.

4 Numerical Results

Here we present some numerical results coming from two different settings. For the internal parameters (e.g., mutation probability) of NSGA-II we have followed the suggestions made in [3], and have taken the same values for $P_{Q,\epsilon}$-NSGA-II.

4.1 Two Impulse Transfer to Asteroid Apophis

For the bi-impulse problem we analyze an apparently simple case: the direct transfer from the Earth to the asteroid Apophis. The contour lines of the sum of the two Δv's is represented in Fig.2 (a) for the parameters $t_0 \in [3675, 10500]^T$ MJD2000 and $T \in [50, 900]$ days. The intervals for t_0 and T were chosen in such a way that a wide range of launch opportunities are included. The solution space presents a large number of local minima. Many of them are nested, very close to each other and with similar values. For each local minimum, there can be a different front of locally Pareto optimal solutions. The best known approximation of the global Pareto front is represented in Fig. 2 (b) and was obtained with an extension to MOPs of the algorithm described in [12]. It is a disjoint front corresponding to two basins of attraction of two minima, see Fig. 2 (a).

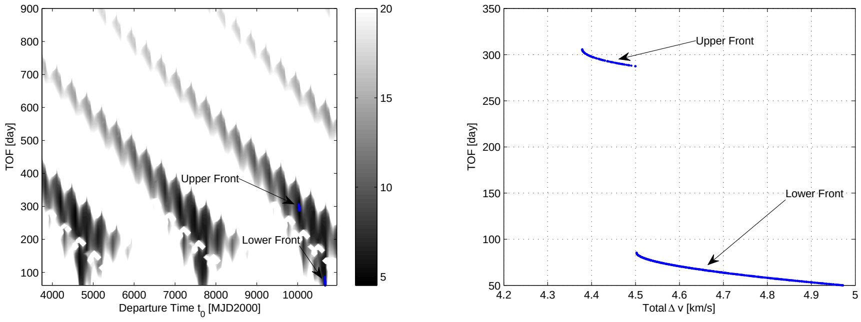


Fig. 2. a) Earth-Apophis search space, b) Pareto front

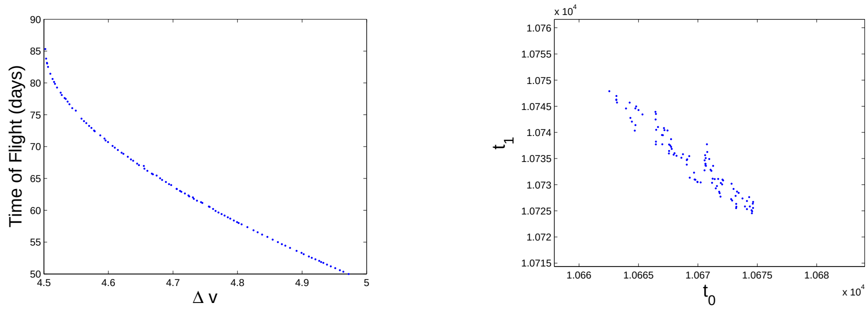
The two basins of attraction present similar values of the first objective function. Converging to the upper front is therefore quite a challenge since the lower front has a significantly lower value of the second objective function. It is only when the optimizer converges to the a vicinity of the local minimum of the upper front that the latter becomes not dominated by the lower front. The upper front contains the global minimum with a total $\Delta v = 4.3786$ k/s while the lower front contains only a local minimum. It should be noted that, though the front in Fig. 2b) is the global one, it represents only two launch opportunities. Furthermore for each launch opportunity we would need to characterize the space around each of the Pareto optimal point.

Figure 3 shows a result from NSGA-II, where the lower front has been found. When using $P_{Q,\epsilon}$-NSGA-II using the same parameter values as for NSGA-II and $\epsilon = (5, 5)$, which seems to be acceptable for this mission, a much broader variety of solutions is offered regardless of the upper front, as shown in Figure 4 (note the difference of the scales). For instance, for the obtained solution c_0 with $F(c_0) = y_0 = (5, 50)$ there are three clusters of solutions which offer a similar cost and which are located around the points $c_1 = (t_0 = 4700, T = 50)$, $c_2 = (7700, 50)$, and $c_3 = (10700, 50)$. That is, the starting times of the transfer differ by a total of 6000 days. In contrast, the maximal difference according to t_0 of *all* the solution displayed in Figure 3 is given by 35 days.

Note that, compared to the accurate solution of the global Pareto front, the extended solution set offers, as required, not only more launch opportunities but also the whole neighboring solutions for each one of them.

4.2 Sequence EVMe

For the MLTGA problem we consider a relatively simple but significant case: the sequence Earth – Venus – Mercury (EVMe). For such a mission we have chosen to allow a deterioration of 5% of the mass fraction and of 20 days transfer time compared to an optimal trajectory which leads to $\epsilon = (0.05, 20)$. Figure 5 shows a numerical result of $P_{Q,\epsilon}$-NSGA-II for 100 generations with population size 100

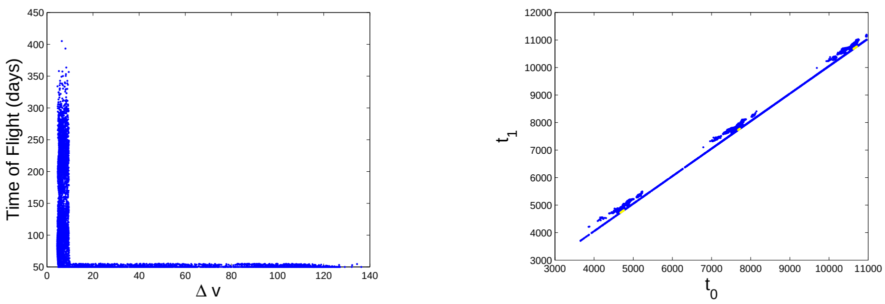


(a) Image space (b) Parameter space

Fig. 3. Numerical result for Example 2 using NSGA-II, $t_1 := t_0 + T$.

(i.e., the size of $\mathcal{P}$ in Alg. 2) and $\Delta = \epsilon/3$, which took several minutes on a standard PC. To compare the result and since so far no such algorithm exists we have taken a random search procedure coupled with $ArchiveUpdateP_{Q,\epsilon}$. For $N_R = 10,000$ randomly chosen points we obtain (averaged of 20 test runs) $\mathcal{C}_{-\epsilon}(A_N, A_R) = 0.4739$ and $\mathcal{C}_{-\epsilon}(A_R, A_N) = 0$, where A_N denotes the result from $P_{Q,\epsilon}$-NSGA-II and A_R the result coming from the random search procedure. For $N_R = 100,000$ the result of the random search procedure can still not compete with the same MOEA result: $\mathcal{C}_{-\epsilon}(A_N, A_R) = 0.4261$, $\mathcal{C}_{-\epsilon}(A_R, A_N) = 0$.

Interesting for every non-dominated point x_0 with $F(x_0) = y_0$ of an archive

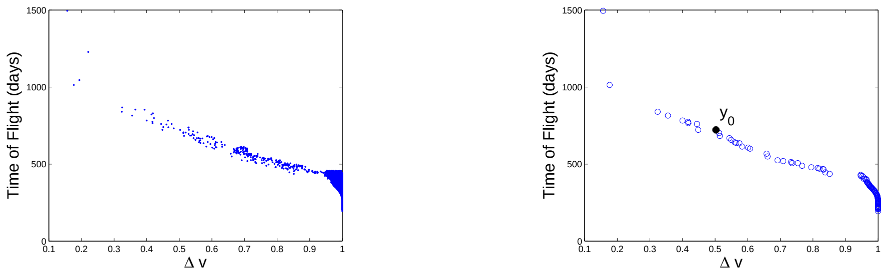


(a) Image space (b) Parameter space

Fig. 4. Numerical result for Example 2 using $P_{Q,\epsilon}$-NSGA-II.

A is the set $N(y_0, \epsilon, A) := \{a \in A \; : \; F(a) \in B(y_0, \epsilon)\}$, where $B(y, \epsilon) := \{x \in \mathbb{R}^k \; : \; |x_i - y_i| \leq \epsilon_i, \; i = 1, .., k\}$, i.e., the set of solutions in A those images are 'close' to y_0. Since in this design problem the starting date t_0 of the transfer is

of particular interest one can e.g. distinguish the entries in $N(y_0, \epsilon, A)$ by the value of t_0. For instance, the final archive displayed in Figure 5 (a) consists of 3650 solutions whereof 106 are non-dominated. The maximal difference of the value of t_0 for a point y_0 inside $N(y_0, \epsilon, A)$ is 449 days, and for 23 solutions this maximal difference is larger than one year (including also values Δt_0 of several days or months which can be also highly interesting for the decision making process). Hence, the number of options for the DM is enlarged significantly in this example.
The consideration above leads to a natural way of presenting the large amount of data to the DM: it is sufficient to present non-dominated front as in the 'classical' multi-objective case. When the DM selects one solution y_0 the set $N(y_0, \epsilon, A)$ can be displayed, ordered by the value of t_0 (see Figure 5 (b)).



(a) ϵ-efficient front

(b) non-dominated front

Fig. 5. Numerical result for sequence EVMe. Left the final archive and right the set of non-dominated solutions.

5 Conclusion

We have considered two multi-objective space mission design problems and shown, that it is desirable to identify not only the Pareto set, but also a number of approximate solutions. In particular, it was shown that each part of the Pareto set belongs to a different launch window. In order to increase the reliability of the mission design, it is required to have a wide launch window (i.e., a large number of solutions with similar cost) and one or more back-up launch windows. In order to address this problem, we have proposed a new variant of an existing MOEA which aims for the computation of $P_{Q,\epsilon}$. As an example of its effectiveness, we have considered two design problems. The results indicate that the novel approach accomplishes its task within reasonable time and that the idea to include approximate solutions is indeed beneficial since in all cases the enlarged set of solutions offered a much larger variety to the DM. Despite these promising numerical results, however, more work is required for the design of a more efficient MOEA for the approximation of $P_{Q,\epsilon}$ which will be part of future work.

Acknowledgements The third author gratefully acknowledges support from the CONACyT project no. 45683-Y.

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