Applications of Evolutionary Algorithms in Astrophysics  
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**1. Introduction**

There have been numerous approaches to solving scheduling problems in the last 50 years, some are deterministic with exact solutions, and some are stochastic, where the solution generated is different every time (Bartschi Wall, 1996). Scheduling problems are often like The Travelling Salesman problem, making solutions very complex to find. Brute forcing solutions is often impractical, scheduling being an *NP-hard* problem, especially when there are lots of constraints and possible objects to consider. This report discusses the application of evolutionary algorithms (EAs) as a dynamic approach to scheduling the target observations of a telescope. Two different approaches for finding optimal schedules are outlined, one for ground level observatories, and the other for a space-based telescope.

**2. Background**

There may be hundreds of possible stars that a scientist can target in a telescope’s observation schedule. Manually creating a schedule for each night can become very time-consuming and expensive, due to the complexity of the problem (Siu and Pankratius, 2019). Dynamic and efficient methods of finding optimal schedule solutions are needed. Simple automatic schedulers, e.g., dispatch and queue-based speed up finding solutions, but they may not be always optimal. Changing constrains and complications can stop a given schedule from functioning. Example obstacles include human error made in the schedule, equipment malfunction, weather changes or new observation priorities (Rajpaul, 2012). The addition of constraints and targets makes finding optimal solutions using non-A.I. approaches less feasible.

The schedules of space-based telescopes have a higher complexity. An example explored in this paper is telescopes that use Starshade technology. Starshades are used in exoplanet exploration, the technology allows higher quality observations, light from exoplanets is sampled separately from the that of the star the telescope is targeting. Scheduling these is more complex because the telescope is in flight, retargeting is needed when moving objects such as the sun and earth limit observation when in orbit (Siu and Pankratius, 2019.)

Regarding observatories, some observations aren’t reproducible for a long time, and need prioritisation. There are obstacles like the horizon and the moon, the moon lowering observation quality when it’s at certain heights and phases (Kubanek, 2010).

**3. Candidate solutions**

Candidate solutions represented a generated schedule. For ground level observatories, individual candidates used chromosome representation as an array of targets for observation. The genes of these ‘targets’ contain the start date/time of observation, duration, and a target ID (Kubanek, 2010).

In an EA solution outlined in Siu and Pankratius’ 2019 paper for scheduling ‘Space-Based Telescopes’, a graph traversal method is used. Candidate solutions are a sequence of vertices that represent targets observations, along with the fuel cost to retarget the telescope and the scientific value of the observation. Half the pool is filled with schedules where random targets were added, until fuel constraints were met. The population is completed via ‘random-introduction process’, where standard crossovers and mutations are performed on undirected versions of parent schedules. Crossovers involve graphs being joined at matching nodes, and mutations changing targets at points. Undirected graphs are then ‘repaired’ into directed ones, by running a random walk traversal.

4. The Fitness Function

The core aim of the EA is to produce a schedule to observe objects who's visibility varies due different constraints e.g. time, environment changes or “bodies being in the way" (Siu and Pankratius, 2019). In the problem with the space-based telescope, a more basic approach to evaluating the fitness of a schedule was used, scientific gain of an observation was the key measure considered. The function finds the maximum scientific value of a candidate path, if a tie breaker is needed, the candidate paths with lower fuel usage are fitter. Probabilistic culling is used to remove candidates, individuals with a higher fitness have a higher probability of survival.

In Kubanek’s (2010) solution for observatories, fitness is the sum of observations quality, reduced with penalties when constraints are breached. When determining fitness of observations factors such as altitude and observation distance that reduced quality are considered. Other merits included is observation diversity and high priority targets. Targets can be high priority when it’s less frequently observable than others. For both approaches, fitness’s of generations are evaluated until the desired level of optimization is reached.

5. Discussion of Strengths & Weakness of the Approach

The use of evolutionary algorithms to schedule the retargeting of telescope observations is much more efficient than other approaches. Using humans to create schedules is time consuming, EAs allow scientists assigned to this task to use their energy on other workloads. Schedules can be generated at high speeds, even when constraints are changing. In the instance of space-based missions, errors in schedules or producing inefficient schedule can be very costly, as retargeting space-based telescopes uses lots of fuel. EAs reduce human error and ensure that there is an efficient use of fuel, but not at the cost of scientific gain.

Brute force methods will find optimal solution, but lots of computational power is needed. This approach becomes unfeasible as soon as thousands of possible targets are introduced, which is likely in the study of exoplanets. EAs enable schedules to consider thousands of possible targets and still produce an optimal solution in a reasonable run time. When there are only a small number of targets that need to be scheduled, brute force may find the optimal solution in the same amount of time as a GA, with the same computational power. Developing EAs for such instances is a waste of resources.

The stochastic aspect to finding solutions means diverse outcomes are produced, this can be a disadvantage as the absolute ‘best’ schedule may not always be found, however the variation of possible schedules could lead to unexpected discoveries being made. One problem that EAs face is that of hill climbing, candidate solutions may get stuck at a local maximum, missing the global optimum. Probabilistic culling allows some weaker candidates to survive, stopping evolution from getting stuck at sub optimal solution.

Another weakness of the EA approach is the subjectiveness of the scientific value of targets, used in fitness calculation. Relying on human judgement is not a strict measure, and if multiple teams of people are making changes to the value, they may rate targets differently. Consequently, strong rules for determining the scientific value of a target are needed.

6. Conclusion  
 Evolutionary algorithms are shown to be an effective approach for creating optimised observation schedules for telescopes. The efficiency and speed means schedules can be quickly adapted to changing environments, constraints and scientific goals. The simplicity of them enables astrophysicists to put their efforts towards other workloads, increasing the productivity of observatories and labs. These problems could have further complexity added, for instance, in the collaboration of multiple telescopes or observatories. There would be little scientific gain to be had from having two telescopes observe the same targets at the same time. Factors such as one telescope having priority to observe targets with more scientific value when one telescope can produce higher quality observations should be considered.

Reference List

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