Scheduling ESPRESSO follow-up of TESS Targets. I. Myopic versus non-myopic sampling

L. Cabona,1,2 ⋆ J.P. Faria,3 M. Landoni2 and P.T.P. Viana3,4

1 Università degli Studi dell’Insubria, Via Valleggio 11, I-22100 Como, Italy
2 INAF, Osservatorio Astronomico di Brera, Via E. Bianchi 46 I-23807 Merate (LC), Italy
3 Instituto de Astrofísica e Ciências do Espaço, Universidade do Porto, CAUP, Rua das Estrelas, 4150-762 Porto, Portugal
4 Departamento de Física e Astronomia, Faculdade de Ciências, Universidade do Porto, Rua do Campo Alegre, 687, 4169-007 Porto, Portugal

Accepted XXX. Received YYY; in original form ZZZ

ABSTRACT
Radial-velocity follow-up of stars harbouring transiting planets detected by TESS is expected to require very large amounts of expensive telescope time in the next few years. Therefore, scheduling strategies should be implemented to maximize the amount of information gathered about the target planetary systems. We present one random scheduler and two types of uniform-in-phase schedulers: one myopic, which selects targets one-at-a-time, and one non-myopic that efficiently explores all the possible combinations between stars to be observed and available time slots. We compare these strategies with respect to the bias, accuracy and precision achieved in recovering the mass and orbital parameters of transiting and non-transiting planets from the mock radial-velocity follow-up of a sample of 50 TESS target stars, with simulated planetary systems containing at least one transiting planet with a radius below $4R_⊕$. For each system and strategy, 10 radial-velocity datasets were generated and analysed using a fully Bayesian methodology. We find the myopic strategies lead to a biased estimation of the order of 5% of the mass of the transiting exoplanets while the non-myopic scheduler is able to provide an unbiased (<1%) measurement of the masses while keeping the relative accuracy and precision around 16% and 23% respectively. The number of non-transiting planets detected is similar for all the strategies considered, although the random scheduler leads to less biased and more accurate estimates for their mass and orbital parameters, possibly due to a higher mean number of scheduled radial-velocities for the datasets associated with non-transiting planets detections.

Key words: Planetary systems – Techniques: radial velocities – Methods: observational – Methods: statistical

1 INTRODUCTION
The radial-velocity (RV) follow-up of exoplanet candidates identified using the transit detection method is important to definitively establish their planetary nature, estimate their masses and further refine orbital parameters. It also makes atmospheric studies more informative by constraining the scale height (e.g. Batalha et al. 2017). Modelling the internal structure of each exoplanet (e.g. Dorn et al. 2015, 2017; Suissa et al. 2018), and population-level studies, e.g. the characterization of the mass-radius relation (e.g. Wolfgang et al. 2016; Chen & Kipping 2016; Ning et al. 2018; Kanodia et al. 2019), are other applications that benefit from the extra information brought by RV data.

In the next few years, RV follow-up of exoplanet transits will most likely be dominated by observations of TESS [Transiting Exoplanet Survey Satellite, e.g. Ricker et al. (2016)] objects of interest (TOIs). Over the two years of its primary mission, TESS is expected to discover more than 14,000 new transiting exoplanets around almost as many stars (Barclay et al. 2018). The RV measurements required to obtain precise mass measurements even for just a few tens of these planets will easily exceed the many hundreds. Most will be part of concerted efforts by several groups, namely those taking part in the TESS Follow-Up Observing Program (TFOP), with access to large amounts of telescope time. In particular, the ESPRESSO collaboration (Pepe et al. 2014) plans to devote around 32% of its Guaranteed Time Observations (GTO) for TOI follow-up, amounting to almost 88 nights distributed across 4 years (N. C. Santos, private communication).

Often RV measurements for a sample of stars known to
host transiting planets are performed in an almost random way, conditional on the target stars being visible at low airmass. More commonly there is some prior planning of the observations, for example to ensure that the RV phase-curves are sampled as uniformly as possible, given the orbital periods inferred from the transit data (e.g. Burt et al. 2018). The most usual stopping criterion for the RV measurements is reaching some relative precision with respect to the transiting exoplanets masses (e.g. Montet 2018). However, in any case, the observations are usually done in a myopic (or greedy) way, i.e. which star is chosen to be observed at a certain time does not take into account all possible scheduling configurations for the future, given the time available and sample of stars to be observed. In principle, this should lead to a less efficient use of available telescope time than non-myopic (also known as batch or block) scheduling. Our main objective in this work is to quantify the difference in efficiency, with respect to the information gathered about exoplanet masses and orbital parameters through RV measurements, between myopic and non-myopic scheduling algorithms. We will concentrate on those algorithms whose objective function leads to a sampling of the RV phase-curves of the known transiting planets as uniform as possible. This strategy, henceforth called uniform-in-phase, is the most widely used when the period of a candidate planet is assumed well known, and has been shown to be more informative compared to random, quadrature or anti-quadrature sampling (Burt et al. 2018).

We start by laying out the procedures used to construct a sample of simulated TOIs, and to generate mock distributions of the ESPRESSO GTO. Next, we describe the scheduling algorithms that will be compared. We then report the results obtained, discuss them, and present our conclusions.

2 METHODS

2.1 Stellar sample

The TESS observing strategy was modelled by Barclay et al. (2018), in order to identify the approximately 200,000 stars in the TESS Input Catalog Candidate Target List that should be observed at 2-minute cadence. The remaining stars were assumed to be observed at 30-minute cadence in full-frame image data. They then associated zero or more orbiting planets to each star, with specific physical and orbital characteristics, according to measured exoplanet occurrence rates (Fressin et al. 2013; Dressing & Charbonneau 2015). Finally, they used the TESS noise model to predict which exoplanets would be detected and their derived properties. It was estimated that TESS would find around 1250 exoplanets in the 2-minute cadence mode, and about 13,100 planets in the full-frame image data.

A sample of stars for possible ESPRESSO follow-up observations was pre-selected among those stars considered in Barclay et al. (2018) by demanding: a declination in the interval [−80°, +30°], to ensure extended periods of visibility at low airmass from Paranal; an effective temperature, $T_{\text{eff}}$, in the interval [4000, 6000] K, and high surface gravity, $\log g > 4.0$, i.e. only G and K dwarf stars. We then included in our final sample the 50 brightest stars among those pre-selected with at least one orbiting planet with a radius below $4R_\oplus$, 3 detected transits and a transit signal-to-noise greater than 10. This final selection step effectively limits our sample to stars with a magnitude, $V$, below 10.5, minimising the RV measurement uncertainty due to photon-noise. It also aligns our sample with a TESS primary science requirement: the estimation of the mass of 50 exoplanets with radius smaller than $4R_\oplus$ (Ricker et al. 2016). We ended up with 53 transiting planets orbiting 50 stars, with 3 systems having 2 transiting planets each. We associated to each transiting planet the expected mass, given its radius, obtained using the Forecaster algorithm (Chen & Kipping 2016). The radii were assumed to be known within an uncertainty of 10% (standard deviation), typical of what is expected by combining data from Gaia (Brown et al. 2016, 2018) and TESS (Burt et al. 2018).

In the publicly available from Barclay et al. (2018) catalogue only planets that transit are identified. But, in order to generate realistic simulations of a RV time series, we need to take into account all planets around each star in the sample. Therefore, we added extra orbiting planets to each star, non-detectable by TESS. In order to be coherent with the choice of occurrence rates made in Barclay et al. (2018), we used for such purpose the occurrence rates published in Fressin et al. (2013). However, these do not extend to orbital periods long enough to include all planets capable of generating a RV semi-amplitude, $K$, larger than 0.5 m/s, roughly the minimum value we expect our simulated follow-up survey to be sensitive to. Therefore, we first extrapolated the occurrence rates in Table 2 of Fressin et al. (2013) up to orbital periods of 2 years, for radius in the intervals [2, 4], [4, 6] and [6, 22] $R_\oplus$, and to 418 days for radius in the interval [1.25, 2] $R_\oplus$. In order to achieve this, we assumed the occurrence rate density, as a function of orbital period, is described by a log-normal distribution (e.g. Fressin et al. 2013; Winn & Fabrycky 2015). The joint posterior probability distribution for the parameters of such function was characterized within each of the four mentioned radius bins, given the occurrence rates provided in Table 2 of Fressin et al. (2013) for the available period bins. The expected values for those log-normal parameters were then used to infer the integrated occurrence rates in the period bins: [145, 245] and [245, 418] days in the case of radius between 1.25 and 2 $R_\oplus$; [245, 418] and [418, 730] days in the case of radius between 2 and 4 $R_\oplus$; [418, 730] days in the case of radius in the intervals [4, 6] and [6, 22] $R_\oplus$. These extrapolated occurrence rates can be found in Table 1, together with the values used from Fressin et al. (2013). With this extrapolation, we are able to take into account all planets, with an orbital period smaller than 2 years, that are capable of inducing a RV signal with $K > 0.5$ m/s, given their expected mass as estimated using the Forecaster algorithm (Chen & Kipping 2016).

The number of planets we associate with each star, within the radius-period bins identified in Table 2 of Fressin et al. (2013) plus those with extrapolated occurrence rates, was then randomly drawn from a Poisson distribution with mean 0.92 (expected number of planets across all such bins). If the number obtained was greater than the number of transiting planets in the system, the radius-period bins where the extra planets are located were randomly drawn from the full radius-period bin distribution taking into account the respective occurrence rates. Then, a specific radius and pe-
The ESPRESSO GTO consists of 273 nights during 4 years, and began on the 1st of October 2018. Exoplanetary science occupies 80% of the time, 10% is allocated to fundamental constants time-variability studies and 10% is discretionary time at the disposal of the ESPRESSO consortium (Pepe et al. 2013). The total amount of time available for exoplanetary science is in turn divided as follows: 30% for exoplanetary atmospheric characterization; 30% for TOI follow-up; 40% for a RV survey. We simulated the scheduling of ESPRESSO GTO observations from the 1st of October 2019 until the 30th of September 2022, i.e. only for 3 years. Furthermore, we assumed that on the 1st of October 2018 all our TOIs would have been observed and characterized by TESS.

The 80% of the ESPRESSO GTO dedicated to exoplanetary science consists of close to 55 half-nights each semester. We randomly spread them in such a way as to mimic the

1 https://www.eso.org/sci/observing/policies/gto_policy.html
Figure 1. From upper to lower panel, distributions of RV semi-amplitudes, $K$, orbital eccentricities, $e$, and periods, $P$, for the transiting (blue) and non-transiting (orange) planets.

ESPRESSO GTO distribution in ESO periods 102 and 103, the only known at the time of writing, including aggregation of some half-nights into full nights. Each full day is divided into 60 observation slots, all with a duration of 24 minutes (15 as integration time plus 9 for overheads), but due to seasonal variation, each astronomical night will have a different number of observation slots associated. The integration time was defined to be 15 minutes in order to average out the RV variability induced by stellar oscillations in the G and K dwarf stars we are considering (e.g. Dumusque et al. 2011). We will only consider observations slots with an associated airmass not greater than 2.0. Thus, taking into account the magnitude and temperature ranges for the 50 stars we are considering, respectively, $[6.69, 10.37]$ and $[4408, 5978]$ K, the ESPRESSO ETC estimated RV variability due to photon-noise will range from $0.1$ to $0.5$ m/s, under normal atmospheric conditions. The average value is close to $0.3$ m/s across all observational slots for which RV simulations were performed.

We further assumed that exoplanetary atmospheric characterization takes precedence, given that they are performed during transit and thus are time-critical. For each semester we thus first randomly sampled, with repetition, the ESPRESSO consortium target list for this type of study, until 30% of the available time was reached. Each scheduled transit observation is composed of enough sequential observational slots to cover the time interval from one hour before the transit starts until one hour after the transit ends. Some of the half and full nights allocated to exoplanetary atmospheric characterization are not completely filled with these type of observations and thus the remaining slots are available for TOI follow-up and the RV survey. We repeated this exercise 10 times, obtaining 10 different distributions for the 80% of the ESPRESSO GTO dedicated to exoplanetary science. These simulations yielded between 2563 and 2628 (24-minute) slots that can be used for TOI follow-up and the RV survey. Among these we decided to schedule 1102 slots for TOI follow-up, which we assume takes precedence over the RV survey. This number is very close to the fraction that can be used for TOI follow-up, i.e. 30% of the total number of slots associated with each GTO realization. Although we could have let that number vary with each GTO simulation,
we decided to fix it to the mean averaged over all simulations so that the results could be more easily compared.

2.3 RV simulations

Stellar activity also induces variations in the radial velocity of a star (e.g. Korhonen et al. 2015; Dumusque 2016; Cameron 2018; Cegla 2019). Here we assume these variations are stochastic and akin to Gaussian white noise, i.e. they are randomly and independently generated (as a function of time) from a Normal distribution with constant mean (zero) and standard deviation, $\sigma_{\text{act}}$. Although we consider only low-activity stars (like G and K types), such a model is of course simplistic, and we plan in future work to consider a more general behaviour for the stellar activity (e.g. by introducing time correlations). In any case, as we will later see, none of the three scheduling strategies under study relies on the model for stellar activity induced RV variations to decide on the best schedule, thus any changes to such model should have little impact on the relative outcomes of those strategies. The value of $\sigma_{\text{act}}$ assumed for each star was randomly drawn from a Normal distribution with mean given by Equation 4 in Cegla et al. (2013), and a standard deviation of 0.4. The mean reproduces the observed correlation between RV variability and a measure of stellar flicker, $F_k$, for stars with low levels of activity, while the value of 0.4 is suggested by Figure 6 in Cegla et al. (2013). The flicker parameter, $F_k$, is determined using Equation 2 in Tayar et al. (2019), which depends on stellar mass, effective temperature and log g, in information we have for all the TESS target stars we consider. The distribution of the assumed values for $\sigma_{\text{act}}$ with respect to all 50 stars in our sample can be seen in Figure 2. We consider two other Gaussian white noise contributions: one due to photon-noise, $\sigma_{\text{ph}}$, which was calculated using the ESPRESSO ETC specifically for each star according to its magnitude, effective temperature and airmass at the time of observation; and another due to the RV variability induced by instrumental-noise, $\sigma_{\text{ins}}$, which we assumed to be about 0.1 m/s (Pepe et al. 2014). Therefore, the full noise model will also take the form of Gaussian white noise, with a variance equal to the sum of the variances associated with each of the three noise components just described.

We also associated to every star a systemic RV relative to the centre of mass of the system, $v_{\text{sys}}$, drawn from a random uniform distribution between $-100$ to $100$ m/s, roughly the observed range for stars in the solar neighbourhood (e.g. Kushniruk et al. 2017). Thus, the RV time series associated with each star was generated based on the following model:

$$v_i(t) = v_{\text{sys}} + \sum_{i=1}^{n_p} v_{\text{act}}(t) + \epsilon(t)$$  \hspace{1cm} (2)

with

$$v_{\text{act}}(t) = K_i \cos[\omega_i t + \phi_i] + e_i \cos(\omega_i t)$$  \hspace{1cm} (3)

$$\epsilon(t) \sim N(0, \sqrt{\sigma_{\text{act}}^2 + \sigma_{\text{ph}}^2 + \sigma_{\text{ins}}^2})$$  \hspace{1cm} (4)

where $n_p$ is the number of planets orbiting the star, $K_i$ is the RV semi-amplitude, $\omega_i$ is the argument of periapsis, $e_i$ is the orbital eccentricity, and $\phi_i(t)$ is the true anomaly

![Figure 2. Distribution of the assumed values for $\sigma_{\text{act}}$ with respect to all 50 stars in our sample.](image)

as a function of time, $t$, calculated from the other orbital parameters (e.g. Perryman 2018), all with respect to planet $i$. Thus, we neglect any gravitational interactions between orbiting planets when calculating the instantaneous RV for every star.

2.4 Scheduling strategies

We will consider three different scheduling strategies. Two of them, labelled A, are myopic, i.e. the best schedule is defined sequentially in time. In strategy A1, the star chosen to be observed at any given time is randomly drawn from all stars in the sample which can be observed at that time, at an airmass equal or smaller than 2, and with a Moon separation greater than 30 degree, henceforth known as the observability constraint. In strategy A2, this sub-sample of stars is further restricted to the stars that have a smaller number of observations than those associated with the sample star with the largest number of allocated observations at previous times, henceforth known as the equalizing condition. Imposing the second condition leads to a more even distribution of the observational slots between the sample stars.

However, in the case of strategy A2, we also want the sampling of the RV phase-curves of the known transiting planets to be as uniform as possible, i.e. to ensure as close as possible uniform-in-phase sampling. This is achieved through the maximization of the following objective function, capable of measuring the overall dispersion of points in a given interval,

$$f(x_i) \equiv \left(\sum_{i=1}^{102} |d(x_i)|^q \right)^{-1/q}$$  \hspace{1cm} (5)

where $d(x_i)$ is the time distance between the observation $x_i$ and its nearest neighbour (including across the orbital phase-curve boundary), as a fraction of the orbital period of the transiting planet targeted by the observation. When more than one transiting planet exists around a star, $d(x_i)$ equals the sum of the distances with respect to all transiting
Figure 3. Total number of RV observations scheduled, averaged over 10 simulations per strategy, as a function of where each observed planet is in the respective phase-curve, for the three scheduling strategies, A1 (left panel), A2 (central panel) and B (right panel). Upper and lower panels only differ in the number of bins, respectively, 20 and 40. Both the vertical axis and the colour gradient indicate the number of RV observations per bin.

planets in the system, which favours the observation of stars for which multiple transiting planets are known. We assume the orbital period and mid-transit time for each transiting planet to be perfectly known a priori. In a real application, this would mean fixing them to e.g. their expected values given the TESS data.

In the context of strategy A2, the best schedule is then also constructed sequentially in time. First, the stars that fulfil both the observability constraint and the equalizing condition are identified. If no stars fulfil the latter, then the star chosen to be observed is the star that fulfils the observability constraint and has the smaller number of allocated observations at previous times. Otherwise, the star selected for observation at the time being considered is that which leads to the maximization of the objective function provided, $f(x_i)$. However, this rule is applied only at those times for which all stars that fulfil the observability constraint and the equalizing condition have already been observed at least once, else the star chosen to be observed is randomly drawn among those that have not yet been so. As a result of this procedure, all 10 simulated schedules, according to strategy A2, associate between 17 and 24 observational slots to each star. In contrast, strategy A1 always leads to some stars being observed only a few times, the minimum ranging from 2 to 8 across the 10 simulations, while some other stars end up being slotted for observation as many as 39 to 49 times.

The third strategy, labelled B, is non-myopic. In this case, the aim is to compare all possible schedules, across the full time-span of 3 years, and then choose that which maximizes the objective function, $f(x_i)$. Given the form taken by such function, this procedure leads to what is known as $L^q$ relaxation of the points in the design space, in our case the orbital phase-space of each planet. It yields a nearly optimal approximation to the maximin solution to the problem (e.g. Pronzato 2017). The larger the $q$, the better should be this approximation. But then the objective function becomes increasingly localised (in the space of all possible scheduling configurations) and it is more difficult to find the region where the function is maximised. After extensive testing we decided to use $q = 2$ (also in the case of strategy A2 to allow for easier comparison between myopic and non-myopic scheduling).

The maximin solution is a classical example of a space-filling strategy (see e.g. Pronzato 2017, for a review). In our case, it corresponds to finding the schedule that maximizes the sum over all stars of the minimum (time) distance, normalized as a fraction of the orbital period(s) of the known transiting planet(s) around each star, between any observation and all others of the same star. An alternative classical space-filling strategy is the minimax solution. In this case, the objective would be to find the schedule that minimizes the sum over all stars of the maximum distance (as defined before) between any observation and all others of the same star. However, the maximin solution is computationally faster to find, because it only requires the calculation of distances between neighbouring observations in the orbital phase-space of each planet. Whereas finding the minimax solution would require the calculation of the distances between all observations with respect to each planet (e.g. Pronzato 2017). Nevertheless, we also implemented an algorithm to
identify the minimax solution, and found it leads to schedules very similar to those obtained using strategy B.

Given the large number of time slots available for scheduling and the fact that the stars considered are observable during most of any given year, the number of possible scheduling configurations is very large. Therefore, it is impossible to compare the values the objective function takes for all such configurations. As a result, we used the acebayes R package\(^2\) (Overstall et al. 2017) to find the schedule that maximizes the objective function. This is done via an approximate coordinate exchange (ACE) algorithm, where a sequence of conditional one-dimensional optimisation steps are used, as described in Overstall & Woods (2017). In our case, the objective function depends on the stellar label and the slot time, which will hence be our coordinates. Each schedule, or design, can be viewed as a collection of points in this two-dimensional space. The search for the maximum of the objective function then proceeds through the sequential change of the coordinates of each point in a given initial schedule. In the case of the stellar label coordinate, a change occurs when it is found that, for the time slot associated with a particular design point, there is another star for which the objective function attains a higher value and each star in the sample continues to be observed within the pre-specified minimum number of times. In the case of the time coordinate, a change occurs if there is another time slot for which the objective function reaches a higher value, among those which are not yet associated with a star and for which the observability constraint is obeyed. The search for such optimal time slot is performed by first approximating the objective function with respect to observation time, for the star associated with the design point under consideration, through a Gaussian process (within acebayes), and then by identifying the time for which the objective function is maximized.

The initial schedule for strategy B is created randomly, with the only conditions being that the observability constraint is obeyed and each star in the sample is observed at least the pre-specified minimum number of times. The closer the latter is to the average number of available obser-

---

\(^2\) [https://cran.r-project.org/web/packages/acebayes](https://cran.r-project.org/web/packages/acebayes)
vational slots per star, in our case 1102/50 \approx 22, the harder it is for the ACE algorithm to optimize the schedule, and the smaller will be the value of the objective function at the end of the optimization process. This means that there is a trade-off between ensuring an (almost) equal number of observations per star and an optimized sampling of the orbital phase-space of each transiting planet. Somewhat arbitrarily, we set the required minimum number of observational slots per star to be 20. If it was much smaller, there would be significant variations in the accuracy and precision with which the mass and orbital parameters of each transiting planet would be recovered.

In our case, each run of the ACE algorithm goes through a sequence of $2 \times 1102 = 2204$ conditional optimisation steps. In order to consolidate the best schedule, we re-run 100 times the ACE algorithm within acebayes, using the output of each ACE run as input to the following one. As the runs progress, we keep track of the objective function value, and choose the final best design (which is not necessarily the last) as that with the highest associated value for the objective function.

In Figure 3 we show how many RV observations are scheduled, for all 10 simulations per strategy, as a function of where each observed planet is in the respective phase-curve. This is equivalent to seeing the phase-curves in overlap, and as expected all scheduling strategies lead to almost uniform distributions. However, this hides significant differences in the phase-space distribution of RV observations between transiting planets. In particular, as expected, strategy A1 leads to a more irregular phase-curve coverage. This gives rise to a larger dispersion in the number of RV observations per phase-space bin. This can be seen in Figure 4, which shows the distribution of the number of RV observations scheduled (across all stars and simulations) per bin, for each strategy.

In practice, our assumption in the case of strategy B that the ESPRESSO GTO schedule can be known a priori for the full 3 years is unrealistic. ESO will only inform the ESPRESSO consortium of its schedule for each semester close to its beginning. Therefore, a more realistic implementation of strategy B would require re-scheduling every 6 months the remaining time for the completion of the 3 years. This should not have a significant impact in the expected efficiency with which information is recovered about planets properties through the implementation of strategy B. This is because what is expected to happen within each semester, as ESO relays the information about the available observational slots, is just an effectively random re-shuffling of their position within the semester. Thus, the expected information gain guiding strategy B should remain essentially the same. A more realistic implementation of this strategy should only suffer from some loss of coherence around the start/end of each semester, the more so the smaller the orbital periods of the systems scheduled to be observed at those times. This near-randomization of the scheduler at such a small fraction of the available time should have a very small impact on the expected information gathered through strategy B. Given the considerable amount of extra computing time required to simulate a re-scheduling every 6 months, we decided to implement strategy B in the more simplified manner previously presented.

3 RESULTS AND DISCUSSION

We used the open-source software kima\(^3\) (Faria et al. 2018) to perform Bayesian statistical analysis of all simulated RV datasets. These were analysed assuming the meta-model described in sub-section 2.3, with \(n_p\) now becoming effectively a label identifying mutually exclusive models. We then have \(n_p = n_t + n_{nt}\), where \(n_t\) and \(n_{nt}\) are, respectively, the number of transiting and non-transiting planets in each system. While the former is fixed, to either 1 or 2, we let the latter vary between 0 and 5, with equal prior probability assigned to each possible value. This means that we assume a priori all the planets detected in transit to have the status of confirmed planets from the point of view of the RV data analysis. The orbital periods and times of mid-transit with respect to the transiting planets were assigned Gaussian priors, centred on the values provided by Barclay et al. (2018), and with standard deviations of 0.001 days (which is the typical level of uncertainty expected from TESS data). Knowledge about the time of mid-transit effectively constrains the mean anomaly at some particular time of choice, e.g. \(M_0\), given the other orbital parameters. For the planets without transit information, the orbital periods were assigned log-uniform (often called Jeffreys) priors between 1 day and twice the timespan of the full dataset (2 \times 3 years \approx 2190 days). We also assumed modified log-uniform distributions for both the semi-amplitudes and the jitter parameters (i.e. the standard deviations associated with the assumed Gaussian white noise), with the knee located at 1 m/s and limited above by the variance of the RV measurements. These modified distributions are defined until the lower limit of 0 m/s. Finally, the prior for the orbital eccentricities was set to a half-Gaussian with \(\sigma = 0.32\) for the transiting planet in systems with only one, and \(\sigma = 0.083\) for both transiting planets in systems with two, as suggested by Van Eylen et al. (2019), and to a Kumaraswamy distribution (Kumaraswamy 1980), with shape parameters \(\alpha = 0.867\) and \(\beta = 3.03\), for all the possible extra, non-transiting planets (which is similar to what was proposed in Kipping 2013). Most other parameters are assigned uniform priors between sensible limits, as can be seen in Table 3.

From the computational point of view, the total amount of datasets is 3 (scheduling strategies) \times 10 (simulations) \times 50 (systems) = 1500, each containing between 4 and 49 measurements (most being around 20). On a single processor, kima requires a few hours to yield converged posterior probability distributions with respect to all model parameters. Thus, it would have been infeasible to perform the analysis sequentially on a single computer. As a result, we adopted a full Cloud architecture by exploiting the services offered by the commercial platform Amazon Web Services (AWS). In particular, since the analysis of each dataset by is independent from the others, we used the architecture described in Landoni et al. (2019) to run parallel applications by using clusters offered by AWS. In this particular case, we fired up a cluster of about 25 instances on AWS, each of them equipped with 64 vCPU. This allowed the analysis of all 1500 datasets by kima in less than 2 hrs, consuming 2500 CPU hrs in the process. This approach is particularly useful when the full analysis needs to be re-done, for some

\(^3\) https://github.com/j-faria/kima
Scheduling ESPRESSO follow-up of TESS Targets

Figure 5. Planetary system architecture as a function of orbital period. Filled circles represent transiting planets (in pink) and non-transiting planets detected at least once (in purple) across the 10 simulations, for the scheduling strategy A1. The numbers inside the later indicate how many times each planet is detected out of 10 simulations. The size of each circle is proportional to the mass of the respective planet. Empty circles denote planets that remained undetected in any simulation. Each system is identified by an incremental number where 1 corresponds to the lowest TESS ID number and 50 to the highest TESS ID number in our sample.

Our main objective with this work is to compare the different scheduling strategies with respect to: (1) the strength of the expected constraints on the values for the mass and orbital parameters of the planets that are known to transit; (2) the number of detected non-transiting planets, as well as the strength of the expected constraints on the values associated with the respective mass and orbital parameters. These criteria are linked, given that a decision on how many extra planets have been detected is effectively equivalent to choosing the model, with some label $n_p$, to be used for parameter estimation. We choose to base such decision on the comparison between the Bayesian evidence or marginal likelihood, i.e. the constant which normalizes the joint posterior distribution, for models with associated consecutive values for $n_p$, starting with $n_p = n_t$, i.e. $n_m = 0$. Because we are assigning equal prior probabilities to all models with respect to the same star, comparing evidences is equivalent to determining the so-called Bayes Factor, $\mathcal{B}$, which is then just equal to their ratio. Its value can be interpreted through the scale introduced by Jeffreys (e.g. 1998) (see also Kass & Raftery 1995), according to which a Bayes factor of at least 150 between models with associated consecutive values for $n_p$ is required in order to claim a planet detection (e.g. Feroz et al. 2011; Feroz & Hobson 2013; Brewer & Donovan 2015).

Applying the described procedure to all datasets, the number of detected non-transiting planets, across the 10 simulations for each strategy, can be seen in Figures 5, 6 and 7. The numbers inside the circles represent how many times a non-transiting planet is detected out of 10 simulations. Note that the procedure we use to decide how many non-transiting planets have been detected never leads to more detections than the true number of such planets. The correspondence between detected and actual existing (non-transiting) planets in a system is based on the proximity of values for $P$ and $K$. It should be noted that by using the full RV datasets in the analysis we are effectively assuming that there is neither partial or full loss of planned RV measurements due to adverse weather conditions or technical problems. Here partial also means substantial degradation of the expected RV measurement uncertainty due to photon-noise, as a result of very bad seeing ($>1.3\arcsec$) or thick cirrus clouds. Although such assumption is unrealistic, the loss should not amount to more than 10 percent of the expected data, according to the ESO annual reporting on the operational conditions at Paranal. Therefore, on average this should affect only a couple of RV measurements per target in three years. In any case, which RV measurements are affected or lost, as a result of such effects, will not be correlated with the actual scheduling strategy chosen to be implemented. Therefore, the data loss will impact in a similar way the information about planetary masses and

4 https://www.eso.org/public/products/annualreports/
Figure 6. As in Figure 5, but for strategy A2.

Figure 7. As in Figure 5, but for strategy B.
Scheduling ESPRESSO follow-up of TESS Targets

Table 3. Prior distributions for the parameters in the RV metamodel.

| Transiting planets |  |
|-------------------|--|
| $P$ [days]        | $\mathcal{U}(P_{\text{TESS}}, 0.001)$ |
| One per system    |  |
| $e$               | $\mathcal{H}\mathcal{G}(0, 0.32)$ |
| Two per system    |  |
| $e$               | $\mathcal{H}\mathcal{G}(0, 0.083)$ |

| Non-transiting planets |  |
|------------------------|--|
| $b_{\text{ut}}$        | $\mathcal{U}(0, 5)$ |
| $P$ [days]             | $\mathcal{J}(1, 2190)$ |
| $e$                    | $\mathcal{B}(0.867, 3.03)$ |
| $M_{\text{b}}$ [days]  | $\mathcal{U}(0, 2\pi)$ |

| All planets |  |
|-------------|--|
| $K$ [m/s]   | $M\mathcal{J}(1, \sigma_{K}^2)$ |
| $s$ [rad]   | $\mathcal{U}(0, 2\pi)$ |
| $v_{\text{max}}$ [m/s] | $\mathcal{U}(\min v_{1,i}, \max v_{1,i})$ |
| $x$ [m/s]   | $M\mathcal{J}(1, \sigma_{x}^2)$ |

orbital parameters that can be recovered under each scheduling strategy. Thus, we decided to ignore it in our analysis since our interest is on the comparison of the relative merit of different scheduling strategies. However, in a practical context, this issue can be addressed and its impact minimised by rescheduling all future observations after some amount of the planned RV measurements are performed, and taking into account which were not or badly affected.

Averaging over the 10 simulations per strategy, a total of 9.8 ± 0.6, 9.8 ± 0.8 and 10.6 ± 1.2 non-transiting planets are detected using strategies A1, A2 and B, respectively, out of the 50 that we simulated orbiting our sample of stars. These numbers are very similar, and the differences not significant given the variation seen across the simulations. They can be mostly explained by the much higher dispersion among the number of RV measurements per star, $N_{\text{RV}}$, in the case of strategy A1. The standard deviation associated with the distribution of $N_{\text{RV}}$ is 8.39 for this strategy, while only 1.44 for A2 and 1.05 for B. This in turn leads to a significant number of datasets obtained with strategy A1 having a very small associated $N_{\text{RV}}$, not high enough to allow for a reliable detection of the vast majority of the simulated non-transiting planets. As a result of this selection effect, the mean value of $N_{\text{RV}}$ among the datasets for which non-transiting planets are detected, is larger for strategy A1 (24.4), than for either strategy A2 (22.5) or strategy B (22.0).

In Figures 8, 9 and 10 the marginal posterior mean and standard deviation for the orbital parameters $K$ and $e$, as well as mass $M$, for the planets that are known to transit are compared with the true values, for the three scheduling strategies and averaged over the 10 simulations. Parameter values are more scattered and uncertain for some planets in the case of strategy A1 mostly as a result of the respective host stars being systematically under-observed (and others over-observed) with respect to average, due to having shorter (longer) visibility windows. The marginal posteriors used for this exercise, and those that follow, are those associated with the model chosen using the detection procedure for the non-transiting planets previously described, given the result of the Bayesian analysis of each simulated dataset.

In order to compare further the results, we define the following quantities, with respect to some planet characteristic $X$, and to a given simulation:

- absolute bias, $E[X] - X_{\text{true}}$
- relative bias, $(E[X] - X_{\text{true}})/X_{\text{true}}$
- absolute accuracy, $|E[X] - X_{\text{true}}|$
- relative accuracy, $|E[X] - X_{\text{true}}|/X_{\text{true}}$
- absolute precision, $\sigma_X$
- relative precision, $\sigma_X/E[X]$

where $X_{\text{true}}, E[X]$ and $\sigma_X$ represent, respectively, the true, expected value and standard deviation of $X$. The latter two are estimated given all values for $X$ present in the MCMC output from the kima analysis of the dataset associated with the simulation being considered.

In Table 4, the absolute and relative bias, accuracy and precision with which $K$, $e$ and $M$, are recovered, averaged over all transiting planets and simulations, is shown for the three strategies. The uncertainties provided are standard deviations, and characterise the dispersion of such values taking into account all transiting planets. They should not be confused with the uncertainties associated with the estimates of $K$, $e$ and $M$ for individual planets. The same quantities shown in Table 4 are provided in Table 5, including with respect to the orbital period, $P$, but now averaged over the detected non-transiting planets.

The estimation of $M$ is most dependent of $K$, but it is also contingent on the values for $e$, $P$ and the stellar mass. Thus, it is not straightforward to extrapolate results for $K$ to what would be expected with respect to $M$. In order to estimate $M$ one also needs to assume an inclination for the orbital plane. We will assume this to be known, and set it to 90°, the same value assumed for all systems when the RV measurements were simulated. Although this situation is not realistic, it allows for a direct comparison between true and estimated planetary masses.

Overall, the non-myopic strategy, B, recovers more information about the true values of $K$ and $M$ for the transiting planets. In comparison, the similar in objective, but myopic, strategy A2, leads to somewhat more biased values. Both these strategies lead to significantly less biased, as well as more accurate and precise values for $K$ and $M$ than strategy A1. Further, this latter strategy also leads to a wider spread in the bias, accuracy and precision with respect to $K$ and $M$, mostly due to the much higher dispersion among the values for $N_{\text{RV}}$. However, there are no significant differences between the three strategies with respect to how well the true values of $e$ are recovered. Given that most of these are about 0.1 or smaller, as can be seen in Figure 1, it is not surprising to find that all scheduling strategies lead to values around 0.1 or smaller for the absolute bias, accuracy and precision, and thus much higher values for the relative counterparts to these quantities.

With respect to the non-transiting planets, overall strategy A1 seems to provide more information about the true values of $K$, $e$, $P$ and $M$, yielding less biased, as well as more accurate and precise estimates. In part, this is due to a slightly larger mean value for $N_{\text{RV}}$ among the datasets as-
associated with non-transiting planets detections in the case of strategy A1, than for the other two strategies. But the more irregular spread of the RV measurements, across the available timespan for the observations (3 years), in strategy A1 may also play a role. This allows for a significantly better characterisation of the periods of the detected non-transiting planets, especially in terms of precision, which then leads to also better estimates for $K$, $e$ and $M$. In contrast, strategies A2 and B, by timing the observations to achieve optimal characterization of the transiting planet(s) phase-curve(s), may systematically sample the orbital periods of some non-transiting planets in a far from optimal way, in fact worse than random sampling. Finally, all that was just said can also be used to explain why strategy A2 seems to lead to more information being obtained about the true values of $K$, $e$, $P$ and $M$ than strategy B, for the non-transiting planets.

All the distributions associated with the bias, accuracy and precision are positively skewed, except those for the bias and precision with respect to $e$ for which the skew is negative. The non-zero mean and positive skew in the distribution of the bias for $K$ and $M$, seems to be the result of the existence of undetected (non-transiting) planets. The mean bias gets closer to zero and the skew greatly diminishes, if only systems with undetected planets are considered in the calculation of these statistics (and the opposite occurs for the other systems). Interestingly, the sampling of the phase-curves of the transiting planets seems to be so close to optimal, in terms of information gathering and in the case of strategy B, that even in the presence of undetected (non-transiting) planets the bias is very close to zero and the skew small.

The differences between the results obtained for each scheduling strategy, regarding both the transiting and non-transiting planets, should increase as the average number of possible RV measurements per star decreases, and vice-versa. For example, if this number was about half of what was assumed, i.e. around 10, we would still expect strategy B to yield fairly strong constraints on the masses and orbital parameters of the transiting planets, but it would be hard to detect any non-transiting planet. On the contrary, in this situation, both myopic strategies, in particular A1,

### Table 4

| Strategy | Parameter | Absolute | Relative |
|----------|-----------|----------|----------|
|          | Bias      | Accuracy | Precision |
|          | Bias      | Accuracy | Precision |
| A1       | $K$       | 0.25 ± 0.36 | 0.52 ± 0.32 | 0.90 ± 0.54 |
|          | $e$       | 0.10 ± 0.08 | 0.11 ± 0.06 | 0.11 ± 0.05 |
| A2       | $K$       | 0.40 ± 0.90 | 1.43 ± 0.85 | 2.27 ± 1.59 |
|          | $e$       | 0.08 ± 0.08 | 0.10 ± 0.06 | 0.10 ± 0.04 |
| B        | $K$       | 0.11 ± 0.21 | 0.44 ± 0.18 | 0.63 ± 0.21 |
|          | $e$       | 0.08 ± 0.08 | 0.10 ± 0.06 | 0.10 ± 0.04 |

### Table 5

| Strategy | Parameter | Absolute | Relative |
|----------|-----------|----------|----------|
|          | Bias      | Accuracy | Precision |
|          | Bias      | Accuracy | Precision |
| A1       | $K$       | -8.56 ± 25.04 | 11.97 ± 23.64 | 10.04 ± 11.64 |
|          | $e$       | 0.04 ± 0.06 | 0.05 ± 0.05 | 0.09 ± 0.05 |
| A2       | $K$       | -5.96 ± 21.12 | 9.32 ± 19.87 | 8.08 ± 9.88 |
|          | $e$       | 0.04 ± 0.07 | 0.06 ± 0.06 | 0.08 ± 0.05 |
| B        | $K$       | -6.27 ± 21.98 | 10.03 ± 20.55 | 8.50 ± 10.39 |
|          | $e$       | 0.05 ± 0.06 | 0.06 ± 0.05 | 0.08 ± 0.05 |

Table 4. Absolute and relative bias, accuracy and precision with which $K$, $e$ and mass, $M$, are recovered, averaged over all transiting planets and simulations, for the three strategies. The uncertainties provided are standard deviations, and characterise the dispersion of such values taking into account all transiting planets. The absolute quantities with respect to $K$ and $M$ are in units of m/s and $M_\odot$, respectively.

Table 5. Absolute and relative bias, accuracy and precision with which $K$, $e$, $P$ and mass, $M$, are recovered, averaged over all detected non-transiting planets, for the three strategies. The uncertainties provided are standard deviations, and characterise the dispersion of such values taking into account all detections of non-transiting planets. The absolute quantities with respect to $K$, $M$ and $P$ are in units of m/s, $M_\odot$ and days, respectively.
Figure 8. Absolute bias, i.e. the difference between the marginal posterior mean and the true value, as a function of the later, for the RV semi-amplitude, $K$, and with respect to the transiting planets. Results averaged over 10 simulations are shown, with the associated standard deviation, for the three scheduling strategies, A1 (upper panel), A2 (middle panel) and B (lower panel). Colour indicates the number of RV measurements per host star, averaged over the 10 simulations: red, less than 15; blue, between 15 and 25; green, more than 25. Units are m/s.

Figure 9. Absolute bias, i.e. the difference between the marginal posterior mean and the true value, as a function of the later, for the orbital eccentricity, $e$, and with respect to the transiting planets. Results averaged over 10 simulations are shown, with the associated standard deviation, for the three scheduling strategies, A1 (upper panel), A2 (middle panel) and B (lower panel). Colour indicates the number of RV measurements per host star, averaged over the 10 simulations: red, less than 15; blue, between 15 and 25; green, more than 25.
Figure 10. Absolute bias, i.e. the difference between the marginal posterior mean and the true value, as a function of the later, for the mass, $M$, and with respect to the transiting planets. Results averaged over 10 simulations are shown, with the associated standard deviation, for the three scheduling strategies, A1 (upper panel), A2 (middle panel) and B (lower panel). Colour indicates the number of RV measurements per host star, averaged over the 10 simulations: red, less than 15; blue, between 15 and 25; green, more than 25. Units are $M_{\odot}$.

would probably fail to deliver reliable constraints for the transiting planets around the least observed stars, but some non-transiting planets would end up being detected around the most observed stars.

We also implemented a slightly adapted version of the (myopic) uniform-in-phase scheduling algorithm proposed in Burt et al. (2018), similar in aims to our strategy A2. The only difference between them is that in the former the star chosen to be observed at each time, among a sub-sample previously selected as in A2, is that for which an observation taken at that moment would be the farthest away from the nearest observation in the respective phase-curve. We obtain results very similar to those for A2, overall better with respect to A1, as Burt et al. (2018) had already found when comparing the results of uniform-in-phase versus random scheduling, but again not as informative as the results obtained with strategy B.

4 CONCLUSIONS

We implemented three different scheduling strategies with respect to the ESPRESSO GTO allocated for radial velocity follow-up of TOIs. Our objective was to determine which strategy maximizes the amount of information gathered about the masses and orbital parameters of all planets in the TOIs host systems. In particular, we considered a sample of 50 TESS target stars, with simulated planetary systems containing at least one transiting planet with a radius below $4R_{\oplus}$ (Barclay et al. 2018).

Two of the strategies were myopic, and implemented either a random or a uniform-in-phase sampling algorithm. The latter was also used in a non-myopic strategy. We found the myopic strategies lead to a biased estimation (on average around 3% to 7%) of the mass of the simulated TOIs. In contrast, the non-myopic strategy is able to provide an unbiased (about 1%) measurement of the masses, while keeping the relative accuracy and precision around 15% and 22%, respectively. Similar numbers of non-transiting planets are detected with all strategies. However, the random scheduler yields less biased and more accurate estimates for their mass and orbital parameters, possibly due to a higher mean number of scheduled RVs for the datasets associated with non-transiting planets detections. Overall, a more uniform-in-phase sampling of the phase-curves of transiting planets seems to lead to a more efficient gathering of information about the masses and orbital parameters of those planets, but in detriment, to a certain extent, of a better characterization of the other (non-transiting) planets in the same systems. However, we emphasize that these conclusions depend to some extent on the absence of significant correlations in the stellar activity induced radial velocity contribution. In particular, their presence should affect more significantly the detection and characterisation of the non-transiting planets, than the characterisation of the assumed detected, with well known orbital periods and ephemeris, transiting planets. In any case, the results of all considered strategies should be affected in a similar way, given that their implementation is not informed by the covariance structure of the stellar activity induced radial velocity variations. Therefore, the relative merits of the three scheduling strategies should not be significantly affected even if significant correlations exist in the
stellar activity induced radial velocity contribution. Nevertheless, we will consider the use of more realistic models for this contribution in future work.

Given the superiority of the non-myopic strategy, in the context of the RV follow-up of transiting planets, we will concentrate our future work in developing it further in the light of the increased interesting of the community in such topics (Bellm et al. 2019; Bryson et al. 2019). In particular, we are currently comparing the results obtained in this paper for the uniform-in-phase sampling algorithm with what can be achieved in the context of optimal sampling (e.g. Mohammad-Djafari 2001; Ford 2008; Loredo et al. 2012; Hees et al. 2019).

ACKNOWLEDGEMENTS

We thank Nuno Santos for insightful discussions. We acknowledge the excellent open-source acebayes R package made available to the community by Antony Overstall. This work was supported by Fundação para a Ciência e a Tecnologia (FCT) through national funds (PIDDAC) and the research grants UID/FIS/0434/2019, UIDB/0434/2020 and UIDP/0434/2020. This work was also supported by FCT through national funds (PTDC/FIS-AST/28953/2017, PTDC/FIS-AST/32113/2017) and by FEDER - Fundo Europeu de Desenvolvimento Regional through COMPETE2020 - Programa Operacional Competitividade e Internacionalização (POCI-01-0145-FEDER-028953, POCI-01-0145-FEDER-032113).

REFERENCES

Barclay T., Pepper J., Quintana E. V., 2018, ApJS, 239, 2
Batalha N. E., Kempton E. M. R., M barren R., 2017, ApJ, 836, L5
Bellm E. C., et al., 2019, arXiv preprint arXiv:1907.07817
Brewer B. J., Donovan C. P., 2015, Monthly Notices of the Royal Astronomical Society, 448, 3206
Brown A. G., et al., 2016, Astronomy & Astrophysics, 595, A2
Brown A., et al., 2018, Astronomy & Astrophysics, 616, A1
Bryson S., Bennett D., Gauli S., Mulders G. D., Wang S. X., Wolfgang A., 2019, in Bulletin of the American Astronomical Society.
Burt J., Holden B., Wolfgang A., Bouma L., 2018, The Astronomical Journal, 156, 255
Cameron A. C., 2018, Handbook of Exoplanets, pp 1791–1799
Cegla H., 2019, Geosciences, 9, 114
Cegla H., Stassun K., Watson C., Bastien F., Pepper J., 2013, The Astrophysical Journal, 780, 104
Chen J., Kipping D., 2016, The Astrophysical Journal, 834, 17
Dorn C., Khan A., Heng K., Connolly J. A., Alibert Y., Benz W., Tackley P., 2015, Astronomy & Astrophysics, 577, A63
Dorn C., Bower D. J., Rozel A., 2017, Handbook of Exoplanets, pp 1–25
Dressing C. D., Charbonneau D., 2015, The Astrophysical Journal, 807, 45
Dumusque X., 2016, Astronomy & Astrophysics, 593, A5
Dumusque X., Udry S., Lovis C., Santos N. C., Monteiro M., 2011, Astronomy & Astrophysics, 525, A140
Faria J. P., Santos N. C., Figueira P., Brewer B. J., 2018, arXiv preprint arXiv:1806.08305
Feroz F., Hobson M., 2013, Monthly Notices of the Royal Astronomical Society, 437, 3540
Feroz F., Balan S., Hobson M., 2011, Monthly Notices of the Royal Astronomical Society, 415, 3462
Ford E. B., 2008, The Astronomical Journal, 135
Fressin F., Torres G., Charbonneau D., Bryson S. T., Christiansen J., Dressing C. D., 2013, The Astrophysical Journal, 766, 81
Gladman B., 1993, Icarus, 106, 247
Hees A., Dezhganfar A., Do T., Ghez A., Martinez G., Campbell R., Lu J., 2019, The Astrophysical Journal, 880, 87
Herman M. K., Zhu W., Yu Y., 2019, The Astronomical Journal, 157, 248
Jeffreys H., 1998, The Theory of Probability 3rd Edition (Reissue)
Kane S., Wolfang A., Stefansson G. K., Ning B., Mahadevan S., 2019, The Astrophysical Journal, 882, 38
Kass R. E., Raftery A. E., 1995, Journal of the american statistical association, 90, 773
Kipping D. M., 2013, Monthly Notices of the Royal Astronomical Society: Letters, 434, L51
Kipping D. M., 2014, Monthly Notices of the Royal Astronomical Society, 444, 2263
Khoronsh H., Andersen J., Psikunov N., Hackman T., Juncher J., Jarvinen S., Jorgensen U. G., 2015, Monthly Notices of the Royal Astronomical Society, 448, 3038
Kumaraswamy P., 1980, Journal of Hydrology, 46, 79
Kushniruk I., Schirmer T., Bensby T., 2017, Astronomy & Astrophysics, 608, A73
Landoni M., Romano P., Vercellone F., Knödlseder J., Bianco A., Tavecchio F., Corina A., 2019, The Astrophysical Journal Supplement Series, 240, 32
Loredo T. J., Berger J. O., Cheneuf D. F., Clyde M. A., Liu B., 2012, Statistical Methodology, 9, 101
Mohammad-Djafari A., 2001, Bayesian inference and maximum entropy methods in science and engineering: 20th international workshop; Gif-sur-Yvette, France; 8-13 July 2000. AIP, American Inst. of Physics
Montet B. T., 2018, Research Notes of the American Astronomical Society, 2, 28
Ning B., Wolfang A., Ghosh S., 2018, The Astrophysical Journal, 869, 5
Overstall A. M., Woods D. C., 2017, Technometrics, 59, 458
Overstall A., Woods D., Adamou M., 2017, arXiv preprint arXiv:1705.08096
Pepe F., et al., 2013, The Messenger, 153, 6
Pepe F., Ehrenreich D., Meyer M. R., 2014, Nature, 513, 358
Perryman M., 2018, The exoplanet handbook. Cambridge University Press
Pronzato L., 2017, Journal de la Societé Française de Statistique, pp 7–36
Ricker G. R., et al., 2016, in Space Telescopes and Instrumentation 2016: Optical, Infrared, and Millimeter Wave. p. 99042B
Suissa G., Chen J., Kipping D., 2018, Monthly Notices of the Royal Astronomical Society, 476, 2613
Tayar J., Stassun K. G., Corsaro E., 2019, ApJ, 883, 195
Van Eylen V., Albrecht S., Huang X., MacDonald M. G., Dawson R. I., et al., 2019, The Astronomical Journal, 157, 61
Winn J. N., Fabrycky D. C., 2015, Annual Review of Astronomy and Astrophysics, 53, 409
Wolfgang A., Rogers L. A., Ford E. B., 2016, The Astrophysical Journal, 825, 19

This paper has been typeset from a TeX/LaTeX file prepared by the author.