# BeyondPlanck results. III. Time-ordered data simulations and validation

M. Brilenkov[11]⋆, M. Galloway[11], K. J. Andersen[11], R. Aurlien[11], R. Banerji[11], M. Bersanelli[4,9], S. Bertocco[8], M. Carbone[14], L. P. L. Colombo[4], H. K. Eriksen[11], M. K. Foss[11], C. Franceschet[10], U. Fuskeland[11], S. Galeotta[8], S. Gerakakis[14], E. Gjerløw[11], B. Hensley[2], D. Herman[11], M. Iacobellis[14], M. Ieronymaki[14], H. T. Ihle[11], J. B. Jewell[11], A. Karakci[11], E. Keihänen[3,7], R. Keskitalo[1], G. Maggio[8], D. Maino[4,9,10], M. Maris[8], S. Paradiso[4], B. Partridge[6], M. Reinecke[13], A.-S. Suur-Uski[3,7], T. L. Svalheim[11], D. Tavagnacco[8,5], H. Thommesen[11], D. J. Watts[11], I. K. Wehus[11], and A. Zacchei[8]

[1] Computational Cosmology Center, Lawrence Berkeley National Laboratory, Berkeley, California, U.S.A.
[2] Department of Astrophysical Sciences, Princeton University, Princeton, NJ 08544, U.S.A.
[3] Department of Physics, Gustaf Hällströmin katu 2, University of Helsinki, Helsinki, Finland
[4] Dipartimento di Fisica, Università degli Studi di Milano, Via Celoria, 16, Milano, Italy
[5] Dipartimento di Fisica, Università degli Studi di Trieste, via A. Valerio 2, Trieste, Italy
[6] Haverford College Astronomy Department, 370 Lancaster Avenue, Haverford, Pennsylvania, U.S.A.
[7] Helsinki Institute of Physics, Gustaf Hällströmin katu 2, University of Helsinki, Helsinki, Finland
[8] INAF - Osservatorio Astronomico di Trieste, Via G.B. Tiepolo 11, Trieste, Italy
[9] INAF/IASF Milano, Via E. Bassini 15, Milano, Italy
[10] INFN, Sezione di Milano, Via Celoria 16, Milano, Italy
[11] Institute of Theoretical Astrophysics, University of Oslo, Blindern, Oslo, Norway
[12] Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Drive, Pasadena, California, U.S.A.
[13] Max-Planck-Institut für Astrophysik, Karl-Schwarzschild-Str. 1, 85741 Garching, Germany
[14] Planetek Hellas, Leoforos Kifisias 44, Marousi 151 25, Greece

October 19, 2021

**ABSTRACT**

In a suite of companion papers, the BeyondPlanck collaboration has presented the first global Bayesian analysis framework for CMB data, and demonstrated this framework on *Planck* LFI measurements. While the primary application and motivation of this work is to perform statistically rigorous end-to-end Bayesian posterior analysis, we note that exactly the same computational infrastructure can, with only trivial modifications, also be used to simulate realistic time-ordered data (TOD). Such simulations are routinely used extensively in any modern CMB analysis pipeline, both for frequentist-style error propagation through forward simulations and for code validation purposes. In this paper, we provide a first demonstration by producing an ensemble of TOD simulations that consists only of CMB, gain fluctuations, correlated noise and white noise, and use these to validate the central components of the low-level algorithm, namely correlated noise and gain estimation and mapmaking. A future publication will consider validation of the full end-to-end algorithm, including component separation and cosmological parameter estimation; that analysis, however, will require far more computational resources per sample than the limited scope analysis presented here, and it cannot match the statistical depth of the current analsis.

**Key words.** ISM: general – Cosmology: observations, polarization, cosmic microwave background, diffuse radiation – Galaxy: general

## Contents



⋆ Corresponding author: M. Brilenkov; maksym.brilenkov@astro.uio.no

## 1. Introduction

High-fidelity end-to-end simulations play a critical role in the analysis of any modern CMB experiment for three main reasons. First, during the design phase of the experiment, simulations are used to optimize and forecast the performance of a given experimental design, and ensure that the future experiment will achieve its scientific goals. Second, simulations are essential for validation purposes, as they may be used to test data-processing techniques as applied to a realistic instrument model. Third, realistic end-to-end simulations play an important role in error propagation for traditional (frequentist-style) CMB analysis pipelines.

Simulations played a particularly important role in the data reduction of *Planck*, and massive efforts were invested in implementing efficient and clean analysis codes that were generally applicable to a wide range of experiments. This work culminated in a software package called *Time Ordered Astrophysics Scalable Tools* (TOAST[1]), which was explicitly designed to operate in a massively parallel high-performance computing environment. TOAST was used to produce the final generations of the *Planck Full Focal Plane* (FFP) simulations (Planck Collaboration XII 2016), which served as the main error propagation mechanism in the *Planck* 2015 and 2018 data releases.

For *Planck*, generating end-to-end simulations represented by far the dominant computational cost of the entire experiment, accounting for 25 million CPU hours in the case of *Planck* 2015 alone (Planck Collaboration XII 2016). In addition, the production phase required massive amounts of human effort, in terms of preparing the inputs, executing the runs, and validating the outputs. It is obviously of great interest for any future experiment to optimize and streamline this simulation process, and reuse both validated software and human work whenever possible.

In this respect, the end-to-end Bayesian analysis framework presented by the BeyondPlanck collaboration offers a novel approach to generating CMB simulations; see BeyondPlanck Collaboration (2021) and references therein. While the primary goal of this framework is to draw samples from a full joint posterior distribution for analysis purposes, it is useful to note that the foundation of this approach is an explicit parametric model for the full time-ordered data (TOD) that is to be fitted directly to unprocessed observations. This model is then compared with the observed data in TOD space. The analysis phase is as such numerically equivalent to producing a large number of TOD simulations, and comparing each of these with the actual observed data. In this framework, each step of the analysis and simulation pipelines are thus fully equivalent, and the primary difference is simply whether the input model parameters are assumed unknown (as is the case during the analysis phase) or known (as is the case for a simulation).

This unified approach to CMB analysis and simulation has a few notable real-world advantages. The first regards code reusability and validation; when a new feature has been implemented, optimized and validated for analysis purposes, it is immediately available also for simulation purposes. Having to maintain only one computational interface for each physical effect leads both to lower development costs and less room for human errors and bugs.

A second important feature regards simulation fidelity. For simulation-based error propagation, it is often non-trivial to determine what model variations should be allowed. This problem can be greatly alleviated by coupling the simulation stage to a previous analysis run, by drawing the simulation input model parameters directly from a set of posterior samples. These are guaranteed to span precisely the range allowed by the real data, and they may therefore serve as a statistically appropriate input definition for a forward simulation.

In this paper, we demonstrate the simulation ability of the BeyondPlanck framework with two main goals. The first goal is simply to demonstrate the feasiblity and convenience of simulating TODs using the `Commander` framework. The second goal is to validate the novel low-level algorithms introduced by BeyondPlanck, namely correlated noise sampling and mapmaking (Keihänen et al. 2021; Ihle et al. 2021) and gain estimation through posterior sampling (Gjerløw et al. 2021). Together, these operations form the core of the low-level algorithm that underlies the entire framework, and they are highly inter-dependent; properly validating these steps with a significant number of Monte Carlo samples and independent realizations is therefore critically important. Validation of the full end-to-end algorithm will be addressed in a separate future publication, but that analysis will necessarily involve far fewer samples and realizations, and not provide a comparable statistical depth as the current analysis. For this reason, a two-stage approach to validation is useful.

The rest of the paper is organized as follows. We first provide a brief overview of the BeyondPlanck framework and data model in Sect. 2. In Sect. 3 we use this framework to generate an ensemble of *Planck* 30 GHz-like simulations, each including only CMB, gain fluctuations, correlated noise and white noise, and only one year of observations. Producing a single Monte Carlo sample with this reduced data model only takes about 5 CPU-hours on a modern computer. In Sects. 4–refsec:maps we compare the resulting gain, correlated noise, and map posterior distributions with the known input parameters, and also study the corresponding burn-in and correlation length properties. We conclude in Sect. 7.

## 2. Data model and Gibbs chain

As described in BeyondPlanck Collaboration (2021) and its companion papers, the single most fundamental component of the BeyondPlanck framework is an explicit parametric model that is to be fitted to raw TOD that includes instrumental, astrophysical, and cosmological parameters. For the current analysis, this model takes the following form,

$$d_{j,t} = g_{j,t}\mathsf{P}_{tp,j}\left[\mathsf{B}^{\mathrm{symm}}_{pp',j}\sum_{c}\mathsf{M}_{cj}(\beta_{p'},\Delta^{j}_{\mathrm{bp}})a^{c}_{p'} + \mathsf{B}^{\mathrm{asymm}}_{pp',j}\left(s^{\mathrm{orb}}_{j,t} + s^{\mathrm{fsl}}_{j,t}\right)\right] + \\ + n^{\mathrm{corr}}_{j,t} + n^{\mathrm{w}}_{j,t}. \tag{1}$$

Here $j$ represents a radiometer label, $t$ indicates a single time sample, $p$ denotes a single pixel on the sky, and $c$ represents one single astrophysical signal component. Furthermore, $d_{j,t}$ denotes the measured data; $g_{j,t}$ denotes the instrumental gain; $\mathsf{P}_{tp,j}$ is a pointing matrix; $\mathsf{B}_{pp',j}$ denotes beam convolution; $\mathsf{M}_{cj}(\beta_p, \Delta_{\mathrm{bp}})$ denotes the so-called mixing matrix, which describes the amplitude of component $c$ as seen by radiometer $j$ relative to some reference frequency $j_0$ when assuming some set of bandpass correction parameters $\Delta_{\mathrm{bp}}$; $a^c_p$ is the amplitude of component $c$ in pixel $p$; $s^{\mathrm{orb}}_{j,t}$ is the orbital CMB dipole signal, including relativistic quadrupole corrections; $s^{\mathrm{fsl}}_{j,t}$ denotes the contribution from far sidelobes; $n^{\mathrm{corr}}_{j,t}$ denotes correlated instrumental noise; and $n^{\mathrm{w}}_{j,t}$ is uncorrelated (white) instrumental noise.

Denoting the set of all free parameters in Eq. (1) by $\omega$, the BeyondPlanck approach to CMB analysis simply amounts to mapping out the posterior distribution as given by Bayes' theorem,

$$P(\omega \mid \boldsymbol{d}) = \frac{P(\boldsymbol{d} \mid \omega)P(\omega)}{P(\boldsymbol{d})} \propto \mathcal{L}(\omega)P(\omega), \tag{2}$$

where $P(\boldsymbol{d} \mid \omega) \equiv \mathcal{L}(\omega)$ is called the likeihood, $P(\omega)$ is some set of priors, and $P(\boldsymbol{d})$ is a normalization constant. In practice,

[1] https://github.com/hpc4cmb/toast

this posterior distribution is mapped out using standard modern Monte Carlo sampling techniques, and in particular Gibbs sampling is used extensively to partition the problem into computationally tractable components.

As described above, full validation of the full data model lies outside the scope of the current paper, primarily for reasons of excessive computational expense: While we are able to run one (or a few) iteration of the full analysis pipeline within currently available resources, a full Monte Carlo exploration that involves tens of realizations and many thousands of samples is not yet realistic. In order to validate the central steps of the algorithm itself using a meaning number of realizations, we therefore instead limit the data volume and model as follows. First, we limit ourselves to only one year of *Planck* 30-GHz observations, which reduces the volume of the TOD themselves (not including pointing, flags etc.) from 638 GB to 22 GB. Second, we simply the data model in Eq. (1) to

$$d_{j,t}^{\mathrm{sim}} = g_{j,t}\mathsf{P}_{tp,j}\mathsf{B}_{pp',j}^{\mathrm{symm}}a_{p'}^{\mathrm{cmb}} + \mathsf{B}_{pp',j}^{\mathrm{asymm}}s_{j,t}^{\mathrm{orb}} + +n_{j,t}^{\mathrm{corr}} + n_{j,t}^{\mathrm{w}}; \tag{3}$$

that is, we only include one single sky component, namely the CMB, and we ignore far sidelobe corrections. (We note that sidelobes are in fact included for the orbital dipole, but since there are currently no free parameters associated with the sidelobe model, this is a purely deterministic correction.) As such, this configuration provides a direct test of the gain and noise estimation and mapmaking parts of the full algorithm, but not the component separation or cosmological parameters.

To explore this distribution, we use the following Gibbs sampling chain, which is a subset of that described by BeyondPlanck Collaboration (2021):

$$\boldsymbol{g} \leftarrow P(\boldsymbol{g} \mid \boldsymbol{d}, \quad \xi_n, \boldsymbol{a}) \tag{4}$$
$$\boldsymbol{n}_{\mathrm{corr}} \leftarrow P(\boldsymbol{n}_{\mathrm{corr}} \mid \boldsymbol{d}, \boldsymbol{g}, \quad \xi_n, \boldsymbol{a}) \tag{5}$$
$$\xi_n \leftarrow P(\xi_n \mid \boldsymbol{d}, \boldsymbol{g}, \boldsymbol{n}_{\mathrm{corr}}, \quad \boldsymbol{a}) \tag{6}$$
$$\boldsymbol{a} \leftarrow P(\boldsymbol{a} \mid \boldsymbol{d}, \boldsymbol{g}, \boldsymbol{n}_{\mathrm{corr}}, \xi_n, \quad ). \tag{7}$$

In practice, the gain is split into three terms, $g_{i,t} = g_0 + g_i + \delta g_{i,t}$, where $g_0$ indicates an overall absolute calibration factor for the entire data channel, $g_i$ is a relative (but time-independent) calibration factor accounting for differences between detectors, and $\delta g_{i,t}$ accounts for time-dependent gain fluctuations (Gjerløw et al. 2021). The motivation for introducing this this split is twofold: First, we want to use the orbtial CMB dipole only for the absolute calibration, but all signal components (and most importantly the Solar CMB dipole) for relative calibration, and, second, the numerical sampling algorithms become much cheaper through this organization. Likewise, the noise PSD parameters, $\xi_n$, are also sampled over iteratively through individual Gibbs step, as described by Ihle et al. (2021).

The CMB sky realizations used in the following analysis are drawn from the best-fit *Planck* 2018 LCDM model (Planck Collaboration V 2020) using the HEALPix[2] (Górski et al. 2005) `synfast` utility. All instrumental parameters are drawn from different realizations of the BeyondPlanck ensemble presented in BeyondPlanck Collaboration (2021), and these are taken as true input values in the following.

## 3. Simulations

(Karin)

[2] http://healpix.jpl.nasa.gov

## 4. Gain posterior validation

(Maksym for 1-paragraph intro)

### 4.1. Absolute calibration

3-panel plot with:

- Histogram of (output-input)/rms (Tamaki)
- Plot of burn-in (Elenia)
- Plot of correlation length (Elenia)

### 4.2. Relative calibration

3-panel plot with:

- Histogram of (output-input)/rms (Jinyi)
- Plot of burn-in (Eirik)
- Plot of correlation length (Eirik)

### 4.3. Time-dependent gain fluctuations

3-panel plot with:

- Histogram of (output-input)/rms for a single PID (Alessandro?)
- Plot of burn-in (Yuyang)
- Plot of correlation length (Yuyang)

## 5. Correlated noise posterior validation

(Barauna)

### 5.1. Time-domain realization

3-panel plot with:

- Histogram of (output-input)/rms (Lukas)
- Plot of burn-in (Lukas)
- Plot of correlation length (Lukas)

### 5.2. Spectral parameters

9-panel plot with:

- Histogram of (output-input)/rms, sigma0 (Barauna)
- Plot of burn-in, sigma0 (Nils)
- Plot of correlation length, sigma0 (Nils)
- Histogram of (output-input)/rms, alpha (Arianna)
- Plot of burn-in, alpha (Maksym)
- Plot of correlation length, alpha (Maksym)
- Histogram of (output-input)/rms, fknee (Eduardo)
- Plot of burn-in, fknee (Maksym)
- Plot of correlation length, fknee (Volunteer)

## 6. Sky map posterior validation

(Lukas)

### 6.1. Correlated noise

4-panel plot with:

- Posterior mean (single realization) (Paz)
- Posterior rms (single realization) (Paz)
- (posterior mean - true input)/posterior rms (single realization) (Paz)
- 20 histograms of (3) (Maksym)

### 6.2. Frequency maps

4-panel plot with:

- Posterior mean (single realization) (Fazlu)
- Posterior rms (single realization) (Fazlu)
- (posterior mean - true input)/posterior rms (single realization) (Fazlu)
- 20 histograms of (3) (Thuong)

### 6.3. CMB component maps

4-panel plot with:

- Posterior mean (single realization) (Artem)
- Posterior rms (single realization) (Artem)
- (posterior mean - true input)/posterior rms (single realization) (Artem)
- 20 histograms of (3) (Karin)

## 7. Conclusions

(Maksym/Hans Kristian)

*Acknowledgements.* We thank Prof. Pedro Ferreira for very useful suggestions, comments and discussions. The BeyondPlanck Collaboration has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement numbers 776282, 772253, and 819478. In addition, the collaboration acknowledges support from ESA; ASI, CNR, and INAF (Italy); NASA and DoE (USA); Tekes, AoF, and CSC (Finland); RCN (Norway); ERC and PRACE (EU).

## References

BeyondPlanck Collaboration. 2021, A&A, in preparation [arXiv:2011.05609]
Gjerløw et al. 2021, A&A, in preparation [arXiv:2011.08082]
Górski, K. M., Hivon, E., Banday, A. J., et al. 2005, ApJ, 622, 759
Ihle et al. 2021, A&A, in preparation [arXiv:2011.06650]
Keihänen et al. 2021, A&A, in preparation [arXiv:2011.06024]
Planck Collaboration XII. 2016, A&A, 594, A12
Planck Collaboration V. 2020, A&A, 641, A5