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# Inverse Problem Approach to Spacecraft Charging Simulations

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***Abstract*— Spacecraft charging is an important topic in space-weather research since charging can lead to spacecraft anomalies, which can range from inconsequential to catastrophic. Spacecraft surface charging calculations use sophisticated numerical codes and are typically conducted with a direct (forward) approach: the local properties of the space environment, the spacecraft geometry and the spacecraft material properties are the input, while the electric field on and around the spacecraft and the corresponding plasma particle distributions are the output. This approach can be limited when some of the critical input parameters are either unknown or have large uncertainties. For instance, the Van Allen Probes (VAP) spacecraft is an example of a modern spacecraft with state-of-the-art measurements capabilities. Predicting the VAP spacecraft potential requires knowledge of the cold and warm plasma populations which dominate surface charging. However, the cold plasma properties (particularly the cold electron temperature) are not well characterized. In addition, the material properties are known from measurements in 'clean' laboratory conditions, but there are uncertainties associated with how materials age in space due to their interaction with the environment. To mitigate these limitations, we developed an inverse approach to use available spacecraft-charging data to infer some of the missing properties of the space environment around the spacecraft and material degradation. This approach is currently based on an analytical model of spacecraft charging, based on the orbital-motion-limited theory, together with a quasi-Newton optimization method. We will present results that show convergence and the ability to estimate the correct parameters in synthetic observation experiments.**

## I. Introduction

Over several decades, sophisticated numerical tools have been developed to predict spacecraft surface charging. Such tools include community codes e.g. NASCAP (Mandell et al. 2006), SPIS (Roussel et al. 2008), MUSCAT (Muranaka et al. 2008), as well as research codes such as CPIC (Meierbachtol et al. 2017), PTetra (Marchand, 2011), etc. These tools are generally applied in a direct or forward approach, i.e. the plasma environment, spacecraft geometry and materials are the inputs of the code. The output is then the electric field on and around the spacecraft, as well as the spacecraft potential, and the plasma particle distributions consistent with this electric field.

We focus on what is perhaps the simplest charging case, i.e. a spacecraft in sunlight immersed in the magnetospheric cold (~eV energy) plasma, where the spacecraft potential is dictated by the emission of photoelectrons balancing the collection of ambient cold electrons. For simplicity, we will consider the ambient cold plasma Maxwellian. In a direct charging calculation, the inputs are: density and temperature of the ambient cold plasma, the photoemission parameters of the specific spacecraft materials, and the geometry of the spacecraft. The output is the spacecraft potential and electric field on/near the spacecraft. There are two major difficulties in performing this direct spacecraft charging calculation accurately. The first is that the parameters that characterize the magnetospheric cold plasma (density and temperature) are typically unknown due to the difficulty of in-situ measurements of the cold populations in the Earth's magnetosphere (see the discussion in the recent review of the impact of the cold plasma in magnetospheric physics, Delzanno et al. 2021). Second, the material parameters have large uncertainties once the spacecraft is in orbit. Materials for space applications are well characterized in the lab prior to launch. However, once in orbit, these materials are exposed to the harsh space environment and their properties are strongly modified. Unfortunately, we do not have any robust methodology to assess and quantify material aging in space. Given the challenges of direct charging calculations in the Earth's magnetosphere, we propose an inverse charging calculation as an alternative. The idea is to use the available spacecraft charging data (for instance, the spacecraft potential or even direct information from the booms measuring the electric field near the spacecraft) together with other available environmental parameters as input to estimate those parameters that are unknown or have large uncertainties.

We note that some form of the inverse spacecraft charging approach has been exploited by several authors in the past, including Grard (1973), Pedersen et al. (1984, 1995, 2008), Schmidt et al. (1987), Escoubet et al. (1997), Ishisaka et al. (1999), Nakagawa et al. (2000), Scudder et al. (2000), Thiebault et al. (2006) and Boardsen et al. (2014). A common technique on space missions is to estimate the plasma density from the spacecraft potential using an inverse approach. However, in such approaches, it is assumed that material properties are known (typically from some in-orbit calibration, other space missions or lab). Moreover, in most works it is also assumed that the plasma temperature is known. To our knowledge, the approach presented here is the first inverse spacecraft charging technique that estimates both material parameters and some of the plasma parameters at the same time.

## II. Methodology

To illustrate our inverse approach, we use the NASA Van Allen Probes (VAP) spacecraft, a modern spacecraft with state-of-the-art measurements, as a reference for an inverse calculation. The measurements available from VAP include the spacecraft potential, total electron density, and fluxes of electron populations with energies larger than 15 eV. The spacecraft geometry is also known. The spacecraft potential, the density of the cold electrons (inferred from the total electron density) and the geometry of the spacecraft are the inputs. The temperature of the cold electrons and the photoemission parameters will then be the output of the inverse technique. Note that we assume that photoemission is dominated by the VAP solar panels coated with ITOC (since, nominally, this is much higher than that from the black Kapton body (Davis, 2006)) so that photoemission can be characterized only by one spacecraft material. Additionally, at present we are only considering a single Maxwellian component for the photoelectrons, although it is known that photoelectrons from past spacecraft missions can be characterized by multiple Maxwellians with different energies [refs]. Sensitivity of the technique to this assumption will be assessed in future work.

To describe our inverse approach, we use the specific charging example discussed above, that is, a conducting, positively-charged spacecraft in sunlight immersed in the cold magnetospheric plasma. The thermal ion current is negligible while the secondary electron emission is not considered here. As such, the spacecraft potential $\boxed{\Phi_{SC}}$ is determined by cold electron collection balancing photoemission. The electron current collected by a conducting spherical spacecraft can be approximated using the Orbital Motion Limited (OML) theory (Mott-Smith & Langmuir, 1926) as

$$I_e = -e4\pi r_{sc}^2 n_e \sqrt{\frac{eT_e}{2\pi m_e}} \left(1 + \frac{e\phi_{sc}}{k_B T_e}\right),\ \phi_{sc} \geq 0 \quad (1)$$

The photoelectron current, approximated with a single Maxwellian distribution (Grard, 1973), is given by

$$I_{ph} = A4\pi r_{sc}^2 J_{ph} \left(1 + \frac{e\phi_{sc}}{k_B T_{ph}}\right) \exp\left(-\frac{e\phi_{sc}}{k_B T_{ph}}\right), \phi_{sc} > 0 \quad (2)$$

Here, $\boxed{e}$ is the elementary charge, $\boxed{k_B}$ is the Boltzmann constant, and $\boxed{m_e}$, $\boxed{n_e}$, $\boxed{T_e}$ are the mass, density and temperature of the electrons, respectively. For photoelectron emission, $\boxed{T_{ph}}$ and $\boxed{J_{ph}}$ are the temperature and current density of the photoelectrons, respectively, while $\boxed{A}$ is the fraction of the spacecraft illuminated area relative to the total surface area. Because of the spacecraft motion, the plasma parameters are expected to change on time scales of the order of seconds. Material parameters change on longer time scales (weeks to months) than plasma conditions and therefore can be kept constant if we use spacecraft data in hours/days periods. The spacecraft surface charging is then computed by solving the equilibrium equation (i.e. floating condition)

$$I_e(\phi_{sc}, n_0^e, T_e) + I_{ph}(\phi_{sc}, J_{ph}, T_{ph}) = 0 \quad (3)$$

Our inverse charging technique will take $\phi_{sc}$, $n_0^e$ and the spacecraft geometry as inputs such that, through Eq. (3), we can write symbolically

$$\phi_{sc} = \phi_{sc}(T_e, J_{ph}, T_{ph}) \quad (4)$$

The output of the technique is then $T_e$, $J_{ph}$, and $T_{ph}$. It is worth to notice that both $\phi_{sc}$ and $T_e$ are both time-varying variables, that is, both are functions of time.

Our technique utilizes a constrained minimization approach to estimate the output parameters such that the appropriate values of the parameters of interest is given by:

$$T_e, J_{ph}, T_{ph} = \underset{T_e, J_{ph}, T_{ph}}{\operatorname{argmin}} \left\| \phi_{sc}(T_e, J_{ph}, T_{ph}) - \phi_{sc}^{obs} \right\|,$$

$$\text{subject to: } I_e(\phi_{sc}, n_0^e, T_e) + I_{ph}(\phi_{sc}, J_{ph}, T_{ph}) = 0,$$

where $\phi_{sc}$ is the surface charging estimation provided by the OML, while $\phi_{sc}^{obs}$ is the observed surface charging data available for instance from VAP.

The problem as stated above is under-determined since both $T_e$ and $\phi_{sc}$ are time dependent variables, so considering a time interval with $N$ discrete time points, we would have a problem of trying to estimate $N$+2 variables ($N$ points in time corresponding to $T_e$ plus the two material parameters that are constant, $J_{ph}$ and $T_{ph}$) with $N$ observations. To solve this issue, we use an expansion of $T_e$ using polynomials (or splines) as

$$T_e = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \cdots = \textstyle\sum_{k=0}^{N_T} \alpha_k t^k, \quad (5)$$

where $t$ is time, and $\alpha_k$ are the coefficients of the polynomial to be determined. Reformulating the minimization problem, we have now more data points than unknowns, i.e. $N \gg N_T + 2$, where the minimization is now:

$$\alpha_k, J_{ph}, T_{ph} = \underset{\alpha_k, J_{ph}, T_{ph}}{\operatorname{argmin}} \left\| \phi_{sc}(\alpha_k, J_{ph}, T_{ph}) - \phi_{sc}^{obs} \right\|,$$

$$\text{subject to: } I_e(\phi_{sc}, n_0^e, \alpha_k) + I_{ph}(\phi_{sc}, J_{ph}, T_{ph}) = 0$$

Finally, we solve the quasi-Newton optimization with a non-linear least-squared fit using the trust-region (Yuan, 2000) method with bounds.

## III. Results

The technique has been tested with synthetic experiments using OML for the surface charging calculations. Here, a spherical and perfectly conducting spacecraft is considered. The synthetic cases are constructed by computing the spacecraft surface potential with OML using given values of the photoemission material parameters, as well as given temperature and density profiles of the cold electrons as a function of time.

### A. *Case I: no-noise in the observations*

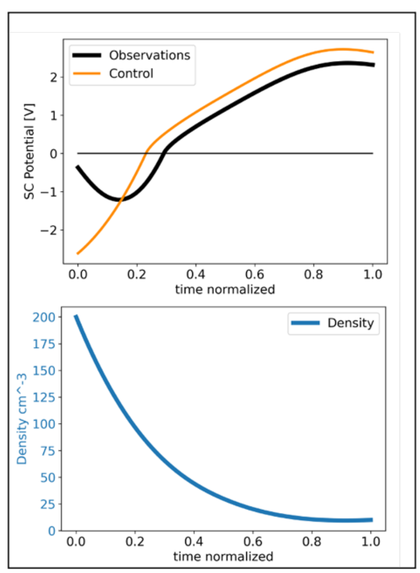

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Fig. 1. *Input to the optimization. Noise-free signal of spacecraft potential (top) and density (bottom) as a function of time. In the top panel, 'Control' (orange line) labels the spacecraft potential used as first guess in the optimization.*

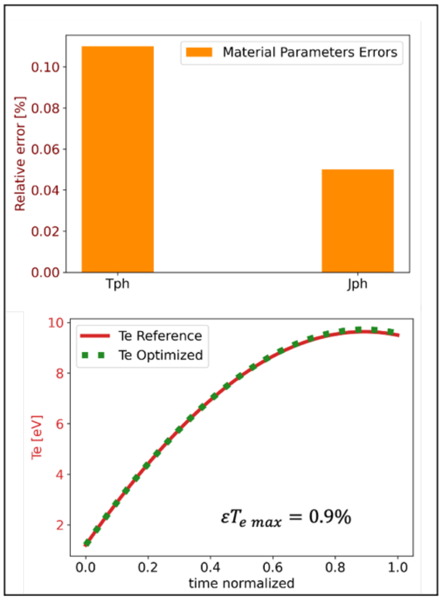


Fig. 2. *Output of the optimization using noise-free input signals. Material paramters presented with their respective relative errors (top), and electron temperature (bottom) estimated by the inverse technique.*

First, we considered noise-free input signals for the density and spacecraft potential. Figure 1 shows an example of input data for the optimization. Figure 2 shows the output of the inverse technique, that is, the electron temperature as a function of time and material parameters. When the input data is free of noise, the technique allows parameter estimation with high accuracy. In this example, the maximum relative error in the electron temperature is 0.9% while that of the material parameters is less than 0.11%.

*B. Case II: noise in the observations.*

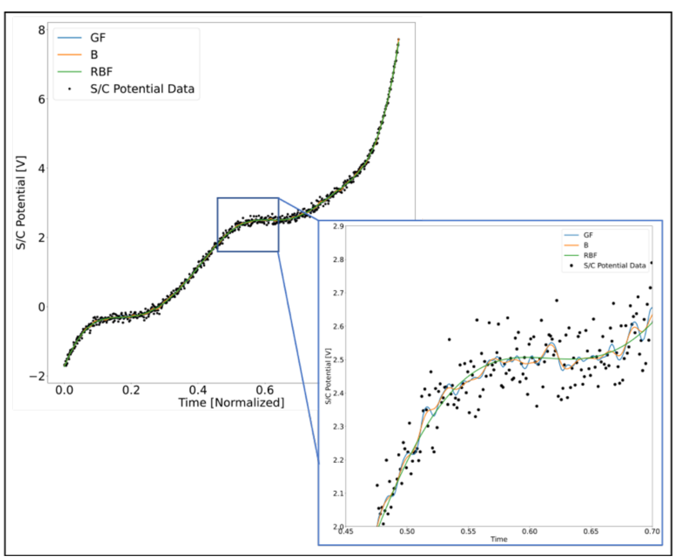


Fig. 3. *Noisy signal of the spacecraft potential (black dots) smoothed using Gaussian-filter (blue), Butterworth-filter (orange), and Gaussian Process Regressor (green).*

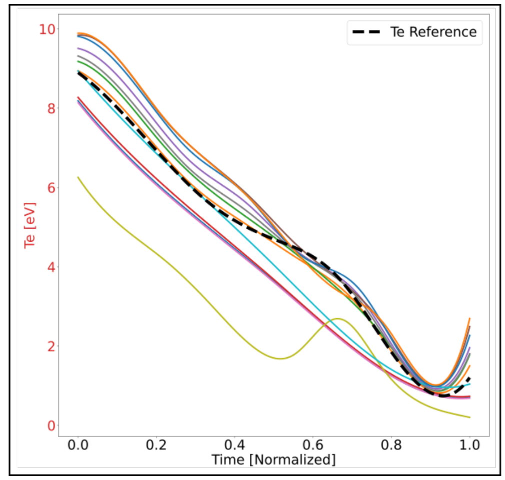


Fig. 4. *Electron temperature solutions obtained from smoothing the noisy input data in Fig. 3 using different techniques while varing parameters in the smoothing filters.*

In practice, in-situ measurements are noisy. White noise was added to the observations to test the robustness of our inverse technique. Figure 3 shows an example of the spacecraft potential with added noise, 7% of white-noise in this case. Since the technique performs exceptionally well with noise-free signals as input, the first obvious approach was to smooth the noisy observations using different filters with various filter parameters. Colored lines in Fig. 3 represent examples of smoothing the noisy spacecraft potential data (black dots) using the Gaussian-filter, Butterworth-filter and Gaussian Process Regressor techniques. Then, the inverse procedure is applied on the smooth data and the results are presented in Figure 4, which shows the estimation of the electron temperature as function of time. Note that nine colored curves are shown in Fig. 4 as a result of varying the filter parameters for each of the three techniques presented in Fig. 3. It can be seen in Fig. 4 that some of the solutions are close to the truth (black dashed line), while some have significant errors. Indeed, we were unable to find a robust approach to smooth the noise in the observations that would lead to consistently highly accuracy estimation of the parameters. These results led us to conclude that the technique is very sensitive to noise in the input data.

### C. Case III: statistical approach to overcome noise.

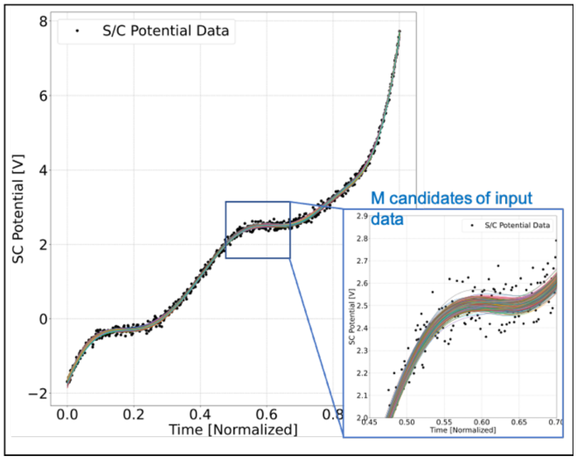


Fig. 5. *Ensemble of inputs generated from the noisy input data using the Gaussian Process Regressor technique.*

To overcome the negative impact of noise in the observations, instead of using a deterministic approach, we resorted to a probabilistic approach. The idea is to create an ensemble of input functions representing the noisy input data, whose probability distribution respects the mean and variance of the original data. For this part, we use the Gaussian Process Regressor (GPR, Rasmussen, 2006). With M functions of the input probability distribution, we solve M optimization problems and construct an ensemble of M solutions of the inverse technique and the related probability distribution. We found that the mean of the probability distribution of the solution ensemble allows one to statistically recover the parameter solution accurately. Figure 5 shows an example of the ensemble of inputs generated with GPR. Using the mean and the variance of the input data, GPR calculates the probability distribution over all admissible functions that fit the data.

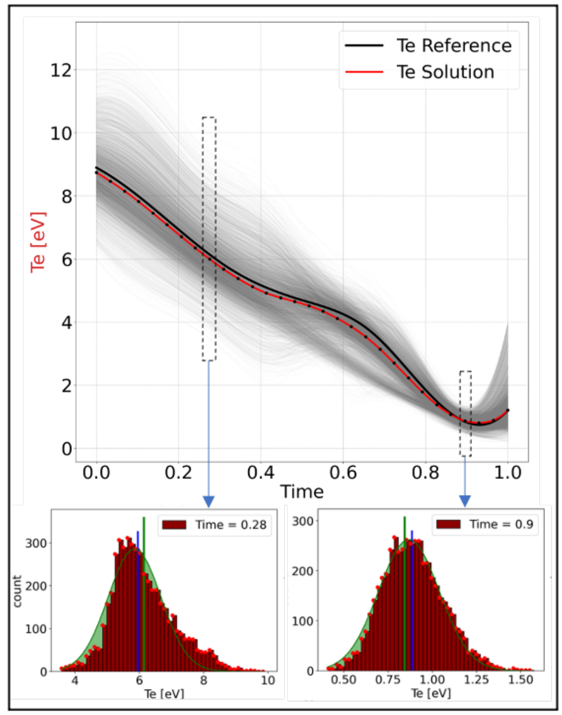


Fig. 6. *Solution ensemble for the electron temperature (top). The probability distributions at selected local times (bottom) follow a normal distribution which allows the computation of the electron temperature as a function of time (red line) by taking the mean of each of these distributions (black dots).*

Figure 6 shows the solution ensemble of the electron temperature as a function of time (grey lines). The red line (with black dots) is the solution computed as the mean of the solution ensemble at each local time. Examples of the probability distribution at two different local times are shown in the bottom row of Fig. 6, where one can appreciate that for these particular time values the probability distribution of the solution ensemble is well approximated by a normal distribution. We have determined that when the distributions follow a normal-type, the mean of the distribution is a good estimate of the parameter solution. This can be seen clearly in Fig. 6, where the reference solution for the $T_e$ (black line) are extremely close to each other. Indeed, the overall Root-Mean-Squared-Error (RMSE) is only 5%.

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*D. Results of 21 Synthetic Experiments*

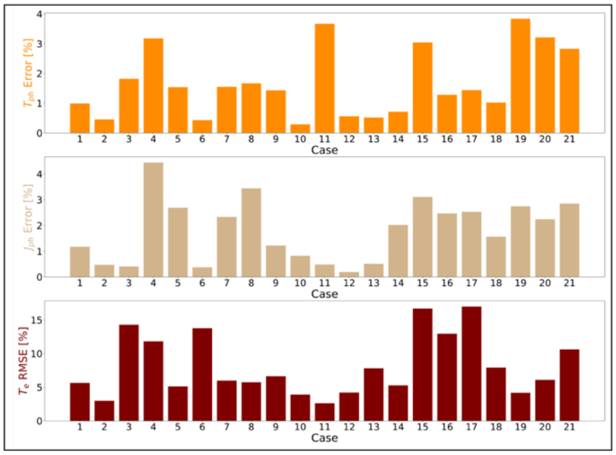


Fig. 7. *Computed errors of the parameters estimated by the inverse technique applied to twenty-one synthetic cases. Relative error is shown for the material parameters in the first and second row, while for the electron temperature as a function of time the Root-Mean-Squared-Error is reported in the bottom row.*

Using the approach described in section IIIC, we applied the inverse charging approach to twenty-one synthetic cases where the density and temperature (as a function of time) were varied in a specific range of parameters. Figure 7 shows the relative errors in the parameter estimation for all cases (the example treated in section IIIC is labelled as Case 1 in Fig. 7). The estimation of the material parameters was extremely accurate, with no more than 4% error across all cases. As for the electron temperature, the RMSE remains below 15% across all cases. Overall, the methodology presented here allows us to robustly overcome the noise in input data to recover the parameters consistently and with high accuracy.

## IV. Conclusions

We developed an inverse spacecraft surface charging technique to estimate material and some cold-plasma properties simultaneously. In this work we have explored it for a special charging situation in which a conducting spacecraft is positively charged in sunlight due to the balance between photoemission and the collection of cold electrons. The inverse technique is based on a statistical approach to overcome issues associated with noise in the input data.

Despite the proof-of-principle nature of this study, once matured this technique could have important scientific and practical applications. It enables a method to obtain some of the properties of the environment (i.e. the cold plasma populations) that are typically very hard to obtain. This is of particular interest to the magnetospheric cold-plasma community and it supports work towards new cold-plasma space missions that are currently being pursued. Another key aspect is that it delivers a new way to study material aging in space. This technique can aid on spacecraft anomaly resolution, since it gives the spacecraft a 'material identification card' which is a necessary ingredient in the forensic work to attribute anomalies to the space environment.

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