METHODS FOR QUANTITATIVE INTERPRETATION OF RETARDING FIELD ANALYZER DATA *

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Abstract

Over the course of the CesrTA program at Cornell, over 30 Retarding Field Analyzers (RFAs) have been installed in the CESR storage ring, and a great deal of data has been taken with them. These devices measure the local electron cloud density and energy distribution, and can be used to evaluate the efficacy of different cloud mitigation techniques. Obtaining a quantitative understanding of RFA data requires use of cloud simulation programs, as well as a detailed model of the detector itself. In a drift region, the RFA can be modeled by postprocessing the output of a simulation code, and one can obtain best fit values for important simulation parameters with a chi-square minimization method.

INTRODUCTION

An RFA provides a local measurement of the energy distribution of the electron cloud through the use of a retarding grid, to which a negative voltage can be applied. Electrons entering the detector will be repelled by the retarding field if they have less than a certain energy [1]. Electrons that make it past the retarding grid are captured by a collector, and the current is measured. Often the collectors will be segmented, allowing the RFA to sample the transverse structure of the cloud.

In principle, a single RFA voltage scan, in which data is collected while the retarding voltage is varied, gives a great deal of information about the local behavior of the electron cloud. In practice, however, it is a highly nontrivial task to map a data point from a voltage scan to any physical quantity, such as cloud density. Typically, this gap is bridged through the use of cloud simulation programs, which track the motion of cloud particles during and after the passage of a bunch train. This paper will deal primarily with results obtained from the code POSINST [2].

METHODOLOGY

The simplest method for simulating the output of an RFA for a given set of beam conditions is post-processing the output of a cloud simulation program. More specifically, these codes can output a file containing information on each macroparticle-wall collision, and one can perform a series of calculations on this output to determine what the RFA would have seen had one been present.

A basic postprocessing script does the following:

- Determine if the macroparticle has hit in the azimuthal region where one of the RFA collectors exists.
- Calculate an efficiency (probability of passing through the beam pipe hole) based on the incident angle and energy of the particle.
- Determine if the macroparticle has enough energy to make it past the retarding field.
- Deposit the appropriate amount of charge on the grid and collector.
- Do a "voltage scan" by repeating this process for several different values of retarding voltage

Note that by proceeding in this way one implicitly assumes that the presence of the RFA has no effect on the development of the cloud. This assumption is probably justified for a drift RFA, but may not be in the presence of a magnetic field [3]. This paper will focus on the drift case.

Bench measurements of RFA efficiency have shown an enhancement of the signal at low retarding voltage due to the production of low energy secondary electrons inside the beam pipe holes [4]. We have developed a specialized particle tracking simulation to quantify this effect. This is included in the analysis as an effective increase in the RFA efficiency at low retarding voltage. The resulting signals are consistent with the data, but we are currently doing more rigorous bench tests with an electron gun to cross-check the model.

SYSTEMATIC ANALYSIS

The sheer volume of RFA data obtained so far at CesrTA necessitates a systematic method for detailed analysis. The goal is, given a set of voltage scan data, to find a set of simulation parameters that bring data and simulation into as close to agreement as possible. The best fit parameters obtained from this method should be close to the real values for the material under study. The following method was employed to accomplish this:

1. Choose a set of voltage scan data, which should cover a wide range of beam conditions.
2. Choose a set of simulation parameters.
3. Do a simulation with the nominal values of each parameter.

* Work supported by the US National Science Foundation (PHY-0734867) and Department of Energy (DE-FC02-08ER41538)

4. Postprocess the output of the simulation to obtain a predicted RFA signal as a function of retarding voltage and collector number.
5. For each voltage scan and each parameter, do a simulation with a high and low value of the parameter, and determine the predicted RFA signals.
6. For each point in the simulated voltage scan, do a best linear fit to the curve of RFA signal vs parameter value. The slope of this line determines how strongly this point depends on the parameter.
7. Find a set of new parameters that should minimize the difference between data and simulation, assuming linear dependence of each voltage scan point on each parameter.
8. Repeat the process with this new set of parameters.

Choosing New Parameter Values

Step 7 above warrants further explanation. Suppose that you a trying to find the best fit values for n simulation parameters. From all the voltage scan data you have simulated, choose m data points (where $m > n$), preferably points which have a strong dependence on the value of one parameter. Then construct a vector $\mathbf{y}$, of length m, which is the difference between the data and nominal simulation at the points you have chosen, and a m x n matrix $\mathbf{X}$, which is the slope of each simulation point in each parameter (step 6 above). Finally you need a weighting matrix $\mathbf{W}$, which is a m x m diagonal matrix whose elements are $\frac{1}{\sigma_i^2}$. Here σ_i is the quadrature sum of the statistical error in your data and simulation at point i ($\sigma_i^2 = \sigma_{data,i}^2 + \sigma_{sim,i}^2$). In order to obtain the best fit values for our parameters, we minimize χ^2, as defined in equation 1. The vector β (the *change* in the n parameters) which will accomplish this is given by equation 2.

$$\chi^2 = (\mathbf{y} - \mathbf{X}\,\beta)^T\,\mathbf{W}\,(\mathbf{y} - \mathbf{X}\,\beta) \quad (1)$$

$$\beta = (\mathbf{X}^T\,\mathbf{W}\,\mathbf{X})^{-1}\,\mathbf{X}^T\,\mathbf{W}\,\mathbf{y} \quad (2)$$

Note that $\mathbf{A}^T$ and $\mathbf{A}^{-1}$ denote the transpose and inverse of matrix $\mathbf{A}$, respectively.

Important Parameters

There are many parameters that characterize the production of secondary electrons in POSINST [2], but a few stand out as being especially important. Among them are:

- **dtspk**, the peak true secondary electron yield
- **P1epk**, the low energy elastic yield
- **P1rinf**, the rediffused yield at infinity
- **E0epk**, the energy at which peak secondary production occurs

In general, primary photoelectrons are less well understood than secondary electrons. Some important primary emission parameters include:

- **queffp**, the quantum efficiency
- **ek0phel** and **eksigphel**, the peak energy and width of the photoelectron energy distribution (see discussion below)
- **refleff**, the photon reflectivity (again, see below)

We have found that in order to have any RFA signal for a high current electron beam, one needs to produce some high energy photoelectrons. Currently this is accomplished by using a Lorentzian photoelectron energy distribution (rather than the default Gaussian distribution), with a low peak energy ($\sim$ 5eV), but a large width ($\sim$ 150 eV). However, the drift RFA data does not seem to constrain the exact shape of the high energy portion of the distribution. Measurements with a shielded pickup detector provide a method to probe this parameter in more detail [5].

The photon flux and reflectivity at the RFA are fixed, based on a 3 dimensional simulation of photon production and reflection in the CesrTA vacuum chamber [6]. Photoelectron parameters were allowed to be different for electron and positron beam data, because the photon energy spectrum at any given location in CESR will be different for the two species. Plans are underway to develop a model for photoelectron production which takes into account the energy of the incident photon.

The analysis is further complicated by the fact that these parameters can be strongly correlated with each other. Fortunately, the CesrTA program has allowed for RFA data to be taken under a wide variety of beam conditions, which is helpful for separating the effect of each simulation parameter. For example, data taken with high beam currents and short bunch spacing tend to depend strongly on the true secondary yield, while for widely spaced bunches the quantum efficiency and photoelectron energy distribution are the most important parameters [7].

Calculating Errors

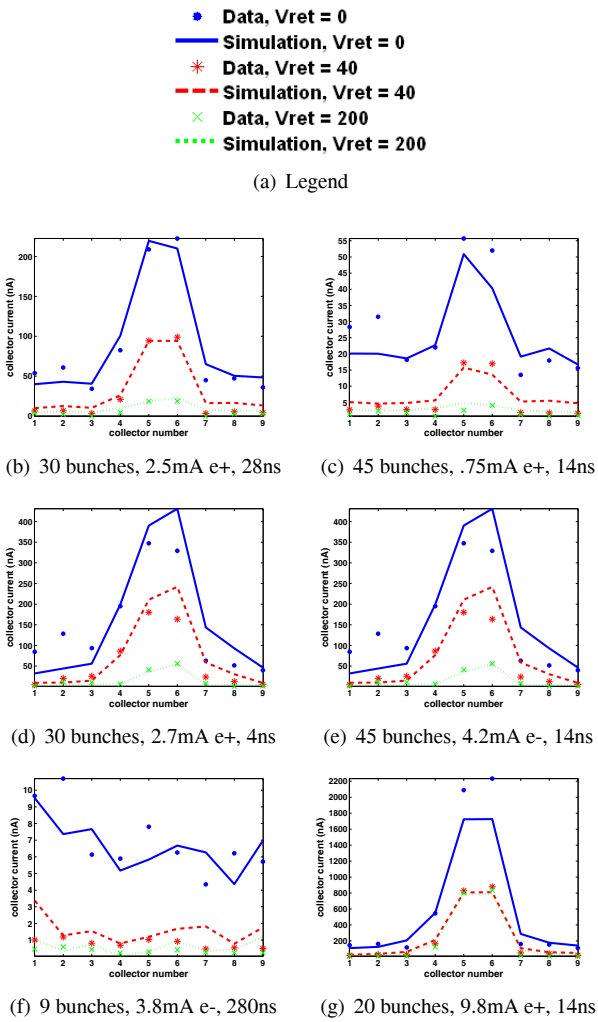
One of the advantages of using a matrix method to obtain new parameter values is that errors are readily obtainable during the course of the analysis. The covariance matrix for the parameters is $(\mathbf{X}^T\,\mathbf{W}\,\mathbf{X})^{-1}$. Errors on each parameter can be derived from the diagonal elements of the covariance matrix, and the correlations between each parameter from the off-diagonal elements.

It should be noted that this analysis may only find a local minimum (as opposed to a global minimum, the true best fit values) if one starts off too far from the real values. To check this, several different starting points in parameter space were tried, some of which did not converge to the same final parameters. The best fit values given below are those which resulted in the smallest difference between data and simulation, in a least squared sense. The quoted errors should be understood as the width of this local minimum.

RESULTS

Fig. 1 shows the results of the parameter finding method for a TiN coated drift chamber. The plots compare the data and simulation for the signal across the 9 RFA collectors at three different retarding voltages. Overall there is good agreement between data and simulation for a wide variety of beam conditions. Note that for CESR, 1mA = 1.6×10^{10} particles.

The best fit values and confidence regions for significant parameters are shown in Tables 1 (for an uncoated Aluminum chamber) and 2 (for TiN and amorphous Carbon coated chambers). It is worth noting that this analysis indicates a low true secondary yield for both coated chambers, as well as a *very* low elastic yield. This is consistent with results obtained from shielded pickup measurements [5]. Meanwhile, the best fit values for the rediffused yield and quantum efficiency did not differ much from the nominal values.



(a) Legend

(b) 30 bunches, 2.5mA e+, 28ns

(c) 45 bunches, .75mA e+, 14ns

(d) 30 bunches, 2.7mA e+, 4ns

(e) 45 bunches, 4.2mA e-, 14ns

(f) 9 bunches, 3.8mA e-, 280ns

(g) 20 bunches, 9.8mA e+, 14ns

Figure 1: Results of parameter finding method for a TiN coated drift chamber. Beam energy is 5.3 GeV.

Table 1: Best Fit Parameters — Aluminum Chamber

Parameter	Nominal Value	Best Fit Value
dtspk	1.8	$2.2 \pm .1$
P1epk	.5	$.42 \pm .03$
P1rinf	.2	$.20 \pm .02$
E0epk	310	334 ± 20
queffp	.1	$.10 \pm .02$

Table 2: Best Fit Parameters — Coated Chambers

Parameter	Nominal	Best Fit- TiN	Best Fit- C
dtspk	.8	$.59 \pm .02$	$.64 \pm .04$
P1epk	.5	$.040 \pm .002$	$.049 \pm .007$
P1rinf	.2	$.20 \pm .01$	$.17 \pm .02$
E0epk	500	500 ± 30	410 ± 60
queffp	.1	$.090 \pm .006$	$.08 \pm .01$

CONCLUSIONS

A systematic method has been used to improve agreement between RFA data and simulation, and best fit simulation parameters have been obtained. This method has generally been successful in fitting the data well, but the uniqueness of the best fit parameters remains an open question. A great deal of work remains to be done, including:

- Repeating the analysis for other surface types
- Continuing work on quantifying errors and correlations in the parameters
- Repeating the analysis for RFAs in magnetic fields, including dipoles, quadrupoles, and wigglers
- Comparing with other local cloud measurements, such as shielded pickups
- Incorporating a more complete description of photoelectron emission

If successful, the end result of this analysis will be a detailed and self-consistent description of the in situ primary and secondary emission properties of the materials under investigation.

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