Machine Learning-Based Optimization of Dose Uniformity for Ion Implantation Systems

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Spatial dose non-uniformity is a key variation of concern in ion implantation. As the ion beam shape and intensity changes as the beam is swept across the wafer (Fig. 1) [1], non-uniform implantation arises when the beam is swept at a constant speed (Fig. 2). Effectively and efficiently compensating for these variations can reduce tool downtime, improve uniformity, and expand the range of feasible recipes.

Here, we present a Bayesian machine learning [2] method for rapidly tuning ion implant processes to compensate for these variations. Our approach adjusts the beam time spent at each point on the wafer, T, in order to achieve a desired implant dose profile, I. This approach is comprised of two components: a model that estimates the relationship between I and T, and an optimization component that uses this belief to solve for a set of beam times that minimizes non-uniformity. When tuning a process, we alternate between selecting new implant times using the current belief, then updating the belief with the observed results, until the beam times give sufficient uniformity.

We assume that the relationship between T and I is linear: scaling the implant time results in a scaled implant profile. The dose profile I is thus a product of the beam times, T, spent above each point on the wafer and the beam shapes, B:

$$I = BT.$$

The task of modeling the relationship between I and T is thus equivalent to estimating B (Fig. 3). We use a method similar to Kalman filters [3] to estimate the unknown variable B. We model B as a multivariate Gaussian random variable expressing our belief in the possible model parameters, and update this belief as new observation pairs, I, T are made:

$$P(B|I,T) \propto P(I|B,T)P(B).$$

We then use this belief in order to select a new set of beam times that seek to achieve our desired profile, I_d. We frame this as a constrained optimization problem:

$$\min \sum (BT - I_d)^2 + \lambda \sum (T_{i-1} - 2T_i + T_{i+1})^2$$
$$s.t. \quad T_{min} \le T_i \le T_{max} \;\; \forall i \in 1{:}|T|$$

This cost function minimizes the mean squared error between the predicted and desired dose profile, with an additional penalty related to the spatial smoothness of T. This smoothness term prevents overfitting to our current belief, and gives solutions which are less susceptible to run to run variations. Finally, T_{min} and T_{max} constraints ensure that the solution meets the physical constraints of the tool.

We compare our proposed method to the existing industry method of record for recipe tuning. We consider edge-case conditions of very wide, very low energy beams where typical industry methods have difficulty achieving high degrees of uniformity. We alternate tuning using our proposed method and the existing method of record, and report results below.

A key metric of interest is the number of tunes required in order to achieve a desired non-uniformity (NU, expressed as dose standard deviation divided by dose mean). Reducing this metric reduces tool downtime required for re-tuning. We record the number of iterations required to converge to 0.5% NU. On average, our proposed method converges in 2.2 iterations, while the existing industry method of record converges in 4.3 iterations. We present histograms showing the number of required iterations for both methods in Fig. 4, and show an example tune for our proposed method in Fig. 5.

In addition to tuning in fewer iterations, our proposed method also enabled a significantly higher implant current, given the same uniformity and total implant time constraints for this recipe (Fig. 6). Practically, this is enormously beneficial, as it allows the same implantation recipe to be performed in less time, increasing the subsequent per-implant tool throughput by a similar amount.

A further benefit of our proposed method is its high tuning success rate. For recipes with extreme variations, the existing industry method of record may fail to converge to the desired non-uniformity. In testing, the method of record failed in 2 out of 27 cases (such failures require a lengthy tool reset), while our proposed method converged in 100% of cases, thus substantially reducing tool downtime and extending process recipe range in addition to reducing tuning time.

[1] L. A. Larson, J. M. Williams, and M. I. Current, “Ion implantation for semiconductor doping and materials modification,” Rev. Accel. Sci. Technol. Accel. Appl. Ind. Environ., pp. 11–40, 2012.

[2] P. I. Frazier, “A tutorial on Bayesian optimization,” arXiv1807.02811, 2018.

[3] G. Welch, and G. Bishop, “An introduction to the Kalman filter,” 1995.

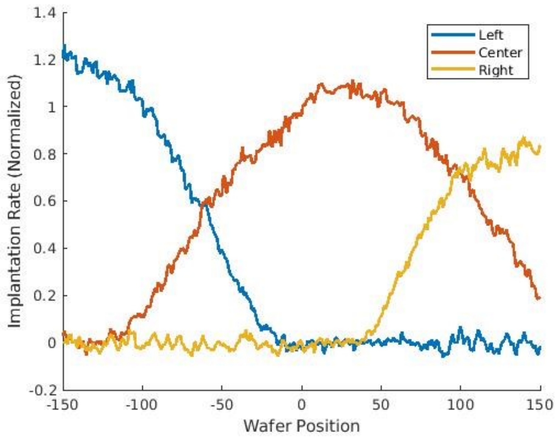

Fig. 1: Experimentally measured implant rate cross sections when the beam is placed at three different wafer locations. Note the change in intensity as the beam location changes.

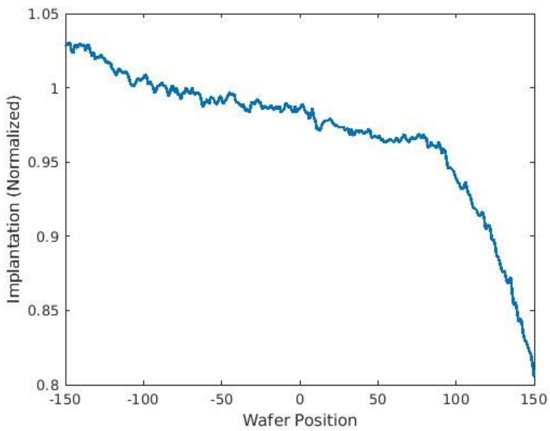

Fig. 2: Cross section of implant dose profile (normalized) when sweeping the beam at a constant speed.

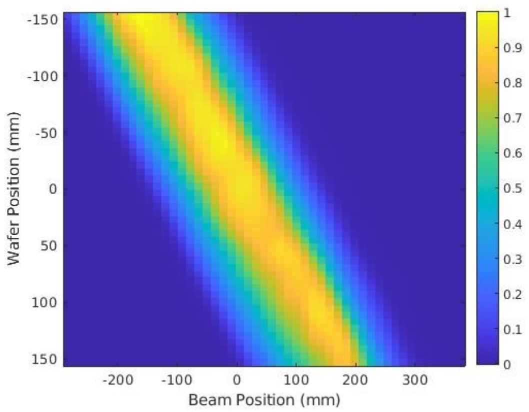

Fig. 3: Inferred beam matrix, B, (normalized), that shows the implant rates as a function of the beam placement, and wafer position.

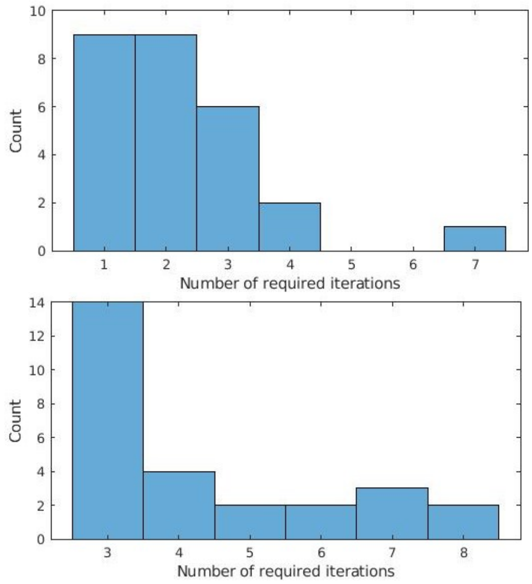

Fig. 4: Histogram of number of iterations required to achieve 0.5% non-uniformity in proposed method (top) and existing industry method of record (bottom).

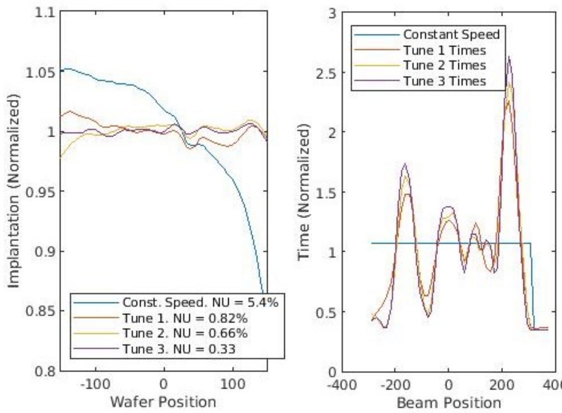

Figure 5: Implant dose (left) and corresponding beam times (right) for an example tuning run.

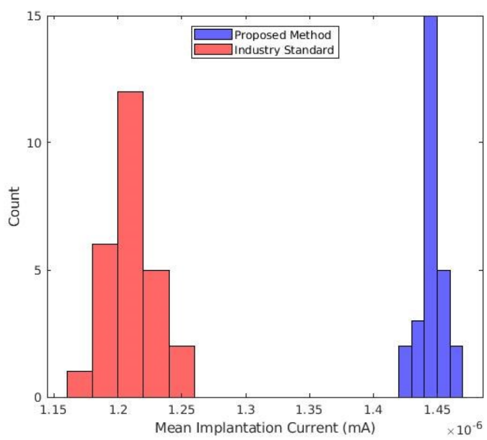

Figure 6: Histogram of mean implant current for proposed and existing industry solutions.