Control of Manufacturing Variations in Emitter Resistivity to Increase PERC Solar Cell Performance

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ABSTRACT

As wafer material feedstock and general processing conditions improve in PV manufacturing, the emitter region of the solar cell makes an increasingly dominant contribution to overall device recombination. This is particularly the case in high-efficiency cells designs such as PERC. These recombination effects act in addition to the process “trade-offs” that have been commonly associated with the emitter properties for some time – most notably device resistance, contact resistance, parasitic absorption of short wavelength light, shielding of carriers from the surface and gettering of the bulk. Due to these many influences, and the tendency for their interaction to vary over time, even on any one production line, it is important to monitor and optimise emitter properties for final device performance. Furthermore, when the emitter properties are continuously monitored, it becomes possible to implement cost-optimised control strategies for the diffusion process. This study presents emitter resistivity data paired with common end-of-line IV data from a high-efficiency PERC manufacturing facility. In the study, we found that emitter fabrication process variations contributed to up to 77 percent of the I-V parameter variations. This demonstrates the large contribution of variations in emitter resistivity to device performance and overall variance in PERC production.

INTRODUCTION

As PV manufacturing approaches the terawatt scale over the coming years, it will become increasingly important for PV manufacturers to adopt the more rigorous process analytics and control strategies in common use in other mature manufacturing industries [1,2], as well as developing their own new approaches. This change in the way PV manufacturing is executed is an example of the “Industry 4.0” revolution for “smart manufacturing” originating in Germany [3]. The Chinese government in particular has a strong agenda to transform its industries using Industry 4.0 approaches with the “Made in China 2025” strategy [4-5].

There are, as yet, only limited works in the public domain that present and describe analytical techniques specifically associated with PV manufacturing [6-11]. The present study, using in-line manufacturing data from a high efficiency PERC production line, quantitatively shows how to optimise and control the manufacturing process with regard to the PV cell emitter properties. The resulting information provides the means to achieve absolute gains in cell efficiency.

Process measurement and analysis are also important for improving product quality. Quality is a measure of a manufacturer’s capability to consistently make the same product, item by item, based on a given design specification [12-14]; and then to improve this design over time. If PV manufacturing follows the trends of other medium to high value manufacturing sectors, then one of the main ways manufacturers will differentiate themselves in the future is on the basis of product quality [15]. Improving quality will confer many benefits to a manufacturer and its customers. On the manufacturers’ side, it will result in tighter performance distributions, improved yields, and accelerated progress for continuous improvement [16]. These factors will also reduce a manufacturer’s warranty liabilities. Furthermore, improved quality can streamline the product range and logistics down to the level of field installations [17]. From an installation perspective, improved quality and consistency between modules will improve energy yield as a system ages [18].

DATA SET

The data used in this study is from 1200 cells made on a high efficiency PERC manufacturing line. The data includes end-of-line IV data, emitter resistivity after diffusion and wafer resistivity at the start of production. Data was collected from a set of 1200 wafers consisting of 200 wafers processed together on one day of the week for 6 weeks, to capture variation in production over a long period of time. Data is shown normalised and unscaled for commercial privacy.

RESULTS

Data Trends and Process Optimisation

Figure 1 shows the common cell performance parameters as a function of the emitter resistivity data. A quadratic fit to the data shows a local optimum in the performance. V_{oc} and I_{sc} initially increase with increasing emitter resistivity, countered by the FF going down due mostly to increasing series resistance. V_{oc} and I_{sc} start to drop for high emitter resistivity, which results in a local optimum for the efficiency.

Figure 2 shows just the V_{oc} and I_{sc} data, this time split by the six processing batches. This shows that the range of sheet resistivity is relatively narrow within any given batch, but also the relationships to the V_{oc} and I_{sc} is quite different in different batches. The apparent quadratic relationship in the overall data entirely arises due to the data in one particular batch (blue dots). Figure 3 is a repeat of Figure 2, but using an Exponentially Weighted Moving Average (EWMA) [19] calculation to more clearly visualise the process average state. This averaged “process state” data clearly shows the improvement to V_{oc} and I_{sc} continuing into the high range emitter resistivity values, on some of the batches. The blue and red batches have a softer trend between the Voc and emitter resistivity, with a few high emitter resistivity samples performing quite anomalously. For these batches, the I_{sc} / emitter resistivity trend is virtually non-existent, with the overall I_{sc} much lower. Figure 4 shows the I_{sc} / V_{oc} relationship, also using EWMA data. The mutual relationship to lifetime is expected to dominate this interaction [9]. Of particular interest, the samples from the blue and red batches clearly belong to a different distribution. This means the optimal emitter fabrication process conditions vary over time, and in unexpected ways, and therefore they need to be continually monitored and controlled. The implications of this are further discussed later in this document.

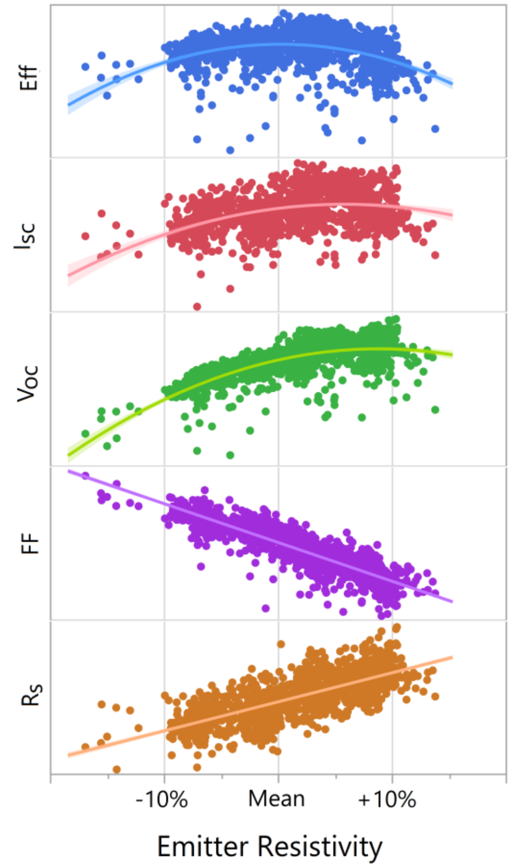

Figure 1: End-of-line data for the series resistance (R_s), fill factor (FF), open circuit voltage (V_{oc}), short circuit current (I_{sc}) and efficiency (Eff) as a function of emitter resistivity. Quadratic or linear line-of-best fit also shown.

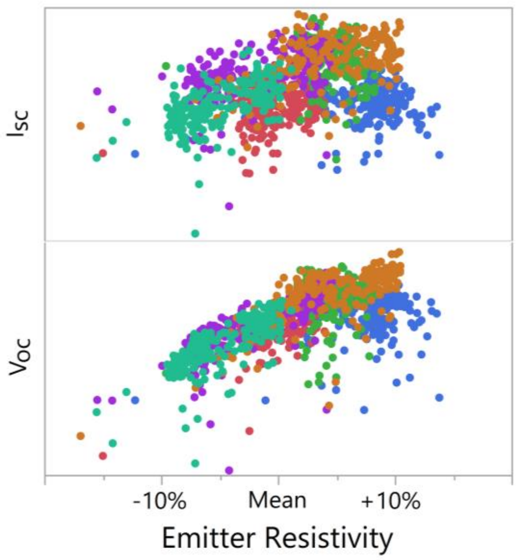

Figure 2: The V_{oc} and I_{sc} data as a function of emitter resistivity, with each of the 6 processing batches represented by a different colour.

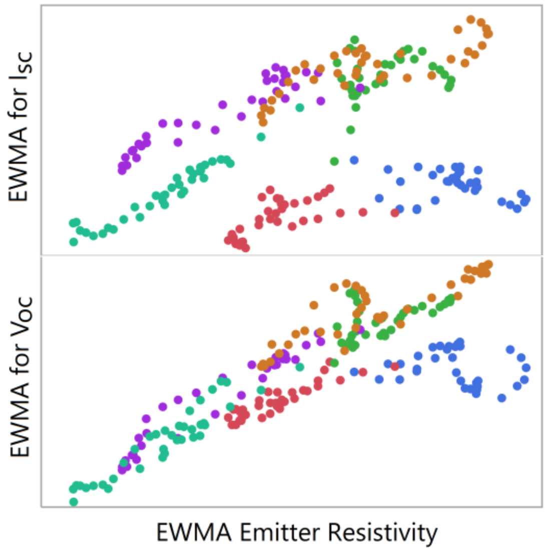

Figure 3: The EWMA data for V_{oc} and I_{sc} data as a function of emitter resistivity, with each of the 6 processing batches represented by a different colour. EWMA data is a good representation of the process average state through each of the batches. Trends are more evident in this data.

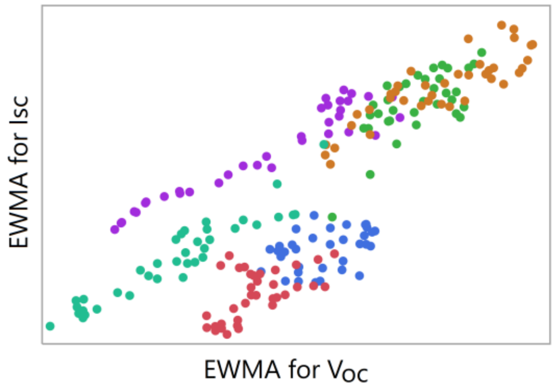

Figure 4: The EWMA data for I_{sc} vs V_{oc}. The dominant trend in this data set is related to material lifetime. The red and blue batches belong to a different distribution. Together with Figure 3, this is most likely to be due to lower I_{sc}.

Optimised Control

Ideally it would be best to tighten the control for the sheet resistivity so that the distribution is more tightly concentrated around the optimal value – the value which results in the highest average efficiency. In this case, that is close to the mean value for the emitter resistivity. This is not always practical or cost effective, so it is useful to quantify the improvements that arise as a function of moving the control limits – i.e. the limits within which the processes should be operating 99% of the time [19]. Figure 5 shows the relative improvement to mean efficiency that could be expected as a function of tightened control limits. It then becomes the role of the individual manufacturing lines to decide which improvements are cost effective based on immediate efficiency gains. Note, however, that other benefits will arise from improved control as previously mentioned. The benefits of these improvements should also be taken into account, but they typically require further investigation to estimate.

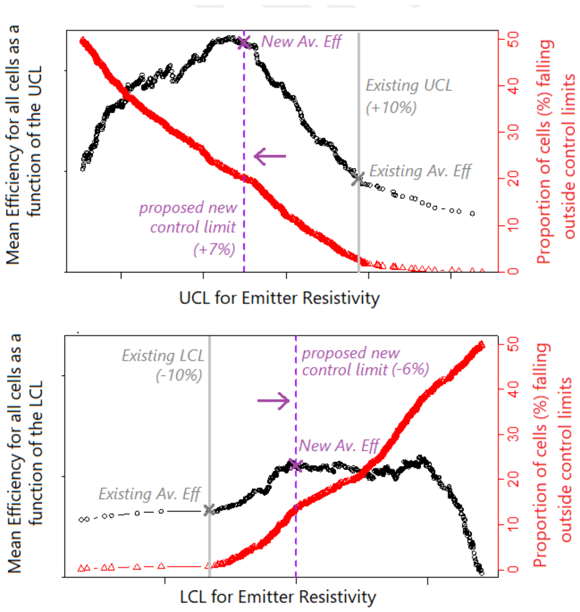

Figure 5: Average efficiency (black points) that could be expected as a function of tightened upper (UCL) and lower (LCL) control limits. The red points show how many samples fall outside of this limit in the existing dataset and represents how challenging it would be to improve the control. Grey lines show existing control limits and dashed purple lines represent a proposed optimised control limit – the most efficiency gain for the smallest change in control limits.

Variance Components

As quality manufacturing is mostly concerned with consistency [11-13], understanding the sources of variance in production becomes very important for achieving high quality. Numerous techniques can be used to calculate variance components [11]. In this case, owing to the relative dominance of emitter resistivity, the variance components were estimated with linear modelling and commonality analysis [11, 20]. The results are shown in Table 1.

Table 1: Contributions of the variation in emitter resistivity to variance in the end-of-line I-V parameters.

End-of-line parameter	Amount of variance in the end-of-line parameter related to Emitter Resistivity
V_{oc}	55%
I_{sc}	23%
FF	77%
R_s	49%

DISCUSSION

The analyses quantitatively demonstrate that variations in the emitter fabrication process are a dominant source of variance in the end-of-line performance. An increasing emitter resistivity will most likely initially increase V_{oc} and I_{sc}, due to a reduced emitter region contribution to recombination. This is offset against an increasing R_s that causes the FF to decrease. There are also components of enhanced recombination in the emitter / FF relationship that can be extracted with further analysis, and the opportunity to moderate the resistive impact with the design of the contacting grid which collects the electricity from the cell.

The initial analysis also suggested that the V_{oc} and I_{sc} start to decrease at high values of the emitter resistivity. This could be due to the doping being insufficient for shielding minority carriers from recombination at the front surface [21]. But Figures 2 to 4 suggest a more complex batch-related interaction. The two unusual batches are characterised by a softer V_{oc} / emitter resistivity trend, and an overall lower Isc, with nearly no I_{sc} / emitter resistivity trend. The series resistance data also shows some anomalous behaviour with many cells with a lower resistance than expected for the given emitter resistivity (not shown). Cell performance models can be used to test and eliminate different theories as to the causation of these interaction. It is unlikely to be explained by overall poorer wafer material quality. It could be an interaction between the emitter process and the material type. It could be explained by a different emitter profile – most notably, a process with a high surface doping concentration but same overall dose could reasonably cause the effects observed.

This data set does show that the interaction between the diffusion process and the final performance is relatively complex. It can change over time, between different input material and possible different process tools. Ongoing monitoring is therefore important for controlling production. In this data set, the control range needs to account for the existence of the anomalous red and blue batches. At the same time the data can be used to better understand these batches, so they can be eliminated to improve overall performance. As these improvements are made, the analysis here also shows how to monitor the control limits for the diffusion process on an ongoing basis. Small improvements to the efficiency can be derived on an ongoing basis by optimising the control of the emitter resistivity.

CONCLUSIONS

A data set collected from a high efficiency PERC manufacturing line has been used to highlight three important issues. Firstly, the emitter resistivity data can be used on a continuous basis to optimise the manufacturing process and improve the efficiency. Secondly, the emitter resistivity is a significant source of overall variance and controlling it is important for product quality. Thirdly, the process relationships and optimal process conditions change on a continual basis, and continual monitoring is important for achieving optimal outcomes for cell efficiency and process quality.

Leading manufacturers today make over a million cells a day, and in the future, this will likely be tens of millions of cells a day. Manufacturers will need measurement tools and analysis techniques to have confidence in the consistency of operations of this scale. This will become more important as the industry matures, and pure technology differentiation further diminishes. History has shown manufacturers will then start to differentiate on factors related to manufacturing execution, most notably quality. The Industry 4.0 approaches that are being embraced and encouraged by the Chinese Government are well suited to meeting these challenges. This includes better use of metrology, data platforms and analytics, and a focus on quality in general.

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