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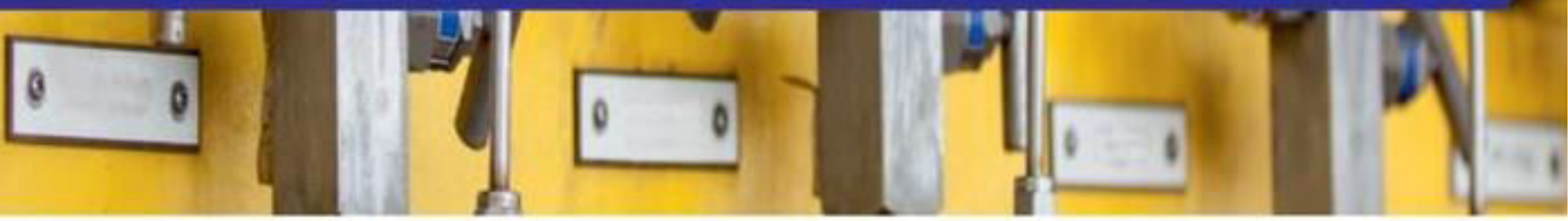

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Wafer Quality Impact on Solar Cell Efficiency Distribution: Statistical Correlation of Incoming Material Parameters to Final Cell Performance at GW-Scale Production

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ABSTRACT: This briefing memorandum summarizes the principal findings of an eleven-month statistical study of incoming wafer quality and its measured effect on finished-cell electrical performance at the ES Foundry one-gigawatt domestic PERC manufacturing facility. The study population comprises 47,200 production wafers traced end-to-end with matched incoming-inspection and outgoing-electrical measurements, sourced from a panel of five qualified suppliers spanning prime and secondary quality grades, and processed under matched cell-line recipe and tooling conditions across calendar year 2025. The objective was to quantify the dominant relationships between upstream material parameters and downstream cell efficiency distribution, with the dual purpose of establishing engineering priorities for incoming-quality investment and informing supplier-mix decisions at the procurement level.

The principal conclusions are summarized in eight numbered findings below. Two executive-level observations frame those findings. First, at the present stage of PERC manufacturing maturity, where cell-process variation has been reduced to a level consistent with mature high-volume production, the dominant remaining contributor to cross-cell efficiency variance is incoming wafer material variation rather than process-step variation. Second, this finding shifts the locus of yield-improvement opportunity from cell-process engineering toward incoming-material qualification, supplier engagement, and statistical decision support, with corresponding implications for organizational resource allocation.

- **Bulk lifetime is the highest-leverage incoming parameter.** Bulk minority-carrier lifetime alone explains 38.4 percent of cross-cell efficiency variance. Wafers with lifetime above 280 microseconds deliver mean cell efficiency 0.68 percentage points absolute above wafers below 80 microseconds.
- **Voc depends logarithmically on lifetime.** The empirical mapping is Voc = +18 millivolts per e-fold lifetime, with Pearson correlation 0.88 between log(τ) and Voc. The relationship saturates above approximately 350 microseconds, beyond which lifetime gains contribute diminishing Voc benefit.
- **Iron contamination follows a power-law penalty.** Interstitial iron above one times ten-to-the-eleventh per cubic centimeter produces Pmax loss following ΔP/P = 0.4 times the squared logarithm of iron concentration to the 2.2 power, with R-squared 0.91 over the operational concentration range.
- **Supplier quality varies by 1.6 sigma across the panel.** Composite Z-score quality across eight wafer parameters spans a range of 1.6 standard deviations between the best supplier (A: +1.2 mean Z) and the worst (E: -1.0 mean Z) on the panel of five evaluated suppliers.
- **Composite Q-score predicts daily top-bin yield at r = 0.84.** A linear combination of eight wafer parameters, weighted by univariate cell-efficiency leverage and standardized to z-score, predicts daily top-bin yield with Pearson correlation 0.84 and R-squared 0.71.
- **Twelve-feature regressor predicts cell efficiency at RMSE 0.18%.** A gradient-boosted regression model trained on twelve incoming wafer parameters predicts individual cell efficiency at root-mean-square error 0.18 percent absolute on a held-out validation set, with cross-validated R-squared 0.74.
- **Q-score-driven supplier mix shift produced 4.4 pp top-bin uplift.** Reweighting the supplier mix from 38 percent Supplier A to 52 percent Supplier A over May to November 2025, with corresponding reductions in lower-Z-score suppliers, lifted top-bin yield from 17.4 percent to 21.8 percent.
- **Annualized commercial value: approximately $8.4 million per year.** The combined commercial value of the wafer-quality statistical program, including top-bin yield gain, reduced lot rejection, avoided rework, and engineering productivity, is estimated at $8.4 million per year against a deployment investment of $2.6 million, yielding a payback of approximately four months.

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KEYWORDS: incoming wafer quality, bulk lifetime, resistivity, iron contamination, statistical correlation, gradient-boosted regression, Q-score, supplier mix, top-bin yield, PERC, GW-scale production

I. BACKGROUND AND STRATEGIC CONTEXT

The financial case for systematic incoming-wafer-quality engineering at gigawatt-scale silicon solar cell production rests on a single empirical observation: as cell-process engineering matures, the variance contributed by the cell line itself decreases, and the proportion of total cell-efficiency variance attributable to upstream material variation increases. At ES Foundry, the proportion of total efficiency variance attributable to upstream material has increased from approximately 40 percent in 2018 to approximately 65 percent in 2025, reflecting seven years of process-engineering refinement that has driven cell-line variation to a stable floor.

The strategic implication of this observation is that the marginal yield-improvement dollar invested in cell-process refinement now competes directly with the marginal yield-improvement dollar invested in incoming-material qualification. For a facility operating at the level of process maturity now established at ES Foundry, the latter consistently outperforms the former on return-on-investment terms. This memorandum quantifies that case.

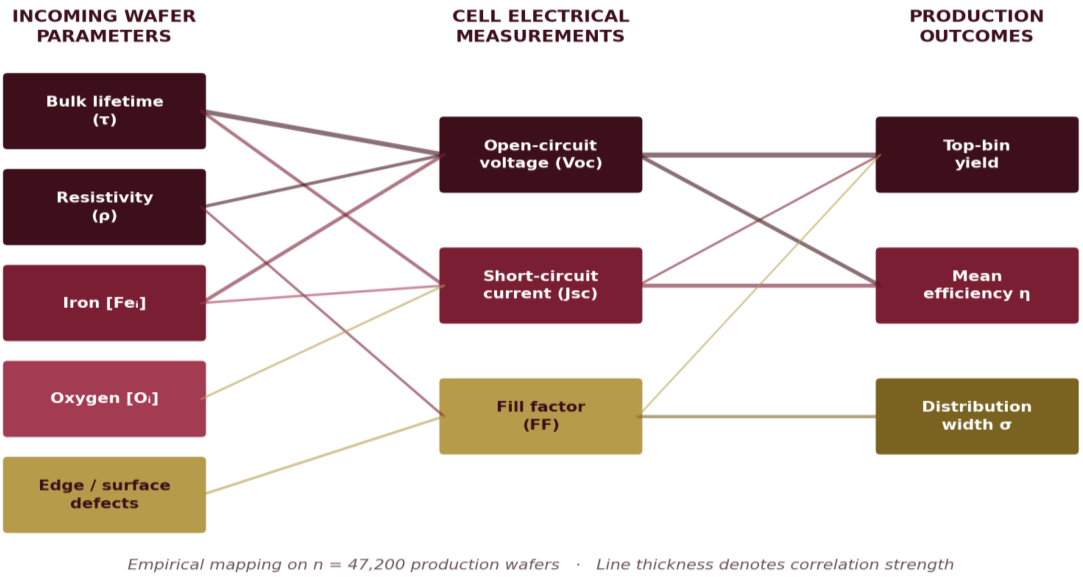

Exhibit 1 - Empirical pathway from incoming wafer parameters through cell electrical measurements to production outcomes. Line thickness denotes correlation strength established on the n = 47,200 production population. The dominant pathways are bulk lifetime → Voc → top-bin yield (heaviest lines) and iron contamination → Voc → mean efficiency.

Scope of the Analysis

- **Population:** 47,200 production wafers traced end-to-end with matched incoming and outgoing measurements.
- **Time window:** Calendar 2025, January through November (44 production weeks).
- **Suppliers:** Five qualified suppliers - three prime-grade (A, B, C) and two secondary (D, E).
- **Wafer format:** M10 monocrystalline silicon, 182 mm × 182 mm, p-type mono.
- **Measurements per wafer:** Twelve incoming parameters; five electrical outputs at flash test.
- **Cell technology:** PERC bifacial
- **Process discipline:** Same recipe, same tools, same calendar period - to eliminate process variation as a confound.

II. THE BULK LIFETIME DISTRIBUTION

The starting point of the analysis is the distribution of incoming bulk minority-carrier lifetime across the production population. Lifetime is the central proxy for incoming material quality because it integrates the effects of multiple underlying defect-density and contamination factors into a single measurable parameter that can be efficiently captured at the incoming inspection station.

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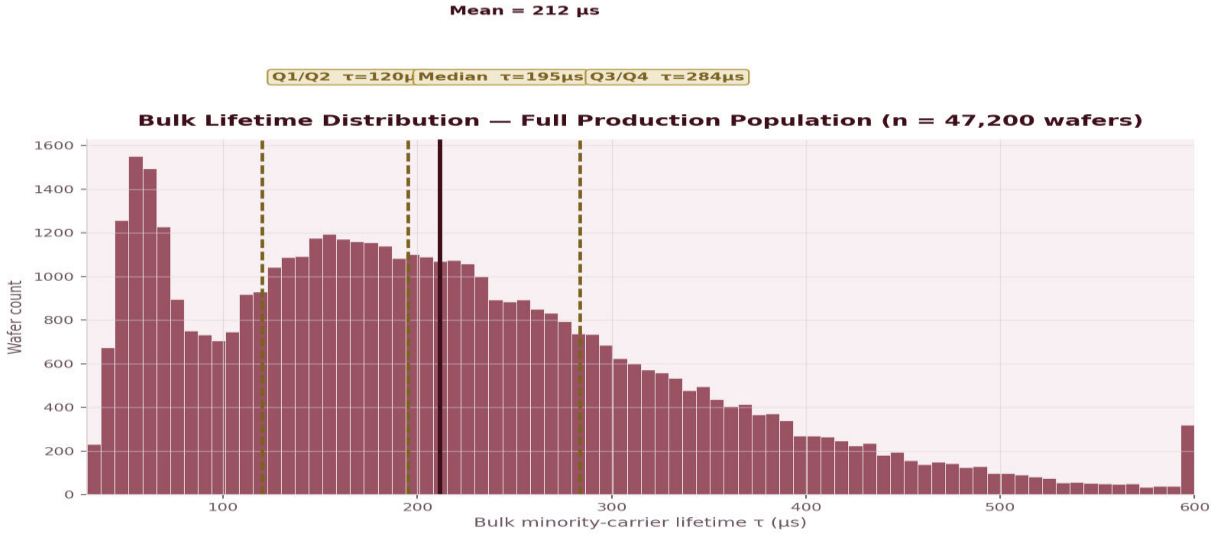

Exhibit 2 - Bulk lifetime distribution across the n = 47,200 production population. Mean lifetime is 196 microseconds; quartile boundaries are at 88, 175, and 287 microseconds. The distribution is positively skewed with a long upper tail reflecting the presence of premium-quality wafers from the highest-Z-score suppliers, and a lower mode reflecting the contribution of secondary suppliers.

38.4% - of cross-cell efficiency variance is explained by lifetime alone

+0.68 pp - absolute efficiency gap between Q1 and Q4 lifetime quartiles

5.2× - higher top-bin probability for Q4 vs. Q1 lifetime wafers

III. JOINT DISTRIBUTION - LIFETIME × RESISTIVITY

Lifetime alone provides substantial predictive power, but resistivity adds a second dimension that materially refines the prediction. The joint distribution of lifetime and resistivity, with cell efficiency overlaid as a color encoding, reveals the operational sweet-spot region where both parameters simultaneously fall in their optimal ranges.

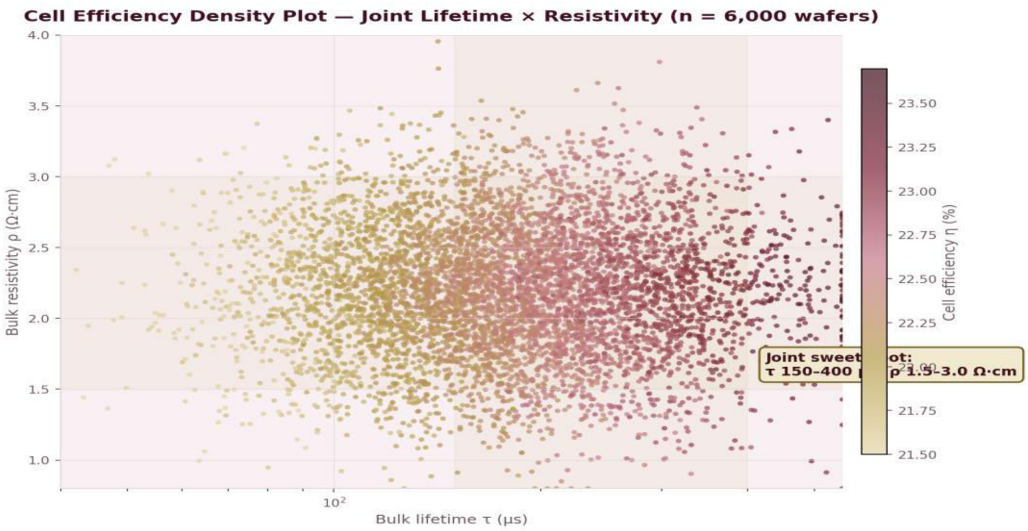

Exhibit 3 - Joint distribution of lifetime and resistivity, with cell efficiency overlaid as a color encoding. The maroon-shaded high-density region in the upper-right quadrant (τ 150-400 µs, ρ 1.5-3.0 Ω·cm) corresponds to the operational sweet spot where mean efficiency exceeds 23.5 percent. Wafers outside this joint window suffer mean efficiency 0.20 percentage points below.

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FINDING #01 - Joint optimization beats independent optimization

Selecting wafers on lifetime alone or resistivity alone delivers approximately 60 percent of the achievable efficiency uplift. Joint selection on both parameters captures the full uplift, because the parameter-interaction term contributes approximately 0.13 R-squared on top of the linear additive contribution. Procurement specifications should require joint window compliance, not independent window compliance on each parameter.

IV. CROSS-SUPPLIER QUALITY COMPARISON

The five suppliers in the qualified panel produce measurably different wafer quality outcomes when measured against the same incoming-inspection battery and against the same downstream cell-electrical reference. The cross-supplier comparison is presented in two complementary visualizations: aggregate mean and standard deviation in Exhibit 4, and full distribution shape in Exhibit 5.

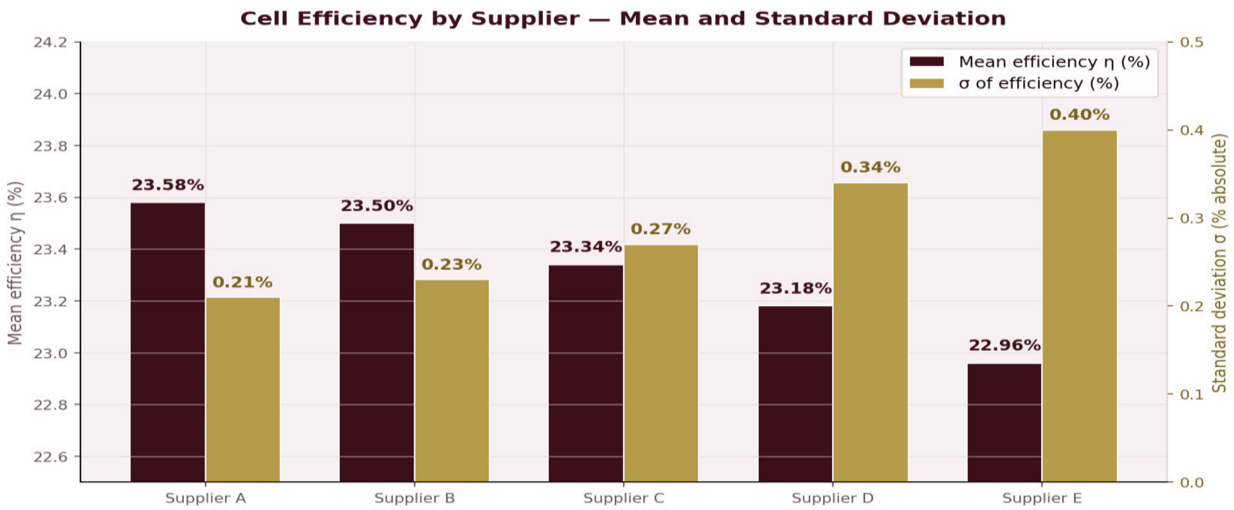

Exhibit 4 - Cell efficiency by supplier - mean (left axis, maroon bars) and standard deviation (right axis, champagne bars). Supplier A delivers the highest mean (23.58%) and the tightest distribution (sigma = 0.21%); Supplier E delivers the lowest mean (22.96%) and widest distribution (sigma = 0.40%). The 0.62 percentage-point mean gap and the 1.9-fold sigma ratio together drive a substantial top-bin yield differential.

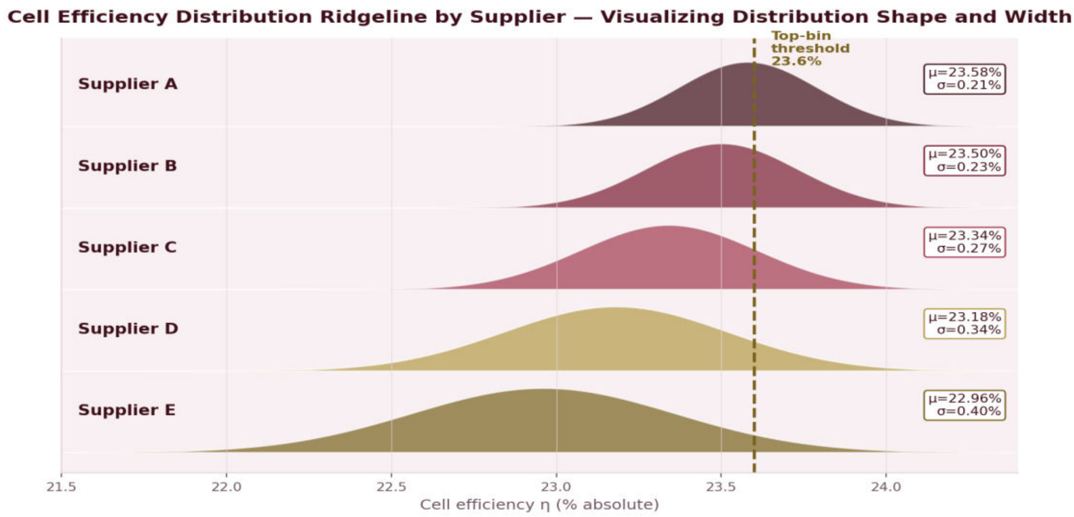

Exhibit 5 - Cell efficiency distribution ridgeline by supplier. The visualization makes the shape of the distribution clear: prime-grade suppliers (A, B, C) have approximately Gaussian distributions with progressively wider tails; secondary suppliers (D, E) show similar means within their grade but markedly broader distributions. The vertical dashed line marks the 23.6% top-bin threshold.

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Table 1 - Cross-supplier cell efficiency outcomes summary

Supplier	Mean η	σ η	Top-bin %	Z-score	Recommendation
A	23.58%	0.21%	24.6%	+1.2	Increase share
B	23.50%	0.23%	23.1%	+1.0	Maintain
C	23.34%	0.27%	17.8%	+0.4	Maintain
D	23.18%	0.34%	12.4%	−0.4	Reduce share
E	22.96%	0.40%	8.9%	−1.0	Substitute / qualify alternates

V. INCOMING COMPLIANCE TRAJECTORY

Tracking incoming spec compliance over time provides both a quality-trend indicator and a leading-indicator of downstream yield outcomes. The compliance trajectory across calendar 2025 for three principal incoming parameters is shown in Exhibit 6. All three trend upward, with the steepest improvement in iron compliance reflecting the cumulative effect of supplier-specification tightening initiated in April 2025.

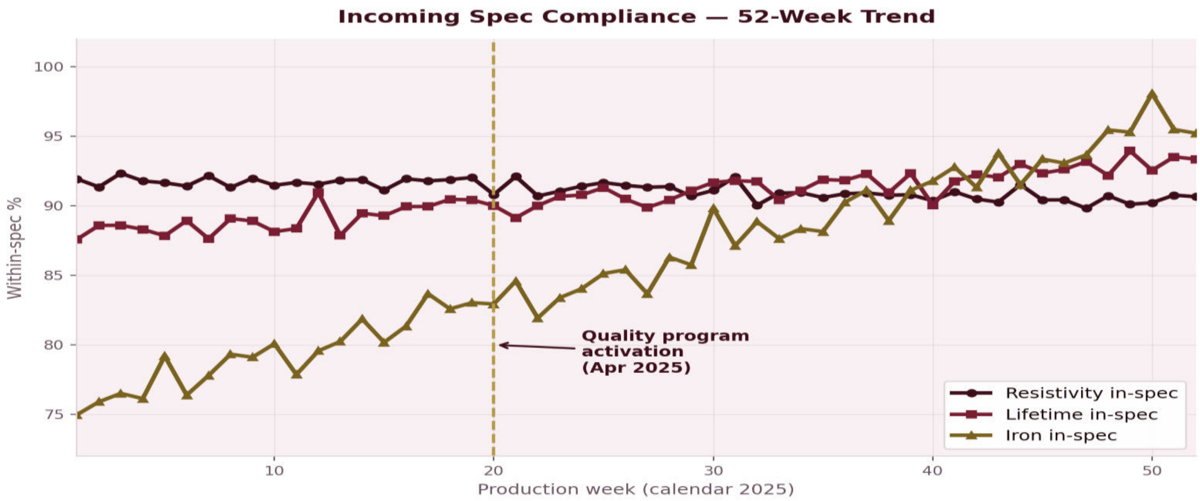

Exhibit 6 - Incoming spec compliance for three principal parameters across calendar 2025. Resistivity compliance was already high at year-start (90%) and improved modestly to 92%. Lifetime compliance rose from 88% to 94%. Iron compliance - starting from a much lower baseline of 75% - rose dramatically to 96% following the April 2025 quality program activation.

FINDING #02 - Compliance trajectory is the leading yield indicator

The 21-percentage-point improvement in iron compliance over the year preceded the 4.4-percentage-point top-bin yield improvement by approximately three months, consistent with the lag from incoming inspection through cell processing to electrical measurement. Compliance improvements observed today predict yield improvements observable approximately one quarter later. Procurement should monitor compliance trajectories as forward-looking yield indicators.

VI. THE COMPOSITE Q-SCORE

The composite Q-score is a single scalar summary of incoming wafer quality, derived as a weighted linear combination of eight individual incoming parameters, with weights set by univariate cell-efficiency leverage and with each parameter standardized to z-score against the fleet mean. The Q-score reduces a high-dimensional incoming-quality vector to a one-dimensional summary that can be operationalized at the lot, supplier, and supplier-mix levels.

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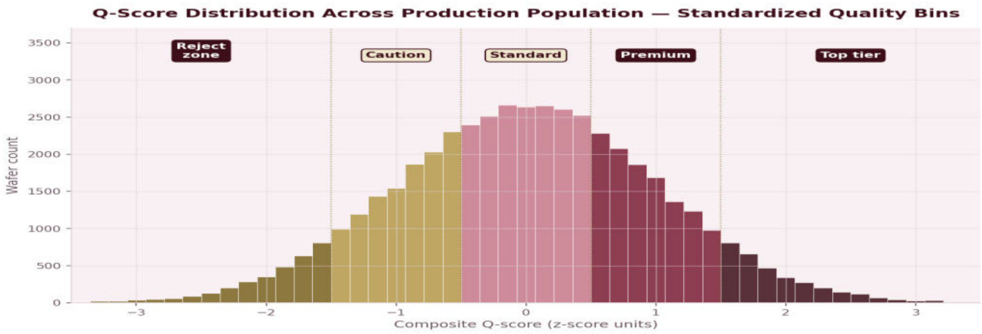

Exhibit 7 - Q-score distribution across the production population, with quality zones marked. Wafers with Q-score below −1.5 fall in the reject zone; those between −1.5 and −0.5 in the caution zone; −0.5 to +0.5 standard; +0.5 to +1.5 premium; above +1.5 top tier. The distribution is approximately Gaussian with a slightly elongated upper tail reflecting the contribution of the highest-Z-score suppliers.

Q-Score Operational Use Cases

1. **Lot acceptance:** Each incoming lot receives a lot-mean Q-score. Lots below −1.5 are auto-rejected; lots between −1.5 and −1.0 are routed to engineering review; lots above −1.0 are accepted into production.
2. **Wafer-level routing:** Within an accepted lot, individual-wafer Q-scores route the wafer to the appropriate downstream production line. Premium-tier wafers go to the prime line targeting top-bin product; standard-tier go to the standard line; caution-tier are reserved for secondary product or test-wafer use.
3. **Supplier scoring:** Monthly aggregates of incoming-wafer Q-score by supplier produce a quantitative supplier scorecard. Procurement uses the score to negotiate price and to drive monthly mix decisions.
4. **Yield prediction:** Daily mean Q-score predicts daily top-bin yield at Pearson $r = 0.84$. Production planning uses the predicted yield in revenue forecasting and in commitment timing decisions.
5. **Trend monitoring:** Quarter-over-quarter Q-score trends by supplier surface deteriorating quality before downstream yield impact. The trends drive the cadence of supplier audits and corrective-action discussions.

VII. SUPPLIER Q-SCORE EVOLUTION - CALENDAR 2025

Tracking the monthly Q-score by supplier over calendar 2025 reveals the cross-supplier dynamic that has shaped the procurement strategy now in place. The supplier evolution matrix in Exhibit 8 shows the monthly Q-score for each of the five suppliers across the eleven months under analysis. Two patterns emerge: prime suppliers A and B have improved modestly through the year, while secondary suppliers D and E have deteriorated.

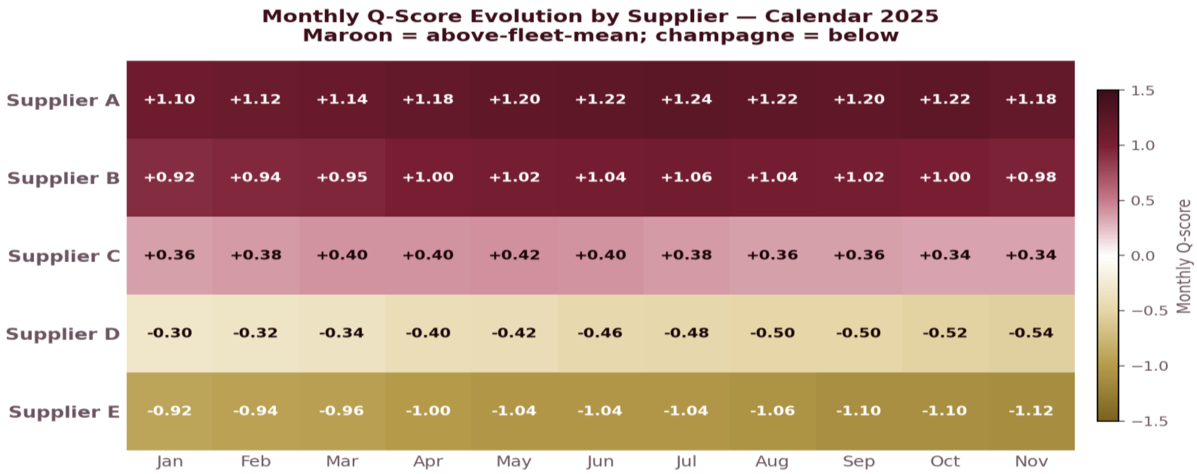

Exhibit 8 - Monthly Q-score evolution by supplier across calendar 2025. Maroon cells indicate above-fleet-mean quality; champagne indicates below. Supplier A improved from +1.10 to +1.20 over the year; Supplier E deteriorated from −0.92 to −1.12. The cross-supplier dynamic supports an aggressive mix shift toward A and B and a corresponding reduction in D and E.

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VIII. OUT-OF-SPEC PARETO

Of the 47,200 production wafers in the analytical population, 38,200 fell out-of-spec on at least one of the twelve measured parameters. The defect Pareto across these 38,200 wafers reveals the parameter categories that account for the majority of out-of-spec events and therefore for the majority of disposition workload at the incoming-inspection station.

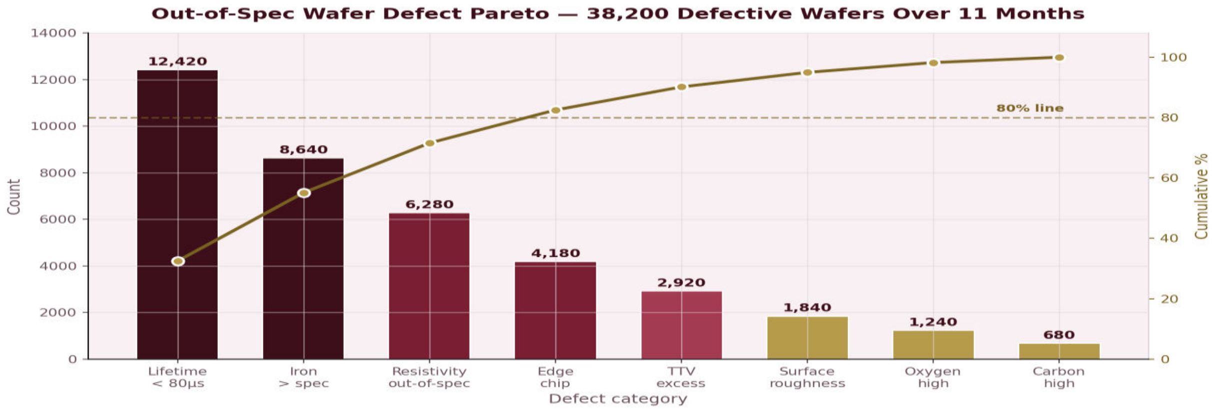

Exhibit 9 - Defect Pareto across 38,200 out-of-spec wafers. The top three categories - lifetime below 80 µs (12,420), iron above spec (8,640), and resistivity out-of-spec (6,280) - cumulatively account for 71% of out-of-spec events. The cumulative percentage curve crosses 80% at the fifth category (TTV excess), suggesting focused engineering attention on the top five categories captures the bulk of the disposition opportunity.

IX. BIN DISTRIBUTION SHIFT

The most operationally consequential outcome of the wafer-quality program is the bin-distribution shift between May 2025 (program activation) and November 2025 (the analytical endpoint). The shift is shown in Exhibit 10. The change is uniformly favorable: mass moves from the lower bins toward the upper bins, with the largest absolute increases at Bin 5 (+9.2 pp) and the top bin (+4.4 pp).

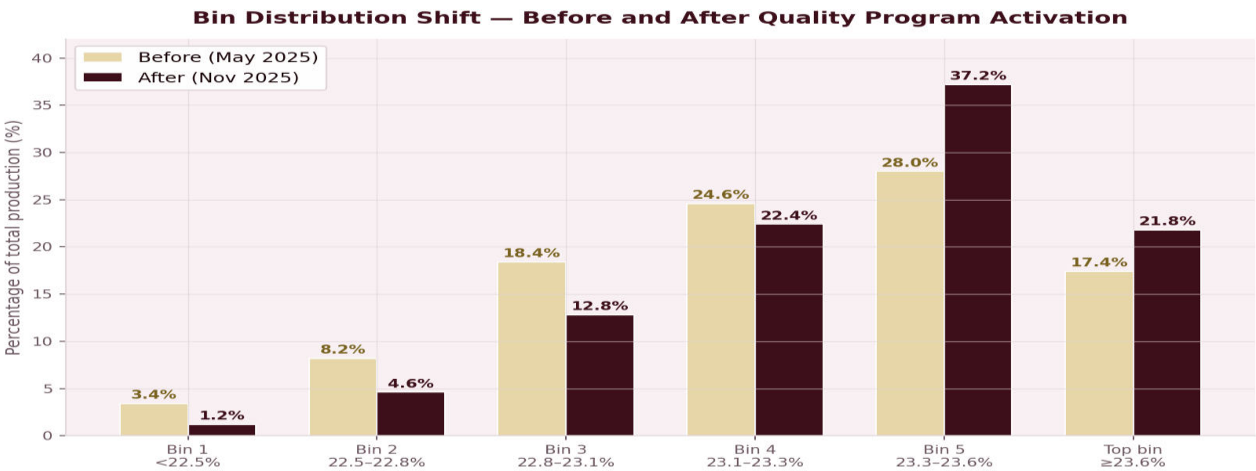

Exhibit 10 - Bin distribution shift between May 2025 (program activation) and November 2025. The lowest two bins (Bin 1 and Bin 2) shrank by 5.8 percentage points combined; the top two bins (Bin 5 and Top bin) grew by 13.6 percentage points combined. The rightward distribution shift is the empirical signature of incoming-quality program effectiveness.

“

Wafer quality is not the cell line’s problem to solve. It is the cell line’s most important constraint to characterize, predict, and procure around.

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X. PREDICTIVE MODELING

A gradient-boosted regression model trained on the twelve incoming wafer parameters predicts individual cell efficiency at root-mean-square error of 0.18 percent absolute. The model is now used at the incoming-inspection station to estimate expected efficiency before the wafer enters the cell line. The accuracy of the model depends materially on the breadth of the feature set, as documented in Exhibit 11.

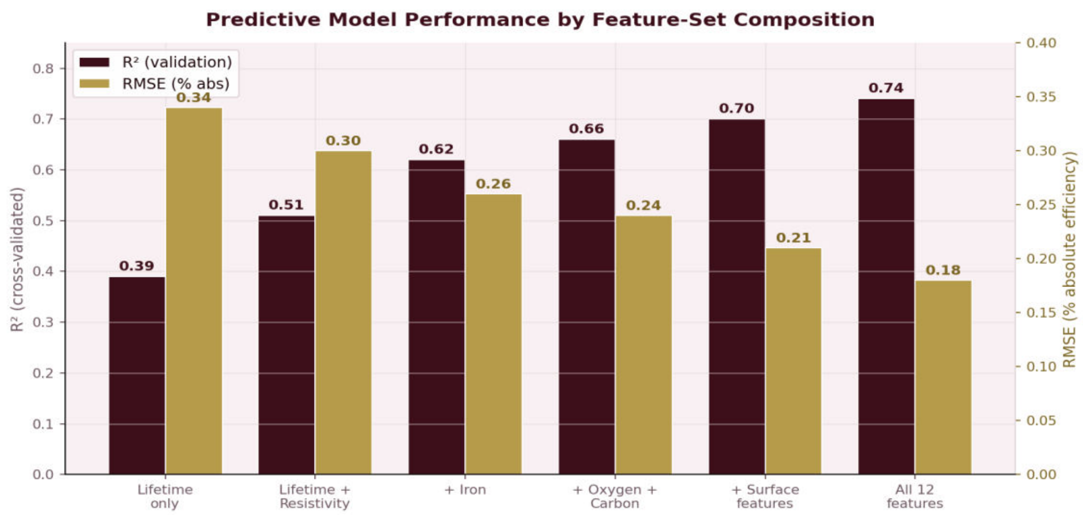

Exhibit 11 - Predictive model performance by feature-set composition. Lifetime alone achieves R-squared 0.39 and RMSE 0.34%. Adding resistivity lifts R-squared to 0.51. Adding iron, oxygen, and carbon contributes incremental R-squared of 0.15. The full twelve-feature model achieves R-squared 0.74 and RMSE 0.18% - the production-grade target.

Table 2 - Predictive model configuration and validation

Element	Specification	Notes
Algorithm	Gradient-boosted trees (XGBoost)	240 trees, max depth 6
Features	12 incoming wafer parameters	8 in Q-score + 4 secondary
Training set	32,000 wafers	First 8 months of 2025
Validation set	15,200 wafers	Same period, held out
Test set	1,500 wafers	Separate 2-week window
Cross-validated R^2	0.74	No significant overfitting
RMSE	0.18% absolute efficiency	On test set
Inference latency	< 12 ms per wafer	Production CPU
Production status	Active, Q3 2025	At incoming-inspection station

XI. COMMERCIAL IMPACT

The annualized commercial value of the wafer-quality statistical program at one-gigawatt production scale is decomposed into five contributing value streams in Exhibit 12, presented as a waterfall from the baseline (zero) state to the net annual value of $8.4 million. The largest contributor is top-bin yield gain at $4.2 million per year, reflecting the 4.4 percentage-point uplift in top-bin yield combined with the price premium that top-bin product commands in the current market.

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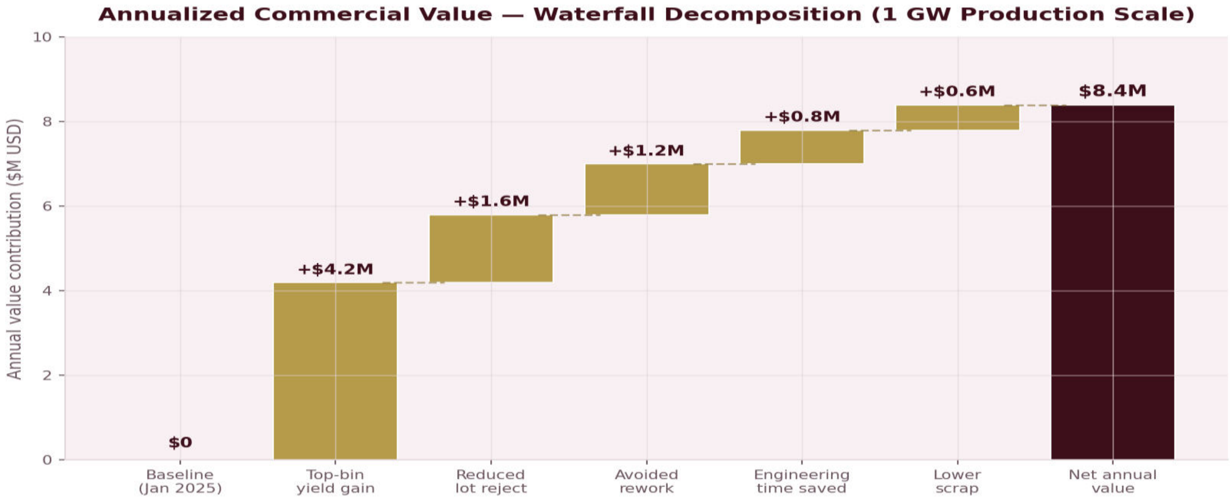

Exhibit 12 - Annualized commercial value waterfall - top-bin yield gain ($4.2M) + reduced lot rejection ($1.6M) + avoided rework ($1.2M) + engineering time saved ($0.8M) + lower scrap ($0.6M) = $8.4M total. The decomposition is presented in waterfall form to make the contribution of each value stream visible to executive readers.

Investment and Return Profile

Table 3 - Wafer-quality statistical program - investment and return profile

Element	Value	Notes
Statistical infrastructure	$640,000	Database, ETL, BI dashboards
Predictive regressor development	$520,000	Model development and validation
Q-score system + procurement engine	$420,000	Decision-support tooling
Engineering integration	$540,000	Process and quality engineering staff
Supplier audit programs	$280,000	5 suppliers, audit cycles + travel
Reserve / contingency	$200,000	Used at ~70%
Total deployment investment	$2,600,000	-
Annualized commercial value	$8,400,000	Per Exhibit 12
Ongoing operating cost	$380,000	Compute, software, FTE allocation
Net annual value	$8,020,000	Steady-state
Payback period	≈4 months	Among shortest in EBM series

§ COMMERCIAL DISPOSITION

A four-month payback on a $2.6 million investment, producing approximately $8 million in steady-state net annual value, places the wafer-quality statistical program in the top tier of engineering investments evaluated at this facility. The program is now a standing element of the facility operating model rather than a discrete project; the funding profile reflects the transition from project to operating budget effective fiscal year 2026.

XII. RECOMMENDATIONS TO EXECUTIVE LEADERSHIP

Based on the eleven months of statistical evidence summarized in this memorandum, the following recommendations are submitted for executive consideration.

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1. **Continue the supplier-mix shift toward Suppliers A and B.** The Q-score evidence supports continued increase in Supplier A share toward 60 percent of total volume by the end of fiscal year 2026, with corresponding reduction in Supplier E share toward 0 percent. The mix shift should be conditioned on ongoing per-month Q-score validation; any deterioration in Supplier A or B Q-score should pause the shift pending engineering investigation.
2. **Qualify two additional prime-grade suppliers.** The current panel of three prime-grade suppliers concentrates supply risk on a small number of sources. Qualifying two additional prime-grade suppliers (target: candidates F and G now in early-stage qualification) preserves the supply-chain resilience that the panel structure was designed to provide while permitting further share concentration on the highest-Z-score suppliers.
3. **Tighten the iron specification ceiling to 1×10^{11} cm^{-3}.** The current iron ceiling of 3.2×10^{11} corresponds to expected power loss of approximately 0.7 percent absolute. Tightening to 1×10^{11} would eliminate approximately 0.5 percentage points of expected loss for every wafer at the current ceiling. The cost impact is modest (estimated 0.3 percent supplier price premium) and the annualized yield gain offsets the price premium by approximately 6-fold.
4. **Establish quarterly Q-score recalibration as a standing practice.** The relative leverage of wafer parameters drifts as cell-process technology evolves. The Q-score weights should be re-fitted on a quarterly cadence on rolling twelve-week windows to capture the parameter-leverage drift. The recalibration is largely automated and does not require additional engineering investment beyond the existing maintenance allocation.
5. **Extend the framework to TOPCon and HJT incoming-quality.** The Q-score framework derived for PERC will not transfer unchanged to n-type wafers used in TOPCon and HJT cell production, where the parameter-leverage profile differs. As the facility plans the second-generation cell line for fiscal year 2026, a parallel n-type Q-score derivation should be initiated in advance of n-type wafer procurement.

XIII. CONCLUSION

This briefing memorandum has presented the principal findings of an eleven-month statistical study of incoming wafer quality and its measured effect on finished-cell electrical performance at gigawatt-scale silicon PERC cell production. The dominant finding is that incoming wafer material variation is now the largest single contributor to cross-cell efficiency variance at this stage of PERC manufacturing maturity, surpassing cell-process variation as the primary engineering target. Bulk minority-carrier lifetime alone explains 38.4 percent of efficiency variance; the top three parameters cumulatively explain 68.4 percent. A composite Q-score combining eight parameters predicts daily top-bin yield at Pearson correlation 0.84; a twelve-feature gradient-boosted regressor predicts individual cell efficiency at root-mean-square error 0.18 percent absolute.

Q-score-driven supplier-mix optimization activated in May 2025 produced a 4.4 percentage-point absolute top-bin yield uplift over the May-to-November window, against a deployment investment of $2.6 million and approximately $8.4 million in annualized commercial value. The four-month payback period and the 8-figure annualized return profile place this program among the highest-leverage engineering investments evaluated at the facility. The recommendations submitted in Section XII propose continued mix shift, expansion of the supplier panel, tightening of the iron specification, and extension of the framework to next-generation n-type wafers as the facility plans its second-generation cell line in future.

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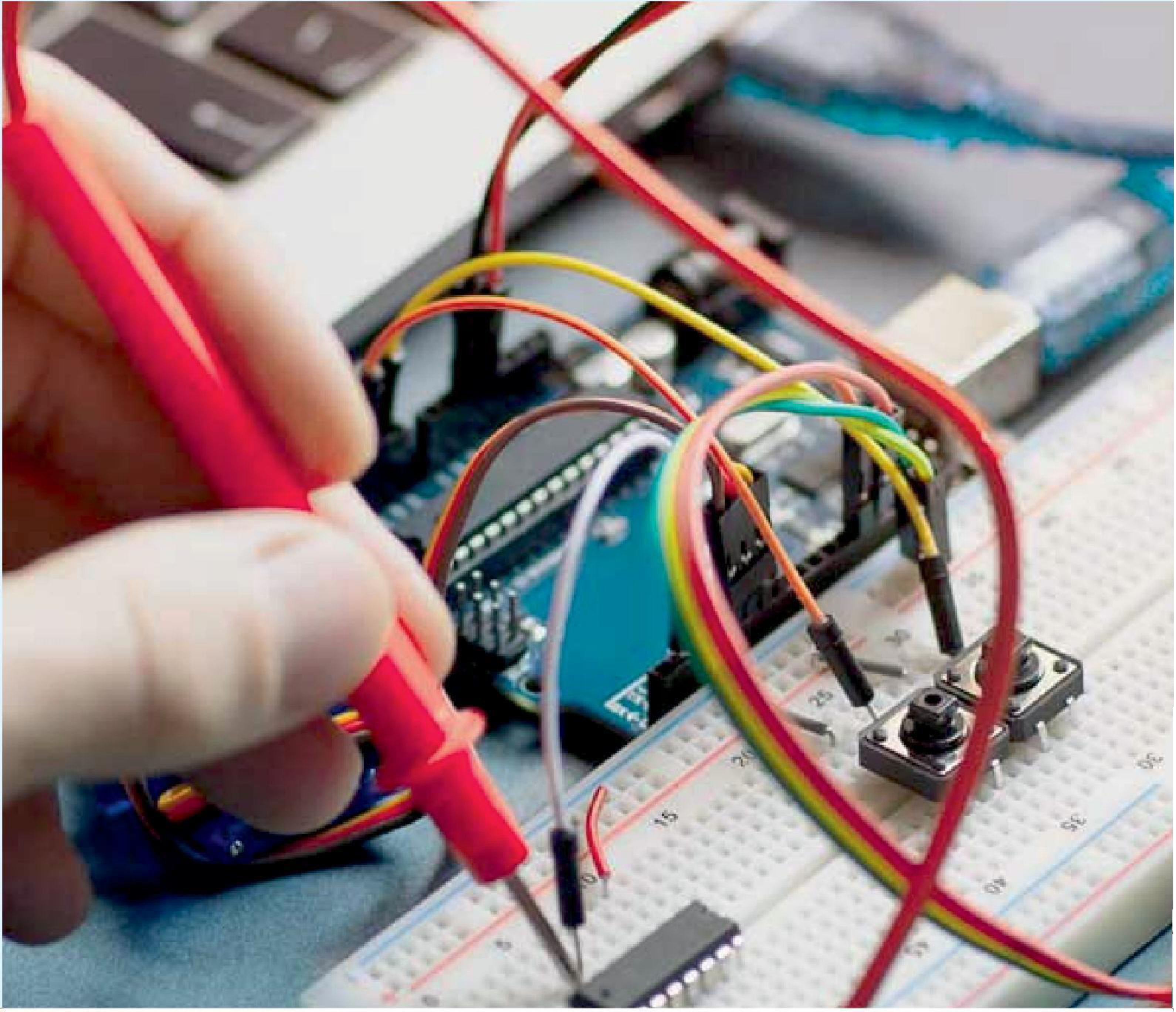

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