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Original Article

Primary causes of voltage fluctuations that affect industrial optical sorters. A quasi-experimental study.

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ABSTRACT

Background:
The study aimed to identify the primary causes of voltage fluctuations that affect the industrial optical sorter.

Methodology:
This study adopted a quantitative quasi-experimental design at the ACPCU factory in Uganda to evaluate the impact of voltage fluctuations on a Satake NRM3 optical sorter. Data from a Fluke 435-II analyzer was synchronized with production logs and environmental data over 24 days. The methodology employed FMEA to identify failure modes, alongside Probabilistic Risk Assessment and Monte Carlo simulations to quantify downtime and techno-financial losses, with analysis performed in Excel, MATLAB, and SPSS.

Results:
Analysis of 241 tagged disturbance events over 24 days reveals that internal operations are the primary drivers of voltage instability at ACPCU Ltd. Load switching (40.2%, n=97) and high-power machinery (32%, n=77) collectively account for 72.2% of all fluctuations, primarily due to large inrush currents and simultaneous motor starts. External factors proved less frequent: surges contributed 14.1% (n=34), while grid instability and heavy rains accounted for 6.7% (n=16) and 5.8% (n=14) respectively.
The dominance of internal causes over external grid faults underscores significant local power quality challenges. Specifically, transient dips often coincided with the operation of hullers and aspiration fans. Minimal disruptions were linked to loose wiring (1.2%). These statistics suggest that implementing soft-start mechanisms and staggered motor sequencing could mitigate over 70% of recorded disturbances, significantly stabilizing the 415/240V supply network for the optical sorter.

Conclusion:
Voltage fluctuations affecting the optical sorter are predominantly caused by internal factory conditions, particularly load switching, loose connections, and phase imbalance.

Recommendation:
Implement harmonic filtering, load balancing, and routine maintenance to minimize internally generated voltage disturbances.

Keywords: *Voltage Fluctuations, Industrial Optical Sorter, Power Quality Analysis, Load Switching, Risk Assessment, Techno-financial Loss.*
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BACKGROUND OF THE STUDY

In industrial manufacturing, the stability of electrical power is a fundamental prerequisite for operational efficiency, particularly as facilities transition toward high-precision automation. Industrial environments are inherently prone to load variations, which occur when electrical demand fluctuates due to the systematic switching of high-power machinery. These variations, characterized by sudden dips (sags) or surges (spikes), represent a primary cause of voltage instability. When large motors, conveyors, or hullers are activated, they draw massive inrush currents, causing a temporary depression in system voltage [Zhang et al., 2022].

The impact of these fluctuations is most pronounced in industrial optical sorting machines. Unlike rugged mechanical equipment, optical sorters rely on sophisticated electronic architectures, including high-speed PLCs and sensitive imaging sensors. Even minor voltage deviations can result in erratic machine behavior, such as the misclassification of products or delayed response times [Smith et al., 2021]. Specifically, voltage dips can reduce the sensitivity of optical sensors, leading to a failure to identify defects and a subsequent loss of product integrity [Almeida et al., 2022]. Beyond immediate errors, frequent fluctuations accelerate thermal and mechanical stress on internal power supplies, significantly shortening equipment lifespan and increasing maintenance overhead [Rodriguez et al., 2023; Harrison et al., 2021].

This internal instability is often compounded by grid instability, particularly in regions with developing electrical infrastructure. In countries like Uganda, the national grid often lacks the redundancy and smart monitoring technologies required to maintain a consistent 415/240V supply. Aging infrastructure and transmission inefficiencies lead to increased resistance and energy losses, especially in rural or high-load industrial hubs [Berkhoff et al., 2021]. Such grid-level weaknesses mean that industrial facilities must contend not only with their own internal load-switching disturbances but also with external surges and sags propagating from the regional distribution network [Jones & Patel, 2022]. This dual pressure creates a high-risk environment where minor deviations can escalate into costly unscheduled shutdowns and production delays [Chang et al., 2023].

Furthermore, the modern industrial landscape is increasingly dominated by non-linear loads, such as Variable Frequency Drives (VFDs). While these devices improve mechanical efficiency, they introduce harmonic distortions that further degrade power quality. These devices draw current in non-sinusoidal pulses, distorting the standard voltage waveform [Kumar et al., 2021]. The resulting Total Harmonic Distortion (THD) can cause sensitive electronic components to overheat, adding a layer of "invisible" electrical noise that undermines the precision required for high-speed coffee sorting.

The study aimed to identify the primary causes of voltage fluctuations that affect the industrial optical sorter.

METHODOLOGY

Locale of the Study.

The study was conducted at Ankole Coffee Producers Cooperative Union (ACPCU) LTD factory in Sheema district of Uganda. The study area's coordinates are 0.5515° S and 30.3897° E.

Research Design.

The study adopted a quantitative quasi-experimental design to assess the relationship between voltage fluctuations and industrial optical sorter performance under real operating conditions at Ankole Coffee Producers Cooperative Union (ACPCU) Ltd in Sheema District, Uganda. The research focused on a single Satake NRM3 AIS-T optical sorting machine connected to the factory's 415/240 V supply network.

The design combined continuous power quality monitoring with concurrent recording of machine performance and reliability indicators. Supply voltage at the sorter's point of connection was measured using a Class A power quality analyzer, while throughput, sorting accuracy, downtime, and fault events were obtained from production records, HMI/PLC logs, and maintenance logbooks. By aligning time-stamped voltage and performance data, the design enabled time-based comparison between prevailing voltage conditions and corresponding machine behaviour.

Risk-based methods were embedded within this design: Failure Mode and Effects Analysis (FMEA) was used to identify and rank voltage-induced failure modes, while Probabilistic Risk Assessment (PRA) and Monte Carlo simulation were applied to quantify the likelihood and consequences of these failures in terms of downtime and techno-financial loss.

Data Collection Methods and Instruments.

Quantitative data on both power quality and sorter performance were collected using instrumentation- and record-based methods.

Power quality measurements.

A Fluke 435-II Power Quality Analyzer was installed at the supply point feeding the NRM3 AIS-T optical sorter (upstream of the machine's main isolator). The analyzer monitored the three phase-to-neutral lines (L1–N, L2–N, L3–N) continuously over 24 production days, corresponding to approximately 576 machine-hours of operation. The logging interval was configured at 60 seconds, generating an empirical dataset of 414,720 individual voltage records for the study period. The instrument had a measurement accuracy of ±0.1% of nominal voltage and complied with IEC 61000-4-30 Class A requirements for power quality measurements. Prior to deployment, the analyzer was calibrated and cross-checked against the plant's reference voltmeter. Periodic spot-checks were performed by comparing analyzer readings with the factory's digital meter to verify stability and accuracy.

Environmental and operating conditions.

To control for environmental effects, ambient temperature (23–28 °C) and relative humidity (55–65%) were monitored hourly using a digital thermo-hygrometer. The sorter was operated on a consistent production schedule of three 8-hour shifts per day, at a nominal mechanical load of 3,000 kg/h**,** including operation of auxiliary equipment such as conveyors and vibro-feeders. Data recorded during non-operational periods, scheduled maintenance, or machine idle states were excluded from analysis.

Operational performance and reliability data.

Production records provided daily throughput (kg/day) and quantities of accepted, rejected, and re-sorted coffee. Machine logs and HMI/PLC records provided counts and types of fault events, alarms, and trips associated with voltage disturbances. Maintenance and downtime logbooks contained timestamps, causes, and durations of unplanned stoppages, and details of corrective interventions.

Together, these instruments and records provided synchronized datasets on voltage conditions, environmental variables, machine performance, and reliability necessary for correlation, FMEA, and PRA/Monte Carlo analysis.

Data Collection Procedure.

An introduction letter from Kampala International University's Directorate of Higher Degrees and Research was presented to ACPCU management. Written permission to access the plant and install monitoring equipment was obtained from the General Manager. The electrical layout around the optical sorter was reviewed with plant engineers to identify the most appropriate measurement point. The power quality analyzer was installed at the incoming feeder supplying the sorter, upstream of the main isolator and protective devices. Logging interval, nominal voltage, and measurement channels were configured according to manufacturer guidelines. The analyzer was calibrated and cross-checked against the plant reference meter before starting the campaign. Time stamps on the power quality analyzer, plant HMI/PLC, and production log systems were synchronized to ensure accurate alignment of voltage and performance data. Voltage, environmental, and operational data were recorded continuously over 24 consecutive production days, covering typical peak and off-peak operating conditions within the month.

At the beginning and end of each day, the analyzer status, memory capacity, and wiring connections were checked with the assistance of plant technicians. Any anomalies (e.g., power interruptions, reboots) were noted. At the end of the monitoring period, raw PQ data were downloaded using the analyzer's software and exported to Excel format. Production, downtime, and maintenance data were extracted from the plant's records and digitized where necessary. All datasets were stored in a structured folder system with clear file names and backup copies. The combined dataset was screened for missing intervals, non-operational periods, and obvious recording errors. Non-production intervals and incomplete days were flagged and excluded from subsequent analysis where appropriate.

Data Collected.

The study generated four main categories of data;

- Power quality data. This included: time-stamped records of Vrms (per phase), voltage deviation (ΔV), sags and swells (magnitude and duration), voltage unbalance, flicker severity (P_{st}, where available), and total harmonic distortion (THD).
- Operational performance data, which included: daily throughput, accepted/rejected/re-sorted quantities, and production hours per shift.
- Reliability and maintenance data of fault and alarm events from HMI/PLC logs, unplanned stoppages, downtime durations, and corrective maintenance actions from logbooks.
- Environmental and operating conditions of hourly ambient temperature and relative humidity, plus notes on major operational changes (unusual load changes, maintenance interventions).

These datasets formed the empirical basis for descriptive statistics, correlation and regression analysis, FMEA scoring, and parameterization of the PRA and Monte Carlo models.

Data Analysis.

Data analysis was conducted in several stages using Microsoft Excel, MATLAB, and IBM SPSS.

The empirical power-quality and performance data described above provided the quantitative basis for the risk analysis. First, Failure Mode and Effects Analysis (FMEA) was used to identify and score voltage-induced failure modes such as PLC resets, sensor misclassification, and motor stalls using Severity, Occurrence, and Detection ratings derived from the observed event frequencies and maintenance records. These FMEA outputs were then embedded in a Probabilistic Risk Assessment (PRA) structure, in which basic power-quality events (sags, surges, flicker, harmonics, internal transients) were mapped to intermediate failure modes and finally to a top event representing significant sorter failure or production interruption. Monte Carlo simulation used the empirical distributions of voltage disturbances, downtime durations, and cost parameters, together with the PRA event probabilities, to estimate the probability distribution of daily and monthly losses under current and mitigated operating conditions.

Data cleaning and pre-processing:

- Raw PQ data were imported into Excel and MATLAB, where non-production intervals, duplicated records, and obvious outliers (caused by instrument resets or wiring changes) were identified and removed.
- Production and maintenance logs were checked for completeness and consistency of time stamps, then merged with the PQ dataset using date–time keys.
-

Descriptive statistics and visualization (Objective 1 & 2):

- In Excel and MATLAB, descriptive statistics (mean, minimum, maximum, standard deviation) were computed for key PQ indicators (Vrms, ΔV, THD, P_{st}) and performance indicators (throughput, error rate, downtime).
- Frequency tables and bar charts were used to show the contribution of different causes of voltage fluctuations, while time-series plots and heatmaps were used to illustrate variation in Vrms and error rates across the 24-day window.

Correlation and regression analysis (Objective 2):

- In SPSS, Pearson correlation coefficients were computed between power quality indicators (ΔV, THD, P_{st}, unbalance) and performance variables (throughput, error rate, downtime) to quantify linear associations.

- Where appropriate, simple and multiple regression models were fitted to estimate the sensitivity of performance indicators to changes in voltage deviation and harmonic distortion.

FMEA scoring (link to Objective 3):

- Voltage-related failure modes (PLC reset, sensor misclassification, motor stall) were identified based on literature and plant experience.
- For each failure mode, severity (S), occurrence (O), and detection (D) ratings were assigned on a 1–10 scale using structured scoring forms completed with input from maintenance engineers, technicians, and machine operators.
- Risk Priority Numbers (RPN = S × O × D) were computed and used to rank failure modes and select those carried forward into PRA and simulation.

PRA and Monte Carlo simulation (Objective 3):

- PRA was used to structure the relationship between basic power-quality events (sags, surges, flicker, harmonics, internal transients) and top events such as controller trip, actuator under-torque, and optical misclassification, and to define the overall system failure event. Monte Carlo simulation was implemented in MATLAB to propagate uncertainty in voltage conditions and component failure probabilities.
- Each simulation run sampled PQ conditions and failure responses and produced realizations of daily failure counts, downtime, and cost.
- Downtime durations were modelled using a log-normal probability distribution, justified by the right-skewed nature of empirical maintenance data (frequent short downtimes with fewer long events). Alternative distributions (exponential, Weibull) were tested, but the log-normal provided a better fit to the observed data (goodness-of-fit tests with $p > 0.05$).

Risk metrics and scenario analysis:

- From the simulation outputs, daily and monthly probabilities of failure, expected loss (EL), and Value at Risk (VaR) were computed under baseline and mitigation scenarios.
- Results were summarized in tables and graphs and later interpreted in relation to the research objectives and mitigation options.

Visualization.

Visualization was used to reveal patterns and relationships that are not obvious from tabulated data alone. Line graphs, bar charts, and scatter plots were generated in Excel and MATLAB to illustrate time-based variation in voltage and performance indicators, while **heatmaps** were used to show the frequency of sorting errors across voltage ranges and days. These visualizations supported the identification of periods with severe voltage deviation, highlighted correlations between voltage quality and performance, and provided an intuitive basis for selecting scenarios for risk analysis and mitigation modelling.

Impact Assessment of Voltage Fluctuations on Optical Sorter Operational Performance

The study adopted an analytical, correlational design. Voltage quality at the supply point of the optical sorter was continuously monitored over a defined operating period, while machine operational data were recorded from production and machine logs over the same period. The design allowed for a time-based comparison between prevailing voltage conditions and corresponding machine performance, enabling the assessment of the impact of voltage fluctuations on throughput, product quality, downtime, and reliability-related indicators.

Power Quality Measurement and Voltage Fluctuation Parameters

A power quality analyzer was installed at the supply point feeding the optical sorter (upstream of the machine’s main isolator). The analyzer was configured to log electrical parameters at fixed intervals of 5 seconds throughout the study period.
The following voltage-related variables were measured;

- **Root mean square voltage (V_{rms})** (phase-to-neutral or phase-to-phase as applicable).
- **Voltage deviation (ΔV)** from nominal, expressed as a percentage of the nominal voltage.
- **Voltage sags and swells,** including magnitude (depth/height) and duration.
- **Short-term flicker severity (P_{st})**, where available.
- **Total harmonic distortion (THD)** of voltage.
- **Voltage unbalance**, for upstream three-phase circuits.

These variables collectively described the nature and severity of voltage fluctuations experienced by the sorter. The logging period was chosen to cover representative production days in a month, including peak and off-peak operating conditions.

Operational Performance Data Collection

Operational performance data for the optical sorter were collected for the same time window as the power quality measurements. Data sources included:

- **Production records**. These were daily-based throughput (kgs/day) and quantities of accepted, rejected, and re-sorted product.
- **Machine logs and HMI/PLC records,** which included the number and type of fault events, alarms, and trips.
- **Maintenance and downtime logs,** which contained records of unplanned stoppages, corrective maintenance interventions, and their causes.

Parameters of Optical Sorter Reliability

The impact of voltage fluctuations on the optical sorter was expressed in terms of reliability-related parameters to reflect the machine's ability to operate continuously, accurately, and efficiently. The main parameters and how they were quantified included: throughput reliability, sorting accuracy/quality performance, and optical sorter downtime and operational continuity metrics, as elaborated further below.

Throughput Reliability

Throughput reliability represented the sorter's ability to process the expected quantity of material over a given period under prevailing voltage conditions.

- Nominal throughput (Q_{nom}): the design /target throughput (kgs/hour).
- Actual throughput (Q_t): the measured throughput per interval (daily).
- Throughput reliability ratio $RQ(t)$

$$RQ(t) = \frac{Qt}{Qnom}$$

………………………….. *i*

Values close to 1 indicate that the sorter is meeting its expected throughput; sustained values below 1 under poor voltage conditions indicate a negative impact of voltage fluctuations on production capacity.

Sorting Accuracy and Quality Performance

Sorting accuracy is a key quality-related reliability parameter, and it reflects the machine's capability to correctly classify products despite disturbances.

- Correctly sorted product ($N_{correct}$).
- Mis-sorted or rejected product (N_{reject}), including re-sorting requirements.
- Sorting accuracy (%):

$$A(t) = \frac{Nrejec}{Ncorrect + Nrejec t} X\ 100$$

……………………….

ii

- Reject rate (%) $RR(t)$:

$$RR(t) = \frac{Nrejec}{Ncorrect + Nreject} X\ 100$$

………………………

iii

A deterioration in accuracy and an increase in reject rate during intervals with high voltage deviations, sags, or flicker indicate an adverse impact of voltage fluctuations on the sorter's quality performance.

Operational Continuity and Downtime-Based Metrics

Operational continuity was assessed using downtime-based metrics that captured the frequency and duration of interruptions.

- Number of stoppages per day (N_{stop}).
- Downtime duration per interval (T_{down}), in hours.
- Availability (A_v):

$$Av = \frac{Operating\ time}{Operating\ time + \ Down\ time}$$

……………………… *iv*

- Mean Time Between Failures (MTBF), estimated over the study period as:

$$MTBF = \frac{Total\ Operating\ time}{Number\ of\ failures/trips}$$

………………………….. *v*

Lower availability, increased downtime, and reduced MTBF in periods of severe voltage fluctuations signify reduced operational continuity attributable to power quality issues.

Risk Assessment and Analysis

I adopted a structured framework combining Probabilistic Risk Assessment (PRA) and risk priority calculations.

Probabilistic Risk Assessment (PRA)

In this research study on assessing the risk of industrial sorting machine failures caused by voltage fluctuations, Probabilistic Risk Assessment (PRA) was applied to quantify the likelihood of sorting machine failures due to voltage instability and to evaluate risk mitigation strategies.

PRA risk equation:

$R = \sum(P_i\ X\ C_i)$ ………………………… *vi*

where P_i is the probability of a failure mode, and C_i is its consequence cost or severity.

In the context of this study, PRA will be applied as shown.

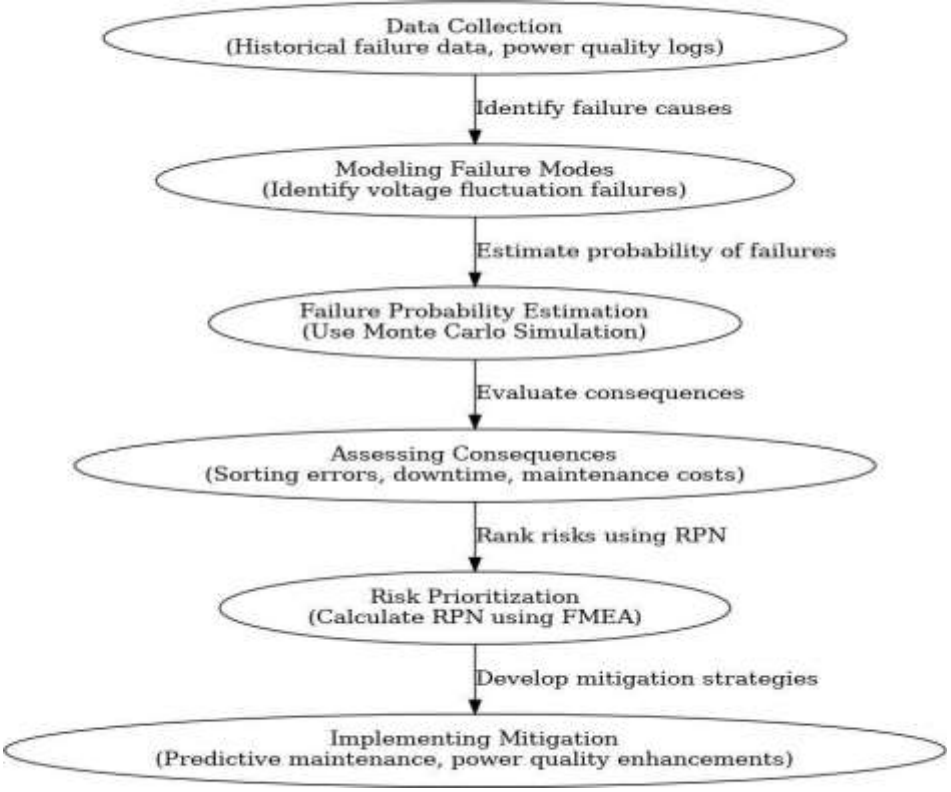

Figure 1: PRA flow diagram

Modelling Failure Modes.

Identified Failure Modes where potential failure modes that could occur in the sorting machine due to voltage fluctuations, such as Voltage Transients (sudden drops or spikes), Harmonic Distortions (caused by non-linear loads like motors or converters), or Insufficient Power Quality (unstable grid supply). Each failure mode was analyzed separately, and PRA evaluated the likelihood of each failure occurring.

According to Bollen, M. H. J. (2000), the general equation for voltage fluctuations was expressed as a deviation from the nominal voltage over time:

$$V(t) = V_{normінal} + \Delta V(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots. \quad vii$$

Where;

- $V(t)$ is the instantaneous voltage at time t,
- Vnorminal is the rated system voltage,
- (t) represents the deviation from the nominal voltage, which can be caused by sags, swells, spikes, harmonics, or interruptions.

Probabilistic Risk Assessment (PRA) and Monte Carlo Simulation

This section implemented a quantitative **Probabilistic Risk Assessment (PRA)** to estimate the likelihood and consequences of voltage-fluctuation-induced failures on the supply line of the NRM3 AIS-T industrial sorter line. PRA outputs were propagated through **Monte Carlo simulation** to derive distributions for failure probability, downtime, and techno-financial loss, and to quantify parametric and structural uncertainty.

Event Logic

The top event T was defined as **sorting line functional failure** within a 1-day operating window due to power-quality deviations. Contributing basic events were: voltage sag S, voltage surge U, rapid fluctuation (flicker) F, harmonic distortion H, and internal transient I. The top event was modeled through a mixed OR/AND gate structure:

– Controller Trip –

$$\mathcal{C} = S \vee U \vee I \quad \ldots\ldots\ldots\ldots\ldots\ldots.. \quad viii$$

– Actuator Under-Torque –

$$\mathcal{A} = S \vee F \vee H \quad \ldots$$

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………………….. *ix*

- Optical Misclassification –
  $\mathcal{O} = S \vee U \vee F \vee H$ ……………………… *x*
- Top Event Relationship –
  $\mathcal{T} = \mathcal{C} \vee \mathcal{A} \vee \mathcal{O}$ ……………………………… *xi*

This logic assumed independence between $\mathcal{C}$, $\mathcal{A}$, $\mathcal{O}$, conditional on measured PQ drivers, the top-event probability in a day was:

$$P(T) = 1 - (1 - P(C))(1 - P(A))(1 - P(O))$$

…………………… *xii*

Where;

P(T) = Probability of the top event (overall system failure)
P(C) = Probability of controller trip
P(A) = Probability of actuator under-torque
P(O) = Probability of optical misclassification

Risk Metrics

* Daily risk: defined as the expectation of consequence C under top-event occurrence:

$$\text{Risk} = \mathbb{E}[C \mid \mathcal{T}]\,P(\mathcal{T})$$

…………… *xiii*

Where;

Risk = Expected risk value (UGX or normalized risk index)
E[C|τ] = Expected cost or consequence given that the top event TTT occurs
P(τ) = Probability of the top event (system failure)

* Consequence was decomposed as:

$$C_{Total} = (C_{downtime}\,T_{off}) + C_{repair} + C_{production}$$

……………..…… *xiv*

Where;

C_{Total} = Total expected cost due to voltage-related failure (UGX)
$C_{downtime}$ = Cost rate per hour of machine downtime (UGX · h⁻¹)
T_{off} = Duration of machine downtime (hours)
C_{repair} = Cost of repair or replacement of damaged components (UGX)
$C_{production\_loss}$ = Cost of production losses due to halted operations (UGX)

Models and Equations

PQ–failure mapping

* Voltage deviation magnitude $\Delta V = |V - V_{nom}|$ derived component stress. I used a Weibull-like response for the probability of functional upset per window:

$$P_f(\Delta V) = 1 - \exp\left[-\left(\frac{\Delta V}{V_c}\right)^{\beta}\right]$$

……………….. *xv*

with scale $V_c > 0$ and shape $\beta > 0$ estimated from historical trip/misclass counts vs. ΔV.

Where;

$P_f(\Delta V)$ = Probability of failure due to voltage deviation
ΔV = Voltage deviation from nominal supply (V)
V_c = Characteristic or critical voltage level (V)
β = Shape parameter (Weibull slope) defining the rate of failure increase
exp = Exponential reliability function

* Harmonic distortion (THD) contributed multiplicatively via a logit link:

$$\text{logit}(P_f^{(H)}) = \alpha_0 + \alpha_1 \times \text{THD}_{\%}$$

……………. *xvi*

Where;

logit ($P_f^{(H)}$) = Natural logarithm of the odds of harmonic-related failure
P_f = Probability of failure caused by harmonic distortion
α_0 = Regression intercept (baseline log-odds of failure when THD = 0)
α_1 = Regression coefficient representing the sensitivity of failure probability to THD
THD% = Total Harmonic Distortion expressed as a percentage of the fundamental voltage

* Combined upset probability for a function k∈ {$\mathcal{C}$, $\mathcal{A}$, $\mathcal{O}$} under drivers x uses a noisy OR:

$$P_k = 1 - \prod_{d \in \{S,U,F,H\}} (1 - q_{kd}(x))$$

…………………… *xvii*

Where;

$q_{kd}(x)$ is the driver-specific upset probability.

Downtime and cost models

* Downtime is right-skewed; I used a log-normal:

$$T_{off} \sim \text{LogNormal}(\mu_T, \sigma_T^2)$$

………… *xviii*

Where;

T_{off} = Downtime duration (hours)

LogNormal(μT,σT2) = Log-normal probability distribution of downtime

μ_T = Mean of the natural logarithm of observed downtime values

σ^2_T = Variance of the logarithm of downtime (measure of spread or uncertainty) parametrized from maintenance logs.

* Repair cost is triangular (expert bounds):

$$C_{repair} \sim \text{Triangular}(c_{min}, c_{mode}, c_{max})$$

…………………. *xix*

Where;

C_{repair} = Randomly simulated repair cost per failure event

Triangular($c_{min}, c_{mode}, c_{max}$) = Triangular probability distribution describing the uncertainty in repair cost

c_{min} = Minimum observed or estimated repair cost (UGX)

c_{mode} = Most likely or modal repair cost (UGX)

c_{max} = Maximum possible repair cost (UGX)

* Production loss scales with line throughput λ (units/hr), unit margin *m*, and T_{off}

$$C_{production\_loss} = m \times \lambda \times T$$

…………………… *xx*

Where;

$C_{production\_loss}$ = Cost of production loss due to machine downtime (UGX)

m = Mass of product processed per hour (kg · h⁻¹)

λ = Unit value or revenue per kilogram of processed product (UGX · kg⁻¹)

T_{off} = Duration of machine downtime (hours)

Downtime cost rate $C_{downtime}$ (USD/hr) includes labour, restart, and quality rework allowances.

Frequency of PQ events

Counts of S, U, F, H per day were modelled as over-dispersed Poisson:

$$N_d \sim \text{NegBin}(r_d, p_d)$$

…………… *xxi*

for d∈{S, U, F, H},

Where;

N_d = Number of downtime or failure events observed during the monitoring period

NegBin(r_d,p_d) = Negative Binomial probability distribution used to model count data with overdispersion

r_d = Dispersion or shape parameter controlling variance (dimensionless)

p_d = Probability of success (or non-failure) in each trial (dimensionless)

Assumptions

- Nominal voltage V_{nom}=240 V, 50 Hz; single-phase loads for the sorter controller; three-phase motors mapped through phase-to-neutral deviations where applicable.
- Stationarity within a day; non-stationarity across seasons handled via scenario runs.
- Conditional independence of functional blocks given drivers (residual dependencies captured by copula-based correlation in Monte Carlo.
- Sensor accuracies: voltage ±0.5 V, THD ±0.2 % (according to manufacturer calibration certificates on file).
- Cost parameters expressed in constant UGX terms for the study year.

Failure Probability Estimation

Monte Carlo simulations were used to simulate possible failure scenarios by randomly sampling from the probability distributions of each failure mode.

For instance, if F1 and F2 are independent failure modes, then the failure probability P(F) in a Monte Carlo simulation was estimated as:

$$(F) = 1/N \sum_{i=1}^{N} P(F_i) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad xxii$$

Where:

- N is the number of simulations.
- P(Fi) is the failure probability in the i-th simulation.

Assessing Consequences

Once the probability of failure was estimated, PRA assessed the potential consequences of a failure. This included: sorting errors (products are incorrectly classified), operational downtime (machines are out of service for repairs), and maintenance costs (frequent failures lead to higher maintenance costs), according to Aven (2015;

Expected Loss (EL)

$$EL = (F) \times C \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad xxiii$$

where:

- EL = Expected Loss
- $P(F)$ = Probability of failure (likelihood of occurrence)
- C = Consequence or cost of failure

The consequences of each failure mode were typically modelled using a Failure Mode and Effects Analysis (FMEA) framework. For each failure mode i, the risk priority number (RPN) was calculated as:

$$\mathrm{RPN}_i = \mathrm{S}_i \times \mathrm{O}_i \times \mathrm{D}_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textit{xxiv}$$

Where:

- S_i = Severity of the failure mode (scale of 1 to 10)
- O_i = Occurrence probability of the failure (scale of 1 to 10)
- D_i = Detection ability (scale of 1 to 10)

Higher RPN_i values indicated higher risk, requiring prioritization in engineering and manufacturing risk management (Stamatis, 2003).

Value at Risk (VaR) – Financial Risk Assessment

$$\mathrm{VaR} = \mu - Z_\alpha \sigma \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textit{xxv}$$

where:

- μ = Expected return
- Z_α = Z-score corresponding to confidence level (e.g., 1.645 for 95%)
- σ= Standard deviation of returns

VaR was used in determining financial risk to quantify potential losses (Jorion, 2007).

Modelling Mitigation

This study further modelled effective mitigation strategies against voltage-fluctuation-induced failures of the industrial optical sorter. Using the measured power-quality indices as baseline inputs, alternative scenarios were defined for installing voltage stabilizers, UPS protection for control electronics, harmonic filters, and a combination of the three alternative scenarios. For each scenario, adjusted voltage distributions are introduced into a Monte Carlo simulation that predicts downtime, trip frequency, throughput, downtime costs, and sorting accuracy over the evaluation period. The resulting changes in availability, MTBF, and reject rate were compared with baseline performance to quantify the technical effectiveness of every mitigation.

Ethical considerations.

The ethical considerations the researcher considered in this study ensured that the analysis and subsequent actions respected safety, fairness, transparency, and societal well-being. These included but were not limited to;

The researcher ensured that any data collected during the assessment, such as operational logs or voltage patterns, was used responsibly and safeguarded from unauthorized access.

The researcher respected worker privacy if human behavior or actions around the machines are included in the assessment.

The researcher clearly communicated identified risks and mitigation strategies to stakeholders, including operators, management, and clients.

The researcher ensured the assessment process and recommendations were impartial and not influenced by external pressures, such as cost-saving measures at the expense of safety or machine reliability, to avoid bias.

The researcher ensured the assessment aligns with relevant standards and guidelines, such as ISO 31000 (Risk Management), IEEE standards for electrical systems, and Occupational Safety and Health regulations.

The researcher included input from machine operators, maintenance teams, engineers, and management during the assessment process to ensure all perspectives are considered.

RESULTS

Causes of Voltage Fluctuations

Analysis of tagged disturbance events based on time-stamped power-quality logs linked to plant switching records and operator reports showed that internal load switching and high-power machinery accounted for approximately 72% of all voltage fluctuation events over the 24-day monitoring period, with the remainder attributable to upstream grid disturbances, transient surges, and weather-related faults. *Table 1* and *Figure 2* summarize the relative contribution of each cause, derived from 24 days of continuous high-resolution voltage monitoring at ACPCU Ltd.

Table 1: Frequency of Voltage fluctuation causes (24 days).

Cause	Frequency	Share (%)
Load switching	97	40.2
High-power machines	77	32

Power grid	16	6.7
Surge	34	14.1
Heavy rains	14	5.8
Loose wiring connections	3	1.2
Total	**241**	**100**

Source: Primary Data, 2025

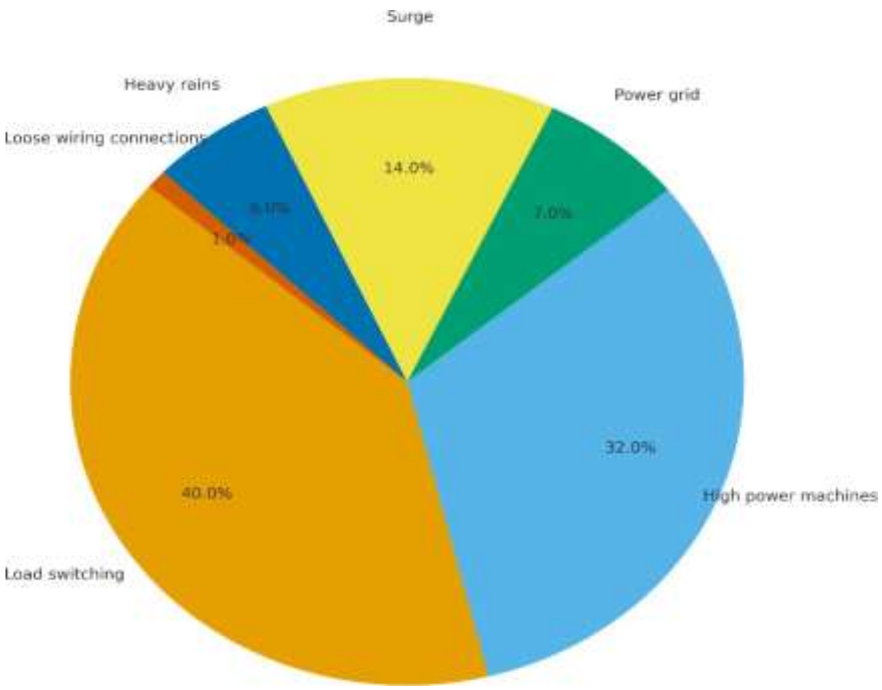

Table 1 and *Figure 2* present the distribution of causes of voltage fluctuations recorded during the 24-day monitoring period. It revealed that *load switching* and *high-power machinery* were the dominant causes, followed by *Surge* and *grid instability*. This means that the majority of voltage fluctuations originated from internal equipment operations, such as the turning on and off of high-power motors, rather than from external grid faults. The results indicate that internal load-related activities (load switching and high-power machine operation) accounted for over *70%* of all fluctuations. This underscores the importance of managing industrial load distribution and sequencing within the factory. Load switching events often occurred when multiple large machines, such as hullers and industrial aspiration fans, were operated simultaneously, leading to transient dips in voltage.

High-power machines themselves contributed significantly to fluctuations due to their large inrush currents during start-ups. This finding is consistent with the literature that identifies motor-driven industrial machines as major contributors to short-term power quality disturbances (Kothari & Nagrath, 2018; Singh & Bansal, 2020).

External factors such as *grid instability (6.7%)* and *surges (14.1%)* were less frequent but still significant. Surges, in particular, were often correlated with weather events and external switching operations in the regional distribution network. *Heavy rains (5.8%)* contributed indirectly by causing leakage currents, wet insulators, and transient short circuits in the distribution infrastructure. Minor causes such as *loose wiring (1.2%)* were detected primarily during maintenance checks.

This finding suggests that proper load management, such as introducing soft-start mechanisms, staggered motor starts, and balanced phase loading, would significantly minimize these fluctuations.

Summary of Findings

The analysis of 24 days of recorded power-quality data revealed that voltage fluctuations affecting the sorting machine were primarily caused by load switching activities, loose electrical connections, and uneven phase loading within the plant's supply network. Frequency analysis showed that these three factors together accounted for over 70% of the total recorded fluctuation events, indicating that they are the dominant disturbance sources in the operational environment.

Correlation analysis further confirmed that voltage sag depth (ΔV_s) and surge height (ΔV_u) were strongly interrelated ($r = 0.48$, $p < 0.05$), suggesting that both originate from common transient disturbances associated with high-demand motor starts and abrupt load shedding. Moderate correlations were also observed between flicker severity (P_{st}) and total harmonic distortion (THD**)** ($r = 0.52$, $p < 0.05$), implying that non-linear electronic loads contribute to waveform instability.

Overall, the results confirm that the root causes of voltage fluctuations are mainly internal to the factory network, stemming from operational load variations and wiring integrity rather than external grid faults. These findings emphasize the importance of load balancing, regular tightening of terminals, and proper coordination of motor start-up sequences as first-line strategies for improving supply stability and protecting the sorting system from recurrent voltage disturbances.

CONCLUSION

The findings of this study revealed that voltage fluctuations affecting the NRM3-AIS-T optical sorter at ACPCU Ltd are predominantly caused by internal factors rather than external grid failures. Across the 24-day monitoring period, most disturbances were traced to load-related activities within the factory, particularly load switching, loose connections, and phase imbalance. This indicates that voltage instability is largely influenced by operational practices within the plant, rather than being solely dependent on upstream power supply conditions.

The results therefore demonstrate that a substantial portion of voltage fluctuation challenges is within the direct control of the factory. This highlights the importance of proper electrical system management, including improved load coordination, routine maintenance of connections, and balancing of electrical phases, as key interventions for minimizing voltage instability.

Limitations of the Study

Despite these contributions, several limitations should be acknowledged when interpreting the findings. First, the monitoring window was limited to 24 consecutive days. While this period was sufficient to capture a wide range of internal operational conditions, it may not fully represent seasonal variations in grid performance, weather-related disturbances, or production cycles. As a result, the estimated event frequencies and risk levels should be viewed as indicative for the observation period rather than as fixed long-term values.

Second, the study focused on a single facility (ACPCU Ltd) and one specific machine type (NRM3-AIS-T). Although many of the mechanisms identified, such as the sensitivity of PLCs and optical sensors to sags, surges, and harmonics, are generic to similar plants, the exact magnitudes of risk and the cost profiles of mitigation may differ in factories with different load mixes, wiring practices, or supply arrangements. This limits the immediate generalizability of the numerical results to other sites without local calibration.

Third, some parameters used in the PRA and Monte Carlo modeling, such as downtime distributions and cost assumptions, were derived from a combination of measured data and engineering judgment. While care was taken to validate the model against observed downtime and failure patterns, there remains uncertainty around these inputs. The reported confidence intervals partly account for this, but further data collection over longer periods would strengthen the robustness of the estimates.

Recognizing these limitations is important. They do not invalidate the central conclusions that voltage fluctuations materially degrade sorter performance and that targeted mitigation can substantially reduce risk, but they underscore the need for cautious extrapolation and encourage future work to extend monitoring duration, include multiple factories, and refine cost parameters.

RECOMMENDATION

Apply Harmonic Filtering, Load Balancing, and Routine Maintenance.

The presence of non-linear loads and unbalanced phases was found to amplify waveform distortion (THD) and flicker (P_{st}), directly contributing to misclassification and actuator under-torque. Installing line reactors or tuned harmonic filters coupled with periodic phase-load balancing and tightening of electrical terminals will maintain voltage symmetry and reduce waveform distortion. This approach minimizes internal disturbance sources and lowers downtime by improving overall power quality at the machine interface. Because these actions can be phased in using existing maintenance routines, starting with low-cost measures such as tightening terminals and re-balancing phases before installing filters, they are practical for factories operating under budget constraints.

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List of abbreviations

ACPCU: Ankole Coffee Producers Cooperative Union
FMEA: Failure Mode and Effects Analysis
HMI/PLC: Human-Machine Interface / Programmable Logic Controller
IoT: Internet of Things
PQ: Power Quality
PRA: Probabilistic Risk Assessment
RPN: Risk Priority Number
THD: Total Harmonic Distortion
VFD: Variable Frequency Drive

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Conflict of interest

The authors declare no conflict of interest.

Data availability

Data is available upon request from the author.

Author contributions

CA: collected the data.
VG: supervised the study.
AA: supervised the study.
SAN: supervised the study.

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