

A Novel Deburn-in Machine Learning Framework for OLED Displays Considering Frame Rate, PWM, Grayscale, and Temperature

Jyun-Wei Su*, Paul C.-P. Chao*, Sheng-Hsun Hsieh**, Shih-Hsun Huang**

*Department of Electrical Engineering, National Yang Ming Chiao Tung University, Hsinchu, Taiwan

**Raydium Semiconductor Corporation, Hsinchu, Taiwan

Abstract

This work proposed a luminance degradation prediction method considering frame rate, PWM, grayscale, and temperature, achieving a prediction error of less than 1%. It delivers $\Delta E_{00} < 1$ for luminance over 50 nits and $\Delta E_{00} < 2$ for luminance over 1 nit, providing precise compensation and significantly improving OLED display visual quality under varied conditions.

Author Keywords

OLED; Burn-In; Neural-Network; Luminance Degradation; Luminance Compensation

1. Objective and Background

Luminance degradation, commonly called burn-in, significantly affects the visual quality of LED, OLED, and Micro-LED displays. This phenomenon arises from prolonged usage, leading to uneven brightness and color shifts across the display panel. The deburn-in process involves mitigating or compensating for such degradation to restore image quality and extend the lifespan of displays. Traditional deburn-in methods, relying on driving current and time [1-3], are hindered by the inability to measure pixel-specific currents and the need for extra circuitry, making them unsuitable for small-size or high-PPI displays. Temperature also critically influences degradation rates [4]. Other parameters, such as pixel circuits, PWM, and frame rates complicate the predictions, making single-variable models inadequate.

This work proposes a multi-variable luminance degradation prediction model incorporating temperatures, frame rates, PWMs, and grayscales. The model aims to enhance display calibration, improve image quality, and extend operational lifespan even in challenging conditions. Figure 1 illustrates the architecture of the luminance degradation AI model.

2. Method

To address the challenges of luminance degradation prediction, recent studies have explored temperature and pixel voltage (V_{data}) as inputs [5]. LTPS OLED displays operate at frame rates of 60 Hz, 90 Hz, and 120 Hz, variations in luminance and color performance [6]. A study [7] focuses on burn-in detection methods that remain essential in manufacturing and calibration but overlook the interplay of other operational parameters. This work collects luminance and color data from OLED panels using a CA-410 color analyzer under diverse operational conditions, including varying temperatures, frame rates, PWMs, and grayscales. The preprocessing incorporating standardization and interpolation ensures data consistency and quality. Based on the collected data, a neural network-based model is developed to predict OLED decay characteristics accurately. Building on this model, a compensation framework is designed to mitigate luminance degradation, offering a comprehensive deburn-in solution for OLED displays.

Experiment: The experiment was conducted using a 6.8-inch (1080 × 2400 resolution) OLED panel, following the guidelines

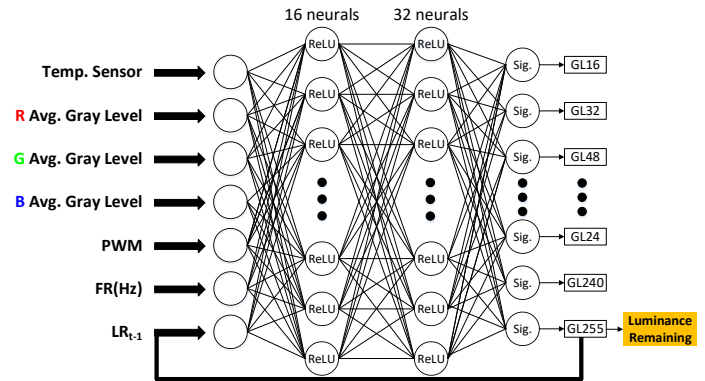


Figure 1. Luminance degradation AI model.

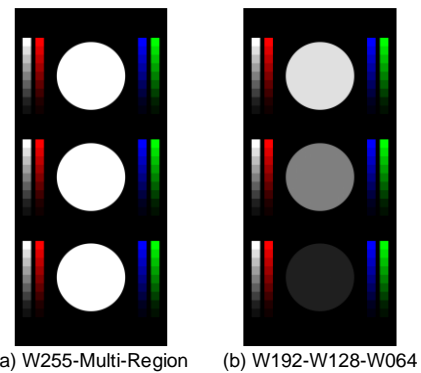


Figure 2. Burn-in pattern for the experiment.

outlined in the International Commission on Illumination (CIE) LM-80 [8] and TM-21 [9] standards. The experimental procedure involved measuring color and luminance at intervals of 10–20 hours over a total duration of 400–700 hours, executed as follows:

1. Calibrate the panel to a target luminance level.
2. Perform burn-in inside a chamber for 10–20 hours under controlled temperatures.
3. Measure color and luminance characteristics for each burn-in period.
4. Repeat steps 2 and 3 (burn-in and measurement) until the total duration reaches 400–700 hours.

Two distinct burn-in patterns were employed to examine luminance degradation under varying conditions, as shown in Figure 2. The W255-Multi-Region pattern assessed spatial variations in burn-in across different panel regions, with all three color channels—red, green, and blue—undergoing simultaneous burn-in due to the nature of white light. The W192-W128-W064 pattern analyzed degradation behavior at 192, 128, and 64 grayscales. Both patterns included three centrally positioned circular regions aligned with the CA-410 color analyzer probe for precise measurement and adjacent check bars to validate post-compensation effectiveness.

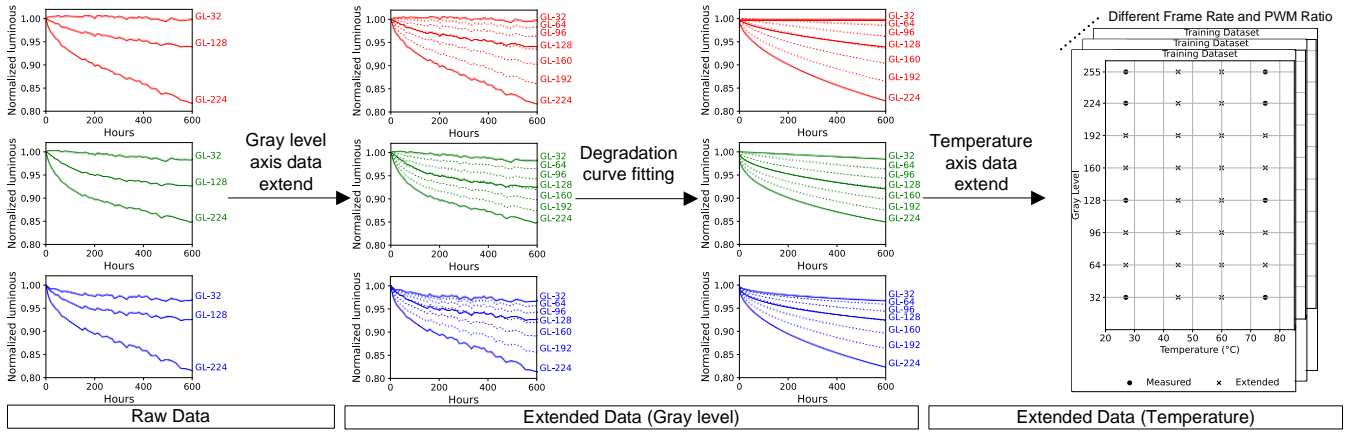


Figure 3. Dataset preprocessing flow.

Datasets and Processing: Outliers in the luminance degradation raw data are excluded to ensure the reliability of the following processing. The stretched-exponential model [10, 11], commonly employed for decay phenomena in electronic materials, is expressed as

$$L(t) = L_0 \cdot e^{-\left(\frac{t}{\tau}\right)^\beta}, \quad (1)$$

where $L(t)$ is the normalized luminance at time t , L_0 is the initial luminance, τ is the characteristic degradation time constant, and β is the stretching exponent describing the curvature of the decay. Both τ and β are extracted for each gray level (GL) and temperature condition by fitting the measured data. Since experimental data were collected for specific gray levels (e.g., GL_{32} , GL_{128} , and GL_{224}) and temperatures (e.g., 27°C and 75°C), interpolation is performed to extend the dataset to intermediate conditions, enhancing the training coverage of the prediction model. The luminance degradation at intermediate gray levels (GL_{target}) is interpolated using the gamma-corrected luminance function,

$$L(GL_{target}, t) = F \{ L(GL_a, t), L(GL_b, t), pf \}, \quad (2)$$

where $G(GL, t)$ represents the gamma-adjusted luminance for the gray level $GL(\gamma=2.2)$ at time t . GL_a and GL_b are the adjacent gray levels bounding GL_{target} . pf is the power factor determined by the experimental fitting.

Temperature interpolation is performed by assuming that the degradation rate is exponentially proportional to temperature. The normalized luminance for a target temperature (T_{target}) is calculated using exponential interpolation,

$$L(T_{target}, t) = E \{ L(T_a, t), L(T_b, t), T_{target} \}, \quad (3)$$

where T_a and T_b are the temperatures bounding for T_{target} . $L(T, t)$ denotes the luminance at temperature T and time t . This interpolation approach aligns with findings in degradation studies, which demonstrate an exponential relationship between temperature and material aging.

The experimental data, measured under varying framerate and PWM conditions, are processed using the data extension method mentioned above. The dataset is extended across varying temperatures, frame rates, PWMs, and grayscales, ensuring a comprehensive representation of all operational conditions. This expanded dataset enhances the generalizability of the luminance degradation prediction model.

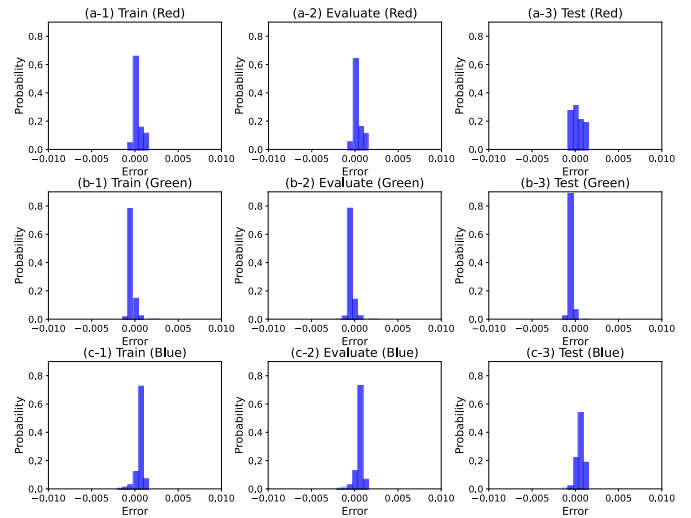


Figure 4. Histogram of training, evaluating, and testing errors for (a) Red, (b) Green, and (c) Blue light luminance degradation model.

Luminance Degradation AI Model: The luminance degradation AI model was trained on an extended dataset, with its architecture depicted in Figure 1. Input features included temperature, RGB gray levels (GL) from the same pixel, framerate, PWM, and prior luminance remaining (LR) at GL_{255} . The model architecture featured two fully connected hidden layers with ReLU activation functions, followed by an output layer utilizing a sigmoid activation function to predict luminance remaining at different grayscales within a 0 to 1 range. This design facilitated high-dimensional, non-linear, multivariable curve fitting, enabling accurate predictions of relative luminance degradation under varying conditions. The dataset spanned a 1,000-hour prediction period, integrating both measured and interpolated data for comprehensive coverage.

The training data encompassed luminance measurements of red, green, and blue light at gray levels GL_{255} , GL_{224} , GL_{192} , GL_{160} , GL_{128} , GL_{96} , GL_{64} , and GL_{32} , captured under temperatures of 27°C , 45°C , 60°C , and 75°C , as well as frame rates of 60 Hz, 90 Hz, and 120 Hz with varying PWM conditions. The dataset was split into training and validation sets in an 8:2 ratio to ensure robust learning and avoid overfitting. A separate test set, which included exclusively measured values not used during training—such as GL_{255} at 55°C , GL_{128} at 27°C , and GL_{128} at 75°C —was

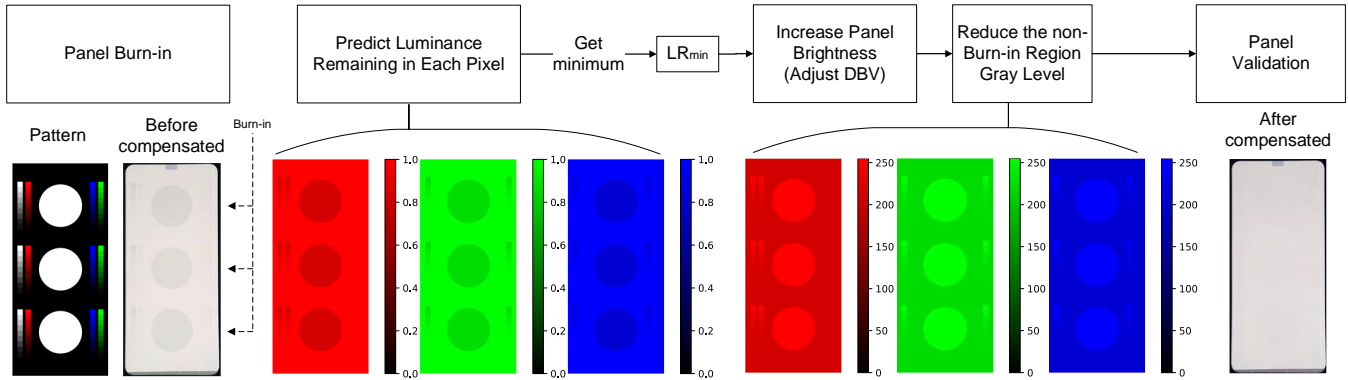


Figure 5. Deburn-in compensation process flow

designated for unbiased evaluation. The error distributions across training, validation, and testing phases demonstrated exceptional accuracy, with prediction errors consistently below 1% and closely centered around zero, as shown in Figure 4. The results confirm the model’s precision, positioning it as a dependable approach for predicting OLED luminance degradation and serving as a baseline for luminance compensation.

Compensation Flow: The compensation process, as shown in Figure 5, mitigates luminance degradation in OLED panels by systematically adjusting brightness and gray levels to improve uniformity. Over time, OLED panels experience uneven luminance degradation across regions. To address this, an AI model predicts the remaining luminance (LR) for each pixel, identifying the most degraded region through the minimum remaining luminance (LR_{min}). The process begins by adjusting the display brightness value (DBV) using the panel’s gamma settings, restoring the luminance of the most degraded region to its target level through a uniform brightness increase. Subsequently, gray levels in less degraded areas are reduced to match their luminance with the adjusted brightness of the most degraded region, ensuring consistent luminance across the panel. By confirming uniform luminance and the absence of visual artifacts, the process ensures optimal display quality while countering the effects of long-term luminance degradation. This systematic flow resolves localized degradation enhances panel performance and prolongs its usability.

3. Characteristic Analysis

Key factors in OLED luminance degradation include position, pixel voltage, frame rate, PWM frequency, temperature. These parameters impact uniformity, longevity, and stability, shaped by thermal, electrical, and operational conditions. AI models effectively address these complexities, enhancing reliability, compensation strategies, and predictive accuracy to optimize OLED performance and durability.

Impact of Position: The W255-Multi-Region pattern, as illustrated in Figure 2(a), reveals through experimentation a consistent trend in RGB luminance degradation characteristics across different regions, further corroborated by the results presented in Figure 6(a). This uniformity not only simplifies the prediction process but also eliminates the complexity of compensation by avoiding the need to account for varying regional characteristics.

Impact of Pixel Voltage (V_{data}): Luminance degradation is crucial to OLED display reliability. Research has modeled this

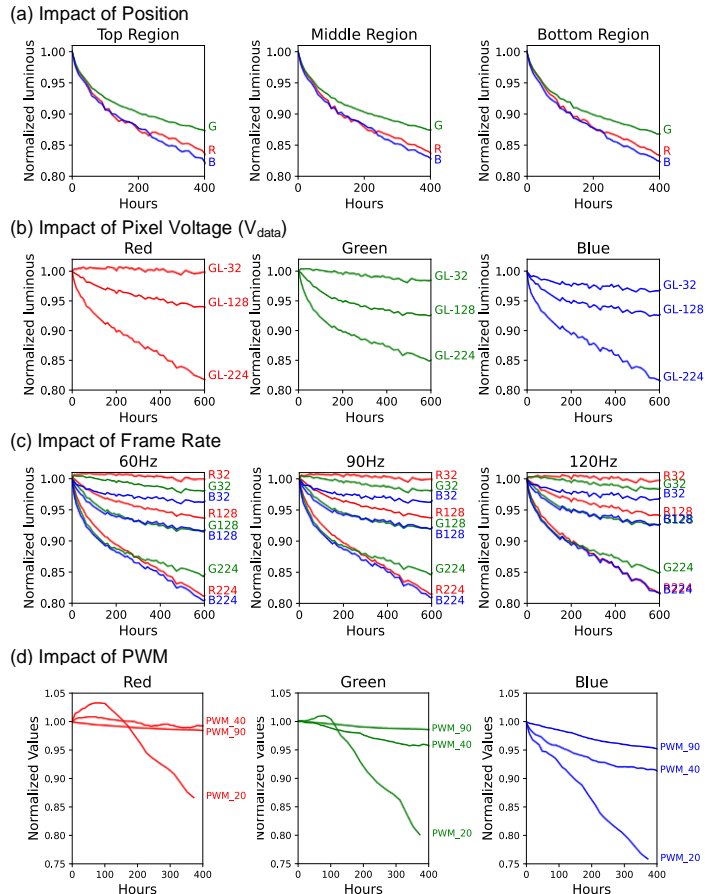


Figure 6. Analysis of luminance degradation characteristics influenced by (a) position, (b) pixel voltage, (c) frame rate, and (d) PWM.

behavior using thermal stress and electrical load [12], highlighting the impact of gray levels and exposure duration. Lower gray levels (e.g., L32) degrade more slowly than higher ones (e.g., L255) due to lower pixel current and heat generation. Luminance degradation over time is non-linear, often requiring stretched-exponential models for accuracy. As shown in Figure 6(b), RGB channels at gray levels 32, 128, and 224 follow the trend of more significant degradation at higher brightness, though the extent varies between channels. These findings underscore the importance of the gray level data extension method outlined in Figure 3.

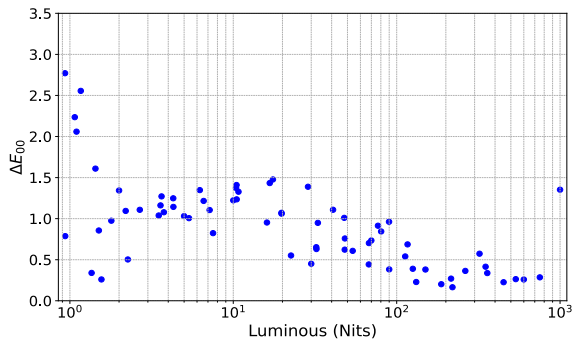


Figure 7. ΔE_{00} after compensation at different luminance.

Impact of Frame Rate: The frame rate affects luminance degradation by altering pixel emission duration and thermal stress. At 60, 90, and 120 Hz, the total emission time shows minor differences, making burn-in noticeable only after prolonged use, as shown in Figure 6(c). LPTS OLEDs, supporting 15 to 360 Hz, are expected to exhibit unique burn-in patterns under different frame rates.

Impact of PWM: Pulse-width modulation (PWM) is widely used to control luminance levels in display systems. Higher PWM duty cycles, such as PWM₉₀, closely mimic direct current (DC) driving, offering stable luminance. In contrast, lower duty cycles (e.g., PWM₄₀ and PWM₂₀) involve frequent on-off transitions, inducing significant thermal and electrical stress and accelerating pixel degradation. Figure 6(d) illustrates burn-in under different PWM for the same target luminance. Both red and green channels initially demonstrate slight luminance overshoot under PWM driving. Over time, however, lower duty cycles result in more pronounced degradation, with PWM₂₀ exhibiting the fastest decline. For the blue channel, degradation occurs across all PWM conditions, with PWM₂₀ showing the steepest decline, underscoring its susceptibility to thermal stress. This degradation behavior deviates from traditional luminance degradation models, which struggle to adapt to the complex dynamics of PWM-driven systems. In this work, machine learning-based models effectively address these characteristics, offering a more accurate approach to modeling and predicting luminance degradation.

4. Impact and Conclusion

This work proposed a Deburn-in Machine Learning Framework for OLED displays, addressing degradation influenced by frame rate, PWM ratio, grayscale, and temperature. The integration of AI enabled the identification and prediction of degradation tendencies, facilitating more informed and targeted interventions. The framework demonstrated practical applicability by generating offline lookup tables (LUTs) that can be integrated with existing OLED systems [13]. Additionally, the use of interpolation techniques allowed the construction of a dataset encompassing various grayscale and temperature conditions, improving the model's adaptability. The model achieved a prediction deviation of under 1%, meeting industry expectations for accuracy. Compensation results showed $\Delta E_{00} < 1$ for luminance over 50 nits and $\Delta E_{00} < 2$ for luminance over 1 nit, as shown in Figure 7. The compensation flow incorporated a strategy that dynamically adjusts display brightness and grayscales in less degraded regions, aiming to improve luminance uniformity and extend panel lifespan while preserving visual quality. The results demonstrate potential, further refinement is necessary to ensure consistent performance across diverse operational scenarios.

This work contributes to the field by offering a feasible approach for real-time calibration and degradation mitigation in OLED displays. The framework enhances reliability and longevity by addressing luminance uniformity and burn-in challenges, supporting sustainability and waste reduction in electronic display manufacturing.

5. References

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