

**Figure 8:** The x-axis represents metric scores for uniform dimming, and the y-axis metric scores for ML-PEA. Scatter color is power saved (%), and the identity line is plotted as a black dashed line. Higher scores equal higher predicted quality.

## 8. Image Quality Metric Results

We ran three metrics on the test dataset from DIV2k: PSNR, SSIM, and ColorVideoVDP. The results are shown in Figure 8, where each scatter point corresponds to one of the 100 test images from the DIV2k test dataset. Note that this plot shows results for the three target power saving rates, so in total there are 300 scatter points for each metric. A model can be considered to perform well if scatter points lie above the identity line, i.e. metric scores for ML-PEA output is higher than scores for uniformly-dimming images.

Selection of PSNR and SSIM as evaluation metrics is based on prior art, which use these metrics to evaluate their models [SDLM24, ADMM25, LMDB23]. The inclusion of ColorVideoVDP [MHA\*24] was meant to introduce a modern metric based on low-level models of human vision, trained on display-related distortions.

## 9. Additional Ablation Studies

Here, we discuss additional ablation studies and experiments, meant to supplement the discussion from Section 4.2.

### 9.1. Ablating Loss Weights

We conducted an ablation on the loss function weights, as described in Section 4.2. The following weights were studied in this experiment:

- $\lambda_{\mathcal{P}} : \{5.0, 50.0\}$
- $\lambda_{\text{VGG}} : \{0.0, 0.05, 0.5\}$
- $\lambda_{\text{SSIM}} : \{0.0, 0.5, 5.0\}$ .

The results for each combination of parameters are shown, for power saving targets of 17%, 32%, and 45% ( $\alpha = \{0.83, 0.68, 0.45\}$ ), in Table 2. Cell colors represent first, second, and third-best performance. Note that the column “Power Target - Pred.” represents the quantity

$$\Delta\mathcal{P} = 100 \cdot (1 - \alpha) - 100 \cdot (1 - \mathcal{P}(\mathcal{I}^*)/\mathcal{P}(\mathcal{I})), \quad (9)$$

which is essentially the difference in power savings between the optimized image  $\mathcal{I}^*$  and the target power saving rate. It is important that the model outputs images which closely match the target power saving rate, and so models that have a value of  $\Delta\mathcal{P}$  close to 0 are ideal. Here, we recall that  $\alpha$  is the target proportion of power consumed by the target, relative to the input. In other words, if we define  $T$  as the target power savings (%), then  $T = 100 \cdot (1 - \alpha)$ .

One important note is that the rankings in Table 2 do not paint a complete story – while we show which combination of parameters perform best in terms of a number of common image quality metrics, these naturally depend on the accuracy of the model to produce images with power savings close to the target. In other words, when inspecting Table 2 we notice that PSNR, SSIM, and CVVDP scores are typically highest for  $\Delta\mathcal{P}$  with large magnitude (or models that do not approximate the target power savings well). As a result, it is important to jointly consider  $\Delta\mathcal{P}$  as well as the metric scores to find a fine balance between the two when selecting model parameters. The ability to control the power savings of the model’s output is crucial to its performance, and the core problem in our constrained optimization. In our experiments, we used the parameters of the last row in each  $\alpha$  block ( $\lambda_{\mathcal{P}} = 50.0$ ,  $\lambda_{\text{VGG}} = 0.5$ , and  $\lambda_{\text{SSIM}} = 5.0$ ).

We make the decision to display Table 2 with ML-PEA and uniform dimming results side by side and mark the rankings within techniques, rather than between techniques. The reason for this is because we want to show optimal parameters for ML-PEA. Comparisons between ML-PEA and uniform dimming can still be made by comparing the results within the same row.

### 9.2. Ablating Element-Wise Dimming Map Application

In Section 3, we allude to the fact that our element-wise multiplication (MULT) function  $f$  is optimal compared to the addition (ADD) operation used in prior art. We conducted an ablation on  $f$  (ADD or MULT) as well as the number of channels (1 or 3) in the output dimming map. The results of these experiments are shown in Table 3. A qualitative comparison is shown in Figure 9, where we can

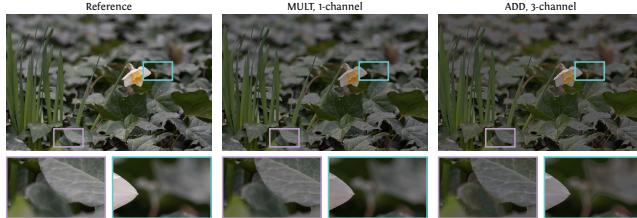
**Table 2:** Here, we display results of ablations on the weights of loss functions used in our experiments. We show results for both ML-PEA (●) and uniform dimming (●). Cell colors represent first, second, and third-best performance in each  $\alpha$  block within power saving techniques.

| $\alpha$ | $\lambda_P$ | $\lambda_{VGG}$ | $\lambda_{SSIM}$ | $\Delta P$ | PSNR ↑ (●) | SSIM ↑ (●) | CVVDP ↑ (●) | PSNR ↑ (●) | SSIM ↑ (●) | CVVDP ↑ (●) |
|----------|-------------|-----------------|------------------|------------|------------|------------|-------------|------------|------------|-------------|
| 0.55     | 5.00        | 0.00            | 0.50             | 1.287      | 18.948     | 0.966      | 8.928       | 19.380     | 0.932      | 9.928       |
|          | 50.0        | 0.00            | 0.50             | 2.495      | 19.398     | 0.967      | 9.050       | 19.551     | 0.939      | 9.937       |
|          | 5.00        | 0.00            | 5.00             | 16.506     | 23.271     | 0.987      | 9.374       | 23.759     | 0.975      | 9.979       |
|          | 50.0        | 0.00            | 5.00             | 0.855      | 18.838     | 0.964      | 8.843       | 19.273     | 0.931      | 9.927       |
|          | 5.00        | 0.05            | 0.00             | 2.816      | 19.495     | 0.951      | 9.755       | 19.765     | 0.939      | 9.940       |
|          | 50.0        | 0.05            | 0.00             | -1.617     | 18.510     | 0.926      | 9.836       | 18.486     | 0.924      | 9.913       |
|          | 5.00        | 0.05            | 0.50             | 4.764      | 19.963     | 0.972      | 9.558       | 20.208     | 0.945      | 9.943       |
|          | 50.0        | 0.05            | 0.50             | -3.785     | 17.944     | 0.955      | 9.467       | 18.123     | 0.912      | 9.904       |
|          | 5.00        | 0.05            | 5.00             | 14.375     | 22.681     | 0.985      | 9.694       | 23.008     | 0.971      | 9.974       |
|          | 50.0        | 0.05            | 5.00             | 3.634      | 19.662     | 0.971      | 9.405       | 19.877     | 0.942      | 9.940       |
|          | 5.00        | 0.50            | 0.00             | -3.914     | 17.763     | 0.940      | 9.228       | 18.464     | 0.903      | 9.893       |
|          | 50.0        | 0.50            | 0.00             | -6.029     | 17.403     | 0.921      | 9.440       | 17.761     | 0.898      | 9.888       |
|          | 5.00        | 0.50            | 0.50             | 6.016      | 20.276     | 0.971      | 9.469       | 20.968     | 0.945      | 9.943       |
|          | 50.0        | 0.50            | 0.50             | -9.064     | 16.767     | 0.936      | 9.356       | 17.035     | 0.882      | 9.862       |
|          | 5.00        | 0.50            | 5.00             | 15.778     | 23.192     | 0.987      | 9.846       | 23.442     | 0.974      | 9.979       |
|          | 50.0        | 0.50            | 5.00             | 0.092      | 18.805     | 0.963      | 9.551       | 19.076     | 0.928      | 9.924       |
| 0.68     | 5.00        | 0.00            | 0.50             | 2.044      | 22.829     | 0.986      | 9.352       | 23.170     | 0.972      | 9.976       |
|          | 50.0        | 0.00            | 0.50             | 0.886      | 22.454     | 0.981      | 9.098       | 22.602     | 0.971      | 9.975       |
|          | 5.00        | 0.00            | 5.00             | 9.554      | 25.574     | 0.992      | 9.440       | 25.900     | 0.985      | 9.989       |
|          | 50.0        | 0.00            | 5.00             | -0.038     | 22.131     | 0.983      | 9.167       | 22.553     | 0.968      | 9.970       |
|          | 5.00        | 0.05            | 0.00             | -5.509     | 20.695     | 0.961      | 9.763       | 20.904     | 0.955      | 9.958       |
|          | 50.0        | 0.05            | 0.00             | -0.688     | 22.108     | 0.970      | 9.927       | 22.078     | 0.968      | 9.970       |
|          | 5.00        | 0.05            | 0.50             | 1.390      | 22.729     | 0.985      | 9.786       | 23.011     | 0.971      | 9.975       |
|          | 50.0        | 0.05            | 0.50             | -2.376     | 21.614     | 0.980      | 9.865       | 21.672     | 0.963      | 9.967       |
|          | 5.00        | 0.05            | 5.00             | 9.627      | 25.736     | 0.992      | 9.817       | 26.008     | 0.985      | 9.989       |
|          | 50.0        | 0.05            | 5.00             | 1.080      | 22.621     | 0.985      | 9.736       | 22.838     | 0.971      | 9.974       |
|          | 5.00        | 0.50            | 0.00             | 6.627      | 24.647     | 0.985      | 9.765       | 25.421     | 0.979      | 9.983       |
|          | 50.0        | 0.50            | 0.00             | -6.007     | 20.551     | 0.969      | 9.707       | 20.853     | 0.952      | 9.956       |
|          | 5.00        | 0.50            | 0.50             | 4.437      | 23.778     | 0.987      | 9.855       | 24.171     | 0.977      | 9.982       |
|          | 50.0        | 0.50            | 0.50             | -3.243     | 21.341     | 0.979      | 9.758       | 21.626     | 0.960      | 9.963       |
|          | 5.00        | 0.50            | 5.00             | 13.992     | 27.434     | 0.993      | 9.744       | 27.976     | 0.990      | 9.995       |
|          | 50.0        | 0.50            | 5.00             | -1.613     | 21.818     | 0.982      | 9.812       | 21.963     | 0.965      | 9.968       |
| 0.83     | 5.00        | 0.00            | 0.50             | -0.046     | 28.038     | 0.994      | 9.443       | 28.441     | 0.991      | 9.994       |
|          | 50.0        | 0.00            | 0.50             | -0.413     | 27.961     | 0.993      | 9.389       | 28.014     | 0.991      | 9.994       |
|          | 5.00        | 0.00            | 5.00             | 4.733      | 31.006     | 0.996      | 9.568       | 31.444     | 0.995      | 9.997       |
|          | 50.0        | 0.00            | 5.00             | -1.445     | 27.367     | 0.994      | 9.428       | 27.618     | 0.990      | 9.994       |
|          | 5.00        | 0.05            | 0.00             | -4.332     | 26.196     | 0.990      | 9.891       | 26.555     | 0.987      | 9.991       |
|          | 50.0        | 0.05            | 0.00             | -0.876     | 27.814     | 0.992      | 9.982       | 27.775     | 0.991      | 9.994       |
|          | 5.00        | 0.05            | 0.50             | 1.609      | 29.257     | 0.996      | 9.942       | 29.535     | 0.993      | 9.995       |
|          | 50.0        | 0.05            | 0.50             | -0.759     | 27.897     | 0.994      | 9.979       | 27.878     | 0.991      | 9.994       |
|          | 5.00        | 0.05            | 5.00             | 4.425      | 31.050     | 0.997      | 9.969       | 31.280     | 0.995      | 9.997       |
|          | 50.0        | 0.05            | 5.00             | -0.374     | 28.060     | 0.995      | 9.819       | 28.302     | 0.991      | 9.994       |
|          | 5.00        | 0.50            | 0.00             | -2.207     | 27.237     | 0.989      | 9.891       | 27.949     | 0.988      | 9.993       |
|          | 50.0        | 0.50            | 0.00             | -3.702     | 26.425     | 0.990      | 9.895       | 26.657     | 0.988      | 9.992       |
|          | 5.00        | 0.50            | 0.50             | 1.741      | 29.279     | 0.995      | 9.924       | 29.775     | 0.993      | 9.996       |
|          | 50.0        | 0.50            | 0.50             | -1.392     | 27.631     | 0.994      | 9.928       | 27.937     | 0.990      | 9.994       |
|          | 5.00        | 0.50            | 5.00             | 7.636      | 33.662     | 0.998      | 9.989       | 33.748     | 0.997      | 9.997       |
|          | 50.0        | 0.50            | 5.00             | -0.718     | 27.937     | 0.995      | 9.926       | 28.222     | 0.991      | 9.994       |

**Table 3:** Ablation study results on the elementwise dimming map application,  $f$ , and the number of channels in the dimming map,  $C$ , are shown here.

| $\alpha$ | $f$  | $C$ | $\Delta\mathcal{P}$ | PSNR $\uparrow$ (●) | SSIM $\uparrow$ (●) | CVVDP $\uparrow$ (●) | PSNR $\uparrow$ (●) | SSIM $\uparrow$ (●) | CVVDP $\uparrow$ (●) |
|----------|------|-----|---------------------|---------------------|---------------------|----------------------|---------------------|---------------------|----------------------|
| 0.55     | ADD  | 3   | 0.537               | 18.566              | 0.955               | 9.074                | 19.166              | 0.930               | 9.933                |
|          | MULT | 3   | 3.543               | 19.599              | 0.972               | 9.560                | 19.930              | 0.940               | 9.939                |
|          | ADD  | 1   | -0.044              | 17.957              | 0.947               | 8.527                | 19.414              | 0.920               | 9.912                |
|          | MULT | 1   | 5.976               | 20.244              | 0.974               | 9.590                | 20.586              | 0.948               | 9.949                |
| 0.68     | ADD  | 3   | -1.610              | 21.523              | 0.982               | 9.490                | 22.221              | 0.963               | 9.966                |
|          | MULT | 3   | 1.199               | 22.642              | 0.985               | 9.835                | 22.856              | 0.971               | 9.975                |
|          | ADD  | 1   | 3.433               | 22.963              | 0.985               | 9.577                | 24.172              | 0.973               | 9.977                |
|          | MULT | 1   | -1.086              | 21.953              | 0.983               | 9.722                | 22.183              | 0.966               | 9.969                |
| 0.83     | ADD  | 3   | -1.360              | 27.405              | 0.995               | 9.890                | 27.900              | 0.990               | 9.994                |
|          | MULT | 3   | -0.483              | 27.976              | 0.995               | 9.910                | 28.168              | 0.991               | 9.995                |
|          | ADD  | 1   | -10.50              | 23.155              | 0.985               | 9.397                | 24.570              | 0.975               | 9.979                |
|          | MULT | 1   | 0.751               | 28.745              | 0.995               | 9.958                | 28.988              | 0.992               | 9.995                |

735 see visible artifacts around edge features in the 3-channel, ADD  
 736 condition which are not visible in the single-channel MULT one.  
 737 We find from this experiment that the MULT operator  $f$  performs  
 738 best. For all metrics, the 3-channel dimming map with MULT per-  
 739 formed 2nd-best or better for all target power saving rates. The 1-  
 740 channel dimming map with MULT performed best for target power  
 741 saving rates of 45% and 83%, and performed in the top 3 for a 32%  
 742 savings target.



**Figure 9:** We ablate the number of dimming map channels and the element-wise function  $f$  for applying the dimming map to input images.

758 ML-PEA and [LMDB23]. It is clear that the method of [LMDB23]  
 759 performs worse in terms of the three image quality metrics.

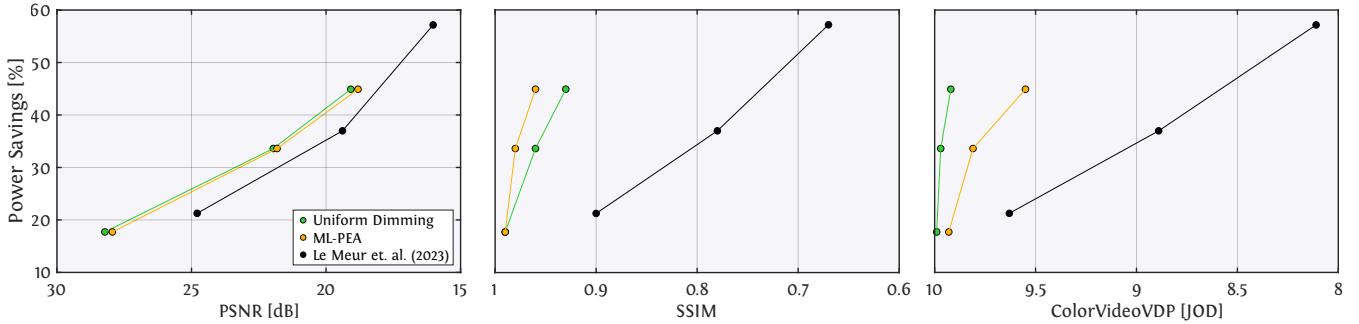
**Table 4:** Average scores are tabulated for uniform dimming, ML-PEA, and [LMDB23].

| $\alpha$ | Method                      | PSNR (dB) $\uparrow$ | SSIM $\uparrow$ | CVVDP (JOD) $\uparrow$ | Power Saved |
|----------|-----------------------------|----------------------|-----------------|------------------------|-------------|
| 0.55     | Uniform Dimming             | 19.08                | 0.93            | 9.92                   | -           |
|          | ML-PEA                      | 18.81                | 0.96            | 9.55                   | 44.91%      |
|          | Uniform Dimming<br>[LMDB23] | 17.46                | 0.89            | 9.83                   | -           |
| 0.68     | Uniform Dimming             | 16.02                | 0.67            | 8.11                   | 51.76%      |
|          | ML-PEA                      | 21.96                | 0.96            | 9.97                   | -           |
|          | Uniform Dimming<br>[LMDB23] | 21.82                | 0.98            | 9.81                   | 33.61%      |
| 0.83     | Uniform Dimming             | 19.39                | 0.78            | 9.93                   | -           |
|          | ML-PEA                      | 21.02                | 0.95            | 8.89                   | 36.98%      |
|          | Uniform Dimming<br>[LMDB23] | 20.22                | 0.99            | 9.99                   | -           |

### 743 9.3. Comparisons with Le Meur et al. (2023)

744 We conducted a comparison between our ML-PEA technique and  
 745 that of [LMDB23], which is the most recent and relevant prior  
 746 machine learning approach to display power optimization. There was  
 747 no open source code, so we attempted to replicate their pipeline as  
 748 best as possible. Their technique optimizes four loss functions: an  
 749 L1, SSIM, and power loss between the input and output images, as  
 750 well as a total variation loss on the dimming map. They also used  
 751 an ADD operation to apply output 1-channel dimming maps to the  
 752 input images.

753 We found that the metric scores of [LMDB23] were lower com-  
 754 pared to uniform dimming and ML-PEA for the three target power  
 755 saving rates we studied, as shown in Table 4. In addition, we make  
 756 a plot for this table, shown in Figure 10, to visualize the result. We  
 757 do this because the power saving rates are not matched between



**Figure 10:** The results from Table 4 are plotted here, for the three methods compared: uniform dimming (●), ML-PEA (○), and [LMDB23] (●). Quality is on the x-axis and power savings are on the y-axis. Note that here we plot lower quality as x increases, similar to Figure 7.

## 760 10. Quality Metric Correlation Analysis

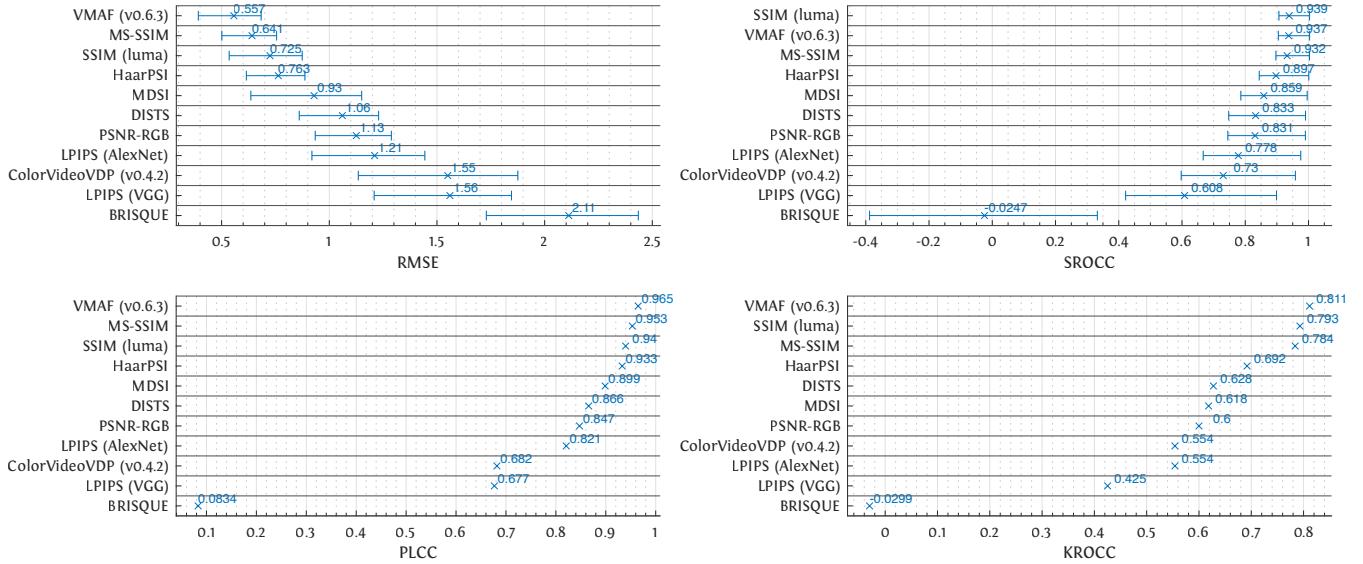
761 The typical evaluation strategy for prior machine learning-based  
 762 display power optimization methods has been to compare the aver-  
 763 age of metric scores computed across a test dataset. In Section 4.1,  
 764 we computed quality scores for PSNR, SSIM, and ColorVideoVDP  
 765 metrics on the DIV2k test dataset, and found that, depending on the  
 766 quality metric used, the conclusions made about the model’s perfor-  
 767 mance are very different. In Figure 11, we computed the root mean  
 768 square error (RMSE), Spearman (SROCC), Pearson (PLCC), and  
 769 Kendall (KROCC) correlation coefficients between scores com-  
 770 puted by an additional set of metrics (summarized in Table 5) and  
 771 subjective quality scores from our user study (see Section 5). We  
 772 recommend PSNR used in prior works should not be used as an  
 773 evaluation metric as it has a low correlation score, and may not be  
 774 robust enough for this task.

## 775 11. Supplemental Analyses

776 We conducted a number of additional analyses of the performance  
 777 of ML-PEA.

### 778 11.1. Power Savings Dependency on Image Statistics

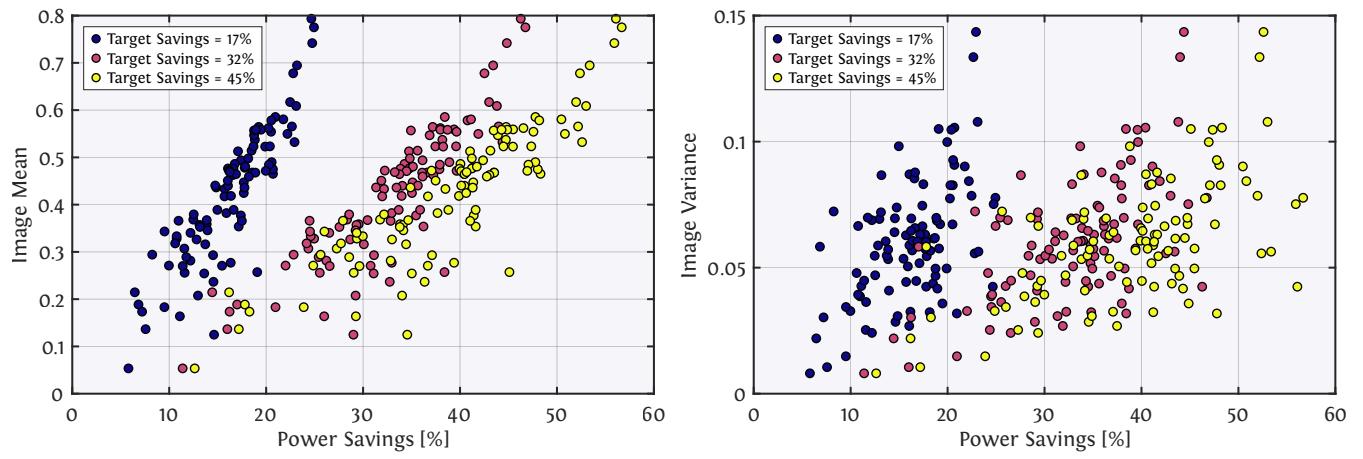
779 In Figure 12, we show that there is a positive correlation between  
 780 power savings and image statistics. Here, we show the mean and  
 781 variance of the image. This effect is likely due to the fact that im-  
 782 ages with many bright regions have greater potential for dimming,  
 783 and vice versa. In the limit, a completely black image has no room  
 784 for power savings, for example.



**Figure 11:** Correlation results for a number of different quality metrics, ranked by performance.

**Table 5:** Description of quality metrics used in Figure 11.

| Metric                 | Description   |
|------------------------|---|
| PSNR                   | Popular metric measuring the ratio between signal and noise.  |
| SSIM [WBSS04]          | Quality metric that considers luminance, contrast, and structural differences.                                  |
| MS-SSIM [WSB03]        | Multi-scaled version of SSIM.   |
| LPIPS (VGG) [ZIE*18]   | Compares feature representation of images from a pre-trained VGG network.                                       |
| LPIPS (AlexNet)        | Same as LPIPS (VGG) but with an AlexNet backbone.   |
| VMAF [LBN*18]          | Perceptual video quality metric that fuses a number of elementary metrics via support vector machines.          |
| HaarPSI [RBKW18]       | Perceptual quality measure based on the Haar wavelet decomposition.   |
| MDSI [NSHC16]          | Quality metric based on structural and color similarity.  |
| DISTS [DMWS20]         | Image quality metric that compares structure and texture similarity using deep features from a pre-trained CNN. |
| BRISQUE [MMB12]        | A no-reference quality metric based on scene statistics.  |
| ColorVideoVDP [MHA*24] | Low-level visual model that considers chromatic and achromatic sensitivity.                                     |



**Figure 12:** We show dependence of power savings on image mean (left) and variance (right).

785 **12. Additional Results**

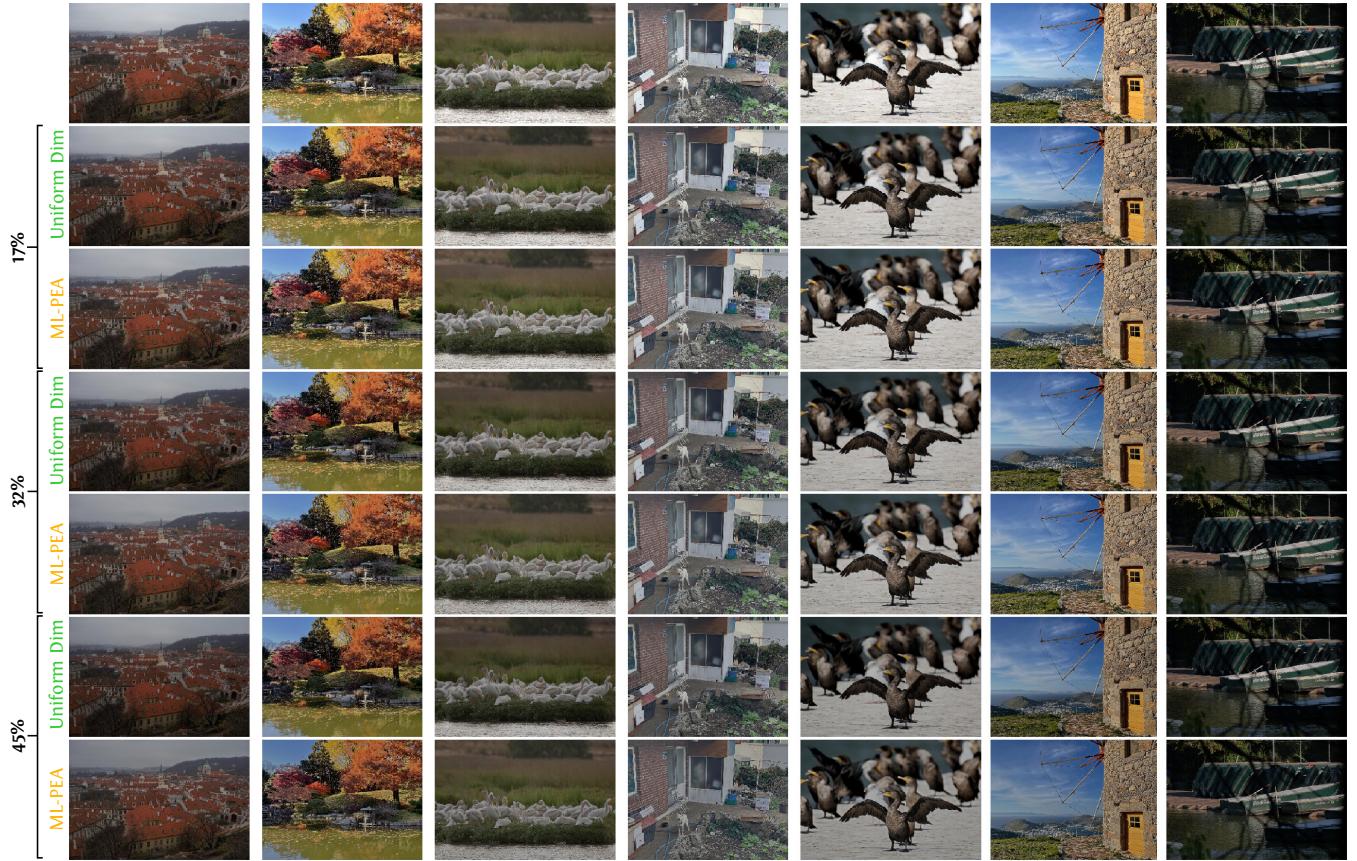
786 In [Figure 13](#), we show additional results comparing uniform dim-  
787 ming to ML-PEA. The first row shows the input images, and the  
788 next rows are power-optimized images at the target power saving  
789 rates shown to the left. Zoom in for details.

790 **13. User Study**791 **13.1. Study Instructions**

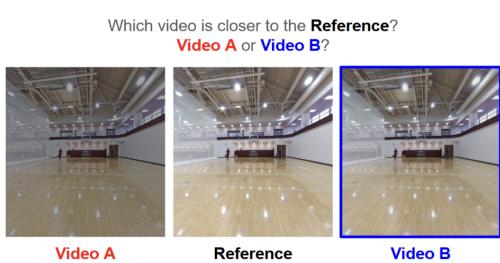
792 In [Figure 14](#), we show a screen grab of the user study instructions  
793 read to the users.

794 **13.2. Just Objectionable Difference**

795 The JOD unit is defined in [\[POM17\]](#). JODs can be mapped to per-  
796 centage preference, as shown in [Figure 15](#). They are scaled in a way  
797 such that 1 JOD between some condition A and another B equals a  
798 percentage selection of A of 75% over B.

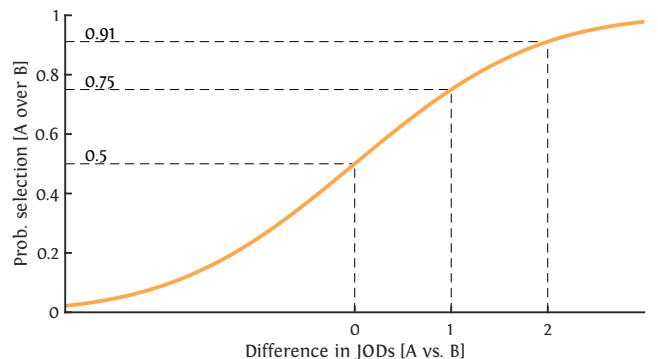


**Figure 13:** Additional results are shown here, comparing uniform dimming and ML-PEA.



You will be doing a user study in a VR headset, and will use the keyboard to interact with the study. There will be 60 trials. During each trial, you will first see a Reference video. You will be allowed to switch between this Reference video and two Test videos A and B using the keyboard **down**, **left**, and **right** keys, respectively. You can switch between these three videos however you want, and do not have to finish watching each video before swapping. Your task is to **select the Test video (A or B) that is closer to the Reference** using the **Space** key. If you cannot make a decision after 15 seconds, make your best guess and continue to the next trial.

**Figure 14:** The study instructions read to users is shown here.



**Figure 15:** We map JODs (x-axis) to units of percentage preference (y-axis). Here, we show the probability of selection of a method A over another B for 0, 1, and 2 JODs (50%, 75%, and 91%, respectively).