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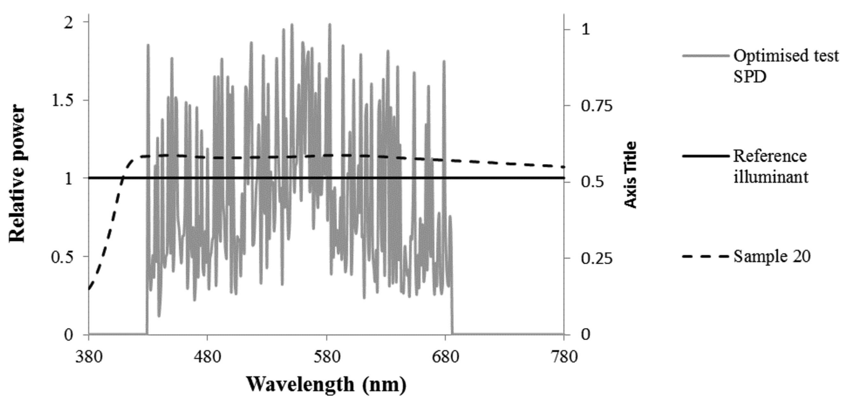

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Appearance of Achromatic Colors Under Optimized Light Source Spectrum

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Abstract: Light source spectrum can be optimized for object reflectance to reduce the energy consumption by reducing the amount of light absorbed by surfaces. While the feasibility of this approach to architectural lighting has been demonstrated, this concept has only been tested with objects of highly saturated colors. Here, the color appearance of 24 Macbeth ColorChecker test samples, which includes achromatic surfaces (i.e., gray, black, and white), illuminated by optimized theoretical test spectra and reference light sources (incandescent, equal-energy radiator, and phosphor-coated white LED) were calculated using a color space based on the International Commission on Illumination's (CIE) color appearance model, CIECAM02-UCS. Results show that energy consumption could be reduced to between 39% and 90%, with small shifts in color appearance, when considering all object colors. When lighting is optimized for achromatic test samples, energy consumption and light absorption were reduced more than when optimized for colorful surfaces, with imperceptible shifts in color appearance.

Index Terms: Optimization, reflectance, energy efficiency, color, absorption.

1. Introduction

Light is necessary to illuminate objects. However, light contributes to visibility only when it is reflected from the surface of an object. Absorbed light turns into heat and can be considered to be lost for illumination purposes. Since the spectral output of solid-state lighting (SSL) devices can be tuned, it is possible to envision a lighting system that detects the surface reflectance characteristics of objects and emits spectrally optimized lighting to each part of the object. Such a lighting system can reduce the energy consumed by lighting without causing shifts in color appearance. The implementation of an absorption-minimizing lighting system is beyond the scope of this paper. However, studies have addressed some of the fundamental engineering issues of absorption-minimization lighting systems, such as the estimation of surface reflectance functions and point-by-point light projection [1], [5].

Previous research has investigated the optimization of light source spectrum for object reflectance and has quantified energy consumption and the color appearance of objects [6], [7]. Theoretical spectral power distributions (SPDs) were optimized using a linear optimization procedure and the color appearance of 15 samples taken from color quality scale (CQS) [8] when illuminated by optimized test SPDs and the International Commission on Illumination (CIE) standard illuminants (illuminants A and E) were calculated using CIE 1976 $L^* a^* b^*$ [9]. Color shifts were quantified using

ΔE^*_{ab}, where $\Delta E^*_{ab} = 1.0$ is considered to be a just-noticeable difference (JND) under controlled conditions [10]. Theoretical test SPDs with a single peak resulted in between 38% and 44% reduction in energy without causing any object color shifts ($\Delta E^*_{ab} < 1.0$) [6]. The optimal test SPDs had bandwidths between 260 nm and 275 nm, and the midpoints of the spectral power were between 537 nm and 548 nm [6].

Similarly, theoretical test SPDs with two peaks resulted in energy savings of between 47% and 71% compared to the reference illuminants A (incandescent) and E (equal-energy radiator), without causing shifts in the color appearance of the test samples [7]. The optimal test SPDs for each sample had two peaks: the first midpoint was between 450 nm and 491 nm and the second midpoint was between 558 nm and 597 nm. The bandwidths of these peaks were between 17 nm and 110 nm [7]. All spectral power in the optimized SPDs ranged between 420 nm and 685 nm when the reference illuminant was incandescent. When the reference illuminant was an equal-energy radiator, the optimized spectral power ranged between 422 nm and 647 nm. These findings suggest that limiting light source spectra between 420 nm and 685 nm can increase the energy efficiency of a light source without degrading its color rendering ability.

Following the computational studies, the naturalness and attractiveness of real objects under optimized light sources were investigated in visual experiments. Observers found the appearance of real objects illuminated by optimized narrowband LEDs and white phosphor-coated LEDs (pcLEDs) to be equally natural and attractive [11]. Objects used in these experiments (tomato for red, mandarin for orange, Granny Smith apple for green, lemon for yellow, and blueberry for blue) were highly chromatic, similar to the test samples used in the computational research [6], [7]. High chroma samples are good choices for color rendering metrics due to the relative ease of rendering low chroma objects [8]. In other words, a white light source that can render highly saturated samples well will also render achromatic or desaturated objects satisfactorily. However, a spectrum optimized to reduce light absorption might be chromatic (non-white), depending on the reflectance characteristics of the object it is optimized for. Therefore, the efficiency and color characteristics of light sources optimized for desaturated and achromatic surfaces (i.e., lacking colorfulness, such as white, gray, and black) should also be investigated.

2. Methods

In this study, theoretical test SPDs were optimized for each of the 24 color samples of the standard Macbeth ColorChecker [12]. In a previous study, three spectral elements (*peak*, *plateau*, and *incline*) were identified in the reflectance function of the test samples, and all test samples were grouped into five categories (peak, plateau, peak+plateau, peak+incline, plateau+peak) according to these elementary spectral shapes [6]. Similarly, other researchers have identified three *basis functions* in object reflectance spectra [13]–[15]. Three basis functions from two studies [14], [15] are structurally similar to the plateau, peak and peak+incline reflectance types. Two of the three basis functions from Vrhel *et al.* [13] are similar to the plateau and peak+incline reflectance type. The third basis function in this study was a horizontal straight line along the visible spectrum, which represents the reflectance function of achromatic colors. In this project, the third basis function from Vrhel *et al.* [13] (named *plain* type herein) is added to the three reflectance types used in previous research [6], [7], [13]–[15]. The four reflectance types were peak (green samples), plateau (red, orange, and yellow samples), peak+incline (blue and purple samples), and plain (achromatic samples), as shown in Fig. 1.

A multi-objective genetic algorithm (MOGA) was used to generate theoretical test SPDs and compare the color appearance of the 24 test samples under optimized spectra and reference light sources (incandescent, equal-energy radiator, and pcLED). Inspired by the process of natural selection, a MOGA solves complex problems that have multiple conflicting objectives, by generating a random population and mutating individuals in each generation until a feasible solution is reached [16]. An individual in each generation is evaluated using user-defined constraints (fitness functions). The optimization process ends when a feasible solution is found, a predetermined number of maximum generations is reached, or the fitness of the highest-ranking solution reaches a plateau.

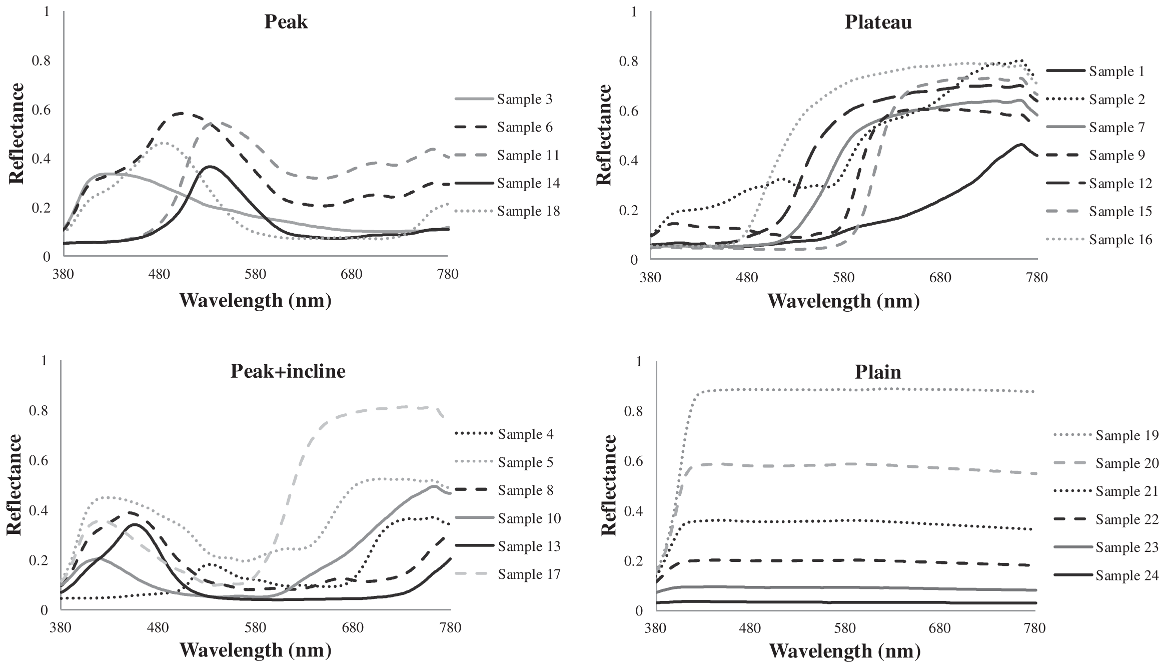

Fig. 1. The spectral reflectance functions of the Macbeth ColorChecker samples are divided into four groups: plateau (samples 1, 2, 7, 9, 12, 15, and 16), peak+incline (samples 4, 5, 8, 10, 13, and 17), peak (samples 3, 6, 11, 14, and 18), and plain (samples 19–24).

MOGAs have been previously used in lighting optimization for color rendition metrics [17], [18], reducing damage to artwork [19], energy efficiency [20], visual preference [21], and the uniformity and efficiency of roadway lighting [22]. Readers can refer elsewhere [23] for a detailed discussion of the light optimization studies.

Here, a controlled elitist MOGA [24] was used to generate test SPDs that result in small shifts in the test sample color appearance and reduced energy consumption (by reducing absorbed light). The method of elitism allows more elite individuals (previously identified solutions that meet fitness functions) to the next generation to improve optimal solutions [25]. The controlled elitism limits the number of elite individuals in each generation to prevent early convergence on a suboptimal solution [24]. Since elitist MOGAs have been found to perform better than non-elitist MOGAs [26], [27], and the objectives (color quality and energy efficiency) are antagonistic [28], a controlled elitist MOGA is best suited for this optimization problem. Here, the optimization problem can be described as

$$\begin{cases} \text{opt} & f(x) = y \\ \min & g(y) \\ \text{subject to} & h(y) = 0 \end{cases} \tag{1}$$

where $f(x)$ is the objective function, x is the amount of relative power at each wavelength, y is the test SPD, $g(y)$ is the fitness function, and $h(y)$ is the equality constraint. The objective function $f(x)$

$$f(x) = \sum_i x_i \tag{2}$$

generates test SPDs by optimizing the amount of power at each wavelength, where subscript i denotes the wavelength.

The spectral range of the theoretical test spectra was limited between 420 nm and 685 nm to increase the energy efficiency of the optimal solutions. Three fitness functions (two regarding color quality and one regarding energy consumption) were introduced to the optimization algorithm. CIECAM02-UCS [29] was used to calculate the color difference ($\Delta E'$) and hue shift (ΔH) of each test sample when illuminated by the test SPD and reference illuminant, while energy consumption (EC) was calculated

$$EC = 100\frac{\int S_{test}(\lambda)\ d\lambda}{\int S_{ref}(\lambda)\,d\lambda} \tag{3}$$

where $S_{test}(\lambda)$ is the test SPD and $S_{ref}(\lambda)$ is the SPD of the reference source (incandescent, equal-energy radiator, or pcLED). Luminous exitance was the only equality constraint ($\Sigma M_{v,test} = \Sigma M_{v,ref}$), which was introduced to prevent the color appearance phenomena, such as the Hunt effect (increase of colorfulness with increased luminance) [30] and the Bezold-Brucke hue shift (hue shift with changes in luminance) [31] and ensure that reductions in energy consumption are not the consequence of reduced surface brightness.

In addition to the three fitness functions used in the optimization process, light absorption (A), CIECAM02-UCS [29] colorfulness (M') and the a' and b' coordinates were calculated and reported. Light absorption (A) was calculated

$$A = 100\frac{\int S_{test}(\lambda)(1 - R(\lambda))\ d\lambda}{\int S_{ref}(\lambda)(1 - R(\lambda))\,d\lambda} \tag{4}$$

where $R(\lambda)$ is the spectral reflectance function of a test sample. A constant (100) was multiplied to scale the values, so that absorption (A) and energy consumption (EC) can be reported as percentages. The colorfulness difference (dM') was calculated

$$\mathrm{d}M' = M'_{\mathrm{test}} - M'_{\mathrm{ref}} \tag{5}$$

where M'_{test} is the colorfulness of the surface under the test SPD and M'_{ref} is its colorfulness under the reference illuminant. A positive dM' indicates an increase in the saturation of the surface color when illuminated by the optimized SPD.

3. Results

The MOGA was run until an optimal solution (minimal color shift and energy consumption) was found for each test sample. Data describing the optimal theoretical SPDs for each test sample are shown in Tables 1, 2 and 3, when the reference source was an equal-energy radiator, incandescent source, and pcLED respectively. When the reference was an equal-energy radiator, color shifts were smaller on average ($\Delta E'_{avg} = 0.8$) than when test SPDs were compared to incandescent ($\Delta E'_{avg} = 2.5$). However, the reduction in energy consumption on average was larger when the reference was an incandescent ($EC_{avg} = 49\%$) than when the reference was an equal-energy radiator ($EC_{avg} = 59\%$). Light absorption was similar for both reference conditions – on average, $A_{avg} = 60\%$ when the reference was an equal-energy radiator and $A_{avg} = 57\%$ when the reference was incandescent.

Compared to the reference equal-energy radiator, optimal theoretical test SPDs resulted in shifts in object color appearance of approximately one JND, except for test samples 5, 6, and 10. Hue shifts were $\Delta H < 0.01$ and colorfulness differences ranged $-1.9 < \mathrm{d}M' < 0.7$. The EC values were quite similar, from 55% to 63%, whereas there was higher variation in A, from 40% to 74%.

When the reference was incandescent, the average color difference was $\Delta E'_{avg} = 2.5$. While only eight samples had a color differences of one JND or less, hue shifts were very small ($\Delta H < 0.01$) and colorfulness differences were in the $-2.9 < \mathrm{d}M' < 1.8$ range. Energy consumption values under optimized SPDs were from 39% to 62%, with an average $EC_{avg} = 49\%$. The reduction in energy consumption and the increase in color shifts, relative to equal-energy radiator optimization, are consistent with the previously-established inverse relationship between color quality and energy efficiency [8], [23], [28].

Theoretical test SPDs were also optimized relative to a commercially available white pcLED (CCT = 4101 K, CRI $R_a = 81$, $R_9 = 15$, CQS $Q_a = 80$) to compare with an energy-efficient, reasonably widely used lighting technology. Energy consumption values were from 82% to 90%, with similar absorption, from 76% to 91%. Color and chroma were not shifted much under optimized

TABLE 1

Characteristics of theoretical test SPDs optimized in comparison to the equal-energy radiator. On average, small differences in surface color appearance ($\Delta E'_{avg} = 0.8$) and reduced energy consumption ($EC_{avg} = 59\%$) and light absorption ($A_{avg} = 60\%$) were found

Sample	Munsell Description	Munsell notation	ΔE'	A (%)	EC (%)	ΔH	dM'
S1	Dark skin	3 YR 3.7/3.2	0.3	65	61	0.0	0.1
S2	Light skin	2.2 YR 6.47/4.1	0.9	67	60	0.0	-0.9
S3	Blue sky	4.3 PB 4.95/5.5	0.6	58	59	0.0	-0.6
S4	Foliage	6.7 GY 4.2/4.1	0.6	59	56	0.0	-0.1
S5	Blue flower	9.7 PB 5.47/6.7	2.2	65	59	0.0	-0.4
S6	Bluish green	2.5 BG 7/6	2.7	56	60	0.0	-0.9
S7	Orange	5 YR 6/11	0.5	61	58	0.0	-0.2
S8	Purplish blue	7.5 PB 4/10.7	0.3	63	62	0.0	0.3
S9	Moderate red	2.5 R 5/10	0.3	66	61	0.0	0.0
S10	Purple	5 P 3/7	1.9	69	63	0.0	-1.9
S11	Yellow green	5 GY 7.1/9.1	0.9	56	59	0.0	-0.9
S12	Orange yellow	10 YR 7/10.5	0.8	60	58	0.0	-0.8
S13	Blue	7.5 PB 2.9/12.7	0.8	62	62	0.0	0.7
S14	Green	0.25 G 5.4/9.6	0.7	55	58	0.0	-0.5
S15	Red	5 R 4/12	0.2	66	59	0.0	0.0
S16	Yellow	5 Y 8/11.1	1.1	56	58	0.0	-1.1
S17	Magenta	2.5 RP 5/12	1.1	74	62	0.0	-1.0
S18	Cyan	5 B 5/8	1.3	57	60	0.0	0.3
S19	White	N 9.5/	1.2	40	57	0.0	-1.2
S20	Neutral 8	N 8/	0.5	52	55	0.0	0.1
S21	Neutral 6.5	N 6.5/	0.3	55	56	0.0	0.3
S22	Neutral 5	N 5/	0.2	56	57	0.0	0.2
S23	Neutral 3.5	N 3.5/	0.1	57	57	0.0	-0.1
S24	Black	N 2/	0.3	57	57	0.0	-0.2

spectra. Although a' b' coordinates did not undergo large shifts ($\Delta a' < 5$, $\Delta b' < 6$), significant hue shifts, ΔH, were calculated. The large ΔH values are likely due to the chroma calculations in CIECAM02-UCS [29]. While chroma is only dependent on a^* and b^* coordinates in CIELAB and CIEDE2000 [9], in CIECAM02-UCS, chroma is a nonlinear function of brightness and other parameters, as well as the a' and b' coordinates [29]. As a result, there were substantial variations in ΔH values, even for test SPDs with very similar spectral shapes.

SPDs optimized for achromatic color samples (plain type reflectance) yielded lower energy consumption, light absorption, and color differences than the other sample types when the reference was an equal-energy radiator. Plateau and peak+incline reflectance types had lower A values than peak reflectance types, although their EC values were quite similar, as shown in Table 4.

TABLE 2

Characteristics of theoretical test SPDs optimized in comparison to the incandescent. On average, moderate color differences ($\Delta E'_{avg} = 2.5$) and reduced energy consumption ($EC_{avg} = 49\%$) and light absorption ($A_{avg} = 57\%$) were found

Sample	Munsell Description	Munsell notation	$\Delta E'$	A (%)	EC (%)	ΔH	dM'
S1	Dark skin	3 YR 3.7/3.2	1.5	65	55	0.0	-0.7
S2	Light skin	2.2 YR 6.47/4.1	3.6	79	53	0.0	-2.6
S3	Blue sky	4.3 PB 4.95/5.5	1.4	41	45	0.0	-0.7
S4	Foliage	6.7 GY 4.2/4.1	2.0	53	47	0.0	0.3
S5	Blue flower	9.7 PB 5.47/6.7	4.4	54	47	0.0	0.6
S6	Bluish green	2.5 BG 7/6	4.0	38	43	0.0	-2.3
S7	Orange	5 YR 6/11	2.0	78	57	0.0	0.4
S8	Purplish blue	7.5 PB 4/10.7	3.4	43	43	0.0	0.2
S9	Moderate red	2.5 R 5/10	2.1	77	58	0.0	-1.5
S10	Purple	5 P 3/7	4.6	63	52	0.0	-1.2
S11	Yellow green	5 GY 7.1/9.1	3.6	50	48	0.0	0.8
S12	Orange yellow	10 YR 7/10.5	1.8	77	54	0.0	0.5
S13	Blue	7.5 PB 2.9/12.7	1.2	40	41	0.0	0.9
S14	Green	0.25 G 5.4/9.6	7.0	42	44	0.0	-1.9
S15	Red	5 R 4/12	2.3	95	62	0.0	-1.0
S16	Yellow	5 Y 8/11.1	2.1	80	53	0.0	1.8
S17	Magenta	2.5 RP 5/12	5.2	94	57	0.0	-2.9
S18	Cyan	5 B 5/8	5.1	35	39	0.0	-0.5
S19	White	N 9.5/	0.5	45	46	0.0	-0.5
S20	Neutral 8	N 8/	0.4	44	45	0.0	0.3
S21	Neutral 6.5	N 6.5/	0.5	46	47	0.0	0.1
S22	Neutral 5	N 5/	0.4	46	46	0.0	0.1
S23	Neutral 3.5	N 3.5/	0.3	47	47	0.0	-0.2
S24	Black	N 2/	0.1	47	47	0.0	-0.1

When the reference illuminant was incandescent, peak type reflectance resulted in the lowest EC and A values. The plateau reflectance types had the highest energy consumption and light absorption values, due to the high emission of power by incandescent lamps in longer wavelengths. Plain type reflectance was the only group that showed color shifts less than one JND, as shown in Table 5. Peak and peak+incline type reflectance resulted in higher color differences, $\Delta E'_{avg,peak} = 4.2$ and $\Delta E'_{avg,peak+incline} = 3.5$ respectively. Test samples with plateau type reflectance resulted in higher light absorption and energy consumption compared to other reflectance types. The plateau type test samples showed a similar trend in a previous study [19].

When the reference source was the pcLED, peak type reflectance samples had the lowest EC and A values. The plateau reflectance types had the highest energy consumption and light absorption

TABLE 3

Characteristics of theoretical test SPDs optimized in comparison to the white phosphor-coated LED. On average, small color differences ($\Delta E'_{avg} = 3.7$) and slightly reduced energy consumption ($EC_{avg} = 86\%$) and light absorption ($A_{avg} = 86\%$) were found

Sample	Munsell Description	Munsell notation	$\Delta E'$	A (%)	EC (%)	ΔH	dM'
S1	Dark skin	3 YR 3.7/3.2	1.2	90	89	-24.4	0.2
S2	Light skin	2.2 YR 6.47/4.1	3.1	90	88	24.3	-1.0
S3	Blue sky	4.3 PB 4.95/5.5	4.2	84	84	28.3	-1.5
S4	Foliage	6.7 GY 4.2/4.1	3.2	86	86	-26.2	-2.9
S5	Blue flower	9.7 PB 5.47/6.7	5.1	87	84	4.7	-2.6
S6	Bluish green	2.5 BG 7/6	3.8	76	82	-40.9	-0.8
S7	Orange	5 YR 6/11	2.9	90	90	-41.3	-0.3
S8	Purplish blue	7.5 PB 4/10.7	6.5	82	82	21.9	-1.8
S9	Moderate red	2.5 R 5/10	2.6	87	87	39.5	2.0
S10	Purple	5 P 3/7	6.0	91	89	-20.3	-5.5
S11	Yellow green	5 GY 7.1/9.1	6.2	79	83	-60.0	-6.0
S12	Orange yellow	10 YR 7/10.5	4.9	90	90	39.5	-2.1
S13	Blue	7.5 PB 2.9/12.7	4.8	83	85	44.5	-0.8
S14	Green	0.25 G 5.4/9.6	5.8	81	83	-54.2	-5.5
S15	Red	5 R 4/12	6.3	82	84	-19.3	5.0
S16	Yellow	5 Y 8/11.1	8.1	88	90	69.3	-5.8
S17	Magenta	2.5 RP 5/12	7.2	89	88	23.1	0.2
S18	Cyan	5 B 5/8	5.3	79	82	47.5	0.5
S19	White	N 9.5/	0.2	87	87	0.2	-0.1
S20	Neutral 8	N 8/	0.2	87	87	-0.4	-0.1
S21	Neutral 6.5	N 6.5/	0.3	87	87	0.5	-0.2
S22	Neutral 5	N 5/	0.3	87	87	-0.2	-0.2
S23	Neutral 3.5	N 3.5/	0.4	85	85	-1.3	-0.3
S24	Black	N 2/	0.4	87	87	1.2	-0.3

TABLE 4

Average color difference ($\Delta E'$), light absorption (A), and energy consumption (EC) when the reference illuminant was an equal-energy radiator, for each reflective sample group

Reflectance type	$\Delta E'$	A (%)	EC (%)
Plateau	0.6	63.0	59.1
Peak+incline	1.2	65.4	60.7
Peak	1.3	56.4	59.0
Plain	0.4	52.9	56.4

TABLE 5
Average color difference ($\Delta E'$), light absorption (A), and energy consumption (EC) when the reference illuminant was incandescent, for each reflective sample group

Reflectance type	**$\Delta E'$**	***A* (%)**	***EC* (%)**
Plateau	2.2	78.6	56.0
Peak+incline	3.5	57.8	48.1
Peak	4.2	41.3	43.8
Plain	0.4	45.7	46.5

TABLE 6
Average color difference ($\Delta E'$), light absorption (A), and energy consumption (EC) when the reference illuminant was pcLED, for each reflective sample group

Reflectance type	**$\Delta E'$**	***A* (%)**	***EC* (%)**
Plateau	4.2	88.1	88.3
Peak+incline	5.5	86.4	85.6
Peak	5.1	79.8	83.0
Plain	0.3	86.5	86.7

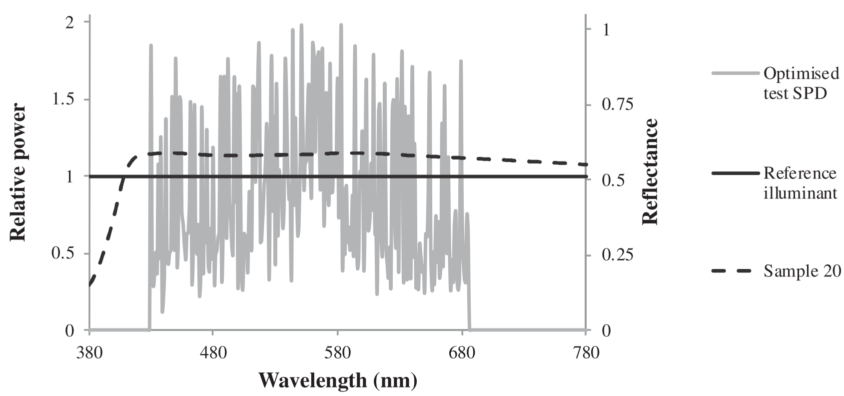

Fig. 2. A test SPD (continuous gray line, left y-axis) optimized for a gray sample (black dashed line, right y-axis) that reduces energy consumption to 55% compared to the reference equal-energy radiator (black continuous line, lefy y-axis), without causing perceptible color shifts ($\Delta E' = 0.5$).

values, which is similar to the results for the incandescent reference. The energy savings values were not very high, and color shifts were moderate, as shown in Table 6.

Initially, the test SPDs were limited to between 420 nm and 685 nm to increase the energy efficiency of the optimal solutions. However, after several optimization trials, the ideal wavelengths for SPDs compared to equal-energy and incandescent references was found to lie from 430 nm to 685 nm, while limiting the spectrum from 450 nm to 675 nm enabled optimal solutions for the pcLED reference. The optimal SPDs had irregular spectral shapes, as shown in Fig. 2, 3 and 4. When the reference was the equal-energy radiator, the optimal test SPDs had a higher peak than the reference illuminant.

When the reference was incandescent, the optimal test SPDs' peaks were lower than the peak of the reference illuminant. However, the color appearance of the green, blue and purple samples

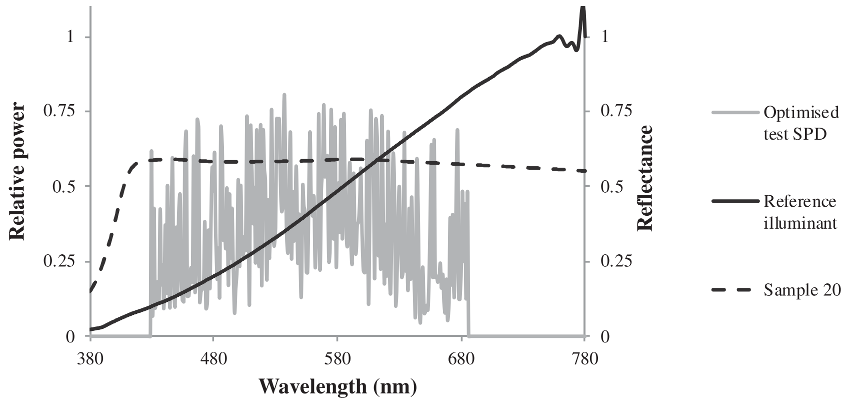

Fig. 3. A test SPD (continuous gray line, left y-axis) optimized for a gray sample (black dashed line, right y-axis) that reduces energy consumption to 55% compared to the reference incandescent (black continuous line, left y-axis), without causing perceptible color shifts ($\Delta E' = 0.4$).

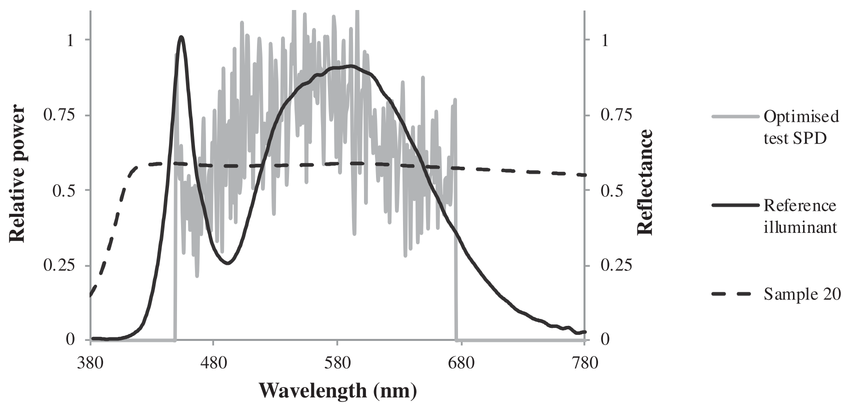

Fig. 4. A test SPD (continuous gray line, left y-axis) optimized for a gray sample (black dashed line, right y-axis) that reduces energy consumption to 87% compared to the reference white phosphor-coated LED (black continuous line, left y-axis), without causing perceptible color shifts ($\Delta E' = 0.1$).

were shifted more when the test SPD was optimized relative to incandescent illumination than when the reference illuminant was an equal-energy radiator.

When the reference was a pcLED, the optimal test SPDs' peaks were around the same power as the peak of the reference source. The color appearance of the green, blue and purple samples were shifted more when the test SPD was optimized relative to pcLED illumination than when the reference illuminant was an equal-energy radiator.

Although optimizing SPDs using the MOGA yielded results similar to previous studies [6], [7], [19] when compared to standard illuminants (equal-energy radiator and incandescent), energy consumption values were higher when optimized test SPDs were compared to the pcLED. This may be due to the spectral optimization method used by the MOGA, which assigns a weighting value (x_i in eq. (2)) for each wavelength without allowing entire spectral ranges of zero power emission ($x_i = 0$). Achromatic objects do not need to reflect power in all wavelengths, due to their relatively flat spectral response functions, so it can be hypothesized that the MOGA failed to find truly optimal solutions for achromatic colors. A two-peak linear optimization method that was used in previous studies [6], [7] was used to explore this idea by optimizing SPDs for achromatic samples (samples 19–24).

The linear optimization resulted in lower energy consumption ($EC_{avg,plain} = 52\%$) and light absorption ($A_{avg,plain} = 52\%$) compared to the results obtained by the MOGA when the reference light source was pcLED, as shown in Table 7. The appearance of the samples did not shift meaningfully

TABLE 7

Characteristics of theoretical test SPDs optimized for achromatic samples using a two-peak linear optimization method [6], [7] in comparison to the white phosphor-coated LED. On average, color differences were imperceptible ($\Delta E'_{avg} = 0.6$), and energy consumption ($EC_{avg} = 52\%$) and light absorption ($A_{avg} = 52\%$) were nearly halved

Sample	Midpoint 1 (nm)	Bandwidth 1 (nm)	Midpoint 2 (nm)	Bandwidth 2 (nm)	$\Delta E'$	A (%)	EC (%)	ΔH	dM'
S19	539	20	568	28	0.2	52.5	52.5	-0.1	-0.2
S20	539	4	556	28	0.4	51.5	51.6	0.0	-0.4
S21	539	4	557	24	0.4	51.4	51.5	-0.2	-0.4
S22	539	4	556	28	0.4	51.4	51.5	0.0	-0.4
S23	539	8	564	40	1.0	51.7	51.8	-0.1	-1.0
S24	539	68	584	20	1.3	55.3	55.3	-1.2	-1.1

in colorfulness or hue. The results obtained from the linear optimization underscores the importance of identifying the relevant limitations of various spectral optimization methods. Selecting the right optimization method, which involves deliberately setting spectral power limitations, can yield significantly increased energy savings.

4. Conclusions

Computational simulations showed that the color appearance of achromatic samples is more consistent when illuminated by optimized spectra than other test samples. Test SPDs optimized for achromatic samples also resulted in lower energy consumption and light absorption than SPDs optimized for other reflectance types. Peak type reflectance (green samples) resulted in the lowest absorption and energy consumption under optimized SPDs when the reference is incandescent. Overall, SPDs optimized for plain type reflectance (achromatic samples) induced imperceptible color shifts and resulted in reduced light absorption and energy consumption. The multi-objective algorithm calculated energy savings similar to previous studies [6], [7], [19], except when the reference was a pcLED. The linear optimization method performed better than multi-objective genetic algorithm for achromatic samples when the object color appearance was matched relative to the pcLED.

Optimizing light source spectrum for the reflectance of each colored part of the object can decrease energy consumption. The spectral reflectance function is widely used to quantify object reflectance. However, more detailed measures, such as the bidirectional reflectance distribution function (BRDF), describe the spatial characteristics of spectral reflectance and are commonly used to investigate various object surface properties, such as gloss and translucency. For example, previous research [11] showed that the color appearance of translucent objects illuminated by absorption-minimizing SPDs should be investigated further using more advanced colorimetric simulations. While spatial modeling is beyond the scope of this study, it warrants further investigation.

In addition to single colors, optimizing light source spectrum for color rendering metrics [32]–[34] or a limited set of color samples [35] can also yield positive results with the caveat of compromised energy savings. Future work will investigate a group of surface colors with similar reflectance characteristics (e.g., same hue, different lightness or chroma).

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