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Original Paper

Research on LED Light Sources Capable of Regulating Circadian Rhythms

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Abstract

The model was implemented using the CIE 1931 color matching function, the CIECAM02 color appearance model, and the ANSI/IES TM-30 method. The calculation results indicate that the light source has a CCT of 3903.7 K, Duv=−0.001045, Rf=96.96, Rg=106.40, and mel-DER=0.0880, exhibiting characteristics of medium-low color temperature, extremely high color rendering fidelity, slightly expanded color gamut, and minimal impact on circadian rhythms.

For the daytime lighting scenario, with the objective of maximizing Rf, high-fidelity lighting with an Rf as high as 97.91 was achieved under the constraints of CCT = 6000 ± 500 K and Rg = 95–105. For the nighttime sleep-promoting scenario, with the objective of minimizing mel-DER, we successfully reduced mel-DER to an extremely low level of 0.0043 under the constraints of CCT=3000500 K and Rf≥80, effectively reducing interference with circadian rhythms.

An optimization model was constructed with dual objectives: spectral shape fitting accuracy and consistency of circadian rhythm effect parameters (mel-DER). Experimental results indicate that this method achieved low spectral similarity error (average DTW distance of 0.2270) and circadian effect deviation (average mel-DER error of 0.0126) at most time points, validating that the proposed model can effectively simulate dynamic spectra and reproduce the circadian effects of natural light.

To comprehensively evaluate the impact of different lighting conditions on sleep quality, a multi-criteria evaluation model based on the Entropy-Weighted TOPSIS method was constructed. This model assessed sleep quality across six dimensions—total sleep time (TST), sleep efficiency (SE), sleep latency (SOL), deep sleep percentage (N3%), rapid eye movement (REM) percentage (REM3%), and number of nighttime awakenings. The evaluation scores indicate that Environment C (dim

light)>Environment A (sleep-promoting light) > Environment B (standard LED), suggesting that optimized lighting can improve sleep quality to a certain extent.

Keywords

Differential Evolution Algorithm, Multi-objective Genetic Algorithm, Entropy-weighted TOPSIS Multi-criteria Evaluation

1. Introduction

With the continuous advancement of lighting technology, light-emitting diodes (LEDs) have gained widespread adoption worldwide due to their high efficiency, energy savings, and environmental benefits. They are gradually replacing incandescent and fluorescent lamps to become the mainstream lighting source. White LEDs not only significantly improve energy efficiency but also offer flexibility in adapting to different lighting scenarios and needs by adjusting color temperature and spectral characteristics. Extensive research indicates that light exposure can profoundly influence the human circadian rhythm system via the retina. For example, light of different wavelengths directly affects melatonin secretion levels, thereby regulating sleep quality, cognitive function, and emotional states. Consequently, how to effectively regulate human circadian rhythms by adjusting the spectral distribution of LED light sources—while meeting basic daily lighting needs—has become a critical issue requiring urgent resolution in the fields of lighting science and health engineering.

2. Model Development and Solution

2.1 Model Development and Solution

2.1.1 Development and Solution of the Model for Calculating Color Property Parameter Values

Since all calculations of core parameters in this problem are based on SPD data, the raw SPD data must first be standardized as follows: ① Standardize the wavelength range to 380–780 nm with a step size of 1 nm; ② Perform interpolation matching against the CIE 1931 standard colorimetric observer function; ③ Construct a unified interpolated SPD curve S(λ) for subsequent integration operations;

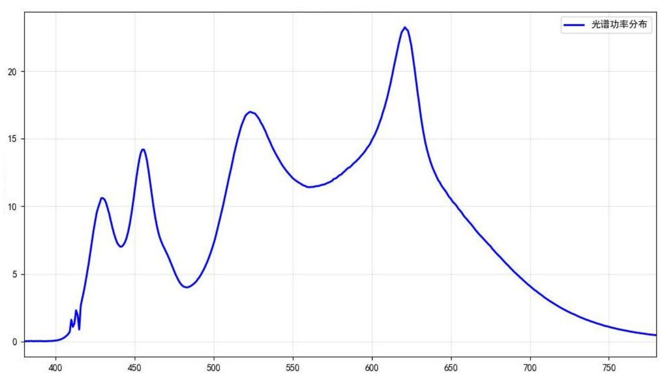

Figure 1. Spectral Power Distribution Chart

Calculating the CIE XYZ trichromatic values serves as the basis for all subsequent parameter calculations. Given that the spectral power distribution of the light source is S(λ) and the standard color matching functions are $\bar{x}(\lambda),\bar{y}(\lambda),\bar{z}(\lambda)$, the formulas for calculating the trichromatic values are:

(1) Development of a Calculation Model for Correlated Color Temperature (CCT)

According to Reference (Zhang & Xu, 2006), the calculated CIE XYZ trichromatic values must first be converted to CIE 1931 chromaticity coordinates (x,y).

(2) Development of a Calculation Model for Color Deviation Distance (Duv)

According to Reference (David et al., 2015), the trichromatic values are first converted to CIE 1960 UCS color coordinates (u, v) .Then, using the Planck formula, generate blackbody spectra for different color temperatures T ∈ [1000 K, 25000 K], calculate the corresponding XYZ and (u, v) coordinates, and form a set of trajectory points.

Finally, calculate the Euclidean distance between the light source's color point and each point on the blackbody trajectory. This minimum distance indicates the degree of deviation in the light source's color. To further improve accuracy, we perform local interpolation optimization on multiple points within the minimum neighborhood.

Calculation results:

Table 1. Table of Color Characteristics and Parameter Values

Color Properties and Parameter Values	
Correlated color temperature (CCT)	3903.0 K
Deviation from the blackbody curve (Duv)	-0.001017

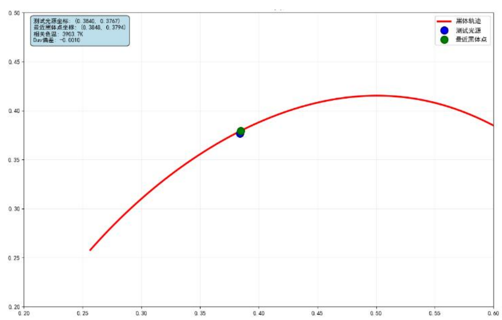

Figure 2. USC Color Map

2.1.2 Model Development and Solution for Calculating Color Reproduction Parameter Values

(1) Calculation Model for the Fidelity Index (Rf)

The fidelity index Rf measures the color difference between a light source and a reference light source when illuminating the same color sample; the closer the value is to 100, the better the color rendering.

CCT < 5000K: Select a blackbody radiation source with the same color temperature

CCT ≥ 5000K: Select a daylight source with the same color temperature

According to Reference (Royer, 2021), first calculate the CIE 1931 trichromatic values for each color sample i under both the test light source and the reference light source. Convert to the CIECAM02 color appearance model to obtain luminance J, chromaticity M, and hue angle h. Then convert to the CAM02-UCS uniform color space to obtain the three-dimensional coordinates (J', a', b').

The calculation results are shown in the table below:

Table 2. Table of Feature Parameter Values

Color reproduction parameters, characteristic parameter values	
Color Fidelity Index Rf	98.17
Color Gamut Index Rg	106.43

2.1.3 Model Development and Solution for Estimating Parameters Characterizing the Effects of Circadian Rhythms

According to Reference (Chang, 2023), CIE S 026/E:2018 defines the α-opic (rhodopsin-containing) spectral sensitivity function for ipRGCs. The melatonin-to-daylight illuminance ratio (mel DER) is defined as the ratio of the weighted irradiance of the test light source at the rhodopsin sensitivity to that of D65.The calculation results are shown in the table below:

Table 3. Table of Parameter Values for Circadian Rhythm Effects

Parameter Values for Circadian Rhythm Effects	
Melatonin-to-Daylight Ratio (mel-DER)	0.0833
Effective response wavelength range	420-580 nm
Primary contribution wavelength range	450-510 nm

2.2 Model Formulation and Solution

2.2.1 Model Formulation

The core objective of Problem 2 is to adjust the weightings of five independent light channels (three monochromatic channels—deep red, green, and blue—and two white light conversion channels—warm white) under the constraints of two different scenarios, and to synthesize a spectrum that meets specific requirements by finding the optimal combination of weightings.Simulates midday sunlight, requiring the correlated color temperature (CCT) of the synthesized spectrum to fall within the range of 6000±500 K, the color rendering index (Rg) to be between 95 and 105, and the color fidelity index (Rf) to be greater than 88, while maximizing Rf as much as possible within these constraints.

$$\begin{aligned} \max_W \quad & R_f(W) \\ \text{s.t.} \quad & 5500 \le \mathrm{CCT}(W) \le 6500 \\ & 95 \le R_g(W) \le 105 \\ & R_f(W) \ge 88 \\ & \textstyle\sum_{i=1}^{5} w_i = 1, \quad w_i \ge 0 \end{aligned} \tag{1}$$

2.2.2 Solving the Model

The optimization models established in Problem 2 are all continuous optimization problems that are nonlinear, non-convex, and lack an analytical gradient, with the optimization variables being the weights of the five channels. In this paper, the differential evolution algorithm is used to solve these problems. The differential evolution algorithm is a population-based global optimization method that continuously updates the population through "mutation—crossover—selection" operations.

(1) Solving the Daytime Lighting Mode

In the daytime lighting mode, maximize color rendering fidelity R_f while satisfying CCT(w) ∈ [5500, 6500] K, $R_g(w) \in [95,105]$, and $R_f(w) \ge 88$. The optimal weights calculated are:

Table 4. Optimal Weighting Table for Daytime Lighting Modes

Passage	Weight
Deep red light	0.222
Green light	0.153
Blue light	0.161
Warm white light	0.014
Cool white light	0.450

The corresponding values for each indicator are:

Table 5. Values for each Indicator

Indicators	value
CCT	5527.20
DUV	0.0040
Rf	97.908
Rg	98.173
mel-DER	0.0180

The optimization results show that the weights of the five channels are 0.222, 0.153, 0.161, 0.014, and 0.450, respectively, and the correlated color temperature (CCT) of the synthesized spectrum is 5527.2 K, which falls within the typical range of midday sunlight [5500 K, 6500 K], and Duv｜ = 0.0040, indicating that the spectral chromaticity is close to the Planckian locus with minimal color deviation. In terms of color rendering, the fidelity index Rf = 97.91 is close to a perfect score, and the gamut index Rg = 98.17 is close to 100, indicating that the light source not only accurately reproduces object colors but also has a color gamut size similar to that of natural light, preventing color saturation distortion. The melatonin-daylight efficiency ratio (mel-DER) is 0.0186, which is within an acceptable range for daytime use and helps maintain a normal circadian rhythm.

(2) Solution for the Nighttime Sleep-Assistance Mode

Under the nighttime sleep-assistance mode conditions, minimize mel-DER while satisfying CCT(w) ∈ [2500, 3500] K and R_f(w) ≥ 80. The optimal weights calculated are:

In night mode, the optimization results clearly exhibit characteristics dominated by red light and significantly suppressed blue light. The CCT is 3483.5 K, which falls within the warm white light range and is close to the upper limit of the recommended range for nighttime sleep [2500 K, 3500 K]. Duv = −0.2066 indicates that the color point deviates significantly from the Planckian locus, which may be related to blue light compression and a warmer spectral shift. Regarding color rendering, Rf = 90.40 exceeds the set lower limit (80), meeting the basic color rendering requirements for nighttime lighting; however, Rg = 43.55 is relatively low.

2.3 Modeling and Solving

2.3.1 Formulation of the Mathematical Model

Over the course of a day (8:30 a.m. to 7:30 p.m.), we need to use a five-channel LED light source (deep red, green, blue, warm white, and cool white) to dynamically adjust the drive weights of each channel so that the synthesized spectrum closely approximates the given solar spectrum sequence and maintains consistency with the target solar spectrum in terms of circadian rhythm effects.

1. Decision variables

Normalization Constraints:

$$\sum_{i=1}^{5} w_{t,i} = 1, \quad w_{t,i} \geq 0 \tag{2}$$

2. Spectral Synthesis Model

Let the normalized spectrum of the i-th channel be

$$S_i(\lambda), \lambda \in \Lambda \tag{3}$$

The composite spectrum at time t is:

$$S_{LED}^{t}(\lambda) = \sum_{i=1}^{5} w_{t,i} S_i(\lambda) \tag{4}$$

3. Spectral Similarity Metric (DTW)

Since there may be peak shifts between the solar spectrum and the LED spectrum along the wavelength axis, dynamic time warping (DTW) is used to measure similarity.

4. Circadian Rhythm Effect Constraints

Calculate the melatonin-daylight illuminance ratio (mel-DER) in accordance with CIE S 026/E:2018: where M(λ) is the visual melanin sensitivity curve.

Constraints:

5. Comprehensive Optimization Model

Constraint:

$$\sum_{i=1}^{5} w_{t,i} = 1, w_{t,i} \geq 0, \forall t \tag{5}$$

Here, α and β are weighting coefficients that control the balance between spectral similarity and consistency of physiological effects.

2.3.2 Solving the Model

In response to the dynamic variations in the solar spectrum throughout the day and its significant impact on human circadian rhythms, this paper proposes a Differential Evolution-based Non-Dominant Sorting Genetic Algorithm II (DE-NSGA-II), building upon the spectral parameter calculations and objective function formulation presented in Problem 2. DE-NSGA-II sets spectral shape fitting accuracy and consistency with circadian effects (mel-DER match) as dual optimization objectives.

Thereby significantly enhancing local search capabilities and global convergence speed. The core solution process is as follows:

Step 0 Data Preprocessing

First, align the spectral data from the five-channel LED with the solar spectrum at the corresponding time points along the wavelength axis to ensure calculations are performed at the same wavelength sampling points. Second, to avoid bias in similarity metrics caused by differences in spectral amplitudes, the spectra can be amplitude-normalized when calculating metrics such as correlation coefficients and cosine similarity (this is used solely for similarity calculations and does not alter the actual spectral values); Finally, load the photopic sensitivity curve $s_{mel}(\lambda)$, the luminous efficiency function V(λ), and the spectral data for the standard illuminant D65 as defined in CIE S 026/E:2018, ensuring they align with the spectral wavelength grid.

Step 1: Fitness Calculation

The fitness function is used to evaluate the quality of a population. In the multi-objective optimization model of Problem 3, the fitness function is designed to maximize both spectral shape fitting accuracy and consistency with the circadian rhythm. In DE-NSGA-II, these two metrics are directly input into the non-dominance sorting process as dual-objective fitness values.

Step 2: Multi-objective Definition and Penalty

During the optimization process, spectral fitting accuracy is measured using D_{DTW} (Dynamic Time Warp distance), while the deviation in rhythmic effects is measured using E_“mel” (mel-DER absolute error). In DE-NSGA-II, these two metrics are directly used as fitness vectors (f_1,f_2) for non-dominance sorting and elite retention;

Step 3: Initialization and Feasibility Region Repair

Before optimization begins, an initial solution set that satisfies the physical constraints must be generated for the population. First, a five-channel LED weight vector $w(t)=[w_1(t),w_2(t),\ldots,w_5(t)]^{\top}$ is generated using uniform random sampling or a Dirichlet distribution to ensure that the weights are non-negative and sum to 1; To accelerate convergence, non-negative least squares (LS) can be used to perform a warm start for the spectral fitting problem, and the normalized fitting results are then injected into the initial population.

Step 4: DE-NSGA-II Main Loop

During the evolutionary optimization phase, the DE-NSGA-II main loop generates new candidate solutions through mutation and crossover using differential evolution (DE), and gradually converges toward the Pareto-optimal frontier by combining this with the non-dominance sorting and elite retention mechanisms of NSGA-II. Specifically, differential evolution employs the DE/rand/1/bin strategy.

Step 5: Preference Selection and Time Series Output

Upon completion of the optimization at each time step, DE-NSGA-II generates a set of Pareto-optimal solutions, representing different trade-offs between spectral shape fitting accuracy and consistency with rhythmic effects. To obtain a single solution that can be directly applied to the control of actual LED light sources, a preference selection must be made from the set of Pareto solutions based on a comprehensive scoring function.

Results:

In terms of overall performance metrics, the average DTW distance is 0.2270, the average mel-DER error is 0.0126, and the average spectral correlation is 0.6946. This indicates that the algorithm maintains minimal waveform differences in spectral shape fitting; regarding circadian rhythm matching, the error is controlled at around 1.3%, meeting the design requirements for circadian rhythm lighting.

The figure shows a comparison of the target solar spectrum with the optimized synthetic spectrum at three representative time points (8:30, 12:30, and 18:30), illustrating the fitting performance of the DE-NSGA-II algorithm under different lighting conditions. It can be observed that the synthetic spectrum successfully reproduces the peak and trough structures of the target spectrum at all time points.

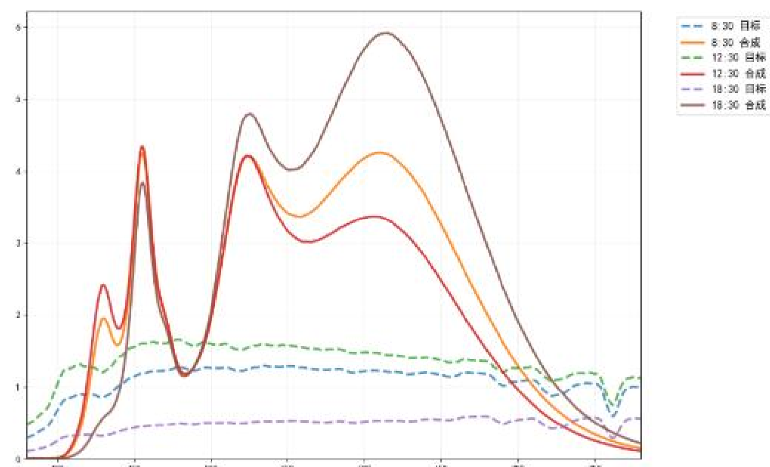

Figure 3. Spectral Comparison Chart of Three Representative Time Points

Numerically, the DTW distance was 0.210 at both 8:30 and 12:30, with mel-DER errors of 0.012 and 0.008, respectively, indicating that the algorithm achieved high accuracy in both spectral fitting and matching circadian effects during the morning and midday periods; At 18:30, the mel-DER error is 0.019, but it remains at a relatively low level, which is consistent with the physical characteristics of the evening sun, where the spectral shape changes significantly and short-wavelength energy attenuates markedly.

2.4 Model Formulation and Solution

In Question 4, our objective is to evaluate the combined effects of three different pre-sleep lighting environments (Environment A, Environment B, and Environment C) on sleep quality. To this end, we constructed a comprehensive evaluation model based on entropy-weighted TOPSIS. While ensuring the objectivity of the weights, we quantified and ranked the overall sleep quality across the three environments to draw specific conclusions: whether the designed “optimized lighting” produces beneficial improvements in sleep quality compared to “standard lighting” and “dark environments.”

2.4.1 Determine Evaluation Criteria

To identify the optimal environment, in accordance with the study’s objectives, this paper uses total sleep time (TST), sleep efficiency (SE), sleep onset latency (SOL), deep sleep percentage (N3%), REM sleep percentage (REM%), and number of nighttime awakenings as indicators to assess sleep quality.

1. Total Sleep Time (TST)

TST refers to the total duration during which an individual is in a non-waking state within the sleep cycle.

Each epoch lasts 30 seconds (i.e., 0.5 minutes).

2. Sleep Efficiency (SE)

SE represents the proportion of total time in bed (TIB) that is actually spent asleep:

N is the total number of valid epochs.

3. Sleep Onset Latency (SOL)

SOL refers to the time interval from lying down to prepare for sleep (start of recording) to the first entry into any sleep stage (i.e., N1/N2/N3/REM):

4. Deep Sleep Percentage (N3%)

N3% refers to the percentage of total sleep time spent in deep sleep (Stage N3):

5. Rapid Eye Movement (REM) Sleep Percentage (REM%)

REM% refers to the proportion of total sleep time spent in the rapid eye movement (REM) stage:

6. Number of Awakenings

The “Number of Awakenings” refers to the number of times a person transitions from a non-awake stage to an awake stage (i.e., “non-4 → 4”) after falling asleep. It is used to assess the degree of sleep fragmentation.

2.4.2 An Integrated Evaluation Model Combining Entropy Weighting and TOPSIS

Second, this paper employs the Entropy-weighted TOPSIS comprehensive evaluation model to quantitatively score overall sleep quality across the three environments. Therefore, we determined the weights using the "Entropy Weight Method" and then performed the ranking using the "TOPSIS method," thereby constructing a comprehensive and objective evaluation system. The specific steps for applying this model are as follows:

Step 1: Construct the Raw Evaluation Matrix

First, process the raw data in the appendix to calculate the average values of the six sleep metrics for the 11 participants across the three environments (A, B, C), and construct a raw evaluation matrix $X=[x_{ij}]\in R^{m\times n}$, where m = 3 evaluation objects (lighting environments) and n = 6 evaluation metrics. Perform vector norm normalization first to facilitate cross-dimensional comparisons:

Step 2: Entropy Weight Calculation

(1) Calculate information entropy and the coefficient of variation

(2) Calculate weights

In the weight distribution based on the entropy weighting method (see Figure 7), there are significant differences in the objective weights of the six core indicators. N3% (deep sleep proportion) has the highest weight (0.255), indicating that this indicator exhibits the greatest variability across different lighting environments and has the most significant impact on the comprehensive evaluation results; SOL (sleep latency) has the second-highest weight (0.214), indicating that the speed of falling asleep plays a crucial role in distinguishing between good and poor sleep quality.

Step3 Comprehensive Evaluation Using the TOPSIS Method

The TOPSIS method primarily uses a distance-based approach to measure how close each alternative is to the ideal solution. Therefore, the specific steps for solving the model are as follows:

(1) Weighted standardization matrix

(2) Ideal Solutions and Negative Ideal Solutions

(3) Distance and Proximity

Based on this formula, calculations performed in Python yielded the following similarity scores: Environment C = 0.8365, Environment A = 0.1725, and Environment B = 0.1697. Therefore, the final ranking is C > A > B.

(4) Calculate the comprehensive evaluation scores for each option:

The radar chart of sleep quality indicators shows that Environment C (dark environment) has a significant advantage in terms of deep sleep percentage (N3%) and sleep onset latency (SOL), and performs best overall; while total sleep time (TST) and sleep efficiency (SE) show little variation among the three environments.

Based on the results of the comprehensive evaluation using the Entropy-Weighted TOPSIS method (Table X), the sleep quality rankings for the three lighting environments are as follows:

Environment C (darkness) > Environment A (sleep-promoting light) > Environment B (standard LED)

Environment C received the highest score and demonstrated a significant advantage in the comprehensive evaluation; Environment A ranked in the middle, showing some improvement compared to standard LED lighting; Environment B received the lowest score and performed the worst overall.

Table 9. Ranking by Overall Score

Environment	Distance to Optimal	Distance to Negative Optimal	TOPSIS	Rank
Environment C	0.016971	0.086799	0.836452	1
Environment A	0.077486	0.016156	0.172525	2
Environment B	0.085502	0.017472	0.169675	3

As shown by the above calculations, Environment C (dark environment) had a TOPSIS score of 0.836452, the highest overall score. This indicates that the dark environment significantly reduces the time to fall asleep and increases the proportion of deep sleep; Environment A (sleep-promoting light) had a TOPSIS score of 0.172525, outperforming standard LED (B) on some metrics and ranking second overall; Environment B (standard LED light) has a TOPSIS score of 0.169675, which is significantly lower than Environment C, ranking second overall. Concurrent Friedman tests indicate significant differences in SOL ($p < 0.01$) and N3% ($p < 0.05$).

3. Conclusions

This research comprehensively addresses optical performance evaluation, lighting optimization, and sleep quality assessment of light sources, providing a complete technical system for adjustable circadian lighting. The established optical performance calculation model accurately characterizes light source parameters, confirming its medium-low color temperature, high color rendering, and minimal circadian impact.

The differential evolution-based optimization model achieves optimal channel weights for daytime and nighttime scenarios, meeting respective lighting requirements. The DE-NSGA-II algorithm effectively simulates dynamic solar spectra with low fitting error and circadian deviation. The Entropy-Weighted TOPSIS evaluation model verifies that optimized lighting (sleep-promoting light and dim light) outperforms standard LEDs in improving sleep quality. Overall, the research provides technical support for intelligent, circadian-friendly lighting design and application.

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