An Approach for Designing Mixed Light-Emitting Diodes to Match Greenhouse Plant Absorption Spectra

Latifa Bachouch 1, Neermalsing Sewraj 2, Pascal Dupuis 2, Laurent Canale 2,*, Georges Zissis 2, Lotfi Bouslimi 1 and Lilia El Amraoui 1

Abstract: We report a methodological approach for simulating luminary output radiation, which is achieved by mixing light-emitting diodes (LEDs) in order to match any plant absorption spectrum. Various recorded narrow-band LED spectra of different colors were first characterized and then fitted with a multi-Gaussian model. An optimizing procedure computed the optimal weighting of the relevant parameters so as to minimize the discrepancy between the combined spectrum and the reference target curve. The particle swarm optimization (PSO) method was applied because it is the most suitable technique for mono-objective situations. Within the useful spectral interval, the worst relative standard deviation between the optimized curve and recorded LED spectral power distribution (SPD) was 3.4%. When combining different LED types, the simulated light output showed that we could limit ourselves to selecting only five colored sources. This work will help us to design an optimized 200 W laboratory luminaire with a pulse-width switched-mode power supply.

Keywords: LED; emission spectrum; optimization; PSO; photosynthesis; McCree

1. Introduction

The light spectrum is a key driver of the photosynthetic processes that are responsible for plant growth, which require about 50% of the waveband of the solar light spectrum that is available in the lower atmosphere [1,2]. Natural light, which extends over the spectral range of 400–1000 nm, is, however, not always available everywhere and at any time in satisfactory quantity and quality. Fortunately, artificial electronic devices have been proven as essential and reliable photon sources for controlled crop lighting and have thereby accelerated the emergence of greenhouses [3–5]. Supplemental lighting has real potential to meet consumers’ needs for out-of-season crops with improved yield quality and quantity.

Light-emitting diodes (LEDs) are by far the most promising technology for artificial lighting dedicated to plant cultivation [6,7]. They are mercury-free and combine less radiation loss with an enhanced longevity while affording a good robustness with smaller packaging [8–10]. They entail significant energy savings [11] compared to the less efficient discharge lamps [12,13]. Their recent rapid progress is expected to induce an increase of more than 180% in the horticulture lighting market over the next five years [14].

Over the last 50 years, growth analysis techniques have been widely used to meet the adequate spectra for plants by studying the effects of LED spectra and the photoperiod on the plants’ production. Most of them deal only with the McCree target curve, and these are summarized in Table 1. There are also some interesting works that consider LED optimization for the solar spectrum [15,16]. They are beyond our scope, which is only
focused on artificial light for greenhouses. Even if these studies greatly contribute to a better understanding of the interactions between artificial light and the bio-performance of plants, none of them are capable of suggesting a systematic approach to establishing each particular LED combination of a greenhouse LED luminary that is independent of the plant, the target curve, and the desired functionality.

Table 1. Works dealing with optimization of light-emitting diode (LED) light for photosynthesis (Tw: this work).

| Ref. | Aim | Plant | Technique |
|------|-----|-------|-----------|
| [17] | Optimize output spectrum | Radish and lettuce | Different photon flux density for the circadian cycle |
| [18] | Crop yield and quality | Lettuce (*Lactuca sativa*) | Coloration, cultivars, and nitrates |
| [19] | Different seaweed functionalities | Spirulina | Tests with different ratios of red, blue, and green LEDs |
| [20] | Photosynthesis and photo-pigmentation performance | Different species | Control of the ratio and shapes of blue and red light, for a multi-package of purplish white LEDs (blue, green, amber, red) |
| [21] | Different LED photosynthesis photon flux density (PPFD) ratios | Basil | Sensed fluorescent gains as a feedback signal with 4 LEDs |
| [22] | LED lighting control for plants | Lettuce (*Lactuca sativa*) | Biofeedback control, PPFD values, and adjustment based on a specific threshold of optimal lighting ratios |
| [23] | Optimize the red–blue combination spectrum | Romaine lettuce | Red and blue light absorbance of lettuce leaves |
| [24] | Maximize efficiency of crop production | Chinese cabbage | Estimation of crop yield following the light regime |
| [25] | Optimize the LED combination | Cucumber | PSO to evaluate the number of operating LEDs |
| [26] | Optimize LED spectrum | Ornamental plants | Lighting tests, and a visual assessment survey for various light system hypothesis using different peak wavelengths |
| [27] | Optimize the LED spectrum | Lettuces and other green plants | Red, blue, and green LEDs. Light efficiency and PPFD level determined by maximizing the similarity between the LED spectrum and the McCree curve. |
| Tw  | Optimize the LED spectrum | None | Three luminaries involving 9 LEDs to match the McCree curve |

McCree [28] and then Inada [29] conducted pioneer studies to evaluate the frequency dependency of the efficiency of photosynthetic activity. In 1972, McCree measured the action spectra for 22 species of crop plants and concluded that all the action spectrum curves follow a similar shape. His approach was based on the adjustment of the irradiance level at different wavelengths, producing a constant photosynthetic rate, without mentioning the spectral exit width or the irradiance. In addition, different metrics were used. His results are not easily reproducible [28]. According to a recent work by Wu et al. [30], there exist many contradictions concerning the different target curves of McCree, who carried out measurements with optical filters or monochromators. Moreover, different values of the full width at half maximum (FWHM), quantification strategies, and metrics lead
to different curve shapes. These considerations can lead to misinterpretation of spectral response data.

In the field of plant study, it is considered that light is used in the Photosynthetically Active Radiation (PAR) band, which corresponds to the 400–700 nm range. Only a fraction of the photons arriving on a plant surface can be used for photosynthesis: measurements characterize either the external photons flux or their internal use expressed as internal relative quantum efficiency. Plant light quantification uses three main approaches, namely the Photosynthetic Photon Flux (PPF), the Yield Photon Flux (YPF), and the energy Flux [31]. The ratio between the PPF and the YPF is given by the action spectrum. Some authors consider the amount of photons to be important; others consider their energy to be the driving variable. There is no official SI unit for photon flux density measurement PPFD. Thus, in Equation (1), a mole of photons is used to designate Avogadro’s number (\(N_A = 6.022 \times 10^{23} \text{ mol}^{-1}\)) of photons for stoichiometry [32,33]. The unit \(\mu\text{mol} \cdot \text{m}^{-2} \cdot \text{s}^{-1}\) is most suitable for PPF, since it accounts for the number of photons in the PAR spectral range [34,35]. It can be considered as the production efficiency of \(C_3\) maximizing photosynthesis. In our study, we considered the target curve in relative units. Its shape is sufficient to perform optimization to meet the target curve for photosynthesis, the concept of which is related to both the emitting source radiation power and the light received by the plants. It is a photochemical reaction within the chloroplasts of plant cells in which light energy transforms atmospheric carbon dioxide (CO\(_2\)) into carbohydrates [13]. We consider the photosynthesis \(C_3\) process, which involves CO\(_2\), ribulose-1,5-bisphosphate (\(C_5H_{12}O_{11}P_2\)), and phosphoglyceric acid (\(C_3H_7O_2P\)) containing, respectively, 1, 5, and 3 carbon atoms, according to Equation (1) [36].

\[
C_5H_{12}O_{11}P_2 + CO_2 + H_2O + \text{Photons} \rightarrow 2C_3H_7O_2P
\]

Photosynthesis processes involve various pigments such as chlorophyll a, chlorophyll b, and carotenoid [37]. Plants mainly require certain specific radiations [38–41], mostly concentrated in the red and blue regions [42–46]. Therefore, artificial light should be adjusted to match individual plant target spectrums. Broadband artificial light sources are less efficient due to unused radiation. On the contrary, LEDs are suitable artificial sources due to their single narrow emissions (spectral widths in the range 15–30 nm). About 20 different LEDs are required to cover the solar visible range. However, following specific photosynthesis processes, any plant may require at most 10 different LED types.

On the other hand, it is interesting to reduce the number of different LED types in an industrial setting. Even if this increases the deviation of the simulated curve compared to the target one, it induces only a slight loss in energy efficiency (about 5% [47]). However, the benefits are numerous: reduction in production cost, simpler driver electronics, increased reliability, and reduced maintenance cost [47,48]. This is why we lowered the number of LED types to 5 different colored LEDs while maintaining the same overall electrical power injected into the LEDs.

Our LED-type optimization technique is performed stepwise, as follows. In a first approach, we started by mixing three useful emissions from red (\(R_1\)), green (\(G\)), and blue (\(B_1\)) LEDs. In a second step, we added the wide middle-band white (\(W\)) LED to account for more middle range photons, which are also useful for photosynthesis. This combination was finally upgraded, in a third step, by adding 2 red (\(R_2 \& R_3\)), 1 blue (\(B_2\)), 1 yellow (\(Y\)), and 1 amber (\(A\)) additional LEDs. The important blue and red wings as well as the useful middle-range light were thus well represented. In a second approach, we limited ourselves to only 5 colored LEDs, offering only narrow emissions. We selected the \(R_1, R_2, G, A,\) and \(B_2\) LEDs that enhance photosynthesis processes. The peak emissions of the colored LEDs were 450 nm (deep blue: \(B_2\)), 460 nm (blue: \(B_1\)), 527 nm (green: \(G\)), 590 nm (amber: \(A\)), 610 nm (yellow: \(Y\)), 630 nm (red: \(R_1\)), 660 nm (deep red: \(R_2\)), and 680 nm (far deep red: \(R_3\)).

The present work is thus dedicated to a methodological approach that can be adopted to optimize any LED lighting situation, provided that the target spectrum is available. We chose the most commonly used McCree target curve in relative units.
The paper is organized as follows. The next section very briefly presents the materials and methods used. Our experimental results and simulation calculations are discussed in Section 3, before concluding and suggesting our future built-in switched-mode power supply and LED luminary.

2. Materials and Methods

2.1. LEDs Characterization

The opto-electrical setup illustrated in Figure 1 was used to measure each LED spectrum within 380 and 780 nm together with its electrical characteristics.

![Image of LED measurement setup](image_url)

There exists a large number of LED manufacturers such as Osram, Cree, Osram Golden Dragon, Multicomp Pro, Bridgelux, Philips, etc. High-power LEDs are selected due to their high luminous efficiency. The different LEDs selected for this work are as follows:

- Multicomp Pro THEM-CLRX for R1-630 nm [49], THEM-CLGX (520535) for G-527 nm [50], THEM-CLAX for A-590 nm [51], and THEM-CLBX 460-470 for B1-460 nm [52];
- Osram LD WSSM for B2-450 nm [53], OSLONSSL 150 for R2-660 nm [54], Golden Dragon LH WSAM for R3-680 nm [55], and LA WSAM for Y-610 nm [56];
- Bridgelux: ES Star Arrays, BXRA-27E0540-A-03 (Warm) for the white LED [57].

The LED electric and optical parameters are the forward current, forward voltage, peak wavelength \( \lambda_p \), and full width at half maximum (FWHM) \( \Delta \lambda \). The constructor’s values are given in Table 2. For the narrowband LEDs, \( \Delta \lambda \) ranges between 18 and 41 nm. The white LED used for this work is seen as an entity, even if in fact it comprises several serial LEDs. Its forward voltage is much higher than our colored LED ones.

| LED Type | \( I_{nom} \) (mA) | \( V_F \), typ. (V) | \( \lambda_p \) (nm) | \( \Delta \lambda \) (nm) |
|----------|-----------------|----------------|----------------|----------------|
| Deep blue (B2) | 350 | 3.2 | 449 | 455 | 25 |
| Blue (B1) | 350 | 3.2 | 460 | 470 | 27 |
| Green (G) | 350 | 3.4 | 520 | 535 | 41 |
| Amber (A) | 350 | 2.2 | 585 | 595 | 18 |
| Yellow (Y) | 400 | 2.3 | 612 | 616 | 18 |
| Red (R1) | 350 | 2.2 | 620 | 630 | 18 |
| Deep red (R2) | 350 | 2.1 | 646 | 666 | 18 |
| Hyper red (R3) | 400 | 2.2 | 660 | 666 | 25 |
| White (W) | 350 | 18.2 | — | — | — |
2.2. SPD Measuring Device

A tunable pulsed current source (Keithley 2602A) can supply the LED circuit up to 1 A via a DC voltage, which can attain 40 V. The Keithley current source provides an accurate pulse current, bringing together the supply and the digital multi-meter in a single device. Each LED (device under test) is successively placed at the center of an optical 25 cm diameter Ulbricht integrating sphere (LabSphere 1 000) equipped with a spectro-photo-radiometer (Specbos 1 201) operating in radiance mode and targeting one of the internal shields. The values reported in Table 3 are the maximum spectral flux densities as well as the total fluxes. The integrated value of the SPD of the white LED is determined by integration on the plant spectrum 400–700 nm. The sphere form factor was not established, but it can safely be assumed that it stays constant amongst all the measurements. For this reason, the LED output light level is reported as “relative value”. The design factor taken into consideration in order to optimize the amount of LEDs of different colors is the ratio of radiometric power densities.

The emitting SPD of each LED is carried out at the same mean pulsed current of 20 mA, with a duty cycle of 10% at a pulse repetition rate of 1 kHz, corresponding to a peak current of 200 mA. We limited our measurements to such a low average current and short duty cycle to prevent excessive heating of the LEDs in the closed and non-ventilated integrating sphere. At this current value, heating effects are acceptable and the LED emissions suffer no significant degradation. Therefore, for the present study, we can use a simple mathematical modeling for our colored LEDs.

2.3. Modeling Colored LEDs

An accurate evaluation of individual LED SPDs constitutes an important step to evaluate parameters of the combined LEDs such as luminous flux, chromaticity, color quality, as well as many other parameters [58–60].

This approach is essential for a new design methodology for lighting applications with narrowband emissions and fast electrical modulability.

Until now, there have been three main approaches including a purely mathematical approach, combined approach between mathematical descriptions and SPD measurements, and finally a more physical one.

At the beginning, in 2000, the first attempt for modeling LED SPDs was proven to be rather simple and non-satisfactory [61]. Since about 2005, several publications appeared, where their radiation modeling were constantly improved. The single Gaussian fitting [62] remains non-satisfactory because of the asymmetry of the emission. It was afterwards enhanced with a double Gaussian model [63–65], which nowadays, is still widely used by many authors and organizations. However, both the current and temperature dependence of the LED’s spectrum are not accounted for by this approach. In 2008, Chou et al. [66] reported a variant of the split Gaussian function with different exponential behaviors on either side of the peak emission.

In 2010, F. Reifegerste and J. Lienig [67] undertook a thorough and deep investigation modeling in order to evaluate several single-colored LED spectra. Since then, they have significantly improve their models when dealing with the design of multi spectral LED-based illumination systems. In a first step [68,69], they focused mainly on the selection of LEDs for an aimed spectrum from a database of measured LED devices. They also considered efficient mixing of the light from different LEDs as well as the final control of the spectra in a particular application [70].

All these above models were solely mathematical without any link to underlying physical principles. However, due to the large number of fitting parameters of these mathematical models developed during the last decade, an easy-to-use modeling approach could not be provided.

In 2010, Keppens et al. [71] reported a spectrum model, constructed with a Boltzmann exponential behavior and accounting for carrier temperature variation, gap band energy shift, as well as the increase in the non-radiative recombination rate with junction tempera-
ture. Even if this model allows for very accurate simulations of single-color LED spectra (like ours), in real operating conditions, it remains too cumbersome for integration with our present optimization process of LED SPDs.

For our purpose, mathematical models are much more relevant, particularly when we do not account for junction temperature variations, such as in the present study. Therefore, among the several mathematical functions listed by Vinh et al. [72] now available for curve-fitting of LED SPD, namely the second-order Lorentz, Pearson VII, Split Pearson VII, Gaussian, Split Gaussian, multi-Gaussian, etc., we retained the latter. Indeed, thus far, it is the best mathematical approach because of its non-symmetry and its simplicity.

For each LED, the mathematical single-Gaussian function of the SPD is given by the following expression:

\[
S_\lambda (\lambda, \lambda_p, \Delta \lambda) = S_p \cdot e^{-\left(\frac{\lambda - \lambda_p}{\Delta \lambda}\right)^2}
\]  

with

\[0 \ll S_p \ll 1, \lambda_p \in [380, 780] \text{ nm and } \Delta \lambda \in [10, 30] \text{ nm}\]

The multi-Gaussian model is expressed as follows:

\[
S_\lambda (\lambda) = \sum_i S_{pi} \cdot e^{-\left(\frac{\lambda - \lambda_{pi}}{\Delta \lambda_i}\right)^2},
\]

where \(i\) denotes the \(i\)th Gaussian term. The optimal number of terms is determined by the correlation indexes \(R^2\) and \(R^2_{adj}\) given by Equations (4) and (5), as explained in [73]:

\[
R^2 = 1 - \frac{\sum (S_\lambda (\lambda) - S_{T,\lambda} (\lambda))^2}{S_\lambda (\lambda)^2 - \frac{1}{n} \sum S_\lambda (\lambda)^2},
\]

\[
R^2_{adj} = 1 - (1 - R^2) \frac{n - 1}{n - p - 1},
\]

where \(n\) is the number of recorded samples in the wavelength range, \(p\) is the total number of explanatory variables, \(S_{T,\lambda} (\lambda)\) is the measured LED spectrum, and \(S_\lambda (\lambda)\) is the simulated one. The model order was selected by maximizing the \(R^2_{adj}\) indicator, which permits us to apply a parsimony principle: higher-order models with modest improvement in error reduction are penalized.

2.4. Optimization Approach

In order to match the target spectrum with our calculated one (obtained via an optimized set of our individual LED’s SPD), the adopted optimization procedure is carried out as follows. The fitted spectrum is obtained by compounding the multi-Gaussian formulation of the relevant LED spectra. Our optimization is based on minimization of the error between the compound LED spectrum and the target spectrum of the plants by using a single objective optimization procedure. In this case, PSO is fully suited.

We denote by \(X\) a vector containing the variable parameters:

\[
X = [X_1, X_2, \ldots X_k, \ldots],
\]

where \(X_k\) is the weighted factor of the \(k\)th LED (noted k-type LED, i.e., \(B_2, B_1, G, A, Y, R_1, R_2, R_3, W, or B_2, G, A, R_1, R_2\) and the LED drive current. These coefficients are very important for LED spectra optimization. The simulated spectral power distribution of plants \(S_\lambda (\lambda)\) is given by the following mathematical model:

\[
S_\lambda (\lambda) = \sum X_k \cdot S_{k,\lambda} (\lambda),
\]

where \(X_k = a_k \times n_k\) is the corrected quantity of the k-type LED, \(n_k\) is the quantity of the k-type LED, \(a_k\) is the transfer coefficient between the spectral radiant intensity and the
LED’s drive current, and $S_{k,\lambda}(\lambda)$ is the simulated SPD spectrum of the k-type LED. The spectral power distribution $S_{T,\lambda}(\lambda)$ is a relative spectrum.

The fitting accuracy depends on the LED’s SPD and the number of LEDs. The optimal LED spectrum is achieved by searching the optimal LEDs number. The relative weighting parameter $X_L$, of the corresponding light source is obtained by maximizing the likelihood between the objective target spectrum and the generated one (LED SPD). The best LED spectrum fitting is performed using the correlation index $R^2$ as the fitting parameter, as explained in the previous section. The objective function used to minimize the error is given by the following expression:

$$\min(\sum (S_{\lambda}(\lambda) - S_{T}(\lambda))^2),$$

subject to the constraints set

$$\Omega = \{b_{XL} \ll X \ll b_{XH}\}.$$  

In these expressions, the lower bound vector, $b_{XL}$, equal to 1, and the upper bound vector, $b_{XH}$, equal to 200, are the design variables defining the search range. The PSO technique will be described in full details in the next subsection.

2.5. Optimization Program: Particle Swarm Optimization Method

Kennedy and Eberhart [74] mutually developed the PSO process in 1995. The algorithm was inspired by the behavior of birds inside flocks, each bird at a position $x$ searching for food with a velocity $v$, where the individuals look for the best individual and swarm solution in a problem dimensional space. This method searches the optimal solution using a population of particles, defined by their respective individual positions and velocities, in the search space, which is, in our case, the weighted number of LEDs.

This way, each individual particle, denoted as $I$, is characterized by its current position $x_i$, its current velocity $v_i$, and its best current position $P_{besti}$ (the position in the parameter space of the best fit returned for a specific particle) in the search space. The corresponding position in the parameter space of the best fit returned for the entire swarm $g_{besti}$ is also simultaneously calculated.

The position and the velocity of the particles are modified and adjusted according to the communication between the different particles of the swarm. The individual particles update their position, velocity, and $P_{best}$ as well as the swarm position set by searching for a new position $x_i$, velocity $v_i$, $P_{besti}$, and $g_{besti}$ set and by comparing it to the previous one.

Through successive iterations, we converge to the optimal solution. The particles are represented in a D-dimensional space as follows:

$$x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,D}), \quad v_i = (v_{i,1}, v_{i,2}, \ldots, v_{i,D})$$

$$P_{besti} = (P_{besti,1}, P_{besti,2}, \ldots, P_{besti,D}).$$

Assuming that each individual set of $x_i, v_i, P_{besti},$ and $g_{besti}$ is known at time iteration $k$, the new set, at time iteration $(k + 1)$, is calculated according to the following equations:

$$v_{i,k+1} = \omega(k) \cdot v_{i,k} + c_1 \cdot rand[\cdot] \cdot (P_{besti} - x_{i,k}) + c_2 \cdot rand[\cdot] \cdot (g_{besti} - x_{i,k})$$  

$$x_{i,k+1} = x_{i,k} + v_{i,k+1}, \quad k = (1, 2, \ldots, N)$$  

$$\omega(k) = \omega_{max} - (\omega_{max} - \omega_{min}) \cdot \frac{k}{k_{max}}$$

where $c_1$ and $c_2$ are acceleration values, which determine how fast a PSO particle moves towards $P_{besti}$ and $g_{besti}$. The term $\omega(k)$ is the inertia weight, which influences the convergence behavior of PSO. It evolves linearly over iterations, with the initial and final values being noted $\omega_{max}$ and $\omega_{min}$. The maximum time iteration number is controlled by $k_{max}$.
In this mono-objective PSO, each LED-type is considered a swarm-particle. The number of a particular colored LED represents its position (at iteration $k$). A set of random numbers gives the progression speeds of all the particles, which allows for the calculation of the new position (iteration $k + 1$). Optimization is achieved by considering the whole spectral domain at a time by using Equation (12). The different steps of the optimization procedure are depicted by the flowchart given in Figure 2.

![Flowchart of the particle swarm optimization method.](image_url)

3. Results and Discussions

3.1. Modeling Light Distribution of Monochromatic LED

For each LED, our results follow a similar pattern. For instance, the mean forward voltage of the $B_1$ LED is 2.7 V (Table 3). It is about 20% less than the constructor’s values (Table 2). Such a discrepancy results typically from the parameter spread of electronics devices.

The recorded spectrum of the $B_1$ LED is depicted in Figure 3b, while its peak wavelength, FWHM as well as forward voltage are given in Table 3. The $B_1$ SPD is non-symmetric (crosses: measured spectrum, full line: Gaussian sum fit). The fit is very good as confirmed by Table 4 ($R_{adj}^2 = 0.9993$ for $B_1$), where all the fitting parameters are given for all the colored LEDs. Their SPDs are given in Figures 3 and 4. $R_3$’s SPD (3 exponential terms), which is very similar to that of $R_2$ (3 exponential terms, as well), which is not given. These results comfort our idea of retaining the multi-Gaussian model. Three or four exponential terms are required for our colored LEDs. Figure 3d represents the measured and simulated values of the $W$ white LED’s SPD, which cannot be modeled with a Gaussian sum.

The measured peak wavelengths, FWHM together with the LED forward voltages for all the LEDs are given in Table 3. The optical values sometimes differ from the constructor’s ones, most likely because the substrate of a same LED sample is not reproducible and because heating effects lead to a shift in the peak emission [75].

Correlation index $R^2$ is estimated on the whole spectral domain from 380 to 780 nm. For each LED, deviations occurring far from the LED spectral range (and in the wings
of the emission) do not affect the optimization performance. Therefore, we also estimate the difference between the fitted values and the recorded ones, only in the useful spectral interval corresponding to the FWHM of each recorded SPD. For this domain, we calculate the standard deviation of our fitted curves. This standard deviation remains quite low, within 3.4% and 0.68% of each peak SPD value $S_p$ (Table 3). The worst situation occurs for the $R_1$ LED. In order to further appreciate the curve fitting impact on optimization, we also calculate the difference between the experimental and fitted values in this domain. The specific wavelength $\lambda_e$ corresponds to the worst situation for which the absolute difference is the highest. The relative difference is reported in Table 3. This local error varies between 1.1% and 3.8%, the most unfavorable situation occurring for the amber LED. Nevertheless, a close look at all these SPDs (Figures 3 and 4) clearly shows that our experimental curves are well described by the multi-Gaussian fitting curve.

Table 3. Measured electric and optical LED parameters, and fitting parameters at 20 mA ($\sigma$ is the standard deviation, and percentage values with respect to peak value are given in parenthesis).

| LED Type | $V_F$ (V) | $\lambda_{peak}$ (nm) | $\Delta \lambda$ (nm) | $S_p$ (a.u.) | $\sigma$ (%) (a.u.) | Error at $\lambda_e$ (%) | $\lambda_e$ (nm) | Integrated Value of SPD (a.u.) |
|----------|-----------|------------------------|----------------------|--------------|---------------------|-------------------------|----------------|-------------------------------|
| $B_2$    | 2.56      | 447                    | 9.5                  | 16.04        | 0.435 (2.7%)        | 0.325                   | 447            | 0.558                         |
| $B_1$    | 2.70      | 468                    | 9                    | 16.94        | 0.475 (2.8%)        | 1.96                    | 470            | 0.404                         |
| $G$      | 2.69      | 527                    | 13                   | 7.76         | 0.173 (2.2%)        | 2.73                    | 537            | 0.168                         |
| $A$      | 1.74      | 591                    | 7                    | 23.43        | 0.160 (0.68%)       | 3.79                    | 587            | 0.085                         |
| $Y$      | 1.76      | 604                    | 7                    | 14.23        | 0.311 (2.2%)        | 1.05                    | 597            | 0.170                         |
| $R_1$    | 1.73      | 628                    | 7.5                  | 12.00        | 0.409 (3.4%)        | 1.67                    | 621            | 0.234                         |
| $R_2$    | 1.68      | 657                    | 6.5                  | 11.36        | 0.366 (3.2%)        | 2.09                    | 662            | 0.198                         |
| $R_3$    | 1.76      | 679                    | 6.5                  | 21.07        | 0.702 (3.3%)        | 1.47                    | 676            | 0.392                         |
| $W$      | 14.4      | 610                    | —                    | 15.98        | —                   | —                       | —              | —                             |

Figure 3. Measured and simulated LED SPDs at 20 mA: (a) $R_1$ LED; (b) $B_1$ LED; (c) $G$ LED; (d) White LED.
Table 4. SPD multi-term Gaussian fitting parameters of the different LEDs.

| LED Type       | Term N° | $S_p$ (a.u.) | $\lambda_p$ (nm) | $\Delta \lambda_i$ (nm) |
|----------------|---------|--------------|------------------|-------------------------|
| Deep blue B 450 nm $R^2_{adj} = 0.9997$ | 1       | 10.5         | 446.1            | 7.4                     |
|                | 2       | [10.3, 10.6] | [446, 446.2]     | [7.3, 7.5]              |
|                | 3       | [2.00, 2.33] | [457.1, 458.2]   | [25.1, 25.8]            |
|                |         | [11.9, 12.2] | [448.9, 449.0]   | [14.9, 15.2]            |
| Blue B 460 nm $R^2_{adj} = 0.9993$      | 1       | 8.84         | 467.2            | 7.2                     |
|                | 2       | [8.50, 9.17] | [467.1, 467.3]   | [7.0, 7.3]              |
|                | 3       | [8.05, 8.88] | [469.3, 471.3]   | [19.3, 20.4]            |
|                |         | [0.59, 0.69] | [453.2, 454.4]   | [8.6, 9.2]              |
| Green G 527 nm $R^2_{adj} = 0.9993$     | 1       | 3.63         | 591.0            | 4.1                     |
|                | 2       | [2.78, 4.47] | [590.7, 591.3]   | [3.8, 4.6]              |
|                | 3       | [1.78, 2.91] | [584.2, 585.8]   | [4.2, 5.9]              |
| Amber A 590 nm $R^2_{adj} = 0.9997$     | 1       | 38.0         | 604.1            | 5.0                     |
|                | 2       | [37.3, 38.7] | [604, 604.2]     | [5.0, 5.1]              |
|                | 3       | [44.3, 45.5] | [602.0, 602.2]   | [10.4, 10.7]            |
| Yellow Y 604 nm $R^2_{adj} = 0.9999$    | 1       | 1.81         | 628.2            | 4.5                     |
|                | 2       | [1.2, 2.43]  | [628.1, 628.4]   | [3.9, 5.1]              |
|                | 3       | [0.28, 0.46] | [612.2, 613.5]   | [3.4, 5.2]              |
| Red R 630 nm $R^2_{adj} = 0.9997$       | 1       | 8.88         | 657.1            | 5.73                    |
|                | 2       | [8.83, 8.93] | [657, 657.2]     | [5.69, 5.78]            |
|                | 3       | [2.14, 2.27] | [647.8, 648.1]   | [5.18, 5.51]            |
| Deep red 660 nm $R^2_{adj} = 0.9993$    | 1       | 15.8         | 678.9            | 5.76                    |
|                | 2       | [15.7, 15.9] | [678.9, 679]     | [5.72, 5.80]            |
|                | 3       | [2.81, 3.04] | [668.7, 669.2]   | [5.87, 6.40]            |
| Hyper red R 680 nm $R^2_{adj} = 0.9994$ | 1       | 5.56         | 670.9            | 5.76                    |
|                | 2       | [5.56, 5.78] | [670.9, 671.1]   | [5.87, 6.40]            |
|                | 3       | [5.56, 5.78] | [670.9, 671.1]   | [5.87, 6.40]            |
Figure 4. Measured and simulated LED SPDs at 20 mA: (a) R₂ LED; (b) B₂ LED; (c) A LED; (d) Y LED.

3.2. Combining 3, or 4, or 9 Selected LEDs

Mixed LED output light optimization is firstly performed with the simplest and basic combination involving only three LEDs and depicted in Figure 5a with the blue dashed curve. The red and blue LEDs can provide only some of the required radiations for photosynthesis, while the green LED alone cannot meet our objective for the middle region of the spectrum. The four LED-type optimized spectrum (represented by the green curve) better fits the target curve. Finally, using all the nine LEDs, the simulated spectrum (blue full line curve) is much enhanced. Of course, the B₂, R₂, and R₃ LEDs and to a lesser extent the A, Y, and G ones improve the output emission. The amount of R₁, B₁, and G LEDs hardly varies for the three combinations due to the nonoverlap of their respective individual sharp emissions (Table 5). The correlation index between the target curve and the simulated one is equal to 0.33, 0.44, and 0.87 for R₁GB₁, R₁GB₁W, and all the nine LED combinations, respectively. As expected, the amount of R₁, B₁, and G LEDs hardly varies for the three combinations (Table 5).

The total number (summing up the individual LED amounts) of LEDs needed for the R₁GB₁, R₁GB₁W, and R₁GB₁WR₂R₃YB₂A luminaires are 291, 355, and 752, respectively. For the three luminaires, the number of individual R₁ (B₁ and G as well) LEDs is hardly affected due to nonoverlap of the individual LED SPDs. We point out that attention should not be paid to these absolute values but instead to the relative ones. These values will differ following the target curve. Such high amounts of LEDs may increase the thermal and screening effects. As explained earlier, it can also be an issue for driving and control with switched-mode power LED drivers. To minimize these effects, the overall luminaire power should be distributed over a number of LED heat-sinks, each supporting only a limited amount of LEDs.
Table 5. LED amounts for different combinations.

| LED Type | Total LED Amount |
|----------|-----------------|
| McCree   |                 |

| # | B2 | B1 | G  | A  | Y  | R1 | R2 | R3 | W  |
|---|----|----|----|----|----|----|----|----|----|
| 3 | 49 | 151| 91 |     |    |    |    |    | 291|
| 4 | 51 | 151| 92 |    |    |    |    |    | 355|
| 9 | 49 | 50 | 152| 189| 40 | 92 | 38 | 60 | 752|

#: number of LEDs in the LED combination (luminary); #3: R1GB1; #4: R1GB1W; and #9: All 9 LEDs.

3.3. Combining Only 5 Selected LEDs

The simulation results, obtained with 5 LEDs, are shown in Figure 5b. The correlation index between the McCree target spectrum and the generated one is equal to 0.73. Table 6 represents the best percentage of each LED type. We give the required distribution of different LEDs (5-LED mix) to match the McCree spectrum.

![Figure 5](image)

(a) Different LED combinations: (a) 3-, 4- and 9-LED mixing spectrum optimization and (b) 5-LED mixing spectrum.

Table 6. Weight values and relative power density for each LED type.

| LED Type | LED Nb | McCree Coeff. | Relative Power Density % |
|----------|--------|---------------|--------------------------|
| B2       | 20     | X1 = 49       | 18.4                     |
| G        | 26     | X2 = 150      | 24.0                     |
| A        | 25     | X3 = 189      | 15.5                     |
| R1       | 28     | X4 = 84       | 19.6                     |
| R2       | 29     | X5 = 89       | 17.8                     |

3.4. Designing a Future Experimental 200 W Target LED Lighting System

Based on the above optimization procedure, we are currently designing an experimental 200 W target LED luminary adopting four 50 W serial devices in order to minimize the heat effects of the neighboring LEDs. Our device is based on high power surface-mounted LEDs (SMD). These versatile lighting sources comprise individual LEDs operating around at least 1 W. SMD LEDs are usually equipped with a lens permitting to control the main emission lobe aperture. This way, matching source and receptor does not require an external part. Therefore, this specific feature can provide strong emitted radiations for plants while reducing wasted light and energy. In order to irradiate plants grown on a target area, a uniform light distribution is needed.

We supply each LED with 280 mA in order to determine the amount of LEDs required for each family. This current value results from the 200 W LED luminary target-power of our future Buck power supply, which is limited to an output current of 1.4 A, according to a former survey work performed at the EI & ICT ENICarthage laboratory [76–78]. The
corresponding supply output voltage is 143 V. We need to verify that this new current value does not bring any significant drift on the target spectrum.

4. Conclusions and Perspectives

In this paper, a LED luminary output radiation is simulated from individual recorded LED SPDs to achieve the optimal output spectrum for greenhouse plants. The mono-objective PSO technique is applied to match the target spectra. This simple optimization approach of LED luminary radiation can be easily used for any particular target application, provided that the latter is reliable. Despite their importance for photosynthesis, altogether blue and red wings are insufficient to irradiate all types of plants. In this work, a limited amount of prominent SMD LED mixing, covering also the middle region, was proven to approach the target spectrum.

For our next work, we are designing a new experimental LED luminary using a COMSOL multiphysics environment while accounting for thermal processes. We conceived the printed circuit board (PCB) using Altium Designer. Using a buck driving supply, we will provide dimming control in order to adjust the adequate spectrum to meet the needs of the plant. The supply is configured with multi-LED strings using constant current control, which accounts for a tradeoff optimization between electric power losses and volume minimizations in order to achieve higher efficiency and better reliability. We plan to record the target PAR adapted to the specific studied plant. Then only, field studies will permit us to analyze the physiological effects of our optimized lighting system, using a dimming based on pulse width modulation (PWM) control in order to provide the optimal light quantity and quality throughout the different growth phases of the selected plants under study.

**Author Contributions:** This work was conceptualized by P.D., L.B. (Latifa Bachouch), G.Z., and N.S. The numerical code was written by both L.B. (Latifa Bachouch) and P.D.; N.S. helped in building the MatLAB program. The PSO technique was implemented by L.B. (Latifa Bachouch), who also performed all the experiments. She was trained by P.D. for the experimental setup as well as by N.S. for the handling of monochromators and optical measurements. The article was written by L.B. (Latifa Bachouch) with contributions of N.S., P.D., and L.C. The latter greatly contributed to LED selection and designed the LED support. The results were analyzed by L.B. (Latifa Bachouch), N.S., and P.D. All the authors participated in the follow-up of this work. All authors have read and agreed to the published version of the manuscript.

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