



**CENTRO UNIVERSITARIO
DE LA DEFENSA
EN LA ESCUELA NAVAL MILITAR**



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Ellipsoid-Based Approximation Method for the Estimation of the Actual Reduced Luminance Coefficients of Road Surfaces for Accurate Lighting Simulations

Abstract

Lighting simulations are a useful tool for developing strategies to minimize lighting pollution and energy consumption in the street lighting field. However, the properties of the standard pavements often used in simulations are out-to-date and might notably diverge from the values of the real system, leading to inaccurate results. This underlines the present need for new methods to generate models that more closely resemble the actual behaviour of the roads and the construction materials currently used. This paper proposes a novel method that approximates the reduced luminance coefficients of asphalts using a geometric estimation based on a three-ellipsoid surface. It focuses on improving the modelling of the road surface material by adapting the reflection properties of the pavement, appraising and mitigating the impacts of pavement deterioration on simulation results. The approximation method is implemented inside a model calibration framework and applied to a real scenario in comparison to other methods. Results are yielded with approximately 0.088 cd/m² error in the luminance calculation regarding measurements taken experimentally while maintaining a realistic photometric model. These experimental figures, corresponding to a relative decrease of 26.5%, support the theoretical contribution of this research work to the management of the consumption and operation of public lighting systems.

Keywords: luminance, model calibration, pavement reflection properties, r-table, reduced luminance coefficients, road lighting, simulation,

1. Introduction

Artificial lighting plays a fundamental role in everyday life, improving quality of life and increasing productivity. However, it requires a significant amount of resources because it accounts for 15% of global electricity consumption and 5% of greenhouse gas emissions (GHG) [1]. Additionally, artificial lighting has significant savings potential considering that conventional light sources are still in service [2, 3] and that the use of more efficient technologies can result in up to 85% improvement in energy efficiency [1]. In this field, many efforts have been made by experts and administrations to implement policies, strategies and recommendations to reduce GHG emissions, increase energy efficiency, increase the use of renewable energy and enhance lighting quality [4, 5]. Researchers have also conducted numerous studies to analyse the impact of a variety of energy-saving measures involving both indoor [6, 7, 8, 9, 10, 11, 12, 13, 14] and outdoor facilities [15, 16, 17, 18, 19, 20]. This work focuses on road lighting installations, taking into account that in Europe, this sector represents approximately 1.3% of the electricity use, consuming approximately 35 TWh to provide lighting for more than 1.5 million km of roads [3].

Road lighting is an indispensable service for cities and their inhabitants because of its great impacts on welfare, safety, security and crime prevention [21, 22, 23], but an inadequate design can lead to serious environmental problems. Light pollution is of great concern among the expert community studying its effects, such as the disappearance

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of the night sky, distortion of circadian rhythms, depression and other human health conditions and severe consequences related to animals and plants [24, 25, 26, 27, 28, 29, 30]. Light pollution appears in 5 different forms: glare, over-illumination, light clutter, light trespass/nuisance and sky glow [29]. However, all these effects can be minimized with correct dimensioning and design of lighting systems. For this purpose, lighting simulation tools have become important since they allow the implementation of optimization techniques and provide a prediction of the operation of designed indoor or outdoor lighting installations. Radiance, Relux, DIALux, Daysim, Oxytech, MATLAB and BuildOpt are tools used by many authors in their research [31, 20, 18, 10, 32, 11]. The recommendations of the EN 13201-2:2015 [33] standard on photometric requirements are followed in the design and optimization stages, depending on the type of use of the road: class M for roads with motorised traffic, class C for conflict areas, and class P for streets with pedestrians and cyclists. Moreover, the study conducted by Doulos et al. [20] reveals the importance of taking into account energy performance indicators in decision-making tools. Yoomak et al. [18] analysed a set of scenarios by introducing variations in the mounting height, pole spacing, street lighting arrangement (opposite, single-sided and staggered) and dry and wet road conditions. Using optimization and simulation techniques, the authors compared high-pressure sodium (HPS) lamps with light emitting diode (LED) lamps and determined that LED technology offers better results in terms of comfort and visualization but worse average luminance than HPS. Carli et al. [34] developed a multi-criteria tool applicable to existing facilities that assists in the decision-making process for the selection of the optimal set of retrofit interventions. The criteria of energy consumption, uplight luminous flux and colour rendering index are used to reduce consumption, protecting the environment and maintaining comfort and quality of life. The study conducted by Rabaza et al. [35] discusses the application of the NSGA-II multi-objective algorithm to calculate the relationship between the most important parameters in the planning of lighting installations using the criteria of energy efficiency and overall uniformity.

The reflection properties of the asphalt also influence the operation of the lighting system and the visual comfort of drivers since the luminance is a function of the quantity of light reflected from the road surface in the observation direction. For this reason, it is important to correctly define the road surface material in the modelling of outdoor scenes using reflection tables, called r-tables. Standard r-tables with the reflection properties of roads constructed using similar materials and methods are often used. The International Commission on Illumination (CIE) [36] classifies road surfaces and recommends classes R, N and C for dry roads while reserving class W for wet road surfaces since the reflection properties change with climatic conditions. Nevertheless, the problem is that these tables include measurements taken in the seventies [36, 37], numerous studies have demonstrated that the data are not representative of today's pavements [38, 39, 40, 41] and their use in the calculation of the average luminance can lead to errors greater than 30% [42]. The CIE recommends scaling the standard tables according to the average luminance coefficient (Q_0), but as Dumont and Paumier [43] indicate in their study, discrepancies are observed even when this measure is applied. For some road materials, the specular and diffuse lobes are not correctly represented in the indicatrix. In addition, new types of surfaces have been developed in recent years. Muzet et al. [44] analysed the photometric properties of a pavement whose average luminance coefficient increases over time, balancing out the ageing of the luminaires and maintaining adequate levels of luminance. In an effort to reduce the temperature of cities in the struggle to mitigate the heat island phenomenon [45], pavements with completely different reflective properties are being developed. These are cool pavements that use highly reflective white paints.

The pavement characteristics are also affected by dirt, ageing and traffic. In addition to optimizing the design of new installations, regularly updated data on the pavement would make it possible to act on the luminous flux of the luminaires to adapt their operation to the current state of the pavement. The most accurate approach for obtaining the reflection properties is to extract and transport a sample from the road surface to the laboratory and use specific equipment such as gonireflectometers to perform the measurements. However, taking into account both the technical and economic complexity of the process, portable equipment has been developed to acquire in situ measurements. The most widely used devices are the Memphis [46], developed by the Schreder group, and Coluroute [47], developed by the Laboratoire des Ponts et Chaussées (LRPC), but there have also been other initiatives such as those proposed by Casol et al [48] and Rice et al. [49]. The drawback of using portable devices instead of laboratory equipment is that the measurements taken are not sufficient for completion of the reflection tables, requiring the development and application of approximation methods to correctly model the pavements. Several authors have conducted research in this field [50, 47, 51, 52]. Debergh and Embrechts [50] introduce a mathematical model based on the use of first- and second-order polynomials to fit the table and compare their application to measurements made with Memphis and Coluroute gonireflectometers. Muzet et al. [47] reconstruct the columns and rows of the table with a combination of

parametric functions: three cubic Hermite polynomials, a log normal law and a decreasing exponential. Korobko [51] developed an analytical model that approximates the three-dimensional distribution of the luminance coefficient by means of two ellipsoids: one with the main axis aligned with the direction of specular reflection and the other along the direction of beam incidence. Maghe suggests functions to complete the table in two different regions [52]. Other non-destructive methods for the estimation of the r-table include the use of lighting simulation tools and the extraction of experimental measurements by means of digital devices [53, 54, 55]. Buschman et al. calculate the luminance coefficients using luminance images of the measurement field and the illuminance caused by one or more calibrated auxiliary luminaires.

The studies mentioned above indicate the need for updated r-tables to correctly represent the actual pavements in the simulation models. However, the most commonly used methods are technically complex and demand specific equipment that is not always available. For this reason, the development of new measurement methodologies is also needed. Ogando-Martínez et al. [55] developed a methodology to characterize new asphalts that combines simulation and model calibration techniques and is fed by experimental luminance measurements collected with a luminance meter. Nevertheless, this methodology also requires an approximation method similar to that used to complete the r-tables generated with portable gonireflectometers. This document describes a new method that approximates the reduced luminance coefficients of a given asphalt by means of three ellipsoids. The validation is then carried out by applying the method to a real case study, and the results are analysed and discussed in comparison to other approximation methods. The aim is to achieve an approximation method that does not exceed other methods in terms of computational time and simultaneously uniformly adapts the form of the reflection indicatrix according to the measurements made.

2. Materials and Methods

A methodology for modelling the reflection properties of road materials is proposed in this work. This new method aims to improve the existing reflection models that are currently used in outdoor lighting simulations both to assess the operation of existing lighting facilities and to design new ones. It is a model calibration process that combines lighting simulation and optimization techniques through Radiance and GenOpt as detailed in previous works [55], but for the sake of completeness, a summary is included in this section. Figure 1 shows the model calibration process, which is carried out in three stages: the modelling and simulation of outdoor lighting installations is performed with Radiance, while GenOpt is used for optimization. Both programs are integrated into a custom software pipeline programmed in Python. Radiance is a set of open-source programs designed at Lawrence Berkeley National Laboratory [56] to perform the analysis and display of lighting scenes using the light-backwards ray tracing algorithm for lighting calculations. In addition, GenOpt is an optimization engine that provides the method with the means to minimize the cost of a function evaluated with Radiance.

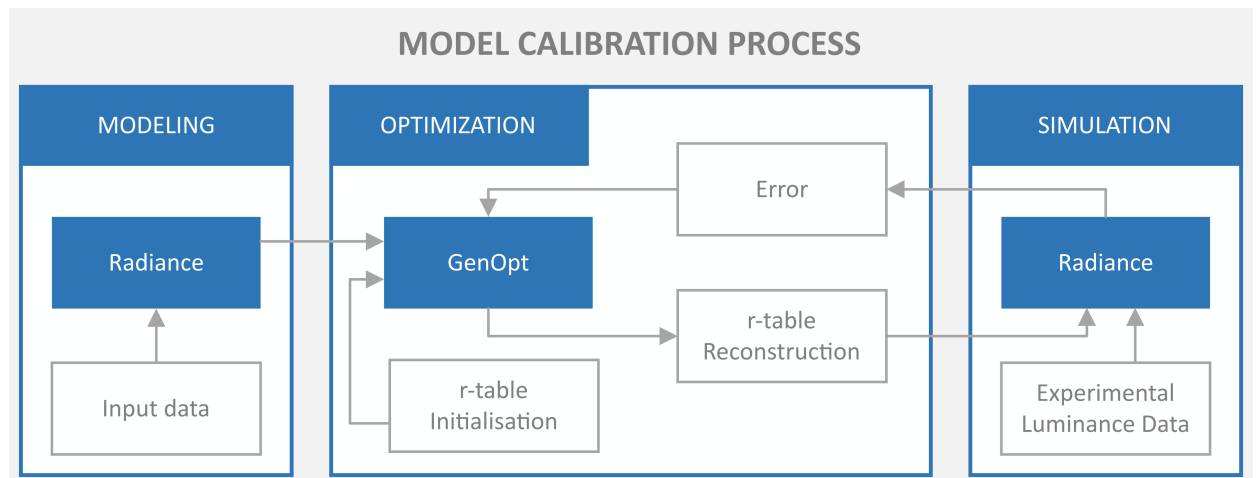


Figure 1: Model calibration process combining Radiance and GenOpt for adapting the reduced luminance coefficients of road surface materials.

The reflection properties are tabulated for standard road surfaces depending on the three angles represented in Figure 2: the angle of light incidence (γ), the angle between the plane of light incidence and plane of observation or deviation angle (β) and the observation angle (α). The r-tables are two-dimensional and include 396 reduced luminance coefficients as a function of γ and β , keeping α constant and equal to 1° . The observation angle is considered constant since the reduced luminance coefficients do not vary significantly between 0.5° and 2° , the range of interest for motorized traffic [57]. The main objective of this work is to develop a general method that allows the adaptation of the luminance coefficients of these tables to the singularities of each pavement according to measurements carried out on the road. Thus, a two-stage process is conducted to fit the table by means of three ellipsoids: first, the mathematical model is defined and initialised with the corresponding standard r-table, while in the second stage, the table is reconstructed from the optimized variables.

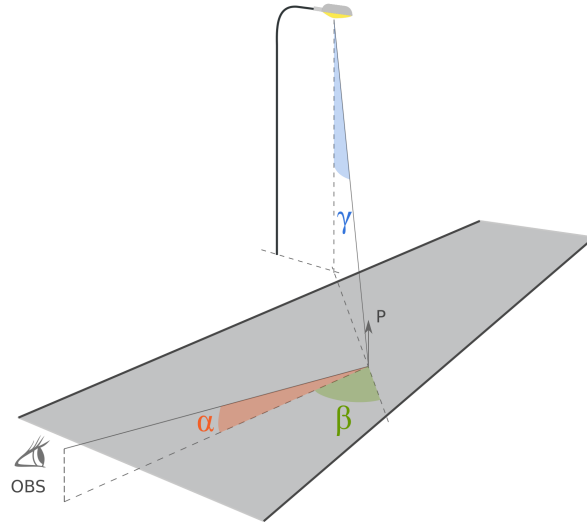


Figure 2: Relevant angles used to define the reflection properties of road surfaces.

Optimization is accomplished by implementing the Hooke-Jeeves algorithm [58] in GenOpt, which merges a sequence of exploratory movements and pattern movements in an iterative process. The purpose of the algorithm is to achieve optimal values for a set of calibration parameters that minimize an objective function. For this, these parameters are modified in each iteration between a range of possible values, and the simulation is executed in Radiance to compare the results of the simulation with measurements made experimentally. The process ends when this difference, evaluated at multiple points, is minimized. The evaluation is made using as objective function the root mean squared error (RMSE) [59], which is calculated using Eq. 1,

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}, \quad (1)$$

where n represents the number of points analysed, $\hat{y}_i$ is the value of the variable measured and y_i indicates the simulation output for this variable.

The luminance is the variable chosen to determine the error, since its value is strongly related to the reflection characteristics of the asphalt. For the luminance calculation, the luminance coefficient (q) is used, which is related to the reduced luminance coefficient through the expression:

$$q = \frac{r(\beta, \gamma)}{\cos^3 \gamma}. \quad (2)$$

To validate the method, the shape of the resulting r-table is also analysed since it has been found that the standard r-tables yield a smooth surface when they are graphically represented. Obtaining a smooth surface as a result is also indicative that no over-adjustments are being made due to the use of a particular pavement section in the case study. Over-adjustments are detrimental, as there may be small defects and occasional potholes caused by traffic or rain that are not representative of the overall condition of the pavement. Therefore, a smooth curve provides a generalizable approximation for other road sections with the same type of pavement and is more reliable and in line with standard r-tables. The procedure followed to determine how smooth the surface is consists of approximating the reduced luminance coefficients of the resulting r-table to a smooth surface using the thin plate spline (TPS) method [60] and considering 0.5 as the regularization parameter. Then, a new r-table is generated from the smoothed spline model, and the RMSE between the two r-tables is determined. As Table 1 reveals, the results for this error are low for the four r-tables of the R classification, which confirms that these standard surfaces are quite smooth.

Table 1: Smoothness of the standard r-tables of the R classification.

Surface type	Shape RMSE [sr^{-1}]
R1	0.300
R2	0.196
R3	0.197
R3	0.228

The results obtained are compared with other approximation methods also detailed in this section to analyse the viability of the developed method and to evaluate its performance.

2.1. Three-Ellipsoid Approximation Method

The proposed method is based on an approximation of the reduced luminance coefficients by a set of three ellipsoid surfaces in a spherical coordinate system. This approximation provides the means to encode the values of the entire r-table in just 15 parameters.

2.1.1. Area Selection

First, the entire set of values for β is divided into three different regions: $\beta^{(1)} \in [0^\circ, 15^\circ)$, $\beta^{(2)} \in [15^\circ, 60^\circ)$ and $\beta^{(3)} \in [60^\circ, 180^\circ)$. This partitioning is done according to the different shape characteristics of the luminance coefficient surface of the four typical r-tables, R1-R4, in spherical coordinates. These surfaces present visible inflexion points at $\beta = 15^\circ$ and $\beta = 60^\circ$, especially for the tables corresponding to highly specular roads. Figure 3 shows the different surface regions for tables R1 to R4. Using a different ellipsoid for each of these three separate surfaces yields a more accurate approximation of the entire space.

2.1.2. Ellipsoid Fitting

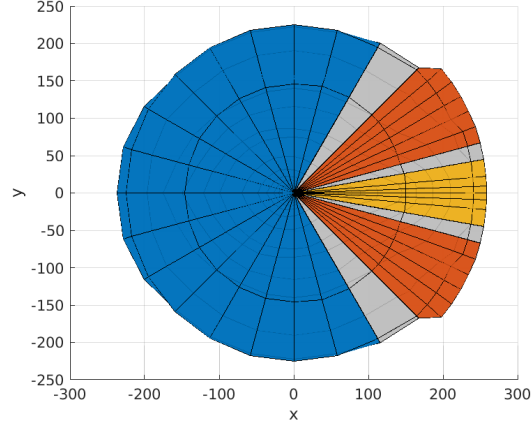
Once the set of values in the table is partitioned, a fitting method is used to approximate the surface defined by each partition with an ellipsoid. Given the general equation for a quadric surface:

$$ax^2 + by^2 + cz^2 + 2fyz + 2gxz + 2hxy + 2px + 2qy + 2sz + d = 0, \quad (3)$$

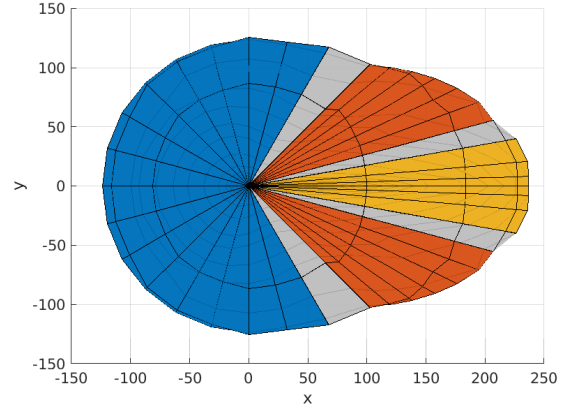
The expression is restricted given the constraints of the indicatrix surface, removing the two rotation terms for the x - and z -axes and the translation term for y . The independent coefficient is also removed to force the ellipsoid to pass through the point $(0, 0, 0)$; this corresponds to the expected behaviour of the indicatrix, removes one degree of freedom from the optimization problem and simplifies the intersection calculations in each iteration, as described in Section 2.1.3.

Introducing these constraints in the modified version of Yuri Petrov's algorithm [61] gives the final expression of the constrained quadric surface:

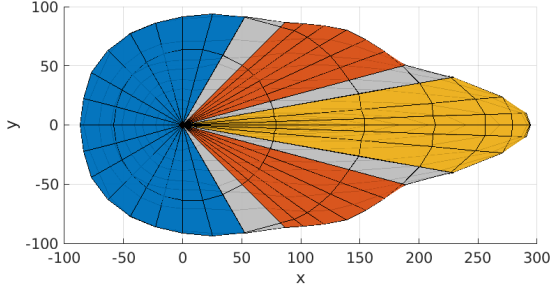
$$a'(x^2 + y^2 - 2z^2) + b'(x^2 + z^2 - 2y^2) + 2gxz + 2px + 2sz = x^2 + y^2 + z^2. \quad (4)$$



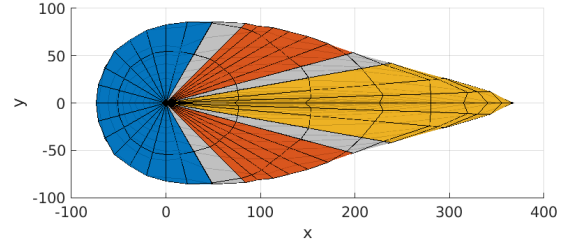
(a) R1.



(b) R2.



(c) R3.



(d) R4.

Figure 3: Upper view of the indicatrix surfaces in spherical coordinates for standard r-tables [36]; $\beta^{(1)}$ in yellow, $\beta^{(2)}$ in red, $\beta^{(3)}$ in blue.

Then, a least squares minimization problem is used based on the algebraic distance for Eq. (4). Let $\mathbf{X}_i$ be the set of vectors of the design matrix $\mathbf{D} = (\mathbf{X}_1, \dots, \mathbf{X}_N)^T$ for each point $\{\mathbf{p}_i(x_i, y_i, z_i)\}_{i=1}^N$ in the set of input points to be fitted:

$$\mathbf{X}_i = (x_i^2 + y_i^2 - 2z_i^2, x_i^2 + z_i^2 - 2y_i^2, 2x_i z_i, 2x_i, 2z_i). \quad (5)$$

Let $\mathbf{v}$ be the coefficients of Eq. (4):

$$\mathbf{v} = (a', b', g, p, s)^T. \quad (6)$$

Let $\mathbf{m} = (m_1, \dots, m_N)^T$ be a vector containing the squared norm of each input point:

$$m_i = x_i^2 + y_i^2 + z_i^2. \quad (7)$$

Then, the solution to the least squares fitting problem is obtained by solving the following normal equation, as described in [61]:

$$\mathbf{D}^T \mathbf{D} \mathbf{v} = \mathbf{D}^T \mathbf{m}. \quad (8)$$

2.1.3. R-table Reconstruction

Using the initial fitted ellipsoid for each region, all the values of the r-table can be reconstructed by calculating the intersection between the ellipsoid surface and a 3D line with a slope determined by the corresponding values of β and γ . First, the first three coefficients of the conventional algebraic form of the ellipsoid are recovered from Eq. (4) as presented in Eqs. (9)-(11):

$$a = a' + b' - 1, \quad (9)$$

$$b = a' - 2b' - 1, \quad (10)$$

$$c = b' - 2a' - 1. \quad (11)$$

Let $\{\beta_i\}_{i=1}^{20}$ and $\{\gamma_i\}_{i=1}^{29}$ be the set of different values in the r-table for β and γ , respectively, and let $r_{i,j}$ be the value in the r-table corresponding to β_i and γ_j . Let $\mathcal{L}_{i,j}$ be a half-line starting at $\mathbf{p} = (0, 0, 0)$ towards $z > 0$, with a slope determined by β_i and γ_j . Then, the intersection between the ellipsoid $\mathcal{E}$ and the half-line $\mathcal{L}_{i,j}$ can be obtained as follows:

$$\begin{cases} \mathcal{E} : & ax_{i,j}^2 + by_{i,j}^2 + cz_{i,j}^2 + 2gx_{i,j}z_{i,j} + 2px_{i,j} + 2sz_{i,j} = 0 \\ \mathcal{L}_{i,j} : & x_{i,j} = r_{i,j} \sin(\gamma_j) \cos(\beta_i) \\ & y_{i,j} = r_{i,j} \sin(\gamma_j) \sin(\beta_i) \\ & z_{i,j} = r_{i,j} \cos(\gamma_j) \\ & \text{s.t. } z_{i,j} \geq 0 \end{cases} \quad (12)$$

Solving this system of equations yields the final value for each point, $r_{i,j}$, with the expression given by Eqs. (13)-(15):

$$\begin{aligned} r_{i,j,\text{den}} &= a \sin^2(\gamma_j) \cos^2(\beta_i) \\ &\quad + b \sin^2(\gamma_j) \sin^2(\beta_i) \\ &\quad + c \cos^2(\gamma_j) \\ &\quad + 2g \sin(\gamma_j) \cos(\gamma_j) \cos(\beta_i), \end{aligned} \quad (13)$$

$$\begin{aligned} r_{i,j,\text{num}} &= 2p \sin(\gamma_j) \cos(\beta_i) \\ &\quad + 2s \cos(\gamma_j), \end{aligned} \quad (14)$$

$$r_{i,j} = \begin{cases} r_{i,j,\text{num}} / r_{i,j,\text{den}} & \text{for } z_{i,j} \geq 0, \\ 0 & \text{for } z_{i,j} < 0. \end{cases} \quad (15)$$

With the three ellipsoids approximating each of the initial space partitions, a continuous surface is finally obtained by merging their individual contributions, smoothing the transitions at the boundaries between regions. Let $\mathcal{I}_\gamma = \{4, 5, 11, 12\}$ be the set of indices for the values of γ at the boundaries. Then, the values of the r-table are updated as described in Eq. (16):

$$r'_{i,j} = \frac{\sum_{k=j-1}^{j+1} r_{i,k}}{3}, \quad \forall i \in \{2, \dots, 29\}, \forall j \in \mathcal{I}_\gamma. \quad (16)$$

For the first row of values, taking into account that all the values represent the same physical point, the average is calculated and assigned to all of them to obtain a constant term according to the three different heights of this point for each ellipsoid:

$$r'_{1,j} = \frac{\sum_{k=1}^{20} r_{1,k}}{20}, \quad \forall j \in \{1, \dots, 20\}. \quad (17)$$

The method phases described in this section can be graphically observed in Figure 4. The figure shows how an approximated r-table for asphalt class R2 can be provided by applying the ellipsoid adjustment to the three differentiated regions and then reconstructing the r-table.

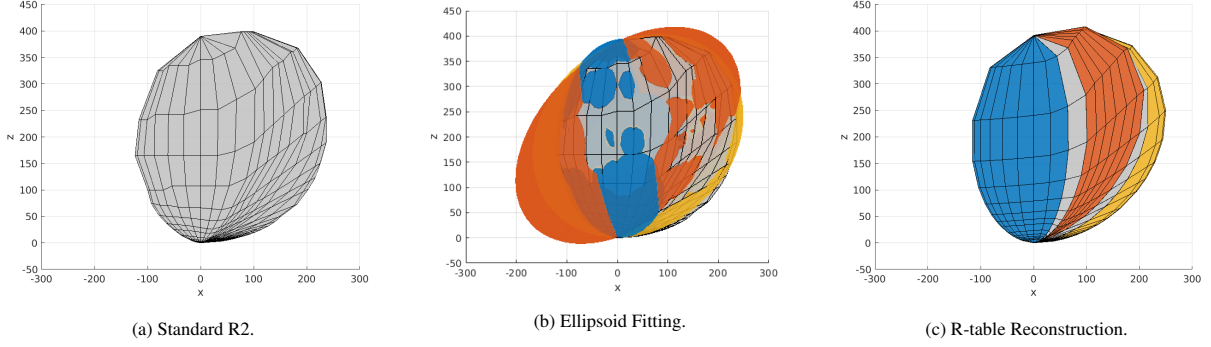


Figure 4: Indicatrix surfaces in spherical coordinates showing the phases of the three-ellipsoid approximation method. The x -axis is $10^4 r \sin(\gamma) \cos(\beta)$, and the z -axis is $10^4 r \cos(\gamma)$.

2.2. Integration of Other Methods in the Calibration Process

The following is a brief description of the methods used to validate the developed approach by comparing the results. Both methods are integrated into the calibration process in the same way: initially, the model is approximated to a standard r-table, then the variables are optimized and finally the r-table is reconstructed.

2.2.1. Factor-based Approximation Method

This method of approximation was presented in a previous work [55] to adapt the reflective properties of road materials by improving the r-tables and consists of weighting the reduced luminance coefficients as a function of the β and γ values. In this method, the segmentation of the r-table is not necessary, the whole table is treated with the same procedure, and a weight is allocated to each γ and β value. Thus, 49 calibration variables are considered, one associated with each angle in the table. The initial values of these parameters are chosen so that the standard table remains unchanged. In addition, the reconstruction of the r-table after each iteration of the calibration process is performed through the expression:

$$r'_{i,j} = r_{i,j} a_i (b_j \tan(\gamma_j) + 1). \quad (18)$$

where a_i is the multiplying factor relative to γ and b_j represents the multiplying factor applicable to β .

2.2.2. Column-based Approximation Method

The approximation method proposed by Maghe [52] is adapted in this section for use in the calibration process. This mathematical model was developed to fill the incomplete r-tables collected with the Schreder company's portable gonireflectometer, since the device is only capable of measuring the reduced luminance coefficients for some angles of the table. Therefore, an approximation method is needed to determine the rest.

The method divides the table into two regions based on the γ values and suggests a function for completing each one:

$$f = (x^2 - 2x + 5) \quad (19)$$

$$r_{i,j}^{(1)} = f^{a_j^{(1)}} ((4^{-a_j^{(1)}} r_{1,1} + b_j^{(1)} + c_j^{(1)})x - b_i^{(1)} + (d_j^{(1)} - c_j^{(1)})x^{-1} - d_j^{(1)}x^{-2}), \quad (20)$$

$$r_{i,j}^{(2)} = f^{a_j^{(1)}} ((4^{-a_j^{(1)}} r_{1,1} + b_j^{(2)} + c_j^{(2)})x - b_j^{(2)} - c_j^{(2)}x^{-1}), \quad (21)$$

$$r'_{i,j} = \begin{cases} r_{i,j}^{(1)} & \text{for } \tan(\gamma_i) \leq 5, \\ r_{i,j}^{(2)} & \text{for } \tan(\gamma_i) > 5. \end{cases} \quad (22)$$

where $C^{(i)} = (a^{(i)}, b^{(i)}, c^{(i)}, d^{(i)})$ represents the parameters that depend on the β angle and $x = \tan(\gamma_i) + 1$. $r_{1,j}$ and also represents the calibration variables that are modified in each iteration of the calibration process. The initial values of $C^{(i)}$ are selected using a fitting method to match the surface defined by the functions to the standard indicatrices of reduced luminance coefficients.

The values in the r-table can be reconstructed by substituting the calibrated parameters in Eq. (19) and considering the expression:

$$z_{i,j} = r_{i,j} \cos(\gamma_i), \quad (23)$$

$$r_{i,j} = \begin{cases} r_{i,j} & \text{for } z_{i,j} \geq 0, \\ 0 & \text{for } z_{i,j} < 0. \end{cases} \quad (24)$$

3. Experimental System

The methodology was tested using data collected experimentally in a real scenario located in Pontevedra, Spain. According to European Standard EN 13201-3:2015 [57], the luminance was measured in an area between two streetlights on the same roadside. The area includes a two-lane road 6.8 m wide and 63.1 m long. The streetlights are positioned on both sides of the road in a staggered arrangement, and each one includes a 7644 lm LED source of 59.3 W on a pole 9 m high. The luminaires closest to the calculation area were included in the calculations, considering a lighting installation of 5 light points located 1 m inside the road margins, as depicted in Figure 5.

An Everfine Corporation's Model CX-2B Luminance Meter, shown in Figure 6, was used to collect the data required for the calibration process. The technical specifications of this charge-coupled device (CCD) are presented in Table 2. The measurements were taken by positioning the luminance meter at three different observation points: the lane separation line and the middle of each lane. These positions were selected to increase the number of experimental data to feed the calibration process and improve the accuracy of the results. For all the measurements the meter was positioned at 60 m from the calculation area and at a height of 1.5 m from the ground, as recommended by EN 13201-3:2015. Thus, the observation angle is always in the range of interest. Table 3 shows the coordinates of the observer positions.

Table 2: Technical specifications of CCD luminance meter.

CX-2B Imaging Luminance Meter	
Resolution	1360 x 1024
Focal length	56 mm
Luminance accuracy	± 5
CCD working temperature	5°C
Field of view	9.1° (horizontal) x 6.7° (vertical)

CCD luminance meters acquire perspective images in which each pixel corresponds to a luminance value. Figure 7 shows the images taken from the three points of view. To reduce the measurement uncertainty, the CCD camera was calibrated through the algorithm developed by Zhang [62] and Bouguet [63] with a suite of 27 chessboard pictures. The average reprojection error was decreased to 0.502 px with this process. The correct selection of the calculation

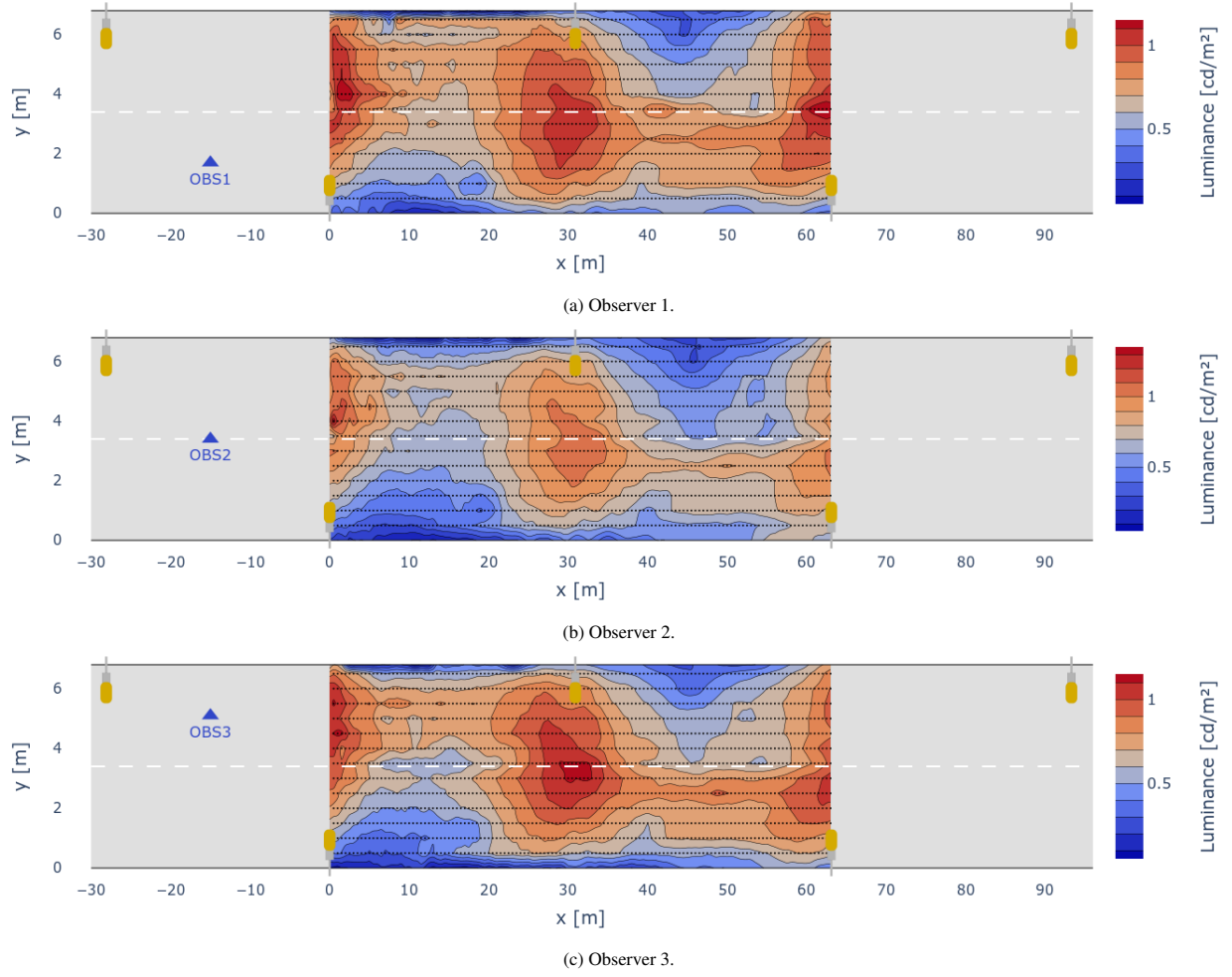


Figure 5: Distribution of the luminaires around the calculation area, luminance map represented from the experimental luminance measurements carried out at the points marked with a black dot and position on the y-axis of the observer.

area in the pictures was made using the PnP (Perspective-n-Point) method based on the known positions of several control points. To solve the PnP problem, the Levenberg-Marquardt optimization [64, 65] was applied in an iterative process. Therefore, the distortion parameters and the intrinsic coefficients of the calibrated CCD sensor were taken into account to establish the correlation between the 2D and 3D points and transform the perspective to a plane.

As part of the processing, the images were filtered with a median filter to remove noise and possible random variations in intensity or contrast. Each pixel value was recalculated and replaced with the median of the neighbourhood values in a 3x3 kernel. Finally, the luminance was obtained in a set of points spaced 0.5 m in the x- and y-axes by using the processed images. Figure 5 represents the distribution of this point matrix for each observer and the map generated from its corresponding luminance values.

The experimental system described in this section was modelled using Radiance, and a first model calibration process was applied in which the maintenance factors of the luminaires and the average luminance coefficient of the road pavement were determined following the procedure indicated in previous works [66, 55]. Using the same procedure, it was determined that the asphalt type R2 more accurately represents the reflection properties of the measured pavement, despite the fact that class R3 is typically used in lighting simulations and road surfaces of this nature. This suggests that the pavement is more diffuse and less specular than expected.

Table 3: Positioning coordinates of the luminance meter at the data acquisition.

	x	y	z
Observer 1	-60	1.7	1.5
Observer 2	-60	3.4	1.5
Observer 3	-60	5.1	1.5



Figure 6: Measurement device used to collect luminance data.

4. Results and Discussion

This section contains the results of the application of the detailed methodology to the case study presented above. The three methods of approximation of the r-tables analysed are compared here, considering the experimental measurements collected from the three observer positions detailed in Table 3. The comparison is made according to three criteria: some data about the process convergence such as the convergence time or the number of iterations until an optimal result is obtained, the shape of the r-table and the error made in the luminance calculation. All experiments were run on the same computer (featuring a Core i7-6700k CPU @ 4.00 GHz, 16 GB of RAM and Ubuntu 16.04 installed).

4.1. Optimization Variables and Convergence

Table 4 includes the values assigned to the calibration variables at the beginning of the process as well as the optimal values finally reached with the Hooke-Jeeves algorithm and using the ellipsoid approximation method. The results for the other approximation methods considered in the analysis are also detailed in Tables 5 and 6. Overall, the comparison between the design values and the results of the calibrated variables indicates that the algorithm focuses on adapting the reduced luminance coefficients of the r-table areas that worst represent the reflection properties of the pavement, keeping the calibration parameters with the minor influence practically unchanged.

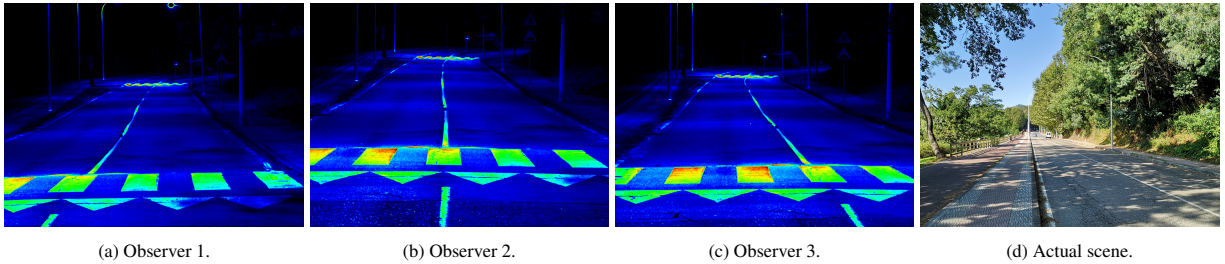


Figure 7: The luminance meter captures three points of view and picture of the road lighting installation.

Table 4: Values of the calibration variables at the beginning and end of the r-table adaptation process using the ellipsoid-based approximation method.

Variable	Ellipsoid 1		Ellipsoid 2		Ellipsoid 3	
	Initial Value	Optimal Value	Initial Value	Optimal Value	Initial Value	Optimal Value
a'	-0.239	-0.284	0.015	0.128	0.005	0.005
b'	0.021	-0.006	0.417	0.630	0.767	0.751
g	0.017	-0.034	0.245	-0.020	0.046	0.073
p	7.368	60.125	-37.764	-64.198	-0.003	0.139
s	98.957	96.978	119.469	183.983	47.494	56.993

Table 5: Values of the calibration variables at the beginning and end of the r-table adaptation process using the column-based approximation method.

j		$a_j^{(1)}$	$b_j^{(1)}$	$c_j^{(1)}$	$d_j^{(1)}$	$b_j^{(2)}$	$c_j^{(2)}$	r_j
1	Initial Value	-0.89	1059.68	-1975.36	2573.44	-931.42	-216.28	390.00
	Optimal Value	-0.76	1282.22	-1975.36	2161.69	-1089.76	-222.77	421.20
2	Initial Value	-1.24	3219.47	-4150.48	4591.42	-5066.95	3039.11	
	Optimal Value	-0.93	3670.19	-4150.48	4545.50	-6283.02	2309.73	
3	Initial Value	-1.72	5589.81	-6896.82	6656.38	-8079.71	4601.18	
	Optimal Value	-1.14	6316.49	-6620.95	6922.64	-10018.84	3496.89	
4	Initial Value	-2.41	23766.38	-23056.73	17961.39	59951.88	-54952.79	
	Optimal Value	-1.78	23766.38	-23056.73	24966.33	49160.56	-64844.28	
5	Initial Value	-2.15	-7449.94	367.41	3633.15	14145.41	-18228.75	
	Optimal Value	-1.98	-8194.94	374.76	3233.50	14145.41	-18228.75	
6	Initial Value	-2.60	-11451.96	-548.99	7915.20	127230.25	-117354.49	
	Optimal Value	-2.29	-12826.19	-653.29	8231.81	127230.25	-117354.49	
7	Initial Value	-2.58	-1301.61	-9941.32	17769.61	20226.45	-25056.98	
	Optimal Value	-2.12	-976.20	-9444.25	17414.25	20226.45	-25056.98	
8	Initial Value	-2.51	12417.77	-21734.60	31287.40	-80918.65	62434.20	
	Optimal Value	-2.41	11051.81	-23473.37	29723.02	-80918.65	62434.20	
9	Initial Value	-2.36	22863.84	-28938.05	37129.22	-75279.23	57324.18	
	Optimal Value	-2.40	20806.10	-31253.09	33787.61	-75279.23	57324.18	
10	Initial Value	-2.39	33903.74	-38646.02	45637.49	-71928.80	53372.06	
	Optimal Value	-2.27	35937.95	-41737.70	43355.62	-71928.80	53372.06	
11	Initial Value	-2.15	18927.24	-23622.07	26112.69	2571.81	-10095.14	
	Optimal Value	-1.87	19684.34	-24566.96	28201.70	2571.81	-10095.14	
12	Initial Value	-2.28	26471.05	-31096.30	31257.54	3089.92	-12037.36	
	Optimal Value	-2.14	22500.39	-32340.15	37821.63	3089.92	-12037.36	
13	Initial Value	-2.34	24734.53	-29989.99	26897.95	3379.50	-13115.77	
	Optimal Value	-1.96	18550.87	-29390.19	40077.95	3379.50	-13115.77	
14	Initial Value	-2.61	45546.41	-50215.98	43201.14	5006.21	-19123.79	
	Optimal Value	-2.32	42358.16	-54233.26	56161.44	5006.21	-19123.79	
15	Initial Value	-2.52	32943.69	-38195.89	29508.57	4425.08	-16985.68	
	Optimal Value	-2.32	29978.75	-41251.57	35115.19	4425.08	-16985.68	
16	Initial Value	-2.49	36945.43	-40711.43	31659.10	4201.73	-16161.77	
	Optimal Value	-2.29	30295.23	-40711.43	34508.47	4201.73	-16161.77	
17	Initial Value	-2.60	57517.05	-58515.62	45836.09	4944.88	-18898.50	
	Optimal Value	-2.13	57517.05	-58515.62	49961.35	4944.88	-18898.50	
18	Initial Value	-2.35	28777.48	-32054.00	22489.94	3437.30	-13330.60	
	Optimal Value	-2.21	23597.53	-32054.00	25413.61	3437.30	-13330.60	
19	Initial Value	-2.32	28744.48	-31654.56	22058.18	3322.32	-12903.08	
	Optimal Value	-2.09	28744.48	-31654.56	18087.70	3322.32	-12903.08	
20	Initial Value	-2.23	24627.38	-27392.70	19210.33	2878.81	-11248.99	
	Optimal Value	-1.83	29060.30	-27392.70	15560.37	2878.81	-11248.99	

Table 6: Values of the calibration variables at the beginning and end of the r-table adaptation process using the factor-based approximation method.

Variable	Initial Value	Optimal Value	Variable	Initial Value	Optimal Value
a_1	1.000	1.030	b_1	1.000	1.370
a_2	0.800	0.968	b_2	1.000	1.360
a_3	0.667	0.740	b_3	1.000	1.500
a_4	0.571	0.571	b_4	1.000	1.390
a_5	0.500	0.470	b_5	1.000	1.140
a_6	0.444	0.409	b_6	1.000	1.080
a_7	0.400	0.344	b_7	1.000	0.970
a_8	0.364	0.291	b_8	1.000	1.030
a_9	0.333	0.260	b_9	1.000	0.950
a_{10}	0.286	0.226	b_{10}	1.000	1.010
a_{11}	0.250	0.213	b_{11}	1.000	1.040
a_{12}	0.222	0.236	b_{12}	1.000	0.880
a_{13}	0.200	0.194	b_{13}	1.000	0.650
a_{14}	0.182	0.273	b_{14}	1.000	0.500
a_{15}	0.167	0.250	b_{15}	1.000	0.500
a_{16}	0.154	0.229	b_{16}	1.000	0.500
a_{17}	0.143	0.214	b_{17}	1.000	0.500
a_{18}	0.133	0.132	b_{18}	1.000	0.500
a_{19}	0.125	0.063	b_{19}	1.000	0.590
a_{20}	0.118	0.059	b_{20}	1.000	0.500
a_{21}	0.111	0.056			
a_{22}	0.105	0.053			
a_{23}	0.100	0.050			
a_{24}	0.095	0.049			
a_{25}	0.091	0.046			
a_{26}	0.087	0.044			
a_{27}	0.083	0.083			
a_{28}	0.080	0.080			
a_{29}	0.077	0.077			

From the point of view of convergence, as the Table 7 shows, the ellipsoid-based method offers good results, although the convergence time and the number of iterations are higher than expected since they exceed the values obtained with the factor-based method. However, when the optimization process is analysed in more detail, the results are more favourable for the ellipsoid-based method. Figure 8 reflects the error achieved by the cost function in each iteration for the methods. The charts show that the ellipsoid-based method has a lower error than the factor-based method before 1200 iterations but continues the optimization for a longer time because the algorithm finds minima in the global and local searches it performs, with more potential for improvement. Furthermore, the column-based method also needs more iterations to reduce the error by the same amount, even if it reaches a slightly lower final value at the cost of greatly increasing the number of iterations. Thus, the ellipsoid-based method is the first to reach an RMSE of 0.88 cd/m², with a good trade-off between error reduction and computational cost.

Table 7: Number of calibration variables, number of iterations and time needed to find the optimal results, RMSE achieved and percentage reduction in RMSE in luminance calculation and RMSE reached in the analysis of the shape.

Method	No. of calibration var.	No. of iterations	Time	Luminance RMSE [cd/m ²]	Luminance RMSE reduction [%]	Shape RMSE [sr ⁻¹]
Standard R2				0.120		0.196
Ellipsoid-based	15	6171	1h 25 min	0.088	26.48	0.567
Factor-based	49	2828	36 min	0.089	25.65	1.088
Column-based	121	10967	2 h 56 min	0.085	28.65	1.858

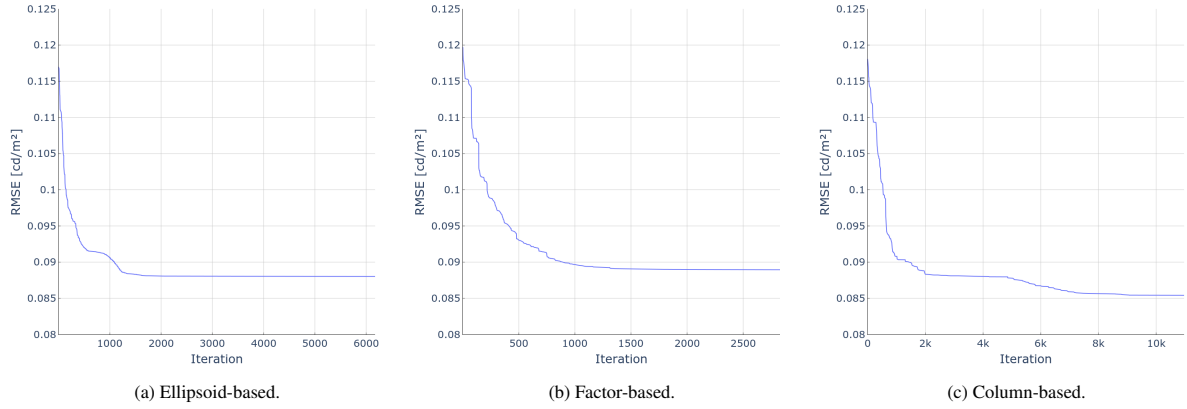


Figure 8: Cost function values for each iteration while the algorithm searches for an optimal result. The iteration time is dominated by the radiance calculations common to all methods, and thus, there is an almost identical ratio between the number of iterations and computing time.

4.2. Shape Preservation

It is also interesting to analyse the changes after calibration by observing the shape of the r-table. Figure 9 graphically details the r-tables achieved with each method in addition to the standard table on which the adaptations are based. Regarding the other methods, it is observed that the ellipsoid-based method provides a smoother surface with a similar shape. This analysis is confirmed by comparing the indicators used to verify the shape of the r-tables. Table 7 contains the RMSE calculated for each approximation method considering the surface resulting from the calibration and the smoothed surface using the TPS method, as indicated in the methodology section. A lower RMSE close to the standard R2 table is achieved using the ellipsoid-based method, while the column-based method provides a much higher RMSE, showing that the proposed method produces much more coherent results in a physical sense. The figure also shows the areas of the table in which the greatest changes have occurred. In general, the reduced luminance values for low deviation angles have been especially increased.

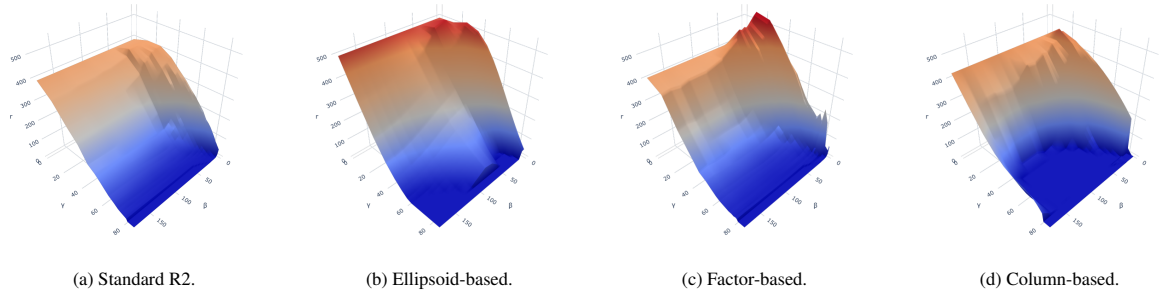


Figure 9: Three-dimensional depiction of r-table for surface type R2 and for the adapted r-tables using the described approximation methods.

Another form of representation of the results is the pavement reflection indicatrix. The horizontal lines in Figure 10 refer to increasing angles of incidence from top to bottom, while the vertical lines represent the angle of deviation in an increasing direction from right to left. Thus, the area on the right depicts smaller angles of deviation and therefore describes the behaviour of the pavement in the specular direction. The shape of this part of the indicatrix is not significantly altered, so the specularity of the calibrated asphalt can be considered similar to that of the original R2 table. However, large variations are apparent for small incident angles, where the reflection is greater than that represented in the standard table. Through this representation, it is detected that the indicatrix generated with the ellipsoid method is physically more realistic than the others since it modifies the curve in a more uniform way,

avoiding small deformations such as those that occur in the specular area for small incidence angles using the other two methods.

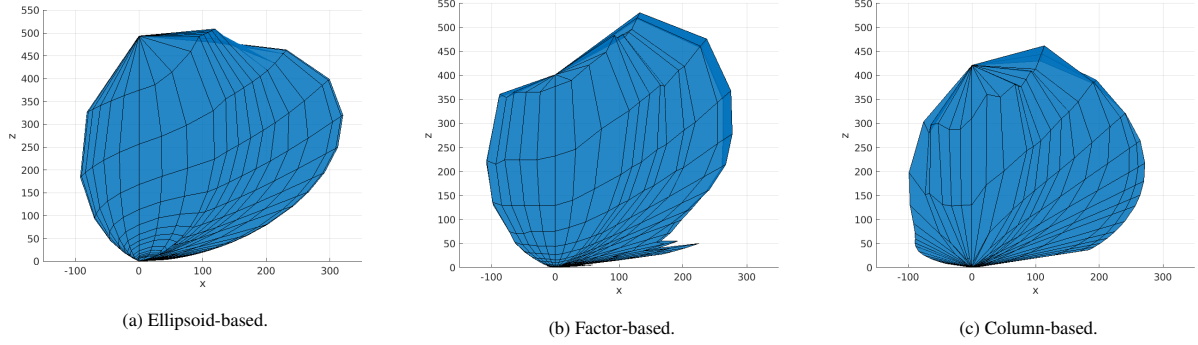


Figure 10: Spherical coordinate representation of the reflection indicatrices of the pavement corresponding to the r-tables generated through the presented approximation methods. The x -axis is $10^4 r \sin(\gamma) \cos(\beta)$, and the z -axis is $10^4 r \cos(\gamma)$.

4.3. Luminance Error

Since the final target of the calibration procedure is a more reliable prediction for the luminance values of a road, it is interesting to analyse to what extent the approximation methods reduce the error. Table 7 lists the RMSE calculated in relation to the luminance collected experimentally and presents the percentage of error reduction achieved with each method compared to that with the use of a standard R2 table. In general, all three methods yield considerable improvements in the calculation of luminance. The ellipsoid-based method stands out, reducing the error to 0.088 cd/m^2 , which is a lower final value than the factor-based method, where the error is decreased to 0.089 cd/m^2 , while producing a much smoother shape. The column-based method reaches a final error of 0.085 cd/m^2 but at the expense of a longer computational time, with an error reduction very similar to those of the other two methods. Overall, the three methods produce similar results in terms of final error reduction, with the ellipsoid-base method generating a much more generalizable approximation.

Figure 11 shows that the complete calibration process can improve the results of the simulations since all the calibration methods of the r-tables decrease the difference between the data predicted by the simulation and the experimental measurements regarding the initial simulation. The luminance values along six longitudinal sections of the road visualized by observer 2 are plotted in the graph. Overall, there are no major differences between the methods tested, as similar luminance distributions are provided by all of them. This indicates that the methods are suitable for their purpose. However, point by point, the luminance values are different because no identical r-tables are achieved.

The maps with the luminance distribution generated by the lighting simulation tool are shown in Figure 12. The r-tables obtained by applying the calibration methodology and the different approximation methods analysed were used for this purpose. A comparison of the maps with the luminance calculated with the standard table, also included in this picture, shows how the methods try to adapt the way in which viewer 2 perceives the scene to be more similar to the experimental measurements shown in Figure 5 for the same viewer. The results are noticeable, for example, in the area under the luminaries, where the luminance values are increased.

4.4. Overall Comparison of Methods

A summary with the comparison criteria discussed above is shown in Table 7. In general terms, the ellipsoid-based method stands out for maintaining a smoother shape of the r-table than the other methods. At the same time, it is a method with a good balance between the computational cost and the reduction of the error in the calculation of the luminance, since it allows to reduce the error to an acceptable value in a short time. Another advantage of the ellipsoid-based method lies in the reduced number of variables, especially in comparison with the column-based method, which makes the calibration process more affordable.

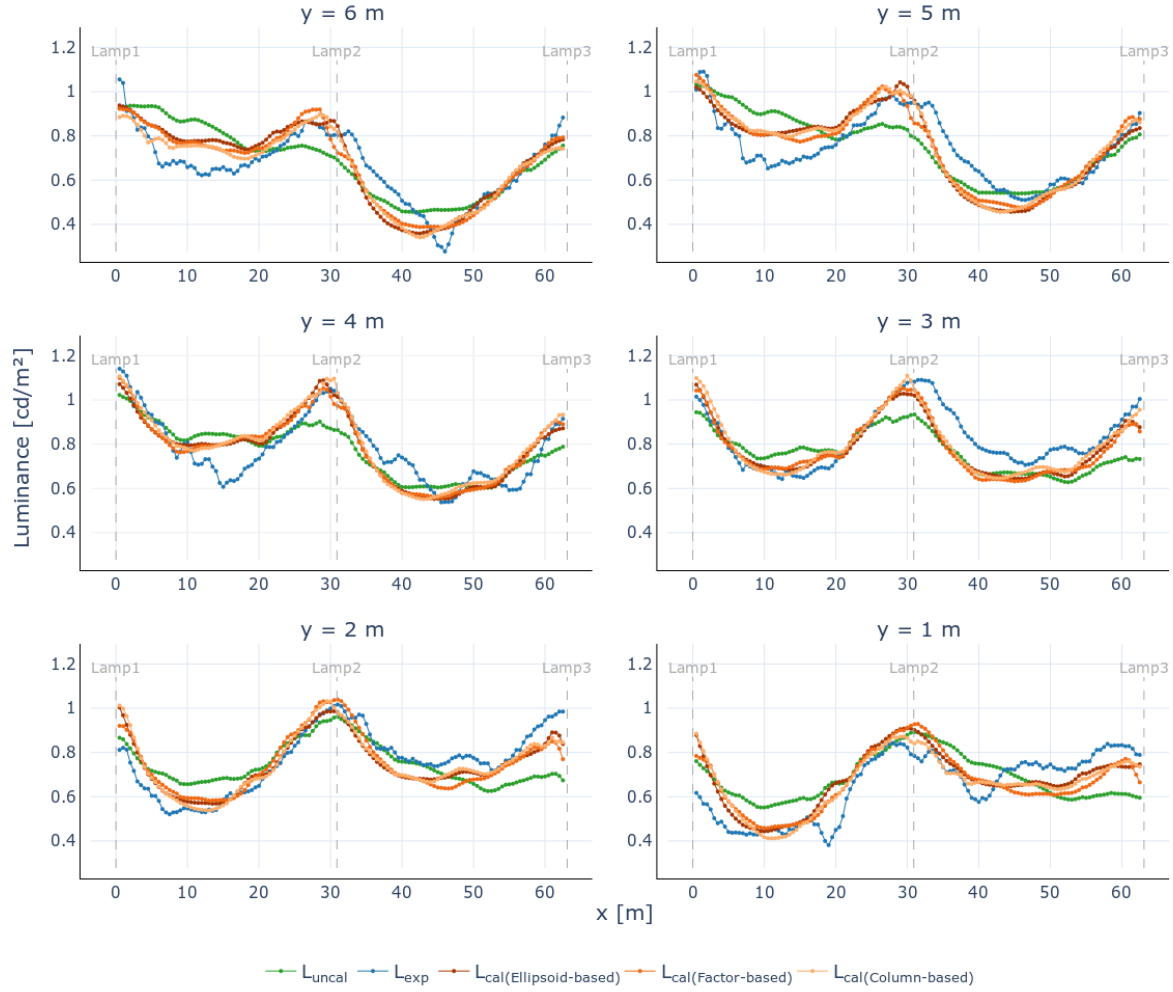


Figure 11: Luminance values for observer 2 at a set of points on longitudinal road sections. L_{uncal} : simulated luminance considering the standard R2 pavement class; L_{exp} : measured road luminance; $L_{cal(ellipsoid-based)}$: simulated luminance after the r-table adaptation process using the ellipsoid-based approximation method; $L_{cal(factor-based)}$: simulated luminance after the r-table adaptation process using the factor-based approximation method; $L_{cal(column-based)}$: simulated luminance after the r-table adaptation process using the column-based approximation method.

5. Conclusions

In this research, an approximation method was developed to adapt the reflection properties of asphalts to updated r-tables. The method was designed to be implemented in a lighting model calibration tool that combines Radiance and GenOpt as simulation and optimization engines. This proposed model was validated by studying a real scenario in which the effect of applying this method was compared with those of two other state-of-the-art approximation methods. The mathematical model is based on three ellipsoids that, in spherical coordinates, represent the indicatrix of the reflections of the pavement. First, the model was fitted according to the standard r-tables recommended by the CIE, and then an adapted r-table was reconstructed from the optimized variables. The process was supplemented with experimental luminance data measured from the road.

The results after the application of the ellipsoid-based method show a good trade-off in terms of computational time and error reduction, reaching the final RMSE value of 0.88 cd/m^2 before the other two methods. In addition, while still reducing the error in the luminance calculation by 26.5%, the shape of the reflection indicatrix is more uniformly preserved, with an RMSE of 0.57 sr^{-1} with respect to interpolated values, which is much closer to the original standard

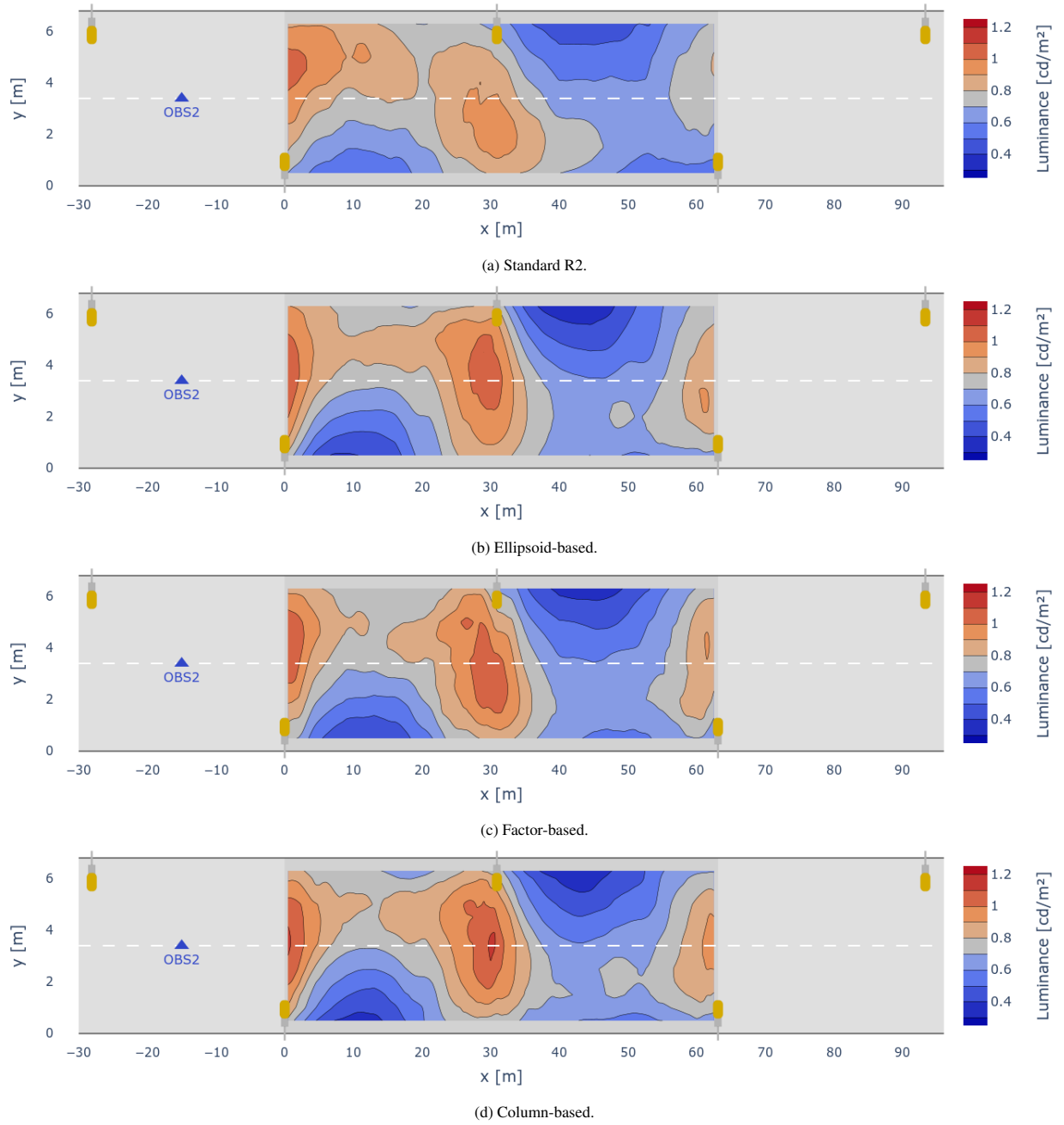


Figure 12: Road luminance distribution calculated using simulation techniques and considering the R2 type of asphalt and the modifications performed with the analysed r-table adaptation methods.

R2 results than the results of the other methods. This generation of a smoother surface helps overcome the potential over-adjustment of the method to small defects and occasional potholes that may exist in a specific road section caused by excess traffic, ageing or rain erosion. These unrepresentative data about the general condition of the asphalt can lead to deformation and errors in the shape of the optimized indicatrix and are minimized in the ellipsoid-based method.

The outcomes of this research show that the complete model calibration methodology, including this new ap-

proximation method, is suitable for obtaining regularly updated data on pavement reflection properties. This can be beneficial not only in the optimized design of new lighting installations but also in the improvement of existing installations so that the luminous flow of the luminaires is adapted by means of control devices according to the condition of the road surface.

It is planned to validate the method in more specular pavements in the future, as well as to compare the method results against the properties measured in laboratories from pavement samples.

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Conflicts of Interest

The authors declare no conflicts of interest.

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