Applying micro genetic algorithm to numerical model for luminous intensity distribution of planar prism LED luminaire

Yu-Sin Kim, An-Seop Choi, Jae-Weon Jeong

1. Introduction

LED has the advantages of lower power consumption, energy saving, high efficiency, long life, environmentally friendly, and a small volume, and as a result it has been getting consideration as a next-generation light source. However, several technological problems have to be resolved for the LED to be used as a general purpose light source. For instance, LED luminaires have a property of high luminance due to a narrow beam angle and a small volume compared to general light sources. There are several differences between existing luminaires and the intensity distribution of an LED luminaire. An optical engineer has the challenging problem of designing a spatially extended and non-uniform light source. It is difficult for LED luminaires to obtain the target luminous intensity distribution required in a space, because the design process requires much trial and error. And the process also requires much design time. In this study, an optimization algorithm of a numerical model for luminous intensity distribution of planar LED luminaires was developed to find optimized prism angles. This algorithm would used the micro genetic algorithm technique which is the improved form of genetic algorithms. Also, this algorithm is capable of deriving the optimized angle of a prism to achieve the target luminous intensity distribution of planar prism LED luminaires. Therefore, the purpose of this study is to introduce a numerical model of a planar prism LED luminaire and to develop an optimization algorithm that is able to find an optimum luminaire optical design solution using the micro genetic algorithm.

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1. Introduction

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Most planar LED luminaires use the “Lambertian” luminous intensity distribution curve. This differs from the “Bat-wing” luminous intensity distribution curve (spreading sideward) found in current generally-used fluorescent luminaires. Consequently, the control of the “Lambertian” distribution curve is necessary to apply a planar LED luminaire to various spaces or to a non-uniform lighting environment [1]. Control of the “Lambertian” distribution curve of a planar LED luminaire is necessary to get an optimum luminous environment by installing optical parts, such as a lens and prism (Fig. 1). To do so, an optimization of the luminous intensity distribution is required especially for planar prism LED luminaire.

The optical design of luminaires has been performed using a combination of ray-tracing techniques and trial-and-error experimentation to obtain a target luminous intensity distribution. The advent of faster computer capabilities allows luminaire optical designers to quickly perform the optical design process. However, time and a great deal of experience are still required. The numbers of trials and errors can be significantly reduced by developing optimization algorithms.

Most previous studies about optical design in the lighting field focuses on the control of luminous intensity distributions of LED luminaires. Recent studies have focused on the secondary optical design of lens or reflector of LED sources [1–10], and most researches focused on the optical design of a prism for backlight [11–13]. In the studies on the optical design of luminaires, many studies on reflectors and light source have been conducted but the ones on prisms and lenses are insufficient in the lighting field at present.

This study develops a numerical model of planar LED luminaires for controlling the luminous intensity distribution. This
2.1. Overview of the numerical model

The numerical model for luminous intensity distribution by tracing the behavior of photons which pass through a prism, emitted from a light source [14]. The luminous intensity distribution of planar LED luminaires is totally dependent on the angles of prism. With a variety of prism angles, the luminous intensity distribution can be varied to satisfy the purpose of such luminaires. However, the determination of the prism angle is not an easy task.

Since 1960, various optimization techniques such as evolution strategies, simulated evolution, genetic algorithms, and simulated annealing were developed to solve the issue of optimization. The genetic algorithm was applied in a wide range of studies for solving optimization problems.

Previous studies in lighting research fields to optimize reflector designs of non-imaging optics introduced the use of genetic algorithm [15]. Automated mirror design (AMD) using the genetic algorithm was developed to design an optimum reflector that provides a desired luminous intensity distribution [16]. In addition to these studies in the optical design, there are studies on the optimization algorithm for the dome pendent prismatic luminaire [17], and a study on the LED lens design using the genetic algorithm [18]. In similar lighting research fields, the optimization for luminous efficacy of a lamp was studied [2].

The study of optimized planar prism design for planar prism LED luminaire, however, has not been researched in the lighting field. So this study aims to develop an optimization algorithm of a numerical model for the luminous intensity distribution of planar LED luminaire that is to find optimized prism angle. This optimization algorithm used the micro genetic algorithm technique which improved forms of the genetic algorithm, which have been applied in a number of fields. This algorithm can derive the optimized angle of a prism to get the target luminous intensity distribution of planar prism LED luminaires. Photopia and LightTools are the commercial optimization optical design simulation software widely used in the lighting field. To optimize optical design simulation by using those softwares, basically, the optical design is positively necessary to get luminous intensity distribution which is similar to target luminous intensity distribution of luminaires. However, the optimization algorithms of this study can derive the optimized angle of prism which can implement the target luminous intensity distribution from optimization simulation without a preliminary optical design.

2. Development of the numerical model for luminous intensity distribution

2.1. Overview of the numerical model

The numerical model for luminous intensity distribution is comprised of four phases [14]:

- First, a numerical model used the luminous intensity of each vertical angle in the photometric data of an LED source applied to planar LED luminaires as the energy of photons for each vertical angle. In this case, the luminous intensity of the photometric data was assumed to be the energy of the photons.
- Second, the numerical model set up the initial position of LED sources and direction vectors of photons for the coordinates of a planar LED luminaire.
- Third, the numerical model calculated the position and direction vector according to the optical behavior of the photons passing through the prism using the ray-tracing technique and the law of refraction.
- Finally, the numerical model produced a new luminous intensity distribution curve of a planar prism LED luminaire using the sum of photon energies in each vertical angle, which indicated the final position of photons.

2.2. Results of the numerical model for luminous intensity distribution

This study used a practical type of planar LED luminaires to conduct the simulation of an optical design of planar prism LED luminaires, using the photometric data of an LED source. The shape of the prism is an isosceles triangle with the vertex of the triangle downwards and the width of the prism is 5 mm. The index of reflection of the reflector of the luminaire was set to 90% and the index of refraction of the prism was set to 1.491, respectively. These are the general properties of ordinary acrylic materials. In order to verify the accuracy of the simulation of the algorithm for the numerical model for luminous intensity distribution developed in the study, the results of the simulation were compared to a simulation using Photopia 2.0 which is the commercial optical design simulation software widely used in the lighting field. The simulation was performed under the same conditions. Fig. 3 and Table 1 shows the characteristics of the optical parts used in the simulation of this study.

This study simulated changes in the angle of the prism (1°, 5°, 10°, 20°, 30°, 40°, 45°, and 60°) to compare the change of the luminous intensity curves of a planar LED luminaire according to the angles of the prism. Fig. 4 shows a comparison between the simulation results using the numerical model for luminous intensity distribution and the simulation results using Photopia 2.0. Two simulation results show almost same shapes. There is a little difference according to the angles of the prism, which is because Photopia 2.0 cannot control the
optical properties such as the number of internal reflection, the
diffuse ratio, and the transmittance. And, in Photopia 2.0, the optical
properties of the prism used the measured characteristics of the
medium. In contrast, in this study, the optical properties of the prism
can be used as input data. Overall, the accuracy of the developed
numerical model was verified.

Thus, the luminous intensity distribution curve of a planar prism
LED luminaire can be forecasted through the optical design algorithm
developed in this study. In addition, more various luminous intensity
distribution controls can be produced by applying various angles and
assigning unit prism angle zones. On the basis of this numerical
model, the next step is to develop an optimization algorithm for
luminous intensity distribution of planar prism LED luminaires that
can derive the optimized angle of the unit prism angle zones to obtain
the target luminous intensity distribution, using an optimization
technique such as the genetic algorithm.

3. Optimization algorithm process

3.1. Micro genetic algorithm

Genetic algorithm is a technique for randomizing search and
optimizing based on the mechanics of natural selection and
genetics. Genetic algorithm uses populations of solutions to find
optimization points. It is difficult to find optimization points with
mathematical optimization methods that use gradient vector and
Hessian, if there are many local optima around the optimization
points and a steep gradient around the optimization points
[20]. Genetic algorithm does not use gradient vector and Hessian,
but uses object function values during their search.

Genetic algorithm starts with a set of possible solutions,
randomly generated, called a population. Each individual solution,
in the population, is known as a chromosome or an individual.
Each chromosome may be represented as a binary string or an
array of genes, whichever contain a part of the solution. The

Table 1
Characteristics of optical parts.

<table>
<thead>
<tr>
<th>Optical parts</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material of the reflector</td>
<td>White paint</td>
</tr>
<tr>
<td>Index of the reflector</td>
<td>90%</td>
</tr>
<tr>
<td>Material of the refractor</td>
<td>Standard acrylic</td>
</tr>
<tr>
<td>Index of the refractor</td>
<td>1.491</td>
</tr>
<tr>
<td>LED source</td>
<td>2 W, 31.1 lm</td>
</tr>
<tr>
<td>Width of the prism</td>
<td>5 mm</td>
</tr>
</tbody>
</table>
reason for using the binary string involves easy-to-use prior genetic operators like crossover and mutation [21]. The values of genes are called alleles. The length of each chromosome in a population should be the same. A fitness function is provided to assign the fitness value for each individual. This function is based on how close an individual is to the optimal solution – the higher the fitness value, the close is the solution to the optimal solution.

As population size increases, genetic algorithm finds better solutions. However, larger population sizes require more computational time to find the optimal solution. To avoid these problems, Goldberg [22] proposed the serial genetic algorithm which uses a small population size. Then, based on the serial genetic algorithm, Krishnakumar proposed micro genetic algorithm in 1989 [23]. Micro genetic algorithm uses a relatively smaller population size than the serial genetic algorithm, resulting in less computational time. Moreover, micro genetic algorithm uses elitism and convergence checking with re-initialization to obtain optimal solutions.

In this study, we used the micro genetic algorithm and a population size of 20 individuals. Each individual is preserved with elite genes to prevent extinction in the next generation. An elite gene will be preserved when the elite gene from the next generation has a poor fitness value compared to the previous elite gene. Moreover, the crossover rate is set to 1.0. Therefore, all populations must perform a crossover operation at every generation. There is no need for a

Fig. 4. Results of simulation by the angle of the prism. (a) Angle of prism: 1°; (b) Angle of prism: 5°; (c) Angle of prism: 10°; (d) Angle of prism: 20°; (e) Angle of prism: 30°; (f) Angle of prism: 40°; (g) Angle of prism: 45° and (h) Angle of prism: 60°.
3.2. Design parameters for optimization

To optimize a numerical model for luminous intensity distribution, this study uses the prism angles of the planar prism LED luminaires as the design parameters. The fixed prism angles of the planar prism LED luminaire result in a lack of various luminous intensity distributions. For various luminous intensity distributions, in this study, we set up the unit prism angle zones of the planar prism LED luminaire. Fig. 5 shows divisions of the unit prism angle zones. The number of the unit prism angle zones is determined by the input data. As a result, the numerical model for luminous intensity distribution of planar prism LED luminaire with various unit prism angle zones parameters can be much more varied than the fixed prism angle.

3.3. The binary string length of design parameters

As the chromosomal composition is a group of genes in biology, the design parameters named as chromosome, have to be converted into binary strings. Fig. 6 shows an example of design parameters converted into binary strings. The initial binary strings are generated by random number generations.

The ranges of the design parameter prism angles are assumed to be varied from 0° to 60°, and the type of values of each angle is an integer number. If the number and range of design parameters are determined, the length of each binary string can be calculated. This method is generally used to optimize a mathematical function, and the length of binary strings is calculated as follows:

\[ F = f(x) \quad (a \leq x \leq b) \]  \( (1) \)

(1) Choose the degree of the required precision \( (K) \)
(2) Calculation \( (b - a) \)
(3) The number of divisions: multiply of \((b - a)\) with \(10^6\)
(4) Determine \( N \), where \(2^{N-1} \leq \text{the number of divisions} \leq 2^N\)

The degree of required spacing \( (K) \) means the number of decimal points that are to be considered in this optimization. \( (b - a) \) is the prism angle range, and \( N \) is the binary string length. An actual value \( (X) \) of the design parameter converted into a binary number can be calculated as follows:

\[ X = a + \text{decimal} (011 \cdots 011x \times (b - a)) / (2^N - 1) \]  \( (2) \)

As indicated in the above, the binary string length of each design parameter is calculated, and the binary string length of an individual is summed from all of the binary string lengths of each design parameter. Therefore, determination of the binary string length for optimization of this study is as follows:

1. The required precision \( K = 0 \); because the precision is \( 1^\circ \) and integer number
2. \( (b - a) = 60 \); because the angle range is from \( 0^\circ \) to \( 60^\circ \)
3. The number division = 60; because \((b - a) \times 10^6 = 60 \times 10^6\)
4. Determine \( N = 6 \); because \( 2^5 = 32 \leq 60 \leq 64 = 2^6 \)

The number of bits for each design parameter used in this study is 6. And all numbers of bits for an individual are determined by the number of unit prism angle zones. Therefore, multi-crossover operations were used to treat long binary strings efficiently.

3.4. Fitness function

The probability of survival of any individual is determined by its fitness. Through evolution the fitter individuals overtake the less fit ones. Fitness functions are used to evaluate the goodness of a chromosome, and they can be either minimized or maximized, depending on the goal of optimization.

In this study, a fitness function is used to optimize the luminous intensity distribution. Most fitness functions are forms composed of design variables. However, the result of the numerical model in this study is not a definite numerical constant, but rather a luminous intensity distribution curve. In fact, a special fitness function is applied to this optimization algorithm.

The fitness function of the micro genetic algorithm used in this study is the luminous intensity value differences of each vertical angle between the target luminous intensity distributions and the results of the optimization algorithm of the numerical model. In this study, the ratio of each vertical angle means the ratio of the value of each vertical angle of the luminous intensity distribution and the summation of the luminous intensity distribution. The result \( F(X) \) is the smallest in this algorithm means this individual generation is the most ‘fitness’. Thus, the fitness function of this study is maximized as follows:

\[ \text{Maximize} \quad \tilde{F}(X) = C_{\text{max}} - F(X) \]

\[ F(X) = |C_w / C_{\text{w.sum}} - C_s / C_{\text{s.sum}}| \]

where,

\( F(X) \) is the fitness function.
\( C_w \) is the value of each vertical angle of the target luminous intensity distribution.
\( C_{\text{w.sum}} \) is the summation of the value of each vertical angle of the target luminous intensity distribution.
\( C_s \) is the value of each vertical angle of the simulation result.
\( C_{\text{s.sum}} \) is the summation of the value of each vertical angle of the simulation result.
\( C_{\text{max}} \) is constant that \( \tilde{F}(X) \) does not become the negative number.

At this time, in this numerical model, the luminous intensity was assumed to be the energy of the photons, and the algorithm calculated the final position of the photons passing through the prism using the ray-tracing technique. Then, the numerical model predicted a new luminous intensity distribution curve using the sum of photon energies in each vertical angle. Therefore, the fitness function of this optimization algorithm used a summation of the luminous intensity values as a denominator.
4. Optimization algorithm of the numerical model

4.1. Results of the optimization simulation by changing the number of unit prism angle zones

The results of optimizing the numerical model for luminous intensity distribution were compared to the number of unit prism angle zones, using random luminous intensity values. Table 2 lists the distribution. After setting the width of the prism to 1mm and changing the number of unit prism angle zones to 1, 2, 3, 5, 7 and 10, an optimization simulation was performed. The simulation conditions were the same as those (Table 1) of the numerical model for luminous intensity distributions mentioned in the previous section.

The optimization simulation produced error rates (luminous intensity value differences) whose differences were minor, depending on the number of unit prism angle zones (Fig. 7). They ranged from 2.48 (1 & 2 units) to 6.88% (3 units) with stable convergence curve. The X axis represents the generation number while the Y axis represents the value needed to maximize the fitness function. $C_{\text{max}}$ was set to 10, meaning that the value needed to maximize and number of errors decrease as they converge into 10. The convergence curve of the “$10 - F(x)$” is illustrated with respect to the generation size in Fig. 7. After a certain number of generations, the value of “$10 - F(x)$” has converged.

Error rates were the lowest when the number of unit prism angle zones was 1 and 2, and stable convergence curve was observed at the lower number of generations. When the number of unit prism angle zones was 3, error rates were the highest with

Table 2

<table>
<thead>
<tr>
<th>Vertical angle</th>
<th>0–10°</th>
<th>10–20°</th>
<th>20–30°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Luminous intensity data</td>
<td>32.58</td>
<td>34.24</td>
<td>34.91</td>
</tr>
<tr>
<td>Vertical angle</td>
<td>30–40°</td>
<td>40–50°</td>
<td>50–60°</td>
</tr>
<tr>
<td>Luminous intensity data</td>
<td>30.55</td>
<td>24.33</td>
<td>5.96</td>
</tr>
<tr>
<td>Vertical angle</td>
<td>60–70°</td>
<td>70–80°</td>
<td>80–90°</td>
</tr>
<tr>
<td>Luminous intensity data</td>
<td>0.074</td>
<td>0.066</td>
<td>0.061</td>
</tr>
</tbody>
</table>

Fig. 7. Convergence curve by change of the number of unit prism angle zones.

Fig. 8. Result of numerical model and the optimized angle by the number of unit prism angle zones.
6.88%, and the number of generations to converge increased as well. However, no correlation was observed between the number of unit prism angle zones and the simulation convergence speed or error rates.

Fig. 8 shows the results of optimized simulations by the number of unit prism angle zones. The shape of the luminous intensity distributions had minor variations, depending on the error rate of optimization convergence. However, regardless of the number of unit prism angle zones, the shape of the angle of the optimization unit prism was nearly the same as the shape of the target luminous intensity distribution.

Fig. 9 shows the results of optimized simulations compared to these of Photopia 2.0 under the same conditions. The shapes of the luminous intensity distributions were almost the same. The applicability and accuracy of the optimization algorithm of the numerical model for luminous intensity distribution was verified.

Various shapes of the luminous intensity distribution can be derived by changing the angle of the unit prism of planar prism LED luminaires. However, as the number of the unit prism angles increases, more iteration are required for performing the optimization simulation due to an increase in the length of the binary string. Thus, it is necessary to set the optimal number of unit prisms to perform an optimization simulation in order to achieve the desired luminous intensity distribution.

4.2. Results of the optimization by change of the luminous intensity distribution

The shapes of the luminous intensity distributions were varied, after setting the number of unit prisms to 10 in order to obtain different shapes of target luminous intensity distributions. The shapes of the target luminous intensity distributions were classified into four categories: Bat-wing, Lambertian-wide, Lambertian-narrow, and asymmetrical.

The asymmetrical shape was a randomly created shape of the luminous intensity distribution while other shapes represent for common luminaires. Error ratios ranged from 3.45% (Lambertian-wide) to 5.41% (Bat-wing) according to the shape of the luminous intensity distribution (Fig. 10). Also, stable convergence was observed within 2500 in terms of the number of generations.
**5. Conclusions**

It is difficult for LED luminaires to obtain the target luminous intensity distribution by using the same optical design of optical parts as a reflector and refractor of conventional luminaires. So this study was to develop the numerical model of planar prism LED luminaire to control luminous intensity distribution of LED luminaires. And a MGA theory was proposed as a methodology for determining the optimized angle of the planar prism with a goal of obtaining the target luminous intensity distribution. In addition, the optimization algorithm with which the planar prism angles can be obtained was developed such a model was developed in order to achieve the target luminous intensity distribution by applying a MGA to the numerical model for the luminous intensity distribution. An efficient optical design was performed by excluding a mutation parameter (operator of genetic algorithm) and setting the crossover rate with the restart operation to 1.0. Luminous intensity distribution control which is more diverse than the uniformed prism angle settings was also enabled by setting the unit prism angle zones as optimization variables.

To obtain a target luminous intensity distribution, in the process of the optical design of planar prism luminaires, the numbers of trials and errors can be significantly reduced by applying optimization algorithms. Also, an optical design of the planar prism LED luminaires applicable to different spaces - depending on the optimized prism angle - may be used for implementing diverse shapes of luminous intensity distributions with planar prism LED luminaires. The development of planar prism-based LED luminaires may be further accelerated using this optimization algorithm of the numerical model for luminous intensity distribution of the planar prism LED luminaires.

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