Available online at www.sciencedirect.com
SCIENCE DIRECT
Engineering Applications of Artificial Intelligence 18 (2005) 473–484
Engineering Applications of ARTIFICIAL INTELLIGENCE
www.elsevier.com/locate/engappai

Optimal design of plant lighting system by genetic algorithms

K.P. Ferentinos*, L.D. Albright

Department of Biological and Environmental Engineering, Cornell University, Ithaca, NY 14853, USA

Received 31 May 2004
Available online 18 January 2005

Abstract

A genetic algorithm technique is developed for the optimal design of a supplemental lighting system for greenhouse crop production. The approach uses the evolutionary parallel search capabilities of genetic algorithms to design the pattern layout of the lamps (luminaires), their mounting heights and their wattages. The total number and the exact positions of luminaires are not predefined (even though possible positions lay on a fixed grid layout), thus the genetic algorithm system has a large degree of freedom in the designing process. The possibilities of mounting heights and luminaire wattages are limited to four different values for each luminaire in this study. A fitness function for the genetic algorithm was developed, taking into account light uniformity, light intensity capability, shading effects of the design, as well as operational and investment costs. The systems designed by the genetic algorithm show improved values of light uniformity and substantial savings without any effect on the light capacity capabilities of the system. Innovative automatically designed systems compare favorably with typical and expert-designed lighting systems.

Keywords: Genetic algorithms; Greenhouse; Supplemental lighting; Lighting system design; Optimal design

1. Introduction

One of the major parameters that influences plant growth is the availability of light. Greenhouse plant production systems have the capability of providing supplemental lighting during plant growth in cases where daylight is insufficient for optimal crop production. Supplemental lighting is provided to increase photosynthesis in plants and is often referred to as ‘‘assimilative lighting’’ because its main purpose is to increase the growth, that is, the assimilation of CO_2 in the crop (Ciolkosz et al., 2001). The effects of supplemental lighting on plant growth have been studied extensively (Austin and Edrich, 1974; Clarke and Devine, 1984; Wheeler et al., 1991) and the results have been applied to either light control (Heuvelink and Challa, 1989; Carrier et al., 1994; Albright et al., 2000) or a combination of light and CO_2 concentration control (Fierro et al., 1994; Both et al., 1998; Ferentinos et al., 2000; Ayari et al., 2000), as these two parameters are highly bounded in their influence on the plant growth.

Supplemental lighting in greenhouse facilities is provided by specially designed lighting systems, which, in the case of assimilative lighting (as opposed to morphogenic lighting where light is provided to control the plant form and not growth), usually consist of high intensity discharge lamps in direct reflectors, mounted in a grid pattern above the plants. The performance of these systems is measured in terms of uniformity of the light supplied and average light intensity provided (Deitzer et al., 1994). These properties are inherent of the design characteristics of the lighting system, the goal of which is to provide a highly uniform light level over the entire growing area in order to facilitate uniform crop production (Ciolkosz et al., 2001).

The structure and operating conditions of greenhouse plant production facilities make design of supplemental

*Corresponding author. Current address: Informatics Laboratory, Agricultural University of Athens, 75 Iera Odos Street, Athens, 11855, Greece. Tel.: +30 697 388 4920.
E-mail address: kpf3@cornell.edu (K.P. Ferentinos).

0952-1976/$ - see front matter © 2004 Elsevier Ltd. All rights reserved.
doi:10.1016/j.engappai.2004.11.005

lighting systems a complex process. Many interactions exist between lighting systems and plants, such as photosynthesis, photomorphogenesis and thermal effects, and between lighting systems and parts of the greenhouse structure (e.g. reflections of the cover) and mechanisms of the production system (e.g. shading by other mechanisms). In addition, design properties of the lighting system are limited by several factors of the greenhouse production system, like the type of cultivated plant, greenhouse layout, available greenhouse height, desired light intensity level, light distribution of the luminaires and their power consumption, and the availability of electric power. Electrical efficiency of the lighting system is the most important parameter in the majority of studies in system design (Sager, 1984; Bubbenheim et al., 1988; Albright and Both, 1994; Both et al., 1997). A more detailed study by Ciolkosz et al. (2001) gave some useful results on the effects of luminaire selection and layout on the level of uniformity of the provided light of supplemental lighting systems. In addition, a decision model was developed for the appropriate lighting system selection for specific plant growth scenarios, based on expert inputs and performance calculations (Ciolkosz et al., 2002).

The limited extent of works on lighting system design for greenhouse plant cultivation systems is mostly due to the complexity of the process and the lack of a design tool that can be applied to specific greenhouse structures with known requirements concerning the cultivation of specific plants. In this work, a goal-oriented design approach is proposed, based on the evolutionary optimization properties of genetic algorithms (GAs) (Holland, 1975). In goal-oriented design, an algorithm is used to search the design solution space looking for high performance solutions in terms of specified goals (Caldas and Norford, 2002). GAs have been used in design engineering applications (Jenkins, 1991; Renner and Ekart, 2003), mostly in the area of construction design, such as optimization of structural design (Hajela and Lee, 1995; Camp et al., 1998; Raich and Ghaboussi, 2000; Nanakorn and Meesomklin, 2001; Chou and Ghaboussi, 2001; Ali et al., 2003), automated design of steel frames (Koumousis and Georgiou, 1994; Foley and Schinler, 2003; Saka, 2003) or concrete frames (Rajeev and Krishnamoorthy, 1998; Camp et al., 2003) and optimal spacing of grillage systems (Saka et al., 2000). In the majority of these applications, common forms of GAs have been used. An interesting modification of the algorithm was introduced by Raich and Ghaboussi (2000), namely the implicit redundant genetic algorithm, where a representation that included redundant genes in the chromosome of the algorithm was used to allow the freedom of having variable number of elements in the encoding of the GA. The design problem considered in the work presented here, sets an upper limit in the number of available elements (i.e., luminaires), thus a different representation approach was used, which was incorporated in a traditional binary encoding scheme of GAs.

2. Materials and methods

2.1. Lighting system

The design problem concerns the development of a lighting system for the supply of artificial lighting in a greenhouse plant production facility. The main design issues in such a system are the layout pattern of luminaires, their wattages and their mounting heights. Philips high-pressure sodium (HPS) luminaires of type PL90M were used in a simulation model, with the availability of four different lamp wattages: 250, 400, 600 and 1000 W. The possible positions for the placement of the luminaires were considered to be arranged on a squared grid with square dimensions 1 m × 1 m and total dimensions of 11 m × 6 m (Fig. 1). This grid was called the "luminaire positions grid". The growing area was the area defined by the luminaire positions grid expanded by 2 m on each side (Fig. 1), measuring a total area of 150 m^2. The common practice in lighting systems design is that all luminaires have the same mounting height. However, the genetic algorithm system developed here allowed the freedom of having different mounting heights for each single luminaire, with the ability of heights of 2.5, 3, 3.5 and 4 m from the level of the crop. Different mounting height of luminaires in a layout is essential because it can be a way to balance the effect of having greater light intensity

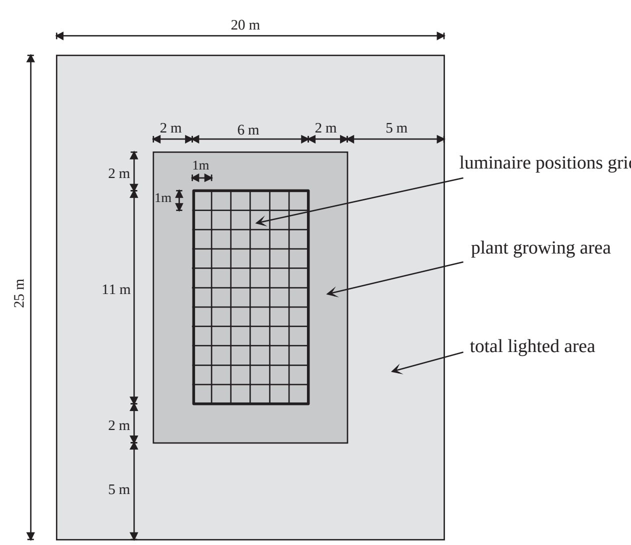

Fig. 1. Schematic representation of the positions grid of the luminaires, the plant growing area and the total area that can be illuminated by the lighting system.

in the middle than around the boundaries of a group of luminaires. In addition, a supplemental lighting system must be able to achieve a specific minimum amount of lighting throughout the day. Light intensity is a parameter that is integrated by plants and some light control algorithms use daily light integrals as control variables (Albright et al., 2000). The light integral capacity of the lighting system (LIC) was measured in photosynthetic photon flux density (PPFD) provided in one second (in $\mu mol\, m^{-2}\, s^{-1}$). The desired light integral capacity (LIC_d) for the cultivated plants was set to $100\, \mu mol\, m^{-2}\, s^{-1}$.

Assumptions made in the course of the development of the optimal design system are as follows: mounting height of the luminaires was measured from the level of the crop, which consists of a flat, horizontal canopy surface. Reflectance of the plant canopy surface, the floor and the ceiling was not taken into account because it was considered to be uniform and thus it did not affect in a large degree the design of the system. The lighting system was situated in the middle area of the greenhouse, thus reflectance of the walls was negligible. Luminaire optical efficiency and intensity distribution were assumed not to be affected by changes in lamp wattage. All light intensity data were simulated with the commercial software package Lumen-Micro (available from Lighting Technologies, Inc., Boulder, CO, USA). Sixteen data matrices were produced for a single luminaire, for the combinations of the four different lamp wattage values and four mounting heights that were mentioned before. Each data matrix contained 15×15 light intensity measurements (225 values in total) in the form of square grid centered around a luminaire with each measurement point at a vertical and horizontal distance of 1 m from each other. The light distribution of some specific design was calculated by adding the light intensities of all luminaires present at the design, as those were represented in the corresponding data matrices according to the wattage and mounting heights for each luminaire. It should be noted that the specific system presented here corresponds to a typical greenhouse for hydroponic production of plants; however, the proposed algorithm is general enough to be applied to greenhouses of different dimensions and standards, as the explored by the algorithm characteristics of the lighting system are common to every greenhouse facility that requires supplemental lighting.

2.2. Genetic algorithms

Genetic algorithms (Holland, 1975) belong to a class of algorithms known as evolutionary computation. They try to imitate natural evolution by assigning a fitness value to each candidate solution and applying the principle of survival of the fittest. They are population-based parallel search algorithms with a wide range of applications, mainly in the fields of optimization, machine learning and design (Goldberg, 1989). Their basic components are the following:

- Representation of candidate solutions to the problem in a "genetic" form.
- Creation of an initial, usually random, population of solutions.
- Establishment of a fitness function that rates each solution in the population.
- Application of the genetic operators to produce new individuals from existing individuals.
- Tuning of the values of the algorithm parameters, like population size and probabilities of performing some genetic operation.

After some specific representation is defined for the genetic algorithm, according to the application type, the first step of the search process is the formation of an initial population of possible (candidate) solutions to the problem. That formation is usually random. In most problems, the quality of initial population is crucial to the performance of the algorithm and thus to the final optimum solution that the algorithm converges to, and because of the stochastic characteristics of the algorithm, it is necessary to run the algorithm several times with different random initial populations. Another solution to that sensitivity to initial population is the use of heuristics and local search methods in order to find a "good" initial population for some specific problem. This leads to hybrid genetic algorithms that form a type of "memetic algorithms" (Moscato, 1989) that, together with other hybridizations, will be used in future work to improve the performance of the GA system developed here. Each individual of the population is then rated according to its fitness value and new individuals are formed by the genetic operator of recombination of existing individuals, with fitter individuals having greater probability of being selected for reproduction. Another genetic operator is then applied to newly formed individuals; that of mutation, during which some elements of the individuals are changed, with a usually low probability. The fitness values of the new individuals are then calculated and a new fitness-proportional selection takes place again, so that the new population of individuals that will form the parents of the next generation is formed. The process repeats until some termination condition is satisfied, usually when a maximum number of generations is reached or the diversity of the population drops below some threshold. The following section analyzes the implementation and development of GAs in the optimal design of the lighting system that was considered here.

3. Implementation of GA

The implementation of GAs in the application of optimal design of the plant lighting system incorporates three basic steps so that the algorithm is formulated for the specific application: the design representation, i.e. the encoding mechanism of the problem's phenotypes into genotypes that GAs manipulate and evolve, the choice of genetic operators, i.e. crossover and mutation types, and finally the formulation of the fitness function that gives to each individual (i.e. possible design) a measure of performance.

3.1. Design representation

The variables that are included in the design representation are those that give all the required information so that the performance of a specific lighting system design can be estimated. These variables are the placement of the existing luminaires of the lighting system, the wattage of each luminaire and the mounting height of each luminaire. The light distribution shape of the luminaires (usually round, oval or rectangular) was not taken into account because it has been shown that shape is not important to light uniformity (Ciolkosz et al., 2001). As mentioned before, the possible positions for the placement of the luminaires are considered to be arranged on a squared grid with square dimensions 1 m by 1 m, which, considering that the diameter of the luminaires is 0.5 m, gives a large degree of freedom in the creation of layout patterns of a wide variety of shapes. Thus, each joint of the grid defines a possible position for a luminaire.

A general grid for the positioning of the luminaires has r rows and c columns (Fig. 2). Each of the rc possible positions for a luminaire was encoded in a bit-string of length rc, where a value of 1 in a specific gene of the string denoted the existence of a luminaire at the corresponding position, while a value of 0 denoted the lack of luminaire at the corresponding junction of the grid. The grid junctions were encoded row by row in the bit-string (Fig. 2). This completes the first part of the bit-strings (chromosomes) used by the GA, namely the "placement part" (Fig. 3). The next part of the chromosomes, the "wattage part", consisted of pairs of bits for each possible luminaire position and encoded in binary form four possible wattage values of the corresponding luminaires: 00 for 250 W, 01 for 400 W, 10 for 600 W and 11 for 1000 W. It should be noted here that values existed even for the positions that no luminaire existed according to the encoding of the "placement part" of the string, because each chromosome should have the same constant length. The same holds for the next and final part of the chromosomes, the "height part", where similarly to the second part, pairs of bits represented the mounting heights of each possible luminaire position, with the correspondences being: 00 for 2.5 m, 01 for 3.0 m, 10 for 3.5 m and 11 for 4.0 m. Thus, each chromosome of the GA had a length of $rc+2rc+2rc=5rc$ genes (Fig. 3). When a gene in "placement part" was 0, the corresponding pairs of genes in "wattage part" and "height part" were not taken into account in the fitness value calculation of the chromosome, because a zero value in "placement part" means that the corresponding luminaire does not exist in the specific design (phenotype). In the specific design problem analyzed here, the values of r and c were 12 and 7, respectively, thus the length of the chromosomes of the GA was equal to 420.

3.2. Genetic operators

The main genetic operators of GAs are crossover and mutation. The two most common types of crossover, one-point and two-point crossovers were tested. In addition, uniform crossover as well as a modification of uniform crossover were also tested. In this modified version of uniform crossover, instead of selecting a single gene of each of the two parent chromosomes to form each child chromosome, each part of genes (as defined in the previous section) was randomly selected between the parts of the two parents to form the parts of

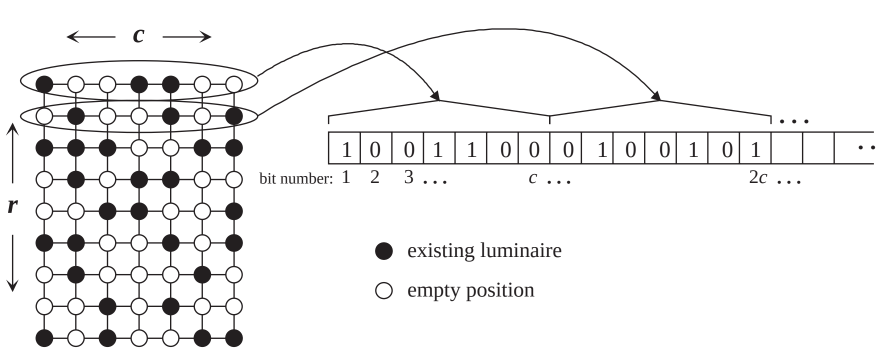

Fig. 2. Binary representation (on the right) of the positions of luminaires in a randomly created lighting system design (on the left). In the binary string, a bit value of "1" represents an existing luminaire while of bit value of "0" represents an empty position. Representation of the first two rows is shown here.

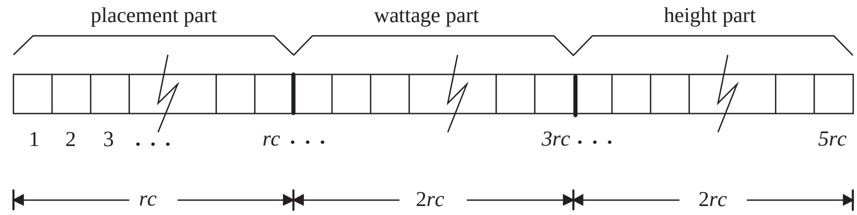

Fig. 3. Structure of a bit-string (chromosome) of the genetic algorithm population, consisted of $5rc$ binary genes. r is the number of rows and c is the number of columns of the luminaire pattern grid.

the children chromosomes. The selection in both cases of uniform crossover (normal with "gene selection" or modified with "part selection") was 50/50 between the two parent chromosomes. The probability of crossover p_c in all cases was a parameter of exploration. The mutation operator that was used was the common bit-flipping of each gene of the chromosomes with a specific probability, the probability of mutation p_m, which was also a parameter of exploration.

3.3. Fitness function

As explained earlier, the fitness function is a weighting function that measures the quality or performance of a solution (in our case, a specific lighting system design) and is the function that the GA system maximizes. The main goal in developing a fitness function is the inclusion and correct representation of all or at least the most important factors that affect the performance of the system. The first step is the decision on which factors are the most important ones. In the lighting system design, those parameters are the light intensity capability of the system, the uniformity of the produced lighting, the operational (i.e. electrical) cost of the system and finally the investment cost for the construction and equipment of the design. The second step in the development of the fitness function is the decision on the importance of each parameter on the final quality measure of the design. This importance is expressed by some weighting factors for each parameter in the final form of the fitness function and these weighting factors are usually based on experience.

3.3.1. Light intensity capability

As mentioned in Section 2.1, the lighting system must be able to achieve a specific minimum amount of lighting throughout the day. The desired light integral capacity ($\mathrm{LIC_d}$) for the cultivated plants was set to $100\,\mu\mathrm{mol\,m^{-2}\,s^{-1}}$. The actual LIC of the system was calculated by

$$\mathrm{LIC} = \frac{\sum_{i=1}^{N}\mathrm{PPFD}_i}{N}, \tag{1}$$

where PPFD_i is the photosynthetic photon flux density measured at point i and N is the number of points of light measurement in the plant growing area. When designing a supplemental lighting system, one is interested in achieving a light integral capacity at least equal to the desired light integral capacity. Thus, a variable to penalize designs that do not reach the value of $\mathrm{LIC_d}$ was estimated by

$$\mathrm{LICP} = \begin{cases} \mathrm{LIC_d} - \mathrm{LIC} & \text{if } \mathrm{LIC} < \mathrm{LIC_d}, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where LICP is the penalty factor used by the fitness function to penalize designs that do not manage to achieve the required lighting level. A weighting parameter α was used in the fitness function to determine the importance of LICP relatively to the other fitness factors, as shown later.

3.3.2. Light uniformity

The main goal of a supplementary lighting system, after having secured the capability of desired light intensity, is to provide a highly uniform light level over the entire growing area, so that crop production is uniform. The measure of light level uniformity used here was the mean relative deviation (MRD) of the provided light intensity, which is a relative measure of the deviation of the light level from the average:

$$\mathrm{MRD} = \frac{\sum_{i=1}^{N}|\mathrm{PPFD}_i - \mathrm{PPFD_m}|}{N\mathrm{PPFD_m}}, \tag{3}$$

where N is the number of points that PPFD is measured, PPFD_i the value of PPFD at point "i" and $\mathrm{PPFD_m}$ the mean PPFD. Thus, low values of MRD mean high uniformity of the provided light. Only the measurements in the plant growing area (Fig. 1) were taken into account for the estimation of light deviation. The measure of light uniformity was the second factor of the fitness function, with a weighting parameter β to determine its importance relatively to the other fitness factors.

3.3.3. Operational and investment costs

An important parameter that needs to be minimized in any greenhouse facility is the operational and investment costs. Operational cost of the lighting system

(C_o) is determined by the electrical consumption of the luminaires while the investment cost (C) is given basically by the cost amount of acquiring the specific model of luminaires that was used in the system. Weighting parameters γ and δ determine the importance of those costs in relation to the other fitness factors. The costs are estimated as follows:

$$C_o = \sum_{w} (\mathrm{NL_w EC_w})\mathrm{UC}, \tag{4}$$

where C_o is the operational cost of the lighting system (in \$/h), w the specific wattage of the luminaires and can take the four possible wattage values that were used in the system, $\mathrm{NL_w}$ the number of luminaires of each wattage w, $\mathrm{EC_w}$ is the electrical consumption of a luminaire of wattage w (in kWh) and UC is the unit cost of electricity (in \$/kWh), and

$$C = \sum_{w} \mathrm{NL_w PL_w}, \tag{5}$$

where C is the investment cost of the lighting system and $\mathrm{PL_w}$ the unit price of a luminaire of wattage w (both in \$).

3.3.4. *Shading effects penalization*

The freedom of having each luminaire of the system design at different mounting heights, may introduce some shading effects from one luminaire to the other, especially if one thinks that the minimum allowed horizontal distance between luminaires is 1 m and the mounting heights range from 2.5 to 4 m. Thus, a penalty term was included into the fitness function to penalize designs with luminaires of large height differences in neighbor positions. For each luminaire, the surrounding (neighborhood) positions were checked and if a luminaire was found at some position, a penalty value was estimated, based on both the distance and the difference of mounting heights of the two luminaires. The neighborhood of each luminaire was defined as all positions with a distance of less than 3 m from the luminaire (Fig. 4). More specifically, the shading penalty of the design (SP) was proportional to the mounting height difference of the luminaires and reversely proportional to their distance:

$$\mathrm{SP} = \sum_{i=1}^{l} \sum_{j=1}^{sl_i} \frac{|\mathrm{d}h_{ij}|}{\mathrm{d}_{ij}}, \tag{6}$$

where $\mathrm{d}h_{ij}$ and d_{ij} are, respectively, the mounting height difference and the distance between luminaires i and j, l is the total number of luminaires in some specific design and sl_i is the number of surrounding luminaires of luminaire i, as shown in Fig. 3. Again, a weighting factor ε was used for that term of the fitness function, to define its importance relatively to the other terms of the function. The proposed technique of the SP term for the estimation of shading effects was used instead of the ray tracing technique (which is used by Lumen-Micro for the estimation of light intensity) because the available software package does not support different mounting heights of luminaires in the same layout.

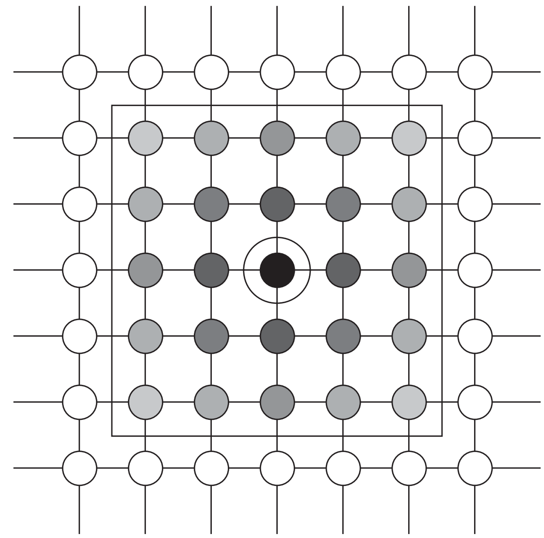

Fig. 4. Neighborhood definition of the central (black) luminaire position for the estimation of the shading penalty term. Gray positions (inside the dashed square) form the neighborhood. The side length of each square of the grid is 1 m.

Thus, the final fitness function that was used by the genetic algorithm was

$$f = \frac{1}{\alpha\mathrm{LICP} + \beta\mathrm{MRD} + \gamma C_o + \delta C + \varepsilon\mathrm{SP}}, \tag{7}$$

where f is the fitness value of a specific lighting system design. The values of the weighting parameters were chosen based on experience about the importance of each factor, according to the values that Eqs. (2)–(6) returned for the specific application, as explained later, in Section 4.

3.4. *Optimal design algorithm*

When specific representation scheme, crossover and mutation operators and a fitness function to rate the solutions have been decided, the final genetic algorithm for optimal design of the lighting system can be developed. The algorithm consists of the following steps:

1. An initial population of randomly generated designs is formulated. The size of the population is a parameter of exploration in GAs. Sizes ranging from 400 to 850 individuals were tested, as explained in the next section.
2. Each individual in the population, which is a binary string (genotype), is divided into the three sections of "placement part", "wattage part" and "height part" and is decoded into a lighting system design (phenotype), with luminaires in specific positions of

a grid and specific wattages and mounting heights for each luminaire.

3. Using Eq. (1), the light capacity of the lighting system design of each individual is evaluated and a penalty factor is assigned to each individual (Eq. 2).
4. For each individual, the lighting pattern produced by the representing system design is simulated and a measure of light uniformity is estimated, based on Eq. (3).
5. The operational and investment costs of the design that each individual represents is evaluated, according to Eqs. (4) and (5).
6. According to the luminaires pattern and mounting heights of each design, a shading effect penalty term is calculated for each individual, based on Eq. (6).
7. Results from steps 3–5 are combined to form the fitness function (Eq. 7) so that a fitness value is assigned to each individual of the population. The best fitness value and the corresponding individual, as well as the average fitness of the entire population are stored.
8. The individuals that will form the parents of the next generation are selected with probability proportional to their fitness value.
9. Crossover is performed between couples of the parent individuals, with probability p_c, which is another parameter of exploration, as explained in the next section. Four different types of crossover were tested and their performance is analyzed in the next section as well.
10. Mutation is applied to the new population with probability p_m, which is again a parameter of exploration, as explained in the next section.
11. The population is replaced by the new population and steps 2–10 are repeated until a predefined maximum number of generations is reached.

The individual with the maximum fitness value represented the optimal lighting system design estimated by the algorithm. In order to assure that the best individual of each generation is not destroyed from the operators of crossover and mutation through the process of evolution, "elitism" was included in the algorithm. Thus, at each generation, the best individual was stored and compared with the best individual of the previous generation. If it was worse than the previous best individual it meant that the best individual found so far from the algorithm was lost in the genetic process, so the worst individual of the entire population was replaced by the best individual of the previous population. In this way, the loss of the best individual found by the algorithm was prevented.

The stochastic processes involved in GAs make them sensitive to the initial population, meaning that the quality of the initial random population affects in a large degree the quality of the final solution that the algorithm converges to. If the diversity of the initial population is low or the majority of the individuals are of poor quality, it is quite probable that the algorithm will converge to some local optimum, that is, a sub-optimal solution. For that reason, the application of the GA has to be repeated several times, with different random initial populations. In addition, the parameters of the algorithm, like the population size, the maximum number of generations, the probabilities of crossover and mutation and the type of crossover, play a very important role in the performance of the algorithm. The exploration of these parameters is presented in the first part of the next section.

4. Results

As explained in the previous section, the fitness function includes five weighting factors that incorporate the common sense of significance of each of the parameters that constitute the final function to be maximized by the genetic algorithm. The exact values of those weighting factors were estimated empirically after some rudimental exploration. The first column of Table 1 shows their values so that in average, about equal importance is given to each parameter of the fitness function. The second column shows the values that were finally used in the application of the GA. As it can be seen, more importance was given to the parameters of light uniformity (weighting factor β) and light capacity of the system (weighting factor α) as these are the most important characteristics of a lighting system design.

4.1. GA experimentation

GAs have a number of parameters that are problem-specific and need to be explored and tuned so that the algorithm performs satisfactorily. In addition, they are stochastic algorithms, as several random decisions take place during the optimization process and they tend to be sensitive in the quality of the initial population, which is generated randomly. Thus, in any exploration and then further application of the algorithm that are presented below, several runs were tested with different

Table 1
Values of weighting factors of GA fitness function. Values that give equal (in average) importance to each function parameter and actual values used are shown

Weighting factor	"Equal importance" value	Final value
α	5	10
β	370	2000
γ	60	60
δ	0.0175	0.0175
ε	1	1

random initial populations. Average results over the several runs as well as the best solutions achieved by each set of parameters were used to draw conclusions. In all explorations, a maximum number of 100 generations was used, as it was found that usually after 90–100 generations the algorithm has converged, meaning that rarely a better solution is found and the diversity of the population becomes very low. The parameters that were explored, using an ad hoc approach, were the population size, the probabilities of crossover and mutation and the type of crossover. Figs. 5 and 6 show the effect of probabilities of crossover and mutation on the performance of the algorithm for four different types of crossover. The explorations led to the use of the following parameters for the final GA: a population of 550 individuals, one-point crossover with probability $p_c = 0.2$ and probability of mutation $p_m = 0.0075$.

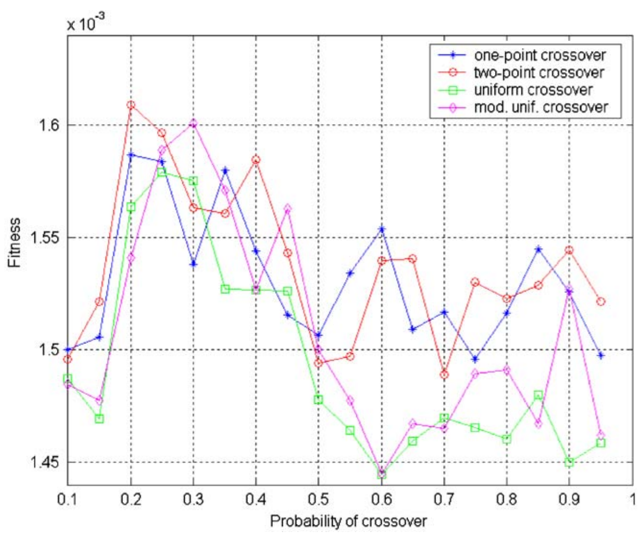

Fig. 5. Average GA performance over several probabilities of crossover for four different crossover types.

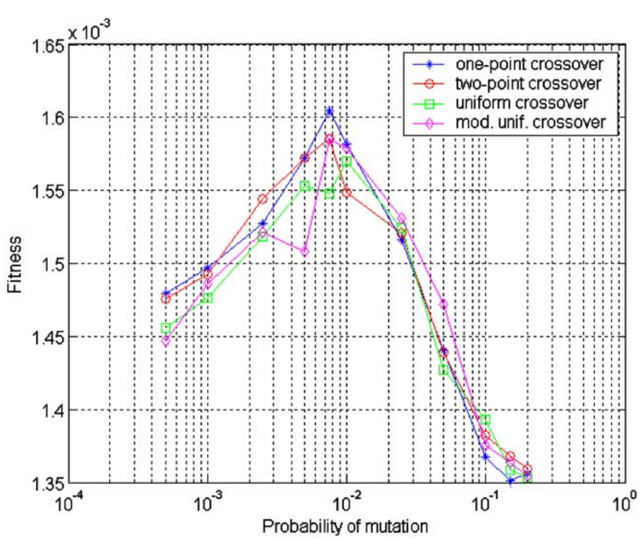

Fig. 6. Average GA performance over several probabilities of mutation for four different crossover types.

4.2. Optimum designs

Several runs of the tuned GA were performed, starting from different random initial populations, and the five best initial populations were used to run the algorithm for up to 2000 iterations. Thus, the five best designs (maximum fitness values) were recorded. The evolution progress of the best GA run is shown in Fig. 7, where both the fitness progress of the best individual found by the algorithm as well as the average fitness of the entire population are plotted. The total running time of the algorithm for the 2000 iterations was about 3 h on a Pentium III at 1 GHz personal computer. The best five designs were compared with some typical supplemental lighting system designs and some more sophisticated systems designed by experts. The comparison was based on several criteria, basically the light uniformity (expressed with the MRD parameter and also some frequency graphs), the LIC of the system and finally the operating and investment costs of the design. Light capacity of the system is the most important parameter and it was dealt as a constraint in the design, meaning that designs that could not achieve the required amount of lighting ($100\,\mu mol\,m^{-2}\,s^{-1}$) were unacceptable. Light uniformity is also a very important feature in this kind of designs, with recommended values below 0.25. In the frequency graphs, the sequence of light intensity measurements (PPFD) produced by the system was plotted and the fraction of measurements that were in the range of $\pm 15\%$ around the average PPFD

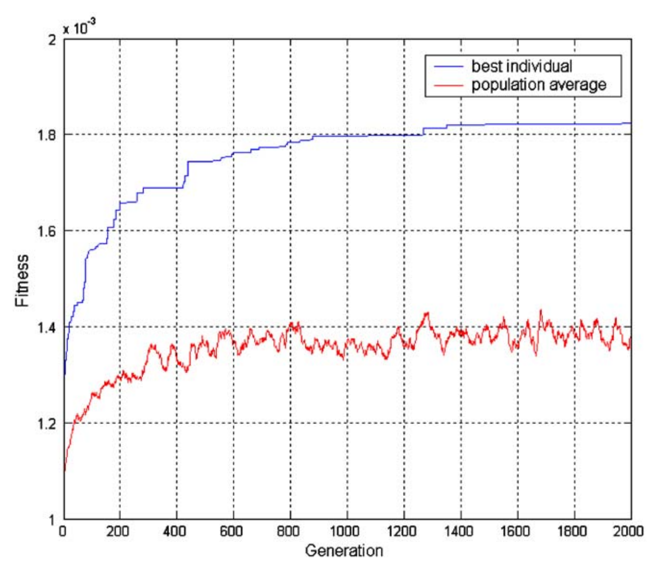

Fig. 7. Evolution progress of the best individual (best fitness value) and the entire population (average fitness value) of the GA during the best run.

was calculated. The closer to 1 this fraction is, the better the uniformity. For all performance calculations, measurements in the growing area only are considered.

The GA-produced designs are symbolized as "GA1", "GA2", "GA3", "GA4" and "GA5", with "GA1" having the best fitness value, "GA5" having the lowest fitness value and the rest in descending fitness value order. The typical designs are represented as "T1", "T2" and "T3" and the lighting systems designed by experts as "E1", "E2" and "E3". A grid full of 400 W luminaires at a mounting height of 3 meters was also considered and symbolized as "FG". A short description of all these systems is included in Table 2, where the different luminaire wattages used in each design are shown, together with the various mounting heights and the distances between luminaires at the edge and the middle of the design.

The values of the performance parameters for all designs are shown in Table 3 (in bold the best two values of each parameter). The design "GA1" gave the best uniformity and "fraction within $\pm 15\%$" of all designs, while both operational and investment costs were quite low. Its frequency graph, together with that of the design "E1", for comparison, is shown in Fig. 8. All GA-generated designs achieved much better uniformity values than those of the typical or expert-produced systems, while the corresponding investment costs were also lower. Operational costs can be considered being similar for most designs. In addition, all GA-generated designs achieved very accurately the required light

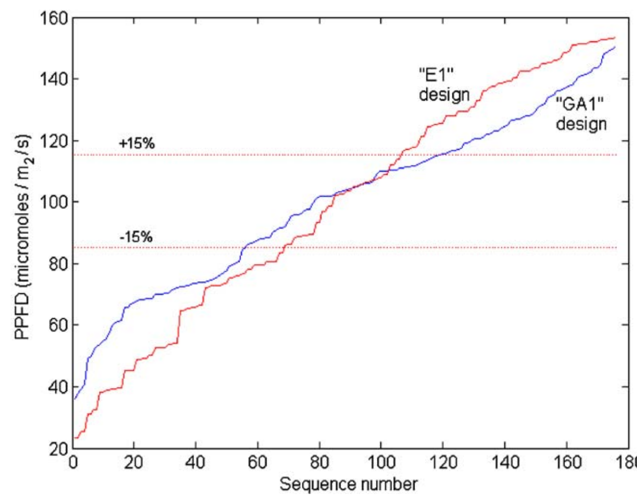

Fig. 8. Frequency graph of the PPFD measurements in the growing area, for designs GA1 and E1. Average for both designs is around $100\,\mu\text{mol}\,\text{m}^{-2}\,\text{s}^{-1}$.

Table 2
Descriptions of the available lighting system designs. Wattage values in Watt. Height and distance values in meters

Design	Existing wattages	Existing heights	Edge distances	Middle distances
GA1	250, 400, 600, 1000	2.5, 3.0, 3.5, 4.0	Varying	Varying
GA2	250, 400, 600, 1000	2.5, 3.0, 3.5, 4.0	Varying	Varying
GA3	250, 400, 600, 1000	2.5, 3.0, 3.5, 4.0	Varying	Varying
GA4	250, 400, 600, 1000	2.5, 3.0, 3.5, 4.0	Varying	Varying
GA5	250, 400, 600, 1000	2.5, 3.0, 3.5, 4.0	Varying	Varying
T1	600	3.0	1	1, 2
T2	1000	4.0	1	1, 2
T3	1000	3.5	2	2, 3
FG	400 (full grid)	3.0	1	1
E1	250, 400, 600, 1000	2.5, 3.0, 3.5, 4.0	1	1, 2
E2	400, 1000	3.0, 3.5	1	1, 2, 3, 4, 5
E3	600, 1000	3.5, 4.0	1	1, 2, 3, 4, 5

Table 3
Performance results for the different lighting system designs. LIC values in $\mu\text{mol}\,\text{m}^{-2}\,\text{s}^{-1}$ (target value is 100). MRD target is close to 0. Target of fraction of light measurements within $\pm 15\%$ of the average is close to 1. Operational costs (C_o) in \$/h. Investment costs (C) in \$

	GA1	GA2	GA3	GA4	GA5	T1	T2	T3	FG	E1	E2	E3
LIC	100.2	100.1	99.9	100.1	100.7	99.0	133.2	115.6	105.6	99.1	100.6	109.3
MRD	**0.23**	**0.24**	0.24	0.24	0.25	0.32	0.29	0.33	0.37	0.33	0.28	0.27
$\pm 15\%$	**0.36**	**0.34**	0.34	0.30	0.31	0.23	0.26	0.23	0.22	0.22	0.25	0.30
C_o	3.38	3.37	3.39	3.43	3.35	**3.23**	5.16	3.91	3.55	**3.18**	3.43	4.06
$C \times 10^3$	9.49	9.59	9.61	**9.47**	**9.11**	10.8	13.5	10.3	15.1	11.1	11.5	12.2
Luminaires	41	42	42	40	38	54	54	41	84	58	56	56

integral capacity of 100 $\mu mol\, m^{-2}\, s^{-1}$, something that does not hold for most of the other designs, where in most cases, larger light capacities were achieved, with a direct negative consequence on the investment cost of the design. Finally, the number of luminaires consisting the GA-generated designs ranged from 38 to 42, numbers much smaller than those in most of the other systems.

The best design ("GA1") consisted of 41 luminaires of all available wattages, while mounting heights of only 3 and 3.5 m were used. Fig. 9 shows the best four lighting systems generated by the GA. As it can be seen, 1000 W luminaires were generally used towards the edges of the luminaires grid in all designs, especially the short edges that are 11 meters apart, while towards the middle of the grid luminaires were sparser and of smaller wattages.

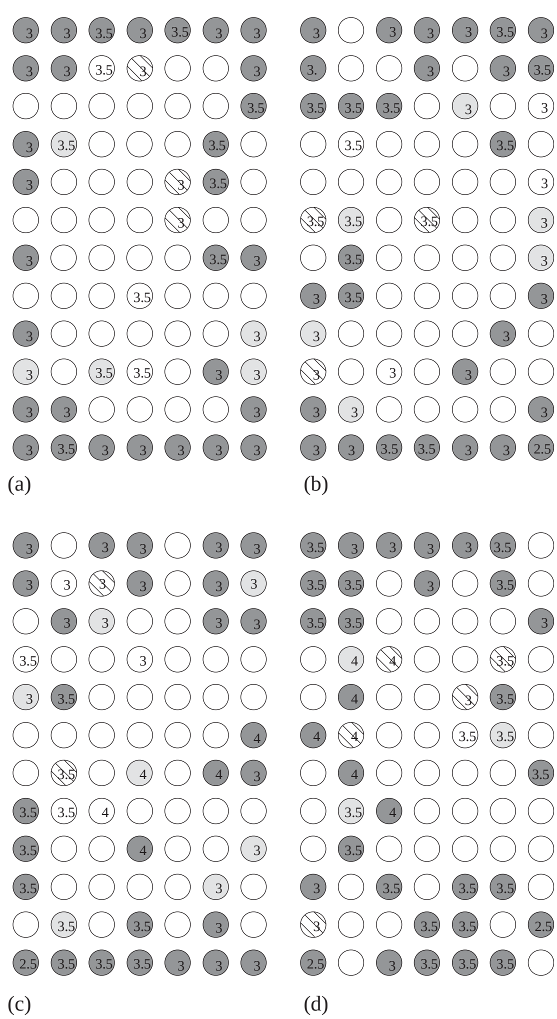

Fig. 9. Representation of the four best GA-generated lighting system designs. (a) "GA1", (b) "GA2", (c) "GA3", (d) "GA4". ⓧ : 1000 W luminaire at mounting height of x meters; ⓧ : 600 W luminaire at mounting height of x meters; ⓧ : 400 W luminaire at mounting height of x meters; ⓧ : 250 W luminaire at mounting height of x meters; ○: empty position.

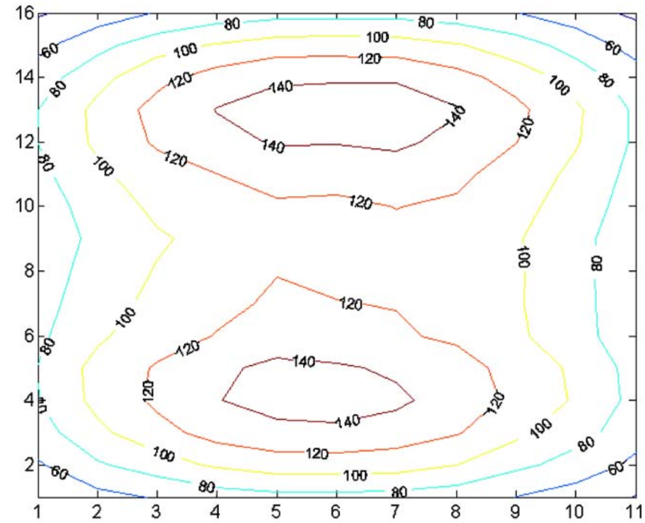

Fig. 10. Contour light intensity graph (PPFD) covering the entire plant growing area, produced by "GA1" optimum design.

Mounting heights of 3 and 3.5 m were extensively used, while 4 m mounting heights were occasionally used in two of the four designs shown, and 2.5 m mounting heights were very rarely used. Differences in mounting heights of adjacent luminaires were kept to minimum in all GA-generated designs (no more than the minimum step difference of 0.5 m) as a result of the inclusion of the shading penalty effect in the fitness function of the GA. Finally, it should be noted that even better uniformity values were achieved by the GA-generated lighting systems when the goal of light integral capacity was set to smaller than 100 $\mu mol\, m^{-2}\, s^{-1}$ values and that the values of uniformity presented here apply to the entire plant growing area and not some small middle portion of that area. Fig. 10 shows the contour representation of light intensity (PPFD) simulated measurements produced by the "GA1" optimum lighting system design, in the entire plant growing area. This design gave the best light uniformity, with MRD equal to 0.23 and the fraction of light measurements within $\pm 15\%$ of the average being equal to 0.36. It is interesting to note that all GA-generated designs gave light distributions with two picks in the plant growing area, similar to that shown in Fig. 10, on the contrary to manually designed systems that usually produce one pick of light intensity towards the middle of the plant growing area.

5. Conclusions

This paper presents a methodology for automatic design of supplemental lighting systems for greenhouse plant cultivation facilities, based on the evolutionary optimization properties of genetic algorithms.

From the comparison of the optimum designs generated by the algorithm with some typical and expert-designed lighting systems, the following conclusions can be drawn:

- The optimization process of genetic algorithms can greatly improve the light uniformity of supplemental lighting systems.
- Genetic algorithms manage to perform a good trade-off between operational cost, investment cost and light capacity of the system, so that the minimum required light intensity is accurately achieved with the most economic system design possible.
- Innovative lighting systems with the use of several different luminaire wattages and mounting heights that achieve substantial savings while having better performance than common lighting systems can be designed by genetic algorithms through the process of evolution.
- Use of large (high wattage) luminaires at middle mounting heights (3–3.5 m) seemed to be preferred by the genetic algorithm system.
- The placement of luminaires at the final systems designed by the genetic algorithm seem to generally follow the common sense of having more luminaires at the edges of the design and less luminaires towards the middle of the plant growing area.

Acknowledgements

The first author would like to acknowledge the financial support of the State Scholarships Foundation of Greece (I.K.Y.) through a post-doctoral research scholarship. The authors would also like to thank the members of the Controlled Environment Agriculture (CEA) group at Cornell University for fruitful discussions.

References

Albright, L.D., Both, A.-J., 1994. Comparisons of luminaires: efficacies and system design. In: Proceeding of the International Lighting in Controlled Environments Workshop, NASA Publications, Madison, WI, CP95-3309, pp. 281–297.

Albright, L.D., Both, A.-J., Chiu, A.J., 2000. Controlling greenhouse light to a consistent daily integral. Transactions of ASAE 43 (2), 421–431.

Ali, N., Behdinan, K., Fawaz, Z., 2003. Applicability and viability of a GA based finite element analysis architecture for structural design optimization. Computers and Structures 81, 2259–2271.

Austin, R.B., Edrich, J.A., 1974. A comparison of six sources of supplementary light for growing cereals in glasshouses during winter time. Journal of Agricultural Engineering Research 19, 339–345.

Ayari, O., Dorais, M., Goddelin, A., 2000. Daily variations of photosynthetic efficiency of greenhouse tomato plants during winter and spring. Journal of the American Society of Horticultural Science 125 (2), 235–241.

Both, A.-J., Albright, L.D., Langhans, R.W., Vinzant, B.G., Walker, P.N., 1997. Electric energy consumption and PPF_i output of nine 400 W high pressure sodium luminaires and a greenhouse application of the results. Acta Horticulture 418, 195–202.

Both, A.-J., Albright, L.D., Langhans, R.W., 1998. Coordinated management of daily PAR integral and carbon dioxide for hydroponic lettuce production. Acta Horticulture 456, 45–51.

Bubbenheim, D.L., Bugbee, B., Salisbury, F., 1988. Radiation in controlled environments: influence of lamp type and filter material. Journal of the American Society for Horticultural Science 113 (3), 468–474.

Caldas, L.G., Norford, L.K., 2002. A design optimization tool based on a genetic algorithm. Automation in Construction 11, 173–184.

Camp, C., Pezeshk, S., Cao, G.Z., 1998. Optimized design of two-dimensional structures using a genetic algorithm. Journal of Structural Engineering 124 (5), 551–559.

Camp, C.V., Pezeshk, S., Hansson, H., 2003. Flexural design of reinforced concrete frames using a genetic algorithm. Journal of Structural Engineering 129 (1), 105–115.

Carrier, M., Gosselin, A., Gauthier, L., 1994. Description of a crop growth model for the management of supplemental lighting in greenhouses. HortTechnology 4 (4), 383–389.

Chou, J.-H., Ghaboussi, J., 2001. Genetic algorithm in structural damage detection. Computers and Structures 79, 1335–1353.

Ciolkosz, D.E., Both, A.-J., Albright, L.D., 2001. Selection and placement of greenhouse luminaires for uniformity. Applied Engineering in Agriculture 17 (6), 875–882.

Ciolkosz, D.E., Albright, L.D., Sager, J.C., Langhans, R.W., 2002. A model for plant lighting system selection. Transactions of ASAE 45 (1), 215–221.

Clarke, E.A., Devine, M.D., 1984. Supplementary lighting for research greenhouses. Canadian Journal of Plant Science 64, 773–779.

Deitzer, G., Langhans, R., Sager, J., Spomer, A., Tibbitts, T., 1994. Guidelines for installation of supplementary lighting in greenhouses. In: Proceeding of the International Lighting in Controlled Environments Workshop, NASA Publications, Madison, WI, CP95-3309, pp. 391–393.

Ferentinos, K.P., Albright, L.D., Ramani, D.V., 2000. Optimal light integral and carbon dioxide concentration combinations for lettuce in ventilated greenhouses. Journal of the Agricultural Engineering Research 77 (3), 309–315.

Fierro, A., Tremblay, N., Gosselin, A., 1994. Supplemental carbon-dioxide and light improved tomato and pepper seedling growth and yield. Hortscience 29 (3), 152–154.

Foley, C.M., Schinler, D., 2003. Automated design of steel frames using advanced analysis and object-oriented evolutionary computation. Journal of Structural Engineering 129 (5), 648–660.

Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley, Reading, MA.

Hajela, P., Lee, E., 1995. Genetic algorithms in truss topological optimization. Journal of Solids and Structures 32 (22), 3335–3341.

Heuvelink, E., Challa, H., 1989. Dynamic optimization of artificial lighting in greenhouses. Acta Horticulture 260, 401–412.

Holland, J.H., 1975. Adaptation in Natural and Artificial Systems. University of Michigan Press, Ann Arbor, Michigan.

Jenkins, W.M., 1991. Plane frame optimum design environment based on genetic algorithm. Journal of Structural Engineering 118 (11), 3103–3112.

Koumousis, V.K., Georgiou, P.G., 1994. Genetic algorithms in discrete optimization of steel truss roofs. Journal of Computing in Civil Engineering 8 (3), 309–325.

Moscato, P., 1989. On evolution, search, optimization, genetic algorithms and martial arts: towards memetic algorithms. Caltech Concurrent Computation Program (C3P), Report 826, California Institute of Technology.

Nanakorn, P., Meesomklin, K., 2001. An adaptive penalty function in genetic algorithms for structural design optimization. Computers and Structures 79, 2527–2539.

Raich, A.M., Ghaboussi, J., 2000. Evolving structural design solutions using an implicit redundant genetic algorithm. Structural and Multidisciplinary Optimization 20, 222–231.

Rajeev, S., Krishnamoorthy, C.S., 1998. Genetic algorithms-based methodology for design optimization of reinforced concrete frames. Computer-Aided Civil and Infrastructure Engineering 13, 63–74.

Renner, G., Ekart, A., 2003. Genetic algorithms in computer aided design. Computer-Aided Design 35, 709–726.

Sager, J.C., 1984. Spectral effects on the growth of lettuce under controlled environment conditions. Acta Horticulture 148, 889–896.

Saka, M.P., 2003. Optimum design of pitched roof steel frames with haunched rafters by genetic algorithm. Computers and Structures 81, 1967–1978.

Saka, M.P., Daloglu, A., Malhas, F., 2000. Optimum spacing design of grillage systems using a genetic algorithm. Advances in Engineering Software 31, 863–873.

Wheeler, R.M., Mackowiak, C.L., Sager, J.C., 1991. Soybean stem growth under high pressure sodium with supplemental blue lighting. Agronomy Journal 83, 903–906.