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Optimal narrowband dispersionless fiber Bragg grating filters with short grating length and smooth dispersion profile

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Abstract

An effective optimization approach to the inverse design problems of complex fiber Bragg grating filters is developed in the present paper. Based on a multi-objective evolutionary programming (MOEP) algorithm, the proposed method can efficiently search for optimal solutions and simultaneously take into account various requirements of the designed filter. To improve the efficiency of the MOEP based algorithm, an adaptive mutation process is proposed and verified. One of the advantages of the proposed optimization method is the capability to impose additional constrains on the desired coupling coefficient, which ensures the convenience and possibility for actually fabricating the designed devices with the commercially available photosensitive fibers. To verify the effectiveness of the proposed method, an optimal narrowband dispersionless fiber Bragg grating filter for DWDM optical fiber communication systems is designed. We successfully demonstrate that complicated dispersionless FBG filters with short grating lengths and smooth dispersion profiles can be obtained by using the proposed algorithm.

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1. Introduction

Due to the increasing demand for transmission capacity, the channel spacing of two adjacent DWDM channels has been as small as 100/50 GHz and there are still some proposals to reduce it further down to 25 GHz, limited only by the bit rate. For such small channel spacing, it is not easy to build narrow-bandwidth OADM/MUX/DE-MUX filters that can separate different channels with small cross-talks and large usable bandwidth ratios. The fiber Bragg grating (FBG) technology is one of the available technologies that can meet the required performance [1,2]. By employing the powerful inverse design methodology [3,4], it is

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possible to design dispersionless FBG filters that have a flat group delay profile. The designed FBGs that can achieve the best performance are typically multi-phase-shifted FBGs with complicated profiles and long lengths. Special UV exposure setups are thus required to fabricate these FBG devices with the targeted performance.

In the literature, most of the reported results on the design of dispersionless FBGs are based on the layer-peeling (LP) inverse scattering algorithm [3,4]. Although theoretically FBGs with sharp reflectivity edges and required dispersion characteristics can be inversely synthesized by using the LP algorithm, however in practice there are still a number of disadvantages for designing a high standard dispersionless FBG filter by using this approach if special care is not taken into account. These include the required grating length is typically long for narrowband designs and the spatial grating profiles are complicated. Especially for designing a strong grating with finite grating length, the synthesized LP coupling coefficient may need to be truncated in order to fit the pre-given grating length. This process is known to degrade the grating spectral response substantially. In a recent reference [5], a LP based two-stage design approach has been developed for apodizing the synthesized coupling coefficient. A 3-cm dispersionless FBG with 99.9% reflectivity, 0.4 nm bandwidth, and a very smooth group delay profile (or dispersion profile) has been demonstrated. This provides one possible solution to overcome the difficulties mentioned above within the framework of the layer-peeling approach.

In the present paper we want to propose and demonstrate another possible solution for overcoming some of the design difficulties mentioned above. We have successfully designed narrowband dispersionless FBG filters by using a multi-objective optimization approach based on evolutionary programming (EP). The EP method is an important branch of the evolutionary algorithms (EAs), which are probabilistic search algorithms gleaned from the organic evolution process. Compared to the existing genetic algorithms (GA) for FBG synthesis [6], the EP algorithm only uses the mutation process of continuous variables and does not use the binary coding and crossover processes. Such a simpler algorithm seems to help solving complex problems in a higher convergence velocity as well as with a higher reliability. We have successfully utilized this EP algorithm to design a single-stage long period grating EDFA gain flattening filter for the entire C-band, in which the transmission spectrum of the designed filter is the only target to be optimized [7]. In the present paper, we further extend the EP algorithm in such a way that it can handle synthesis problems involving multi-objective optimization. This is particularly important for designing optimal dispersio-nless FBGs for which both the reflectivity and dispersion spectra have to meet the required performance. As common to optimization approaches, our EP method has the advantages of making the design results more practical by imposing additional constrains. With these advantages, in this paper we are able to demonstrate that an optimal dispersionless FBG with a 0.2 nm bandwidth can be realized with a grating length of 4 cm. We believe this is the first demonstration that the designed results of dispersionless FBGs from the optimization approach indeed can achieve excellent performance.

2. Analysis of FBG filters

In our work the well-known transfer matrix method (TMM) is applied to solve the couple mode equations and to obtain the spectral and phase responses of the fiber grating filters [8]. The grating length is divided into m uniform grating sections and each section is described by an analytic transfer matrix. The transfer matrix for the entire grating structure can be obtained by multiplying the individual transfer matrices:

$$\begin{bmatrix} E_a(0) \\ E_b(0) \end{bmatrix} = T_1 \cdot T_2 \cdots T_k \cdots T_m \begin{bmatrix} E_a(L) \\ E_b(L) \end{bmatrix}. \quad (1)$$

Here E_a and E_b represent the forward and backward complex electrical fields, and T_k is the transfer matrix of section k. By applying the boundary condition $E_b(L) = 0$, the complex reflection coefficient r defined by

$$r = \frac{E_b(0)}{E_a(0)} \tag{2}$$

can be readily obtained. The group delay time τ for the light reflected from the grating can then be calculated according to

$$\tau = -\frac{\lambda^2}{2\pi c}\frac{d\theta}{d\lambda}. \tag{3}$$

Here, θ is the phase of r, λ is the wavelength and τ is usually given in units of picoseconds.

The dispersion D (ps/nm) defined as the derivative of the group delay with respect to the wavelength can also be calculated:

$$D = \frac{d\tau}{d\lambda} = -\frac{2\pi c}{\lambda^2}\frac{d^2\theta}{d\omega^2}. \tag{4}$$

3. Multi-objective evolutionary programming (MOEP) algorithm

Evolutionary programming was one of the techniques in the field of evolutionary algorithm. It has been well accepted that EP is a powerful and general global optimization method which seeks the optimal solution of optimization problems by evolving a population of candidate solutions through a number of generations or iterations [9–11]. In recent years, there has been growing interest in solving multi-objective optimization problems using evolutionary approaches [12,13]. It is due to the fact that most of the real-life design problems will typically involve multiple objectives which have to be optimized simultaneously. In general, a general multi-objective minimization problem can be expressed as follows:

$$\min \mathbf{y} = f(\vec{\mathbf{X}}) = (\mathbf{f_1}(\vec{\mathbf{X}}), \mathbf{f_2}(\vec{\mathbf{X}}), \ldots, \mathbf{f_q}(\vec{\mathbf{X}}), \quad \mathbf{q} \geqslant \mathbf{2}, \tag{5}$$

$$\text{subject to } \vec{\mathbf{X}} = (\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_n}) \in \mathbf{X}, \tag{6}$$

$$\mathbf{Y} = (y_1, y_2, \ldots, y_q) \in Y, \tag{7}$$

where $\vec{\mathbf{X}}$ is called the *decision variable vector*, X is the *parameter space*, $\mathbf{Y}$ is the *objective vector*, and Y is the *objective space*.

Theoretically, there are many approaches to solve the multi-objective problems [12]. In a plain aggregating approach, the multiple objectives are often artificially combined, or strategically aggregated, into a scalar function according to some understanding of the problem. In this way, by optimizing a combination of the objectives, one gains the advantage of producing a single compromise solution which simultaneously minimizes or maximizes different criteria. This is the approach we are going to use in the present paper.

4. Synthesis of narrowband FBG using MOEP algorithm

The stochastic mechanism and evolutionary process of the MOEP algorithm used in this paper for synthesizing the optimal dispersionless fiber Bragg gratings can be briefly described as follows. Starting from a population of N "individuals" (parent), a new set of N individuals (offspring) is generated through some selection rules and an adaptive mutation process. This set of offspring is then used as the parents for next iteration. Since the main objective of FBG synthesis is to find a grating coupling coefficient profile $\kappa(z)$ that produces the corresponding reflectivity and dispersion profiles as close as possible to the desired targets, the "individual" in the EP algorithm thus naturally corresponds to the coupling coefficient function $\kappa(z)$ of the FBG. For numerical purposes, the whole grating will be discretized into m uniform sections and $\kappa(z)$ can be represented by a vector $\vec{\kappa}$. To reduce the complexity of the designed results, we will constrain $\vec{\kappa}$ to be real in the optimization procedure. The precise procedure we use to implement the multi-objective EP algorithm can be stated as follows:

Step 1. Generate a parent set of N coupling coefficient profiles $\vec{\kappa}_i$, $i = 1, 2, \ldots, N$, by selecting the value of their components randomly within a preset range.

Step 2. Calculate the reflectivity and dispersion spectra for each $\vec{\kappa}_i$ using the coupled-mode equation model.
Step 3. Find the error functions for each $\vec{\kappa}_i$ and evaluate the performance of each $\vec{\kappa}_i$.
Step 4. Check if the target performance is reached for any $\vec{\kappa}_i$ in the parent set.
Step 5. If the target is not met or the number of generations is less than the pre-specified constant, apply the elitism and roulette wheel selection processes to the parent set to generate a set of "healthier" individuals.
Step 6. Apply the mutation process to create a new set of N individuals from the "healthier" set in step 5. Go to step 2 and use the new set as the parent set.

To complete the description of the MOEP algorithm, we then need to define the error functions and explain how the selection and mutation processes are implemented. One of the natural choices for the error function is given below, where the absolute values of the deviations from the targeted reflectivity or dispersion spectrum are summed over all the "desired" spectral points:

$$E_{\mathrm{R}}(\vec{\kappa}_i) = \sum_{\ell=1}^{n} |R_\ell^{(\mathrm{target})} - R_\ell(\vec{\kappa}_i)|, \tag{8}$$

$$E_{\mathrm{D}}(\vec{\kappa}_i) = \sum_{\ell:\ \text{in-band}} |D_\ell^{(\mathrm{target})} - D_\ell(\vec{\kappa}_i)|. \tag{9}$$

In the above equations, ℓ is the index for the spectral point, n is the total number of spectral points in the whole spectral window, $R_\ell^{(\mathrm{target})}$ and $D_\ell^{(\mathrm{target})}$ are the target reflectivity and dispersion, $R_\ell(\vec{\kappa}_i)$ and $D_\ell(\vec{\kappa}_i)$ are the calculated reflectivity and dispersion corresponding to the individual $\vec{\kappa}_i$, $E_{\mathrm{R}}(\vec{\kappa}_i)$ and $E_{\mathrm{D}}(\vec{\kappa}_i)$ are the error functions for the reflectivity and dispersion, respectively, and $E_{\mathrm{R}}(\vec{\kappa}_i)$ and $E_{\mathrm{D}}(\vec{\kappa}_i)$ are the functions to be minimized at the same time. The error function for dispersion is only summed over the spectral points in the stop-band. In order to perform the multi-objective optimization algorithm more smoothly, we also introduce the following normalized error functions:

$$\bar{E}_{\mathrm{R}}(\vec{\kappa}_i) = \frac{E_{\mathrm{R}}(\vec{\kappa}_i)}{\left[\frac{1}{N}\left(\sum_{i=1}^{N}(E_{\mathrm{R}}(\vec{\kappa}_i))^2\right)\right]^{1/2}}, \tag{10}$$

$$\bar{E}_{\mathrm{D}}(\vec{\kappa}_i) = \frac{E_{\mathrm{D}}(\vec{\kappa}_i)}{\left[\frac{1}{N}\left(\sum_{i=1}^{N}(E_{\mathrm{D}}(\vec{\kappa}_i))^2\right)\right]^{1/2}}, \tag{11}$$

$$\bar{E}_{\mathrm{tot}}(\vec{\kappa}_i) = [W_{\mathrm{R}} \times \bar{E}_{\mathrm{R}}(\vec{\kappa}_i) + W_{\mathrm{D}} \times \bar{E}_{\mathrm{D}}(\vec{\kappa}_i)]. \tag{12}$$

Here the original two error functions are normalized with respect to their root mean square values over the whole "individual" set and a "total" error function is defined as a weighted mean of the two normalized error functions. Such a normalized error function has the advantage that the relative magnitudes of $\bar{E}_{\mathrm{R}}(\vec{\kappa}_i)$ and $\bar{E}_{\mathrm{D}}(\vec{\kappa}_i)$ will not differ too much even the original parent set is chosen randomly. We find that this property can greatly help the stochastic search to converge smoothly. The W_{R} and W_{D} in (12) are two weighting factors for $\bar{E}_{\mathrm{R}}(\vec{\kappa}_i)$ and $\bar{E}_{\mathrm{D}}(\vec{\kappa}_i)$, respectively, their values are set to be 0.5 in our simulation and can be adaptively adjusted if necessary. In this case, $\bar{E}_{\mathrm{tot}}(\vec{\kappa}_i)$ is an aggregated objective function combining the two defined objectives, $\bar{E}_{\mathrm{R}}(\vec{\kappa}_i)$ and $\bar{E}_{\mathrm{D}}(\vec{\kappa}_i)$. With these defined error functions, the selection process is similar to the probability method described in our previous paper on single-objective optimization [7]. However, in this study the concept of elitism is applied to further improve the efficiency. That is, the best individual $\vec{\kappa}_i$ in the parent set will be directly selected as a new individual in the next generation without going through the mutation process. Also the normalized error function in (12) is used in order to have a smoother convergence. The mutation process is similar to the continuous variable perturbation method described in [7]. In order to improve the overall efficiency of the algorithm and achieve better final accuracy, in this study $\vec{\kappa}_i$ is kept real and an adaptive mutation process is utilized as shown in the following expressions:

$$\widehat{\kappa}_{i,j,k} = \kappa_{i,j,k} + \Delta\kappa_{i,j,k}, \tag{13}$$

$$\Delta\kappa_{i,j,k} = A \times \left[\left(\frac{E_R(\vec{\kappa}_i)_k}{\frac{1}{N}\left(\sum_{i=1}^{N} E_R(\vec{\kappa}_i)_{k=1}\right)}\right)^2 + \left(\frac{E_D(\vec{\kappa}_i)_k}{\frac{1}{N}\left(\sum_{i=1}^{N} E_D(\vec{\kappa}_i)_{k=1}\right)}\right)^2\right]^{1/2} \times r_i. \quad (14)$$

In the above equations, $\kappa_{i,j,k}$ and $\widehat{\kappa}_{i,j,k}$ are, respectively, the individuals in the parent and offspring sets of the kth generation, $\Delta\kappa_{i,j,k}$ is the perturbation for the jth component of the ith coupling coefficient vector $\vec{\kappa}$ in the kth generation, r_i is a random number between −1 and 1, A is a weighting factor for the mutation, $(1/N)(\sum_{i=1}^{N} E_R(\vec{\kappa}_i)_{k=1})$ and $(1/N)\ (\sum_{i=1}^{N} E_D(\vec{\kappa}_i)_{k=1})$ are, respectively, the average error values of reflectivity and dispersion calculated from the first generation of coupling coefficients, and k is the generation number. $E_R(\vec{\kappa}_i)_k$ and $E_D(\vec{\kappa}_i)_k$ are, respectively, the values of reflectivity and dispersion errors obtained from the individuals in the kth generation. By using the proposed adaptive mutation and elitism selection scheme, the magnitude of the mutation perturbation decreases smoothly along with the values of $E_R(\vec{\kappa}_i)$ and $E_D(\vec{\kappa}_i)$ throughout the evolution process.

To have a clearer picture about the proposed MOEP algorithm, a flow chart is shown in Fig. 1. A comparison of our EP algorithms for the single-objective [7] and multi-objective optimization cases is also given in Table 1.

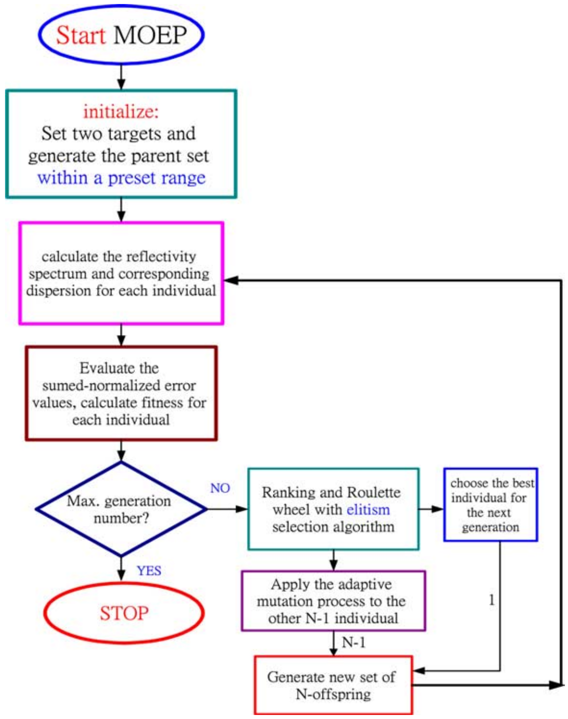

Fig. 1. Flow chart for the multi-objective evolutionary algorithm used in the present work.

5. Design results and discussions

To demonstrate the effectiveness of the algorithm, we design an ideal narrowband dispersionless FBG filter that has a bandwidth of 0.2 nm and a grating length of $L = 4$ cm. Such a FBG filter will be very useful for DWDM systems with small

Table 1
Comparison of the single- and multi-objective EP algorithms

Examples	LPG EDFA gain flattening filters [7] (single-objective optimization)	FBG dispersionless filters for DWDM OADM (multi-objective optimization)
Number of targets	1	2
Targets	• Desired transmission spectrum	• In-band zero-dispersion • Desired reflectivity spectrum
Error functions	$E_T(\vec{\kappa}_i) = \sum_{\ell=1}^{n} \lvert T_{\text{target},\ell} - T_{i,\ell}\rvert$	$\bar{E}_{\text{tot}}(\vec{\kappa}_i) = [W_R \times \bar{E}_R(\vec{\kappa}_i) + W_D \times \bar{E}_D(\vec{\kappa}_i)]$
Fitness functions	$F(\vec{\kappa}_i) = \frac{1}{E_T(\vec{\kappa}_i)}$	$F(\vec{\kappa}_i) = \frac{1}{\bar{E}_{\text{tot}}(\vec{\kappa}_i)}$
Selection process	Roulette wheel selection algorithm	Roulette wheel with elitism selection algorithm: • Keep the best $\vec{\kappa}_i$ for the next generation • The $\vec{\kappa}_i$ with higher F has higher probability to be chosen
Mutation process	Adaptive with single fitness value: $F(\vec{\kappa}_i)$	Adaptive with multiple actual error values: $E_R(\vec{\kappa}_i)$ and $E_D(\vec{\kappa}_i)$ (Eq. (14))

channel spacing. The designed Bragg wavelength is set to be $\lambda_C = 1550$ nm and the target reflectivity coefficient spectrum is chosen to be $r(\delta) = \sqrt{R} \times \exp[-(\delta/3.84^{50})]$, where δ (cm^{-1}) is the detuning parameter. We divide the grating into $m = 20$ uniform sections and the optimal coupling coefficients for these sections are stochastically searched by the procedure stated above. Here, we set $n = 241$, and the weighting factor for the proposed mutation scheme, A is set to be 0.01 (cm^{-1}). The typical evolution error-curves of the reflectivity spectrum and the in-band dispersion profiles using the proposed algorithm are shown in Fig. 2. From the results, it is obvious that the two objectives $E_R(\vec{\kappa}_i)$ and $E_D(\vec{\kappa}_i)$ can be readily minimized at the same time when the proposed adaptive mutation process is utilized.

In Fig. 3 we show the simulation results of the target and designed reflectivity spectra from different methods and with different grating lengths. From the figure it can be clearly seen that the proposed MOEP algorithm can achieve better spectra even with a short grating length of 4 cm. In comparison, when the layer-peeling algorithm with direct truncation is used to meet the same design target, the spectral performance is much poor if the same 4 cm grating length is used. This is due to the truncation effect in the synthesized LP coupling coefficient. In Fig. 4 we show the calculated dispersion profiles for the above design cases and

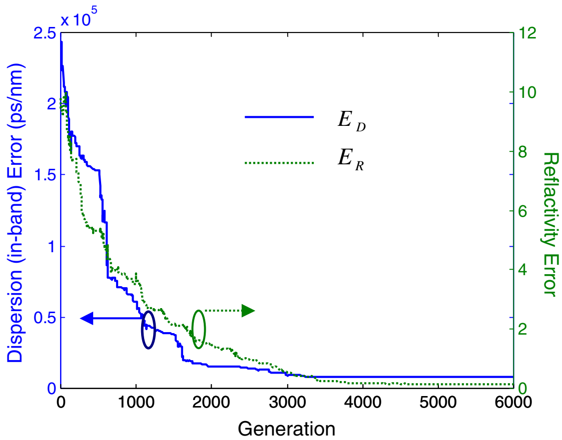

Fig. 2. Error evolution curves for the in-band dispersion and reflectivity spectra profiles.

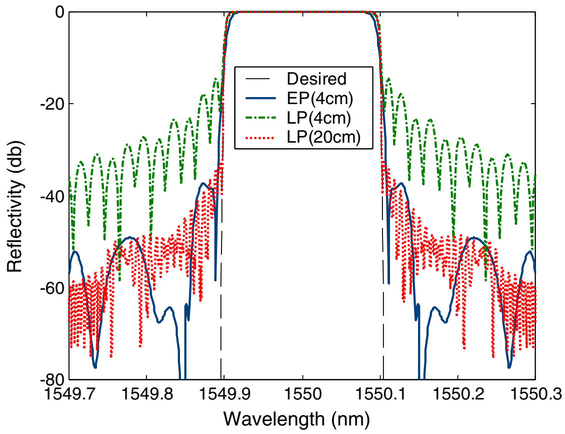

Fig. 3. Reflectivity spectra from different methods and with different grating lengths.

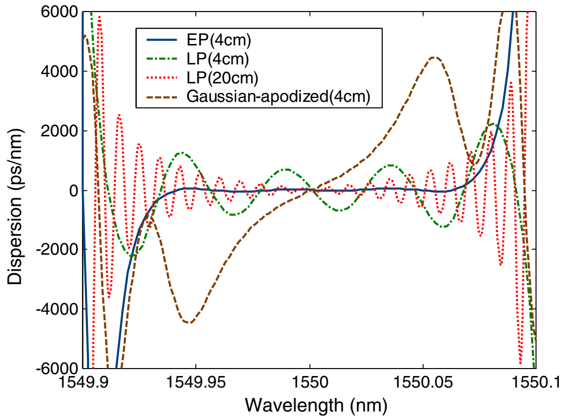

Fig. 4. Dispersion profiles from different methods and with different grating lengths.

also for a Gaussian-apodized FBG. It can be observed that a nearly ideal dispersionless spectral profile can be obtained by using the MOEP algorithm with a 4 cm grating length. In comparison, even when increasing the grating length up to 20 cm, the result from the LP algorithm with direct truncation still produces larger ripples, even though its performance on spectral sidelobes is acceptable now as shown in Fig. 3. However, if the new two-stage LP design algorithm with apodization is used, we expect comparable performance may be possible, given with the demonstrated excellent results in [5] (3-cm dispersionless FBG with

99.9% reflectivity, 0.4 nm bandwidth, and a very smooth group delay profile). In Fig. 5 we show the simulation results of the corresponding coupling coefficient profiles for the studied example. The designed profile from our EP method is piecewise uniform with the number of sections equal to 20, which is roughly the minimum number of required sections for this design example to meet the required performance. Our design may also have some advantages for actually fabricating these designed devices by using a state-of-art step-scan FBG exposure system that can expose the FBG section-by-section with nm position accuracy on the step-scan [14]. During the optimization we have also constrained the maximum allowable coupling constant to be 5 cm^{-1} so that the designed results can be practically implemented with the available photosensitive fibers.

It is well known that the EP optimization method seeks the optimal solution of the optimization problems by evolving a population of candidate solutions through a number of generations or iterations. Therefore, the complexity of the algorithm mainly depends on the requirement of the targeted results and on the degrees of freedom (control variables) of the optimization. In general, the required computation time of stochastic optimization approaches will be much larger than that of direct inverse approaches (i.e., the LP methods).

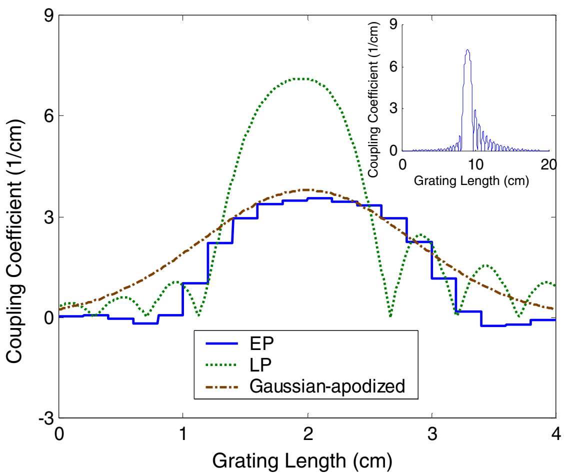

Fig. 5. Designed coupling coefficients from different methods with a grating length of 4 cm and the LP method with 20 cm.

Table 2
Comparison of the CPU time for the EP and LP algorithms

Designed methods for the designed example	CPU time
EP (4 cm) with 20 sections, $n = 241$	1–4 h
LP (4 cm) with $N = 800$, $M = 1600$	12 s
LP (20 cm) with $N = 4000$, $M = 8000$	3 min 20 s

Here N is the number of layers and M is the number of spectral points in the LP algorithm.

As a rough comparison, the CPU execution time for the EP and LP methods based on the designed example presented in this paper is given in the Table 2. The EP and LP algorithms are both implemented using the MATLAB5.3 program environment and executed on a Pentium III 550-MHz personal computer. For the design example described above, it takes about 1–4 h to achieve an acceptable solution while the LP algorithm needs only 12 s. Even though it may still be possible to reduce the computation time by implementing more complicated algorithms (i.e., a two-stage hybrid algorithm incorporating the artificial neural network as the pre-processor to generate initial populations for improving the overall efficiency), it is quite obvious that the EP based methods should compete with the LP based methods not on the computation time, but on the flexibility of imposing additional constrains and on the achievable performance through stochastic search.

6. Conclusion

In this paper, we have presented an effective FBG synthesis method based on the MOEP method which is able to take into account multiple optimization objectives. In our solution method the two design objectives (the reflectivity spectrum and the in-band dispersion profile) are strategically aggregated into a scalar function according to some prior understanding of the problem. This is especially important in our design case, in which both the performances in reflection and dispersion spectra of the designed filter must be simultaneously optimized and our evolutionary algorithm requires scalar fitness information on which the selection process can be properly preformed. Since the proposed EP-based algorithm is basically a stochastic search approach, the required computation time cannot be precisely predicted. Normally, the computation time tends to increase when the complexity of the design targets is increased. However, it has been found that the adaptive mutation process can improve the overall efficiency and reliability of the algorithm to a considerable extent. Compared to the existing results from the layer-peeling inverse scattering methods, we have demonstrated for the first time that an optimal narrowband 25 GHz (0.2 nm) dispersionless FBG filter with a very short grating length of 4 cm and with a very flat in-band dispersion spectral profile can be obtained by using the proposed method. This design example also proves that our MOEP approach is an effective method for optimally designing complicated fiber grating devices. As a final note, except for the longer computation time, a number of advantages for using the proposed EP-based optimization approaches to solve the inverse design problems of FBGs have been identified. These advantages include the possibility to constrain the patterns of the coupling coefficient profiles, to constrain the fiber grating length, and to obtain better solutions through stochastic search. These features certainly may have great merits in designing practical fiber grating devices with special requirements.

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