

# OPTICAL FIBRE DESIGN WITH EVOLUTIONARY STRATEGIES: COMPUTATIONAL IMPLEMENTATION AND RESULTS.

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## ABSTRACT

The design of optical fibres for applications where many performance targets have to be met simultaneously is a non-trivial process. An Evolutionary Strategy combined with an algorithm to model the appropriate fibre parameters was used to design an optical fibre suitable for long haul high bandwidth communications. The Evolutionary Strategy code was developed using an object-oriented approach and a parallel version was also incorporated. This allowed for the rapid implementation and subsequent design of fibres with properties of interest. Design constraints were applied as a result of the fibre manufacturing process. Results are presented for the optimal fibre designs, including convergence information.

## 1. INTRODUCTION

Optical fibres are generally made of glass where changes in the refractive index across the fibre lead to their waveguiding properties. These fibre characteristics or traits are important in the design of fibres and they vary depending on the application of the fibre: from long haul systems that stretch over thousands of kilometers to fibre devices that operate on centimeter scales. As more demands are made on the complexity of fibre designs, human based design becomes increasingly difficult, and other more automatic methods must be sought. General rules of thumb do exist for the design of simple fibres, but not for more complex structures, where no inverse methods exist to obtain a fibre structure given the desired fibre properties. This brings us to the area of optimisation.

Optimisation techniques can be separated into two main classes. Linear optimisation, where there are standard matrix methods available to find solutions, and non-linear optimisation where there is no unique solution method to use. Evolutionary Strategies themselves fit into stochastic based non-linear optimisation schemes. They use biologically inspired concepts such as random mutations, breeding and selection of individuals to arrive at an optimal solution. Often the non-linear fitness landscapes involved can be multimoded and contain many local optima. The major advantage in evolutionary based methods is their use of global

information (since a large number of solutions (individuals) are generated at each step), compared to other methods such as the Simplex algorithm which rely only on local information for the search.

The use of evolution-based algorithms in electromagnetic problems is prevalent. Examples include thin-film design [1] and antenna design [2]. The use of Evolutionary Strategies (ES) for the design of optical fibres is sparse, where an example of work includes the use of evolutionary computation [3]. In this paper we present the application of an ES algorithm to the problem of optical fibre design. The computational implementation of the scheme is also examined, where it forms an integral part of the functionality of the algorithm. The dynamics of the ES are explored, along with optimal fibre designs found.

## 2. OPTICAL FIBRES: DESIGN AND NUMERICAL MODELLING.

Most optical fibres today are made from long filaments of glass (silica). Positive and negative changes in the refractive index  $n$  of the glass are introduced through the inclusion of chemical dopants such as germanium, phosphorus and fluorine. The refractive index of the glass is then dependent on the species of dopant used (if any), the concentration  $c$  of dopant, and the wavelength  $\lambda$  of light. The Sellmeier equation with empirically determined constants is used to evaluate  $n(c, \lambda)$ . In this paper we only consider the case of a single dopant: germanium. Negative changes in refractive index can be artificially emulated by using a negative concentration of dopant. The characteristics of the fibre then depend on the details of the refractive index profile  $n(r, \phi)$ .

In this paper, we consider a fibre suitable for a Wave Division Multiplexing (WDM) application. This serves as an excellent example since up to six fibre properties have to be met simultaneously. Given that the fibre may require up to 50 or more design parameters, this is a very non-trivial relationship, even in the simplest cases. Existing designs of similar fibres are also publicly available for comparison.

Using the refractive index profile  $n(r, \phi)$  and the wavelengths we will be operating at, the effective index  $n_{\text{eff}}$  and mode field distributions  $\psi(r, \theta)$  can be calculated through the solution of Maxwell's scalar wave equation:

$$\nabla^2 \psi(r, \theta) + k^2 n^2(r, \theta) \psi(r, \theta) = k^2 n_{\text{eff}}^2 \psi(r, \theta) \quad (1)$$

where  $n_{\text{eff}}$  is the effective index of the mode and  $k = \frac{2\pi}{\lambda}$ . Generally in silica waveguides the refractive index only varies

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slightly across the fibre cross section. Because of this, we can simplify the full vector Maxwell equations to a single component of the electric field. This is known as the *weak guidance approximation*, and results in negligible loss of accuracy [4].

There are many numerical methods available to solve Eqn. 1. Examples include the Finite Element Method, Gaussian Approximation and the Beam Propagation Method. The method used here is the Fourier Decomposition Method (FDM) as outlined in [5]. The advantage of this method is that it can deal with arbitrary refractive index profiles, where the fields are expanded radially and azimuthally using a Fourier expansion technique. In this paper we only present results for circularly symmetric structures, such that  $n(r, \phi) = n(r)$ . The resulting matrix equation is solved for the dominant eigenvector and eigenvalue (fundamental mode). These are then used to calculate characteristics such as the dispersion, non-linear effective area, and the mode field diameter.

### 2.1. Fibre properties

In a WDM fibre, data is transmitted over channels of tightly equally spaced wavelengths, achieving transmission rates of up to 10Gb/sec or more on each wavelength channel. To reduce channel interference and increase the overall quality of transmission, a few conditions need to be met: dispersion, mode field diameter, non-linear effective area, and the cutoff wavelength.

The dispersion parameter  $D$  is a property of the fibre which causes different wavelengths of light to travel at different velocities. Since pulses of laser light in fibres consist of a small range of wavelengths, these pulses spread out over time, which can cause adjacent wavelength channels to become indistinguishable. The mode field diameter,  $\omega_d$  (also known as the spot size) is also very important. Individual fibres often have to be joined to other fibres, and maintaining the maximum coupling of light between the two fibre cores is essential. Non-linear effects in optical media at low laser powers are generally very low, but in long distance WDM systems where higher laser powers are used, they proliferate and must be controlled. Non-linear effective area ( $A_{\text{eff}}$ ) refers to the average area over which these effects occur. Generally many modes can be supported in an optical fibre. The cutoff wavelength  $\lambda_c$  is the shortest wavelength for which the fibre only supports one mode, and for  $\lambda < \lambda_c$  the fibre is multi-moded.

Although it may seem ideal to design a fibre with zero dispersion, this would lead to the proliferation of non-linear effects. A small non-zero dispersion, along with a controlled non-linear effective area and cutoff wavelength reduces these effects that can corrupt the data transmitted. The target design values are outlined in Table 1.

## 3. OPTIMISATION WITH EVOLUTIONARY STRATEGIES

In biology, we often talk about the genotype and phenotype of an organism, where genotype refers to the genetic composition of the organism (the genes), and phenotype refers to the physical characteristics of the organism, the

| Trait                                  | Target             | Range      |
|--|--------------------|------------|
| D (1.53 $\mu\text{m}$ )                | -4.0 ps/nm/km      | $\pm 0.5$  |
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| D (1.565 $\mu\text{m}$ )               | -4.0 ps/nm/km      | $\pm 0.5$  |
| $\omega_d$ (1.55 $\mu\text{m}$ )       | 8.0 $\mu\text{m}$  | $\pm 1.0$  |
| $A_{\text{eff}}$ (1.55 $\mu\text{m}$ ) | 70 $\mu\text{m}^2$ | $\pm 10.0$ |
| $\lambda_c$ ( $\mu\text{m}$ )          | 1.3 $\mu\text{m}$  | $\pm 0.1$  |

Table 1: Outline of the six target traits for an optimal WDM optical fibre design. The corresponding ranges  $w_i$  (Eqn. 2) are the acceptable ranges of a particular trait.

traits. In a given environment, the combination of these traits determines the fitness of that individual relative to that environment. We can relate this to the computational version of these natural themes. Genotype refers to the variables (genes) of an individual, which describe the optical fibre structure. The traits refer to the characteristics of that individual, or fibre, such as dispersion and spot size.

Using a population of individuals (parents and children), we cycle through the biomimetic processes of breeding, gene recombination and gene mutation to create new individuals. The traits are then calculated for each individual. Given these multiple traits, we choose some method of judging these solutions relative to one another. A Figure of Merit (FOM) function is used to combine the traits into a single value. Our FOM function is defined as

$$F(\mathbf{x}) = \left[ 1 + \sum_{i=1}^N \left( \frac{x_i - t_i}{w_i} \right)^2 \right]^{-1} \quad (2)$$

where  $N$  is the number of traits,  $x_i$  are the traits,  $t_i$  are the target values and  $w_i$  are the ranges over which those are acceptable (Table 1). This forms an inverse  $N$ -dimensional parabola with a maximum of  $F_{\text{max}} = 1$  if  $x_i = t_i \forall i$ . Through a selection process, the FOM is used to select the best fibre designs and the ES cycle continues by using these individuals to create new ones.

Although many variants of ES exist, the version used in this study is that as outlined in [6]. The mapping of the genes to fibre structure is straightforward, where the genes are natively stored as arrays of decimal values in an individual. Two examples of encoding are shown in Fig. 1.

One of the key features of the ES is the implementation of *adaptive mutation*. In the simplest case, genes can be mutated by adding a random number to them. This assumes that the mutation rates of each gene are known. The ES avoids this problem by using *strategy variables* to vary the mutations of each gene parameter accordingly. The strategy variables themselves form part of the genetic makeup of the individual, undergoing recombination and mutation, expanding and contracting the search along the gene parameter axes. These search directions are then generalised through the use of *correlation angles*. These features render the ES less description dependent, since over time the strategy parameters adapt to the landscape.

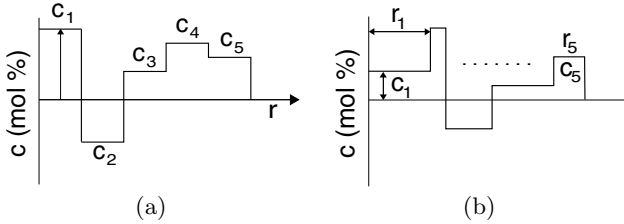


Figure 1: Examples of genetic encoding of fibre designs. In (a) the number of layers and total radius of the structure remain fixed. The genes vector is then  $\mathbf{x} = (c_1, \dots, c_n)$  where  $n_{\text{genes}} = n_{\text{layers}}$ . An extension of this case is to set the total radius as a gene, giving  $n_{\text{genes}} = n_{\text{layers}} + 1$ . In (b) Both the concentration and width of each annulus are encoded,  $\mathbf{x} = (c_1, \dots, c_n, r_1, \dots, r_n)$  where  $n_{\text{genes}} = 2n_{\text{layers}}$ .

## 4. COMPUTATIONAL IMPLEMENTATION

Ideally, we would like to apply this ES optimisation scheme to various problems. To do this, we require an ES implementation that is easy to apply to other design problems, and one which has the ability to conduct large scale optimisations in reasonable time frames. For these reasons, the ES was written using an object oriented design strategy, and a parallel computing version was implemented.

### 4.1. Object oriented (OO) design

Although nature itself is an extremely complex system, we can decompose it into simpler elements such as the environment, individuals and populations which are easier to deal with. Similarly, the Evolutionary Strategy which mimics the way nature works, can be decomposed into simpler elements. When implementing an OO design scheme, deciding how to decompose is generally the most difficult step, but here that work has been done by nature, we can just mimic it.

The most basic object is the individual, which contains data structures such as the genes array, traits array and FOM value. Member functions which apply only to individuals include Mutate and Recombine. The C++ notion of *public* and *private* is also used. For example, the individual's genes are deemed private, but the FOM value is public. On the next level, the population object contains an array of individuals. Examples of member functions include Breed, Select and Sort. For the calculation of traits, the genes array of individuals are sent to the Ribosome object. Its main member function is simply CalculateTraits. For input and output purposes, Census is used for the whole population and GeneProbe for individuals. Generalising the input/output routines through the use of OO classes means that we can operate the ES via screen, file, or network link without influencing the other parts of the code. For example, a graphical user interface is being developed for users on slower desktops to run the ES on faster server farms.

This leads us to the two greatest benefits of using an OO design scheme - flexibility and modularity. Most of the details of the ES are buried in the implementation of the various classes. These implementations can then be altered

without ever directly affecting other parts of the system, making the application to various problems trivial.

### 4.2. Parallelisation

The time required to calculate the traits of individuals requires much more computational work than other simpler functions such as breeding, fitness evaluation and selection. In the ES algorithm, once all individuals have been bred and the genetic material determined, the calculation of their traits can proceed independently of one another. This is similar to a simplified natural scenario, where once individuals are born, they develop individually. Thus, we can decompose the calculation of these multiple individuals into a parallel scheme.

A master-worker parallel scheme was implemented. The master processor completes tasks such as breeding and selection, whereas the worker processes only calculate traits. The original serial object-oriented code simplified the implementation of a parallel scheme, where at the beginning of an ES run, an instance of the ribosome class is setup on each worker processor. Work is then sent to each waiting worker processor in the form of a genes array. Once the calculation is complete, work is sent back to the waiting master processor as a traits array.

The algorithmic decomposition can take one of two forms, static or dynamic. In a static decomposition, we assume that each trait calculation requires the same amount of work. In our study, the fibre modelling technique relies on an inverse iterative scheme to find the eigenvalues and eigenvectors, and the number of iterations can vary depending on the structure and wavelength used. As a result, a dynamic decomposition scheme was used where the master processor sends out units of work, waits, and as it receives results back in the form of traits, sends out more remaining work. The publicly available implementation of the Message Passing Interface, MPICH [7] was used to achieve this.

The final result is an implementation that can be run in both serial and parallel modes, and can easily be adapted to various design problems.

Figure 2 compares the expected speedup and actual speedup of the parallel algorithm in terms of elapsed wall clock time. The speedup is proportional to  $(n_{\text{cpu}} - 1)^{-1}$  since one CPU is declared the master.

## 5. RESULTS

The ES design process was conducted for the two types of refractive index profiles as shown in Fig. 1, for various values of  $n_{\text{genes}}$ . For the type of structure as shown in Fig. 1(a), an initial individual was created with a flat index profile of zero germanium concentration. The initial parent population was then generated as random variants of this. For the structure in Fig. 1(b), the annuli thicknesses were initially set to  $1 \mu\text{m}$ . Runs were conducted using 10 parents and 100 children, where selection of individuals took place from the whole population. Using these population sizes was found to be optimal, as using less individuals slowed convergence, and using more individuals (more computational work) gave no benefits.

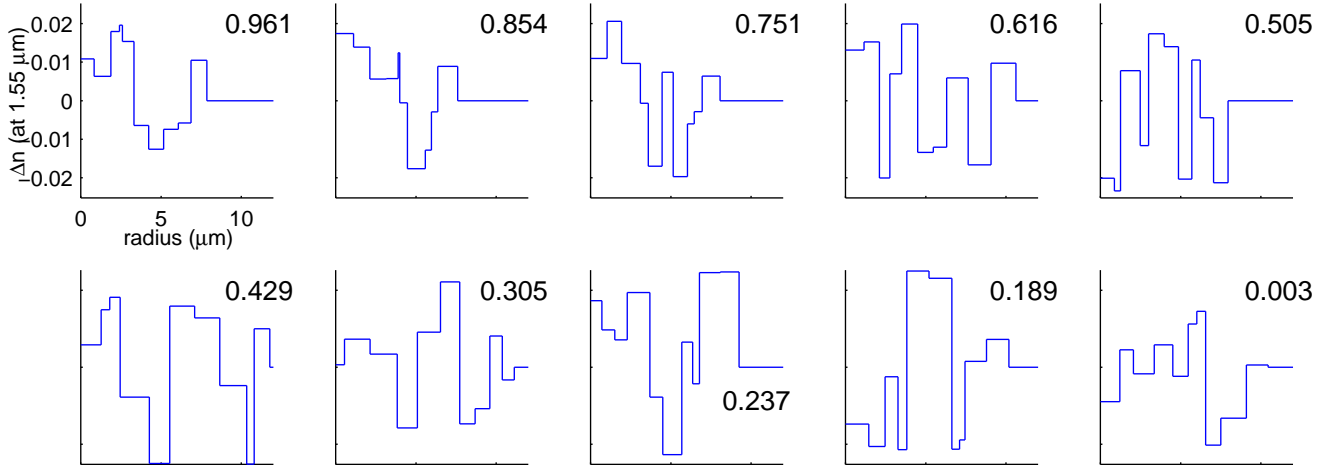


Figure 3: Examples of various refractive index profiles generated using  $n_{\text{genes}} = 20$ . The corresponding FOM values are shown. Axis labels have been removed for clarity.

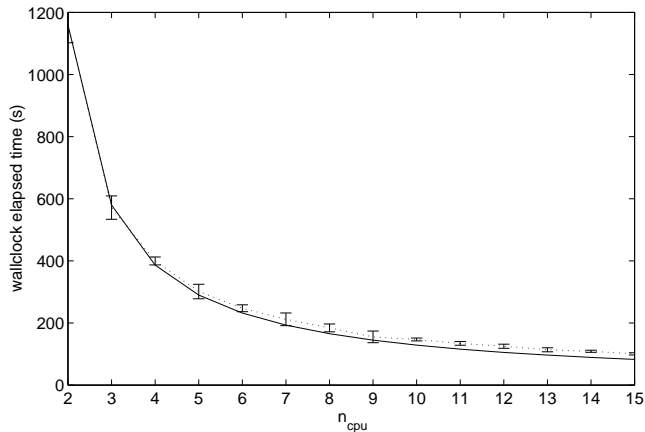


Figure 2: Parallel benchmark results for the ES over one generation with 10 parents and 100 children. The solid line represents the expected speedup and the dotted line the actual results. The error bars indicate the fluctuations in elapsed time since the machine used was under load.

Two constraints were introduced during the ES. Firstly, there is a maximum limit to the amount of dopant that can be introduced into the silica matrix. Upon discussion with fibre fabricators, a value of 8.0% was used. Secondly, most silica fibres have a standard outer diameter of  $125 \mu\text{m}$ , constraining the maximum core radius to  $62.5 \mu\text{m}$ . Results suggest that these ceiling values were never approached as optimal values anyway (Fig. 3). The constraints were enforced by breeding individuals until enough were generated to fill the population which conformed by default to the constraints. Using this method to enforce constraints, rather than re-scaling unfavourable individuals back within limits, greatly enhanced both the convergence properties and final optimal FOM found.

### 5.1. WDM fibre design

Figure 3 demonstrates the diversity of structures and their corresponding FOM's generated during an ES run. Multiple runs were conducted using the fibre descriptions as outlined in Fig. 1 for various values of  $n_{\text{genes}}$ . In all cases, the optimal refractive index profiles were found to qualitatively converge to a common shape and quantitatively converge to similar peak values and ring thicknesses (first structure in Fig. 3).

The dispersion curves of optimal structures were found to be better than current commercially available fibres. For example, the dispersion of the optimal design in Fig. 3 has a maximum variation of  $0.16 \text{ ps/nm/km}$ , whereas the *TrueWave* fibre has a variation of  $1.4 \text{ ps/nm/km}$  over the wavelength range considered [8]. As a further comparison, a standard SMF28 single mode fibre has a dispersion variation of  $2.4 \text{ ps/nm/km}$ . Examples of other optimal trait values found were  $\omega_d = 7.8 \mu\text{m}$ ,  $A_{\text{eff}} = 52 \mu\text{m}^2$  and  $\lambda_c = 1.36 \mu\text{m}$ . However, we have not yet included other factors into our analysis, such as the effect of small random profile variations on fibre properties, which can be introduced during fabrication.

### 5.2. ES dynamics

A typical example of the population dynamics of an ES run is shown in Fig. 4. The best parent generally converged to a FOM  $> 0.9$  within 10 to 15 generations. Suitable designs with excellent traits were found within 100 generations. Over time, the parent population converges to a similar FOM, subsequently containing almost identical gene values (which suggests that for this problem, there is essentially a unique global maximum). The parent designs are refined as new children with good traits are included in the parent population. Meanwhile, the parent population still have largely fluctuating strategy and correlation variables, which results in a coarse (global) search as new children are

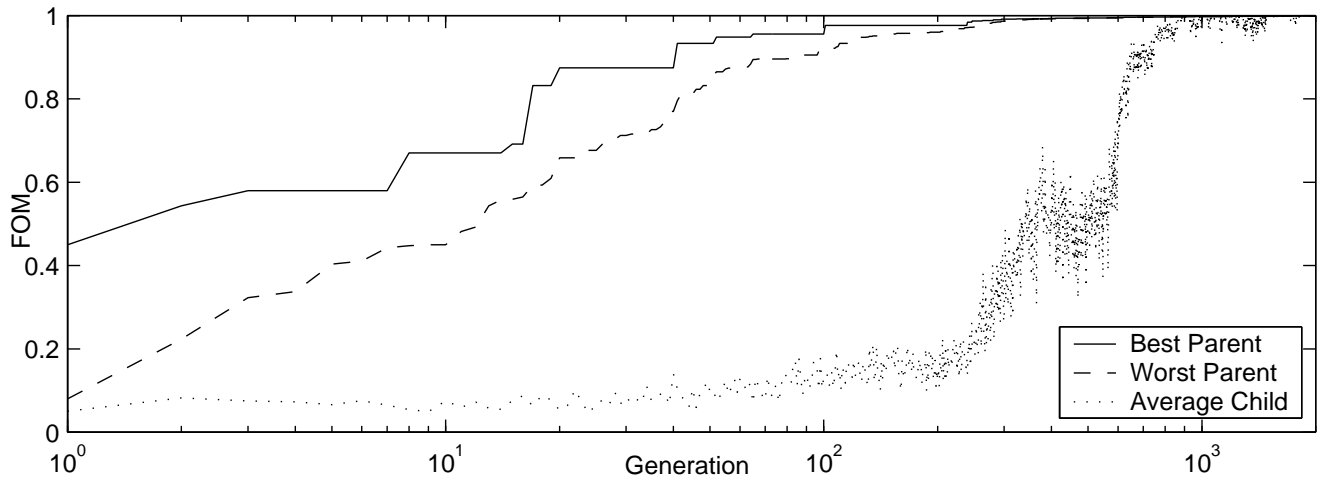


Figure 4: Typical dynamics of the FOM over 2000 generations.

breed. Eventually the child population also settles (converges), suggesting that the strategy variables and correlation angles of the parents have themselves converged to stable values. Examination of the strategy variables (Fig. 5) confirmed this assumption, where the convergence of the child strategy parameters along with the best child FOM can clearly be seen. This behaviour was only expressed when the ES was run for a significant number of generations ( $> 500$ ).

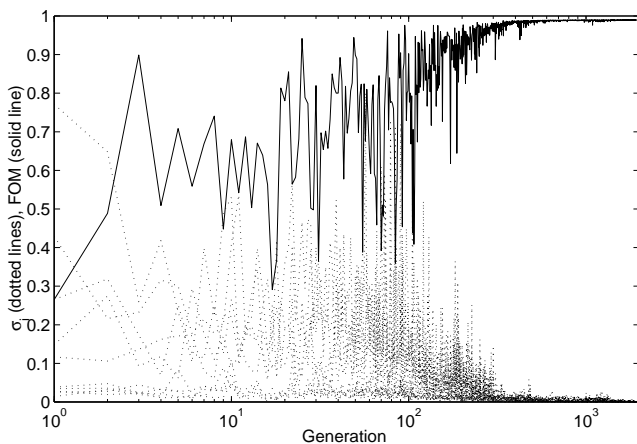


Figure 5: Data showing the convergence of the strategy variables for an ES run using  $n_{\text{genes}} = 10$  over 2000 generations. The dotted lines represent the  $\sigma_i$  values of the best children at each generation. The solid line is the FOM of the best child at each generation.

## 6. CONCLUSION

In this paper we have successfully demonstrated the application of an Evolutionary Strategy to a complex optical fibre design problem. Effort in the computational develop-

ment led to a fast, parallel algorithm with a simple implementation. The results obtained were exceptional, obtaining fibre designs with characteristics very close to the target values. The various ES runs resulted in large amounts of data being generated (since many designs were considered). At our centre, other fibre data is available in the form of experimental results and numerical results. This leads to the possibility of using data mining techniques to develop heuristics and provide further insights into the area of fibre design.

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