Review for using Genetic Algorithm in Fiber Optics Management

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Abstract

The highly need usage for the fiber optics in connecting varied devices in order to carry huge amount of data. Fiber optics is used for long-distance and high-performance data networking. It is also commonly used in telecommunication services, such as internet, television and telephones. Fiber optic cables have a significant advantage over copper cables in terms of Internet connectivity. Fiber optics can carry a much more substantial amount of data at far higher speeds; because of this, they are necessary for smooth Internet connections and efficient transfer of data. As more people work from home and rely on telecommunications, fiber optics become essential.

Key Words: Fiber, optics, Genetic Algorithm, fitness, bandwidth

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Introduction

Recently Internet entered the world of all (Scientists, art, construction, kids, engineering, medicine, sports). The great need for the high speed transmission medial t carry especially media files. Is fiber the future?
Fiber-optic networks can provide Internet service with symmetrical upload and download speeds. In addition to these benefits, fiber Internet networks can meet future demand, and many consider it a future-proof technology.

Fiber Optics

The fiber optic used to carry big data. Fiber links provide over 1,000 times as much bandwidth as copper and can travel more than 100 times further as well. A typical bandwidth-distance product for multi-mode fiber is 500 MHz/km, so a 500 meter cable can transmit 1 GHz.

Bandwidth: 60 Tbps and beyond

Distance: 12 Miles+ @ 10,000Mbps

Energy Consumed: 2W per User

Security: Nearly impossible to tap

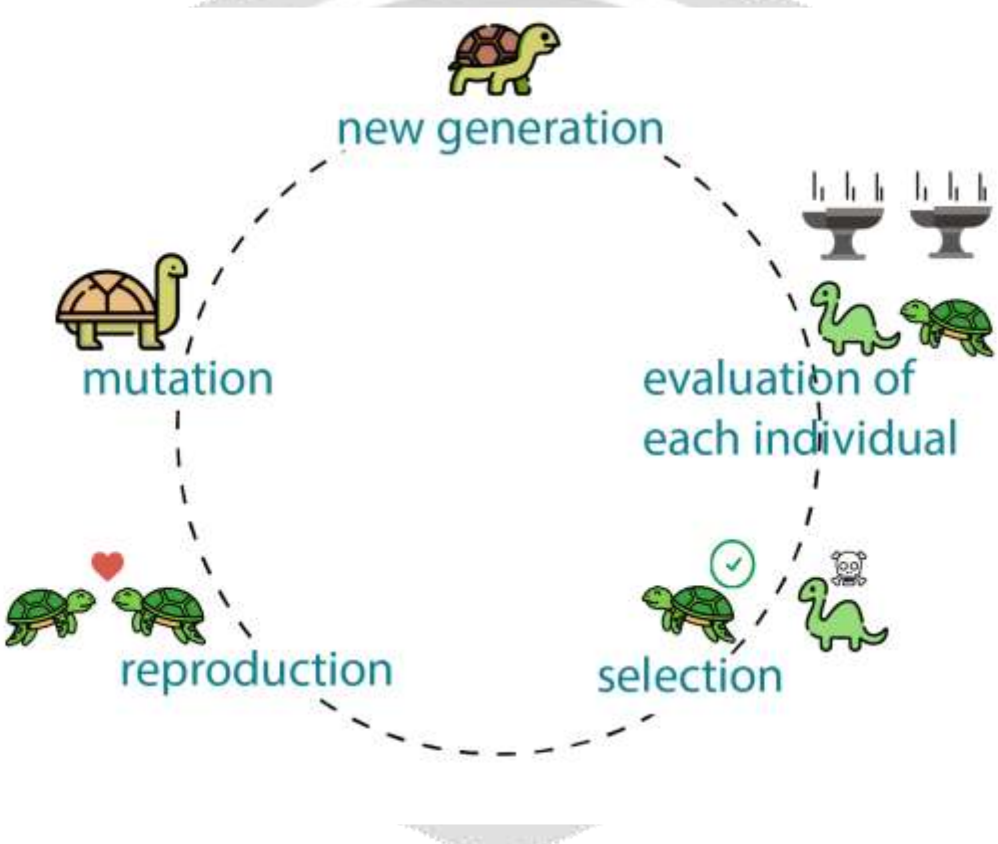
Fiber relies on light instead of electricity to transmit data, which facilitates much faster Internet connections that are capable of handling higher bandwidth. According to the FCC, fiber providers consistently offer 117 percent of advertised speeds, even during times of peak demand.

It has become increasingly easier to transfer data between computers across a network by using fiber optic cables. This allows for incredible time savings and improved efficiency at the workplace, which no longer has to wait for critical data to be transferred. For instance, modern stock exchanges rely on fiber optics within their computer networks because they need data transferred within the shortest times possible. [1]

Genetic Algorithm (GA)

An Introduction to Genetic Algorithms Jenna Carr May 16, 2014. [3]

Since genetic algorithms are designed to simulate a biological process, much of the relevant terminology is borrowed from biology. However, the entities that this terminology refers to in genetic algorithms are much simpler than their biological counterparts [8]. The basic components common to almost all genetic algorithms are: • a fitness function for optimization • a population of chromosomes • selection of which chromosomes will reproduce • crossover to produce next generation of chromosomes • random mutation of chromosomes in new generation The fitness function is the function that the algorithm is trying to optimize [8]. The word “fitness” is taken from evolutionary theory. It is used here because the fitness function tests and quantifies how ‘fit’ each potential solution is. The fitness function is one of the most pivotal parts of the algorithm, so it is discussed in more detail at the end of this section. The term chromosome refers to a numerical value or values that represent a candidate solution to the problem that the genetic algorithm is trying to solve [8]. Each candidate solution is encoded as an array of parameter values, a process that is also found in other optimization algorithms [2]. If a problem has Npar dimensions, then typically each chromosome is encoded 2 as an Npar-element array chromosome = [p1, p2, ..., pNpar] where each pi is a particular value of the i th parameter [2]. It is up to the creator of the genetic algorithm to devise how to translate the sample space of candidate solutions into chromosomes. One approach is to convert each parameter value into a bit string (sequence of 1’s and 0’s), then concatenate the parameters end-to-end like genes in a DNA strand to create the chromosomes [8]. Historically, chromosomes were typically encoded this way, and it remains a suitable method for discrete solution spaces. Modern computers allow chromosomes to include permutations, real numbers, and many other objects; but for now we will focus on binary chromosomes. A genetic algorithm begins with a randomly chosen assortment of chromosomes, which serves as the first generation (initial population). Then each chromosome in the population is evaluated by the fitness function to test how well it solves the problem at hand. Now the selection operator chooses some of the chromosomes for reproduction based on a probability distribution defined by the user. The fitter a chromosome is, the more likely it is to be selected. For example, if f is a non-negative fitness function, then the probability that chromosome C53 is chosen to reproduce might be P(C53) = f(C53) PNpop i=1 f(Ci) . Note that the selection operator chooses chromosomes with replacement, so the same chromosome can be chosen more than once. The crossover operator resembles the biological crossing over and recombination of chromosomes in cell meiosis. This operator swaps a subsequence of two of the chosen chromosomes to create two offspring. For example, if the parent chromosomes [11010111001000] and [01011101010010] 3 are crossed over after the fourth bit, then [01010111001000] and [11011101010010] will be their offspring. The mutation operator randomly flips individual bits in the new chromosomes (turning a 0 into a 1 and vice versa). Typically mutation happens with a very low probability, such as 0.001. Some algorithms implement the mutation operator before the selection and crossover operators; this is a matter of preference. At first glance, the mutation operator may seem unnecessary. In fact, it plays an important role, even if it is secondary to those of selection and crossover [1]. Selection and crossover maintain the genetic information of fitter chromosomes, but these chromosomes are only fitter relative to the current generation. This can cause the algorithm to converge too quickly and lose “potentially useful genetic material (1’s or 0’s at particular locations)” [1]. In other words, the algorithm can get stuck at a local optimum before finding the global optimum [3]. The mutation operator helps protect against this problem by maintaining diversity in the population, but it can also make the algorithm converge more slowly. Typically the selection, crossover, and mutation process continues until the number of offspring is the same as the initial population, so that the second generation is composed entirely of new offspring and the first generation is completely replaced. We will see this method in Examples 2.1 and 2.2. However, some algorithms let highly-fit members of the first generation survive into the second generation. We will see this method in Example 2.3 and Section 4. Now the second generation is tested by the fitness function, and the cycle repeats. It is a common practice to record the chromosome with the highest fitness (along with its fitness value) from each generation, or the “best-so-far” chromosome [5]. Genetic algorithms are iterated until the fitness value of the “best-so-far” chromosome stabilizes and does not change for many generations. This means the algorithm has converged 4 to a solution(s). The whole process of iterations is called a run. At the end of each run there is usually at least one chromosome that is a highly fit solution to the original problem. Depending on how the algorithm is written, this could be the most fit of all the “best-so-far” chromosomes, or the most fit of the final generation. The “performance” of a genetic algorithm depends highly on the method used to encode candidate solutions into chromosomes and “the particular criterion for success,” or what the fitness function is actually measuring [7]. Other important details are the probability of crossover, the probability of mutation, the size of the population, and the number of iterations. These values can be adjusted after assessing the algorithm’s performance on a few trial runs. Genetic algorithms are used in a variety of applications. Some prominent examples are automatic programming and machine learning. They are also well suited to modeling phenomena in economics, ecology, the human immune system, population genetics, and social systems. 1.1 A Note About Fitness Functions Continuing the analogy of natural selection in biological evolution, the fitness function is like the habitat to which organisms (the candidate solutions) adapt. It is the only step in the algorithm that determines how the chromosomes will change over time, and can mean the difference between finding the optimal solution and finding no solutions at all. Kinnear, the editor of Advances in Genetic Programming, explains that the “fitness function is the only chance that you have to communicate your intentions to the powerful process that genetic programming represents. Make sure that it communicates precisely what you desire” [4]. Simply put, “you simply cannot take too much care in crafting” it [4]. Kinnear stresses that the population’s evolution will “ruthlessly exploit” all “boundary conditions” and subtle defects in the fitness function [4], and that the only way to detect this is to just run the algorithm and examine the chromosomes that result. 5 Figure 1: Graph of f(x) = −x 2 10 + 3x x 5 10 15 20 25 30 f(x) 5 10 15 20 The fitness function must be more sensitive than just detecting what is a ‘good’ chromosome versus a ‘bad’ chromosome: it needs to accurately score the chromosomes based on a range of fitness values, so that a somewhat complete solution can be distinguished from a more complete solution. Kinnear calls this awarding “partial credit”. It is important to consider which partial solutions should be favored over other partial solutions because that will determine the direction in which the whole population moves [2].



Fig(1): Genetic algorithm Cycle

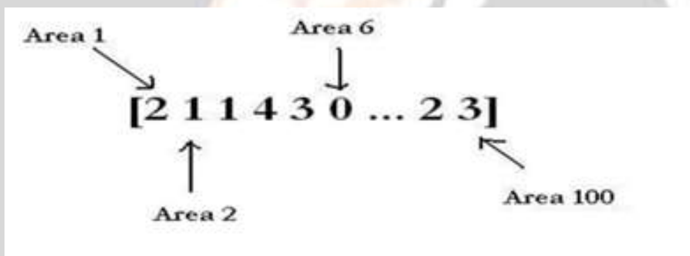
Work Review

- Wen Qi Zhang, Shahraam Afshar V., and Tanya M. Monro with paper entitled “A genetic algorithm based approach to fiber design for high coherence and large bandwidth super continuum generation.

  The paper present a new approach to the design of optical micro structured fibers that have group velocity dispersion (GVD) and effective nonlinear coefficient (y) tailored for supercontinuum (SC) generation. This hybrid approach combines a genetic algorithm (GA) with pulse propagation modeling, but without include it into the GA loop, to allow the efficient design of fibers that are capable of generating highly coherent and large bandwidth SC in the mid-infrared (Mid-IR) spectrum. To the best of our knowledge, this is the first use of a GA to design fiber for SC generation. We investigate the robustness of these fiber designs to variation in the fiber's structural parameters. The optimized fiber structure based on a type of tellurite glass ($70TeO_2$-$10Na_2O$-$20ZnF_2$) is predicted to have near-zero group velocity dispersion (<±2ps/nm/km) from 2 to 3 µm, and a effective nonlinear coefficient of $y \approx 174 W^{-1} km^{-1}$ at 2 µm. The SC output of this fiber shows a significant bandwidth and coherence increase compare to a fiber with a single zero group velocity dispersion wavelength at 2 µm.[3]

- Michael Kampouridis, Tim Glover, Ali Rais Shaghaghi, Edward P. K. Tsang introduce "Using a genetic algorithm as a decision support tool for the deployment of Fiber Optic Networks" discuss on Fiber optics, which is a relatively new technology, one which has not yet been extensively used, because of its high cost. In order to evaluate the viability of such a costly investment, techno-economic models are employed. These models evaluate the investment from both technical (e.g., optimal network design) and economical (e.g., profitability) perspectives. However, an area that has not received much attention is the deployment plans of a given fiber optic investment.

  Existing works usually compare manually predefined deployment plans that are considered profitable, and then apply techno-economic analysis. While this indeed offers valuable information, it does not guarantee that the examined plans are the optimal ones. This should be considered as a major disadvantage, because there could be other deployment plans that could offer significantly higher profit. This paper offers a first attempt at looking for the optimal deployment plan of fiber optics, based on profit. For comparison purposes, we compare the GA's results with results under other profitable plans. Results show that the introduction of the use of the GA is very advantageous and leads to a significant increase in profit.



Fig(2): An example of an individual's representation

$$\text{Fitness} = N\,P\,V$$

In the above equation, the fitness function of the GA is simply the Net Present Value (NPV) of a given deployment plan. Thus, 'fit' GA individuals are the ones that return the highest profit. [4]

- Samad Jafar-Zanjani, Sandeep Inampudi, Hossein Mosallaei; Adaptive Genetic Algorithm for Optical Meta surfaces Design work on **Adaptive Genetic Algorithm;** In this paper a brief introduction to the adaptive genetic algorithm (AGA) technique, which is employed to optimize the structures presented in this paper. In the simplest form an optimization problem to be solved with a GA can be expressed as

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$$\max p \in RF(p) \qquad \max p \in R F(p)$$

where F(p)F(p) is called the objective or fitness function, and P = (p1, p2, ..., pn) is a vector representing the parameter space. It is worth mentioning that, although we employ GA for maximization purposes in this paper. Also, sometimes there are constraints that must be considered while maximizing the fitness function, which we have ignored here for the sake of simplicity. For a multi-objective optimization problem the fitness function can be written in the most general form as

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F(p)=W1×f1(p)+W2×f2(p)+...+Wn×fn(p)F(p)=W1×f1(p)+W2×f2(p)+...+Wn×fn(p)

where f′isf′is are multiple objective sub-functions and W′isW′is are the corresponding weights. In a conventional multi-objective GA optimization, the weights corresponding to different objective functions in eq. 2 are constant throughout the optimization. The objective functions with higher priorities are given higher costs, compared to the less significant objectives36. This procedure, however, might cause GAs to become stray and deviated from the acceptable solutions in a reasonable optimization time. To overcome this issue, we use a technique called adaptive GA (AGA) in this paper. A flowchart of AGA is given in Fig. 1. We start by considering non-zero costs only for high-priority objectives (for instance, retardation phase with high accuracy). We also consider an objective update criteria for updating the objective function. The conventional GA is used to initialize a population and evolve it based on the initial objective function (see section S-1 of the Supplementary Information). At the end of each generation replacement iteration of the GA, if the overall stop criteria is met, the optimization will be terminated. Otherwise, the objective update criteria is checked and the objective function is updated if necessary. This technique allows the GA to first converge to a generation of individuals with satisfactory high-priority sub-objectives, and then try to improve the low-priority sub-objectives. This process will continue until the GA stop criteria is met.[5]

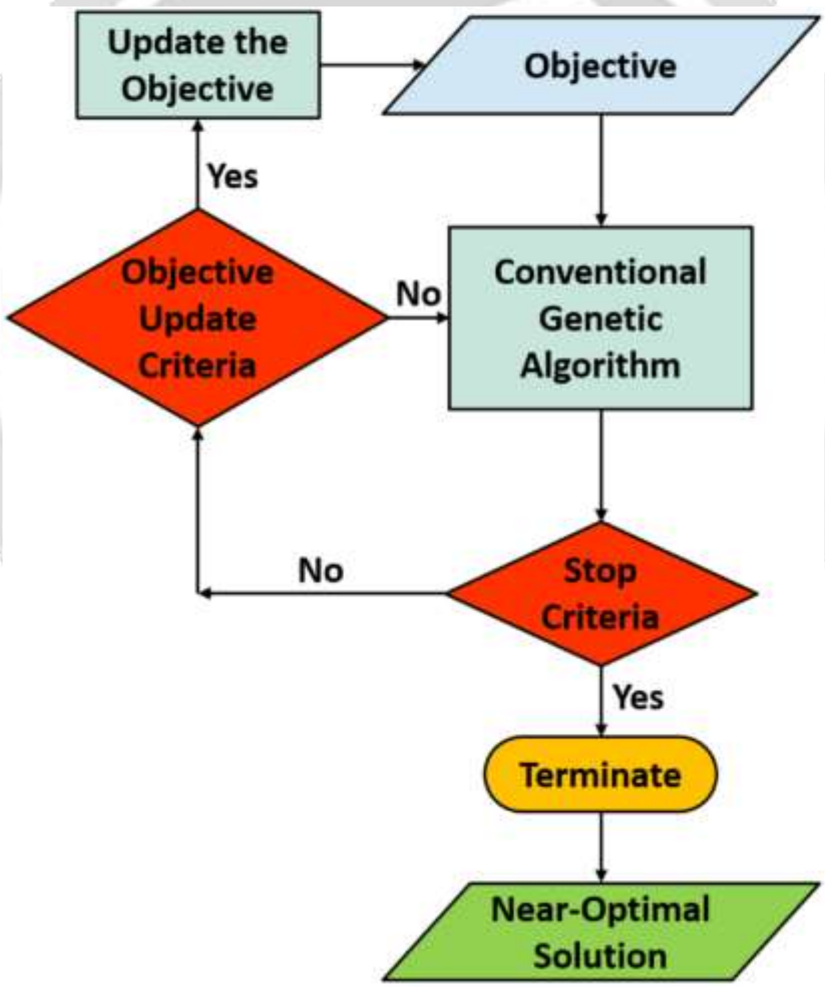

Fig (3) Flowchart for Adaptive Genetic Algorithm (AGA).

Results and Discussion

In this paper a quick review has been made for the use of Genetic Algorithm in handling Fiber Optics. Genetic algorithm is new branch that is resemble the flow of human activity. By introducing flexible model and its fitness which is tha main issue concerning genetic algorithm the model will be success and get many points. Genetic algorithm characterize by its simplicity, high processing speed where these two criteria play a key role in most of the new problems. The work need to be studied very well and collect all the properties of the fiber optics. When the collect data get large the result that could be obtain will be suited for the problem.

References

1. A The Everyday Uses of Fiber Optics, https://www.fiberplusinc.com/ helpful-information/everyday-uses-fiber-optics/, 17-8-2022
2. Jenna Carr; An Introduction to Genetic Algorithms; May 16, 2014.
3. Wen Qi Zhang, Shahraam Afshar V., and Tanya M. Monro; "A genetic algorithm based approach to fiber design for high coherence and large bandwidth super continuum generation"; Vol. 17, Issue 21,pp. 19311-19327, (2009); https://doi.org/10.1364/OE.17.019311.
4. Michael Kampouridis, Tim Glover, Ali Rais Shaghaghi, Edward P. K. Tsang introduce "Using a genetic algorithm as a decision support tool for the deployment of Fiber Optic Networks"; June 2012; DOI: 10.1109/CEC.2012.6252864
5. Samad Jafar-Zanjani, Sandeep Inampudi, Hossein Mosallaei; Adaptive Genetic Algorithm for Optical Metasurfaces Design; Scientific Reports volume 8, Article number: 11040 (2018).