The Design of Quantum Cascade Lasers using a Memetic Multiobjective Evolutionary Algorithm *

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Categories and Subject Descriptors

J.7 [**Computer Applications**]: Computers in Other Systems—*Military*

General Terms

Algorithms, Performance

Keywords

MOEA, Optimization

ABSTRACT

In 2000, Zhores Alferov and Herbert Kroemer received a share of the Nobel Prize in Physics for their work in developing a semiconductor laser using a double heterostructure. These types of lasers are now quite common in our society, and can be found in everyday devices such as laser printers, compact disk players, and laser pointers. Unfortunately, these devices can only operate in a limited range of wavelengths, because it has been found that these devices are inefficient and unreliable for wavelengths greater than $2\mu m$ when operated at room temperatures [1].

Quantum cascade lasers (QCL) are semiconductor lasers that are not based on the heterostructure design, but on quantum mechanics. The QCL does not have the same limitations of the double heterostructure design. As such, QCLs are used in applications where the standard double heterostructure cannot [11].

*The views expressed in this article are those of the authors and do not reflect the official policy of the United States Air Force, Department of Defense, or the United States Government.

GECCO 2006 July 8-12, 2006, Seattle, WA, USA
ACM 0-89791-88-6/97/05.

This research focuses on developing good QCL designs in the terahertz frequency range. A terahertz QCL can have potential applications in spectroscopy, astronomy, medicine, free-space communication, near-space radar, and possibly chemical/biological detection [10]. Of particular interest is its potential use as a sensor for security purposes, particularly in the realm of homeland security. In an attempt to find better laser designs, a memetic multi-objective evolutionary algorithm (MOEA) was developed. The local search technique attempts to find better solutions in the vicinity of the current chromosome. If a better solution is found, the chromosome is replaced by the new value.

Quantum Cascade Laser Overview

The first QCL was created in 1994 by researchers from Bell Laboratories. A QCL uses only electrons, so it is classified as a unipolar laser. The laser name comes from its operation. It operates using quantum mechanics and a cascading electronic waterfall, hence the name. The semiconductor crystals are grown is such a way that identical energy steps are created for the electrons cascade down. At each energy step, the electrons emit photons. A normal diode laser can only emit one photon in per cycle where a QCL can emit many more. In fact, a QCL operating at the same wavelength can outperform a diode laser by a factor greater than 1000 in terms of power because of both the cascading effect and its ability to carry large currents [2]. Additionally, the QCL can can be designed to emit wavelengths over a broad spectrum of frequencies using the same combination of materials in the active region.

Since QCLs operate at room temperature (and in the mid-infrared spectrum) they are ideal candidates to be used as sensors. Many pollutants, explosives, industrial chemicals, and medical substances can only be detected with high accuracy with mid-infrared lasers [9]. Given the wide range of capabilities listed, QCLs can be applied in the environmental, military, security, and medical fields.

Lasers work by controlling the photon emissions of atoms as electrons move from higher energy states to lower ones. The wavelength of a laser is determined by the electrons change in energy state.

QCLs work by utilizing quantum wells (QWs). QWs are formed in semiconductors by placing a thin layer of narrow bandgap semiconductor between two potential barriers with a higher energy bandgap. After an electron emits a photon, it is collected and injected into the next stage so that an additional photon can be emitted. Each emitter and collector/injector pair is defined as one period of the laser. This cascading, which causes emission of photons and in turn lasing, is the attribute of the quantum *cascade* laser that gives it its name [8]. In addition to these attributes, QCLs are unique because their performance is not directly related to the properties of the specific semiconductor used, but rather is governed by the thickness of the fabricated layer. In essence, this means a QCL is tunable to the terahertz frequency.

The QCL problem domain utilizes two fitness functions. These fitness functions are different from previous fitness functions used and attempt to model two of the most important properties of a QCL. The first fitness function determines how well the energy levels are lining up. The goal is to have good injection of electrons at the top of each quantum well, but at the same time, have good drainage at the bottom of the well. If a laser has good injection, but poor drainage, then the electrons at the top of the well won't be able to jump to the next energy state since it drains slower than the injection process. The second fitness function determines the overlap ratios. This describes how electrons jump from one state to another. In essence, the fitness function is a measure of how close states are and the ability of the electron to transfer between the states.

Memetic MOEAs

GAs often have difficulty fine-tuning chromosomes that are close to the optimal solution [4]. Memetic MOEAs are designed as an attempt to find better solutions in these instances. The algorithm is a combination of an MOEA and a local search algorithm. By balancing the genetic search and local search, researchers can improve their results for some problem instances. Permutation problems are an example of where memetic MOEAs have performed well. For this research effort, the focus is on finding good solutions with a an approximation model of a QCL so a more accurate model can be used to validate the solution is good. Since the goal is finding the best solutions to analyze further, a Lamarckian approach is the most appropriate method to use. With the Lamarckian method, the best solution from the local search is saved, and this is the solution that we analyze in depth.

Local Search Approach An evolutionary algorithm can implement local search in three different ways: after each generation, on the final generation, and after a predefined number of generations. Based on results found in [3], this research applies local search after predefined generations. By applying local search this way, good early solutions can be improved multiple times as opposed to only once at the end. Since a stochastic local search method is used in this research, the multiple local searches have a better chance of finding good solutions in a rugged search landscape.

Algorithm Selection

For this problem, the general multi-objective parallel (GENMOP) algorithm was selected because it incorporates some of the major operators NSGA-II , SPEA2, and Genocop. The algorithm is extended to include the local search procedure. GENMOP has been applied successfully to a broad range of problems ranging from in-situ bioremediation of contaminated groundwater [7] to solving the aircraft engine maintenance scheduling problem [6]. The algorithm has been applied to the QCL problem twice before [5, 10] with mixed results. But in order to build a working laser, better solutions are required, because the more accurate model takes a long time to run and tweaking the solutions to produce better quality solutions is not practical. So a local search was added to GENMOP and new fitness functions were created in an effort to produce better solutions.

GENMOP is a pareto-based algorithm that utilizes real values for crossover and mutation operators. The algorithm employs fitness sharing through a niche radius and a ranking structure that is similar to the one employed in NSGA-II.

For the QCL problem, the individual chromosomes are encoded with values denoting the physical size of the barriers and wells for cascading region of the semiconductor, as well as the electrical field that is applied to the laser.

If no input file is specified to begin GENMOP execution a population of size Pop_0 is randomly initialized. Instead of utilizing a repair function after new individuals are created, all parameters have minimum and maximum values that constrain the chromosome construction. These initial chromosomes are stored in the cumulative population, Pop_{cum}. Each individual within this population is evaluated for its fitness and then these fitnesses are granted a Pareto rank. This Pareto rank corresponds to the number of chromosomes that dominate the particular individual. A non-dominated chromosome would hold the Pareto rank of zero.

Once Pareto ranking has terminated, selection for the mating pool begins. Individuals are selected first based on their Pareto rank. When more individuals are present in a particular rank than spaces left in the mating pool, defined by MP, then the equivalence class sharing technique is used to measure crowding within the objective space. Chromosomes relating to less crowded areas of the objective space will be chosen for the mating pool to help preserve diversity within the population.

Crossover Crossover occurs in one of four ways. For the first three types of crossover mentioned below a second individual, is chosen at random from the mating pool to be crossed with the selected individual. The type of crossover to be performed is chosen based upon an adaptive probability distribution. Each of the four crossover types begins with the same probability of being chosen. As the algorithm progresses through generations, these probabilities are adapted through the fitness of the individuals they create.

1. Whole Arithmetical Crossover
2. Simple Crossover
3. Heuristic Crossover
4. Pool Crossover

Mutation The new individuals created through a crossover operation are subject to mutation with a probability defined by the user. If mutation occurs, then one of three mutation operators listed below is chosen. The mutation operator is selected using the same adaptive probability distribution described previously for crossover operations.

1. Uniform Mutation
2. Boundary Mutation
3. Non-uniform Mutation

Local Search Description The local search procedure looks for allele values that are in the vicinity of the previous value. Specifically, the procedure limits its search to the area that is within .1 of the total values that the allele can take on. The algorithm stochastically selects an equal number of neighbors that are above the current allele value and below. The number of local searches per chromosome is 40. This number is chosen in an effort to balance efficiency and effectiveness. The local search is applied at set generations. It is applied after every generation, every 20 generations, every 50 generations, and at the end of the algorithm. This setting is changed to see if it has any effect on the outcome.

Results and Analysis

Each implementation of GENMOP and memetic GENMOP is run 100 times and the Pareto front generated by the best results are compared to the other runs. Each implementation is run for 200 generations and starts with 25 individuals. Memetic GENMOP is run with local search applied on the last generation, every 50 generations (local search applied 4 times), every 20 generations (applied 10 times), and after every generation (applied 200 times). In all instances, the memetic GENMOP was able to find high quality solutions. But when comparing memetic GENMOP to the baseline GENMOP, very little improvement was gained. Figure 1 shows graph comparing GENMOP with GENMOP with local search applied every 20 generations.

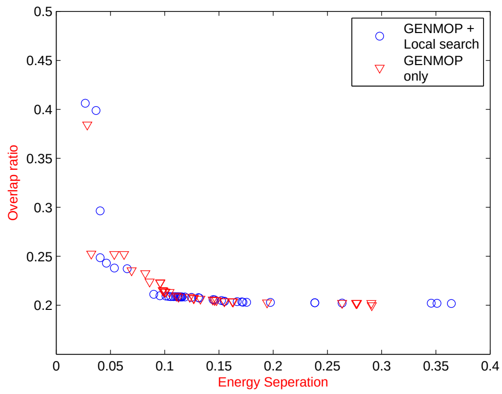

Figure 1: Comparison of GENMOP with a local search applied every 20 generations and GENMOP run without local search

These results can be explained by two operators used in GENMOP. The uniform mutation operator mutates the allele value within a certain range. This range was set at a range that was within the 10% local search range. Additionally, the non-uniform mutation operator mutates the alleles within a certain range. But this range shrinks as the generations increase, much like the simulated annealing local search technique. And since our mutation rate was set at 25%, mutation occurred at a fairly high rate. More thorough analysis revealed that, in fact, the local search improved the current solution less than 1% of the time. Table 1 lists the key findings of the various local search techniques.

Table 1: Local Search Results

When LS applied	Last gen	Every 50 gens	Every 20 gens	Every gen
Avg # of LS	804.8	2154	5094.4	98,548.8
Avg # improve	3.77	11.26	25.31	106.05
Percent of LS improvements	.468%	.523%	.497%	.101%
Avg time (sec)	804.8	564.01	616.29	2493.82
Std Dev	51.71	55.94	61.72	337.11

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