1 Wind Farm Layout Optimization using Genetic Algorithms

In 1994, Mosetti et al. successfully utilized the genetic algorithm on the wind farm layout optimization problem [Mosetti et al., 1994]. To model the wind decay Mosetti et al. used a model similar to the Jensen model [Jensen, 1983]. Mosetti et al. divided the wind farm terrain into a 10×10 quadratic grid so that a wind turbine could be installed in the middle of each cell. The optimization problem would then be to find which cells wind turbines should be installed in, in order to maximize power production and minimize cost. With this representation, an individual of the genetic search could be represented as a binary string of length 100, where each index represents a cell in the grid, so that a value of 1 means that an wind turbine is installed in the corresponding cell, and a value of zero means that there is no wind turbine in the corresponding cell. The genetic algorithm used was a simple, single-population genetic search where the fittest individuals where selected for reproduction using crossover and mutation. The crossover operation was performed at random locations with probability $0.6 < P_c < 0.9$ and mutation was performed with probability $0.01 < P_m < 0.1$. The fitness of the individuals was determined by the objective function

$$Objective = \frac{1}{P_{total}} w_1 + \frac{cost_{total}}{P_{total}} w_2 \tag{1}$$

where P_{total} is the total energy produced in one year, $cost_{total}$ is a function of the number of wind turbines installed, and w_1 and w_2 are weights. In the current study, w_1 was kept small so that the focus would be on lowest cost per energy produced. The model was tested on a single type of turbines in three different scenarios (a) constant wind direction and intensity, (b) constant wind intensity, but from a 360° variable direction, and (c) a realistic wind scenario. This work laid the foundation of numerous studies of wind farm optimization using genetic algorithms. The genetic algorithms have been optimized, and they now run on much more realistic wind scenarios, and cost models.

Huang improved the results of Mosetti et al. by using a distributed genetic algorithm [Huang, 2007]. Huang stated that using a distributed genetic algorithm will not only decrease the computation time by using parallelism, but also achieve higher fitness because more of the solution space will be explored. The distributed algorithm distributed the population of 600 individuals among 20 demes, using a ring-topology as shown in figure 1.

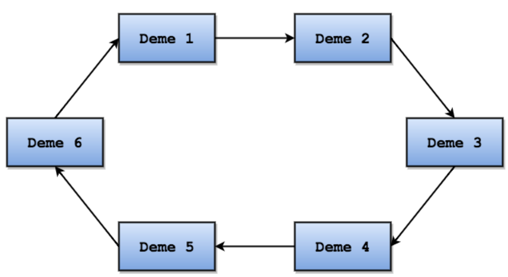

Figure 1: Ring topology example with 6 demes.

The simulation was run for 2500 generations with the migration strategy that 3.3% of the individuals with highest fitness was selected as migrants, to replace the individuals with lowest fitness in the new population every 20th generation.