Optimization via Gene Expression Algorithms:

```
import numpy as np
def objective_function(x):
  Define the mathematical function to optimize.
  Example: Sphere function f(x) = sum(x^2).
  return np.sum(x**2)
def initialize_population(pop_size, num_genes, bounds):
  Generate an initial population of random genetic sequences.
  return np.random.uniform(bounds[0], bounds[1], size=(pop_size, num_genes))
def evaluate_fitness(population):
  Evaluate the fitness of each genetic sequence.
  return np.array([objective_function(individual) for individual in population])
def selection(population, fitness, num_parents):
  Select genetic sequences based on their fitness for reproduction.
  parents = np.zeros((num_parents, population.shape[1]))
  for i in range(num_parents):
    best_idx = np.argmin(fitness)
    parents[i, :] = population[best_idx, :]
    fitness[best_idx] = float('inf') # Exclude the selected individual
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def crossover(parents, offspring_size):
  Perform crossover between selected sequences to produce offspring.
  offspring = np.zeros(offspring_size)
  num_parents = parents.shape[0]
  for i in range(offspring_size[0]):
    parent1_idx = i % num_parents
    parent2_idx = (i + 1) % num_parents
    crossover_point = np.random.randint(1, offspring_size[1])
    offspring[i, :crossover_point] = parents[parent1_idx, :crossover_point]
    offspring[i, crossover_point:] = parents[parent2_idx, crossover_point:]
  return offspring
def mutation(offspring, mutation_rate, bounds):
  Apply mutation to the offspring to introduce variability.
  for i in range(offspring.shape[0]):
    if np.random.rand() < mutation_rate:</pre>
      gene_idx = np.random.randint(0, offspring.shape[1])
      offspring[i, gene_idx] = np.random.uniform(bounds[0], bounds[1])
  return offspring
def gene_expression(genetic_sequences):
  Translate genetic sequences into functional solutions (if needed).
  Here, the genetic sequences directly represent solutions.
  111111
```

```
def gene_expression_algorithm(
  pop_size, num_genes, bounds, num_generations, mutation_rate, crossover_rate
):
  Main implementation of the gene expression algorithm.
  # Initialize population
  population = initialize_population(pop_size, num_genes, bounds)
  # Track the best solution
  best_solution = None
  best_fitness = float('inf')
  for generation in range(num_generations):
    # Evaluate fitness
    fitness = evaluate_fitness(population)
    # Track the best solution
    current_best_idx = np.argmin(fitness)
    if fitness[current_best_idx] < best_fitness:</pre>
      best_fitness = fitness[current_best_idx]
      best_solution = population[current_best_idx]
    # Selection
    num_parents = int(crossover_rate * pop_size)
    parents = selection(population, fitness, num_parents)
    # Crossover
    offspring_size = (pop_size - parents.shape[0], num_genes)
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return genetic_sequences

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offspring = crossover(parents, offspring_size)
    # Mutation
    offspring = mutation(offspring, mutation_rate, bounds)
    # Gene Expression (if needed)
    offspring = gene_expression(offspring)
    # Create the new population
    population[:parents.shape[0], :] = parents
    population[parents.shape[0]:, :] = offspring
  return best_solution, best_fitness
# Parameters
pop_size = 100 # Population size
num_genes = 5 # Number of genes (dimensionality of the solution space)
bounds = [-10, 10] # Bounds for the solution space
num_generations = 50 # Number of generations
mutation_rate = 0.1 # Probability of mutation
crossover_rate = 0.5 # Fraction of population involved in crossover
# Run the algorithm
best_solution, best_fitness = gene_expression_algorithm(
  pop_size, num_genes, bounds, num_generations, mutation_rate, crossover_rate
print(f"Best Solution: {best_solution}")
print(f"Best Fitness: {best_fitness}")
```

)

Output:

Best Solution: [-0.06016522 0.28760975 0.48263338 9.17836477 0.08649596] Best Fitness: 0.3300982665540435