Performance Metrics of Genetic Algorithm

The first graph shows in Figure 4.32 Average Fitness Over Generations improves dramatically in the initial generations and then stabilizes. This suggests that the algorithm quickly found better solutions but then reached a plateau where further improvement is minimal. And The second graph in Figure 4.33 suggests convergence of the population, indicated by the sharp decrease, which then levels off. The metric might measure some aspect of population homogeneity – for example, how similar the individuals are to each other. A high level of convergence can indicate that the population may be getting stuck in local optima, reducing the genetic diversity necessary to explore the search space further. The third graph shows in Figure 4.34 Genetic Diversity Over Generations and the number of unique individuals in the population. The diversity decreases over time, which is typical as the algorithm converges to what it deems as optimal solutions. However, it's important that the diversity does not drop too low, as this could mean the population is becoming too similar and innovation may be stifled.

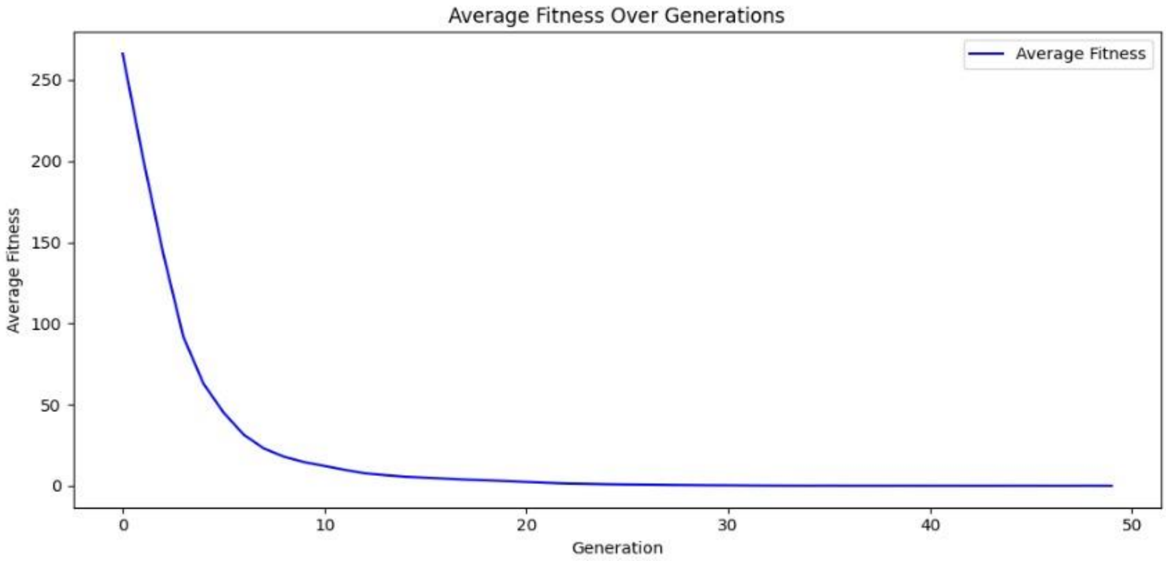

Figure 4.32: Average Fitness Over Generations

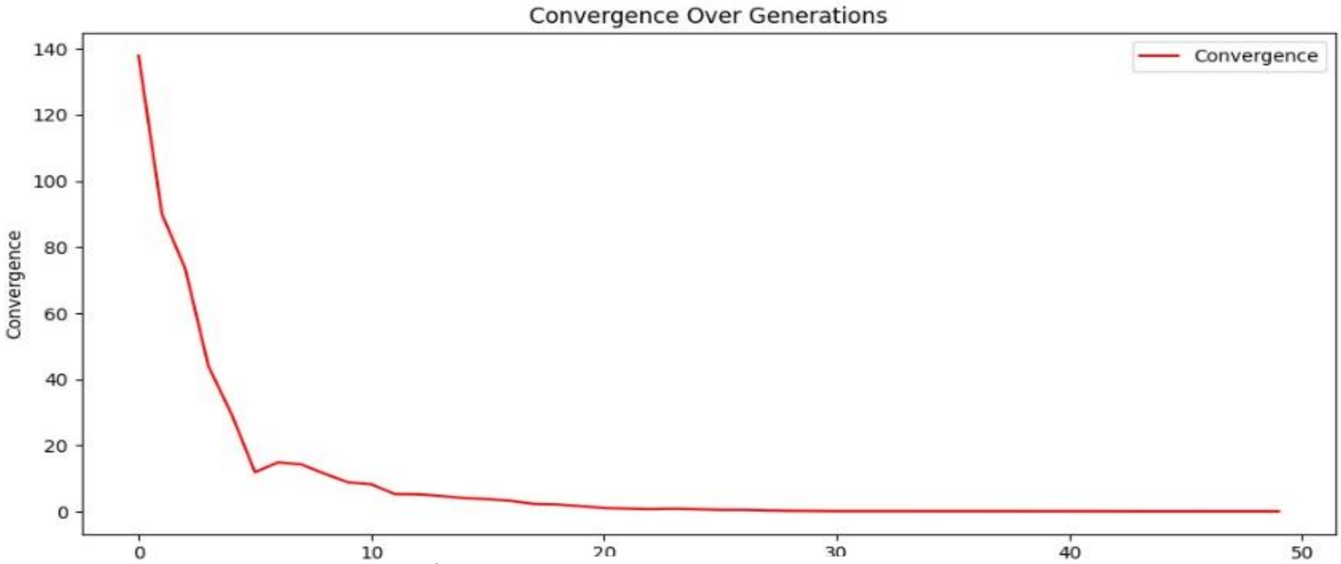

Figure 4.33: Convergence Over Generations

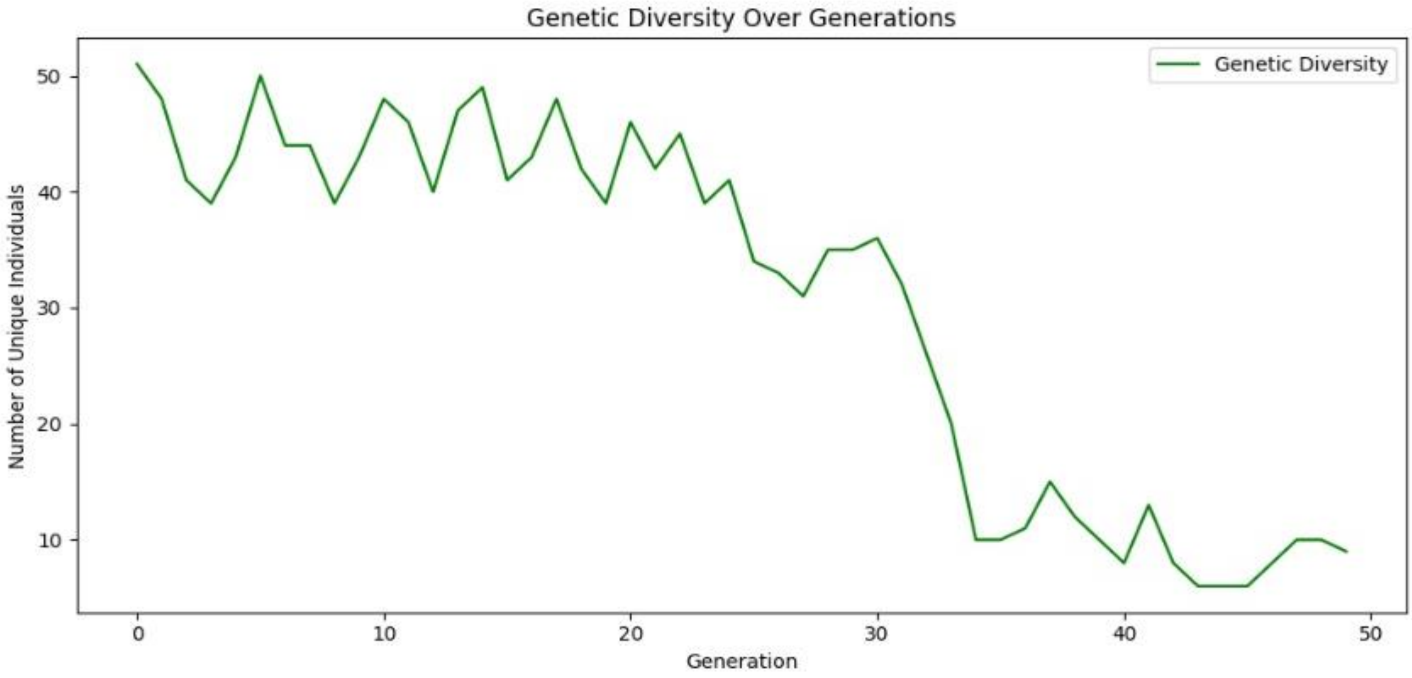

Figure 4.34: Genetic Diversity Over Generations

Overall, these results are indicative of a functioning genetic algorithm, these metrics collectively illustrate how the genetic algorithm systematically improves and refines solutions, highlighting its efficacy and efficiency in tackling complex optimization problems, It has successfully proven its capability in solving link budget problems of satellite communications effectively.

- **Mean Square Error (MSE)**

The MLP model was designed to estimate distances based on features including path loss (PL), received signal strength (RSS), signal to interference plus noise ratio (SINR), and throughput, and was initially trained with default parameters. The initial configuration of the MLP model resulted in a mean square error (MSE) of approximately 138.78 on the test set. This baseline provides a quantitative measure of model performance before parameter optimization and serves as a control to evaluate the effectiveness of GA optimization. Next, a genetic algorithm was used to optimize four critical hyperparameters of the MLP: the L2 penalty term (alpha), the momentum terms (beta_1 and beta_2), and the numerical stability term (epsilon). The algorithm was run over 10 generations with a population size of 50, including mutation and crossover operations to efficiently explore the parameter space. The optimization process led to the identification of an optimal set of parameters, which significantly improved the performance of the MLP. The best individual GA produced an average MSE of 65.27, Figure 3.35 showing a significant improvement of approximately 52.94% in error reduction compared to the pre-optimization phase. This experimental evidence supports the hypothesis that incorporating genetic algorithms for hyperparameter tuning can significantly enhance the predictive accuracy of neural network models in distance estimation tasks.

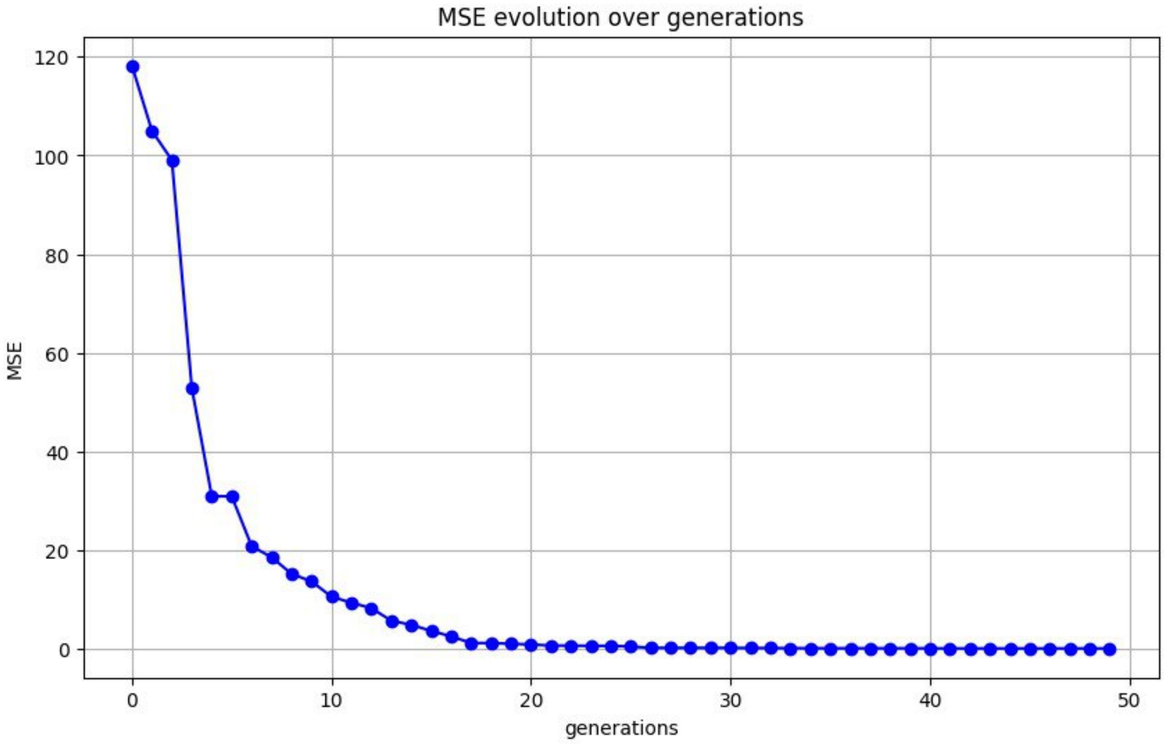

Figure 4.35: Mean Squared Error (MSE) Comparison