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Genetic Algorithm Modelling For Soft Computing Applications

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ABSTRACT

Genetic algorithms (GAs) represent a class of optimization techniques inspired by the principles of natural selection and genetics. These algorithms have gained prominence in the domain of soft computing due to their ability to efficiently solve complex problems in diverse fields. Soft computing encompasses methods that aim to handle uncertainty, imprecision, and partial truth, making it particularly suitable for real-world problems. Genetic algorithms are integral components of soft computing, where they are used for optimization, decision-making, and modeling. This paper provides an overview of genetic algorithms and their application in soft computing. It explores the fundamental concepts of GAs, their encoding techniques, and operators. Additionally, it delves into the synergistic relationship between GAs and soft computing, highlighting their joint application in areas such as machine learning, data analysis, and expert systems. This study focuses on designing a Genetic Algorithm model for finding the shortest path of a travelling salesman within cities in Nigeria. The dataset of the predefine cities was collected using Google Map. The dataset collected will be used to construct and populate the distance matrix. Genetic Algorithm was used to solve the Travelling Salesman Problem (TSP), and the Implementation was done with Java Programming Language. The result of the study was base and evaluated on two criteria; the minimum distance and computing time.

Keywords: Genetic Algorithm, Modelling, Soft Computing, Applications, Efficiency, Programming

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1. BACKGROUND OF STUDY

The field of soft computing has emerged as a response to the inherent complexities of real-world problems. Characterized by its adaptability to imprecision, uncertainty, and partial truth, soft computing encompasses a suite of computational techniques aimed at mimicking human-like cognitive processes.

Within this landscape, Genetic Algorithms (GAs) have carved a distinct niche, harnessing principles drawn from biology and natural selection to address optimization, modeling, and decision-making challenges.Genetic Algorithms, conceptualized by John Holland in the 1960s, have evolved into a robust class of optimization algorithms. They mirror the process of biological evolution, where candidate solutions to a problem are subjected to selection, reproduction, and genetic recombination. Through successive generations, these algorithms refine solutions, seeking the optimal or near-optimal outcome. GAs offers a departure from traditional mathematical optimization methods by exploring solution spaces through stochastic exploration rather than deterministic search.The resilience and adaptability of GAs have made them invaluable in a multitude of applications.

They have been employed in engineering, finance, logistics, bioinformatics, and artificial intelligence. The GAs' ability to traverse complex solution landscapes, adapt to changing environments, and incorporate domain-specific knowledge has elevated them as problem solvers in dynamic and uncertain scenarios.The synergy between GAs and soft computing is notable. While soft computing principles like fuzzy logic, neural networks, and evolutionary computation have each made significant contributions to problem-solving, their convergence enhances their problem-solving capabilities. Genetic Algorithms, with their ability to adapt and optimize, align seamlessly with the overarching philosophy of soft computing. They enable the handling of uncertainty and vagueness in a structured and efficient manner. Recent advancements in GAs focus on improving their efficiency and applicability. For instance, hybrid approaches that combine GAs with other soft computing techniques like neural networks and fuzzy logic have been developed to enhance performance and adaptability (Yang et al., 2021.

Gas are employed for feature selection, hyperparameter tuning, and evolving neural network architectures. Recent studies have shown that GAs can effectively reduce the dimensionality of datasets while preserving essential features, thus improving model accuracy and efficiency (Rastegar et al., 2023). In the face of an ever-evolving and unpredictable world, the synergy between Genetic Algorithms and soft computing provides a beacon of hope for more effective problem-solving methodologies. It opens new vistas of opportunity to address real-world challenges, fostering adaptability, optimization, and intelligence. In this study, we delve into the rich tapestry of Genetic Algorithms and soft computing, seeking to unravel the intricacies of their partnership and the transformative potential it holds for computational intelligence.

1.1 Motivation of the Study

The study is motivated by the growing complexity of real-world challenges, the need to address uncertainty, and the potential of Genetic Algorithms and soft computing to offer efficient solutions. With applications spanning multiple domains and a continually evolving research landscape, this investigation aims to unlock the transformative power of this computational partnership.

1.2 Problem Statement

1. The practical relevance of Genetic Algorithms within soft computing is a driving force for this study. It aims to uncover the tangible impact of this computational merger in optimizing industrial processes, enhancing decision-making systems, and addressing multifaceted real-world problems."

2. "Optimization underlies many critical applications, but traditional methods often struggle with high-dimensionality and non-linearity. This research examines the potential of Genetic Algorithms within a soft computing framework to enhance optimization processes."
3. Performance Comparison: "To what extent do Genetic Algorithms, when integrated with soft computing, outperform traditional optimization methods in terms of efficiency, adaptability, and robustness in complex problem-solving scenarios?

1.3 Aims and Objectives of the Study:

The overarching aim of this study is to comprehensively explore the integration of Genetic Algorithms (GAs) within the framework of soft computing and to understand how this synergy can address complex, real-world challenges. The study seeks to unravel the transformative potential of this computational partnership in the domain of computational intelligence.To achieve the aims, the following objectives are specified to;

1. Investigate the Foundations of Genetic Algorithms
2. Examine Real-World Applications
3. Evaluate Emerging Trends and Challenges.
4. Compare Performance Against Traditional Methods

1.4 Scope of the Study

The scope of this study extends to the integration of Genetic Algorithms (GAs) within the framework of soft computing, a versatile computational approach. Within this scope, we can specifically examine how GAs have been applied to address complex optimization problems, including the Traveling Salesman Problem (TSP), within the context of four cities in Nigeria. The cities are Benin City, Ikeja, Port-Harcourt and Uyo.

1.5 Research Methodology

This study employs a multifaceted research methodology to investigate the integration of Genetic Algorithms (GAs) within the framework of soft computing for optimizing the Traveling Salesman Problem (TSP) within four Cities in Nigeria. The combined methodology encompasses various approaches; problem definition, coordination of data collection of the distance matrix. Review of two existing metaheuristic algorithms and custom genetic algorithm design. It includes algorithm implementation using java programming language, rigorous evaluation, and result comparison.

2. RELATED WORKS

2.1 Introduction

Artificial Intelligence (AI) has rapidly evolved, impacting various fields including healthcare, finance, transportation, and more. This review explores recent advancements, applications, and ethical considerations in AI, drawing on literature from the past few years. Therefore, it is very necessary to review the basics of AI, generally, and Genetic Algorithms (GA), more specifically as GA has been applied during this research. This chapter identifies the different AI tools, whereas GA has been discussed in detail.

2.2 Artificial Intelligence (AI):

Artificial Intelligence (AI) is defined as the capability of a machine to imitate intelligent human behavior. This encompasses a broad range of technologies and applications that enable machines to perform tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language translation. According to recent advancements, AI systems are designed to learn from and adapt to new data, enhancing their performance over time through machine learning techniques (Russell & Norvig, 2021). The different branches of AI include Expert Systems (ES), Fuzzy Logic (FL), Artificial Neural Networks (ANN), Hybrid Systems and Genetic Algorithms (GA). Since GA has been more frequently utilized during this research, therefore, it has been further elaborated in detail, below..

2.3 Genetic Algorithms (GA)

Genetic Algorithms (GAs) are a cornerstone of soft computing techniques and have been extensively applied across various domains. This review provides an overview of recent advancements and applications of GAs within the broader context of soft computing. GA is AI methodology that is inspired by the evolution theory of Darwin. In comparatively simpler words it can be said that in GA an evolutionary process solves problems and the final result is the best (fittest) solution (survivor) or in other words, it can be said that a solution is evolved. A brief description of the natural evolution process is discussed below which would help in thoroughly understanding GA. In nature all living organisms basically consist of cells. Every cell consists of a set of chromosomes. Each chromosome, in turn, is a string of DNA and serves as a model for the whole organism. A chromosome is basically a collection of genes, where each gene can be defined as a block of DNA and encodes a particular protein.

In other words it can be said that each gene encodes a trait, for instance, the colour of eyes. The possibilities of different trait settings could be black, brown or blue. These settings are known as alleles. Every gene has a particular position in a chromosome and that position is termed as locus. As complete set of genes is called a chromosome, like wise a genome consists of a complete set of chromosomes. Whereas, a genotype is specified by a particular set of genes. It is the genotype that is mainly responsible for the after birth developments of the organism's phenotype, the different characteristics (mental & physical) for example colour of the eyes, level of intelligence, etc. Reproduction is the process during which new chromosomes are created. The first thing that occurs and is very important in the creation of new chromosomes is called crossover or recombination. During crossover genes from the parent chromosomes recombine and create new chromosomes.

The other important operator that takes place during reproduction is called mutation. During mutation, basically, a small change is incorporated in the elements of DNA. Obitko [1998] observes that errors in copying genes from parents result in these changes. Survival is the measure of fitness of an organism. Initially, Holland [1975] developed a methodology for GA that consists of a sequence of steps which are followed to move from one generation to another. In each generation the operators such as mutation and crossover are used for reproducing new chromosomes. Each chromosome's performance or suitability is measured by some fitness value. This fitness value of a chromosome serves as a basis for its selection into the next generation. Crossover is an operator during which two different chromosomes exchange their parts and hence develop offspring. Whereas, mutation is an operator during which a randomly selected gene of a chromosome is changed.

As already discussed that fitness value is the basis on which the selection of the chromosome in the next generation depends, therefore, it can be said that a fitter chromosome has more chances of getting selected in the next generation. This fitness based selection ensures that the fittest chromosomes survive through generations whereas the least fit becomes extinct. The basic requirements of GA are: a fitness function that can measure fitness of a chromosome, an encoding criterion to encode a solution of a problem, defining the different constraints and criteria for the optimum value, and finally incorporation of suitable crossover and mutation operators. GA has the ability to perform efficiently in the evolution of an optimum solution, but the major difficulty in its implementation is the encoding of a problem solution, as improper encoding may lead to a complete change in the shape of a problem (Obitko [1998], Negnevitsky [2002]). The first step in the implementation of GA is encoding i.e. the representation of a problem solution/ chromosome. Encoding is mainly dependent upon the problem to be solved

2.4 Deep Learning:

Deep learning, a subset of machine learning, has seen significant advancements, particularly in natural language processing (NLP) and computer vision. Transformer models, such as BERT and GPT, have revolutionized NLP tasks by enabling better contextual understanding of text (Vaswani et al., 2017; Brown et al., 2020). In computer vision, architectures like Vision Transformers (ViTs) have achieved state-of-the-art performance on image classification tasks (Dosovitskiy et al., 2021).

2.5 Explainable AI (XAI):

As AI systems become more complex, the need for transparency and explainability has grown. XAI aims to make AI decisions interpretable by humans. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) help in understanding model predictions, fostering trust and accountability in AI applications (Lundberg & Lee, 2017; Ribeiro et al., 2022).

2.6 Reinforcement Learning:

Reinforcement learning (RL) has made strides in both theoretical and practical applications. AlphaFold, developed by DeepMind, utilized RL to solve the protein folding problem, achieving unprecedented accuracy (Jumper et al., 2021). Additionally, RL has been applied to autonomous driving, robotic control, and game playing, demonstrating robust performance in complex environments (Silver et al., 2018).

3. METHODOLOGY

3.1 Background Knowledge

Optimization is the process of finding the best solution or outcome from a set of possible choices, with the goal of maximizing or minimizing a certain objective function while satisfying specified constraints. In other words, it involves making the most efficient use of resources or finding the best possible configuration to achieve a desired result.

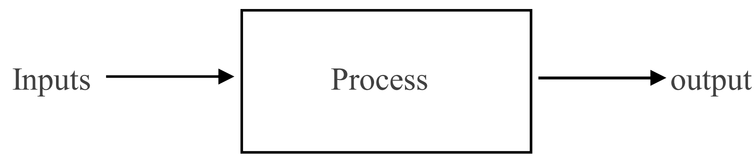

Fig 1: General Model for Genetic Algorithm

In the realm of optimization, inputs are deliberately selected to yield the most favorable outcomes. The precise interpretation of "favorable" typically involves maximizing or minimizing specific criteria determined by input variables.

3.2 Merits of Genetic Algorithm

Genetic algorithms (GAs) offer several merits, making them valuable for solving optimization and search problems in various domains. Some of the key advantages of GAs include:

1. **Global Optimization:** GAs are effective at searching large solution spaces and can find near-optimal or global solutions. They excel in scenarios where traditional gradient-based methods may get stuck in local optima.
2. **Adaptability:** GAs are highly adaptive and can handle problems with changing or dynamic landscapes. They continuously evolve and explore new solutions as circumstances evolve.
3. **Versatility:** GAs are versatile and can be applied to a wide range of problem types, from numerical optimization to combinatorial problems. They are used in engineering, economics, biology, and many other fields.
4. **Parallelism:** GAs are amenable to parallel processing, allowing multiple candidate solutions to evolve concurrently. This can significantly speed up the optimization process, especially for complex problems.
5. **Robustness:** GAs are robust in the face of noisy or imperfect data. They can handle uncertainties and variations in the input data, making them suitable for real-world applications.
6. **Exploration and Exploitation:** GAs strike a balance between exploration (searching for new solutions) and exploitation (improving known solutions). This balance enables them to discover novel solutions while refining existing ones.

3.3 Demerits of Genetic Algorithm

1. Genetic algorithms (GAs) have several limitations and potential drawbacks, which should be considered when choosing them as an optimization technique. Some of the common disadvantages or demerits of GAs include:
2. Computational Intensity: GAs can be computationally expensive, especially when dealing with large problem spaces or complex fitness functions. This can result in lengthy optimization processes.
3. Lack of Guarantee: GAs do not guarantee finding the global optimum. They are probabilistic in nature, and there's no assurance that the best solution will be discovered in a finite number of generations.
4. Parameter Sensitivity: The performance of GAs is sensitive to the choice of parameters, such as population size, mutation rate, and crossover probability. Selecting appropriate parameter values can be challenging.

5. Premature Convergence: GAs can converge prematurely to suboptimal solutions. This occurs when the population narrows its search too quickly and gets stuck in a local optimum.
6. Complexity: Implementing GAs requires a good understanding of the algorithm and careful tuning of parameters. It can be challenging for users who are new to the technique.

3.4 Algorithm For Travelling Sales Person Using Genetic Algorithms.

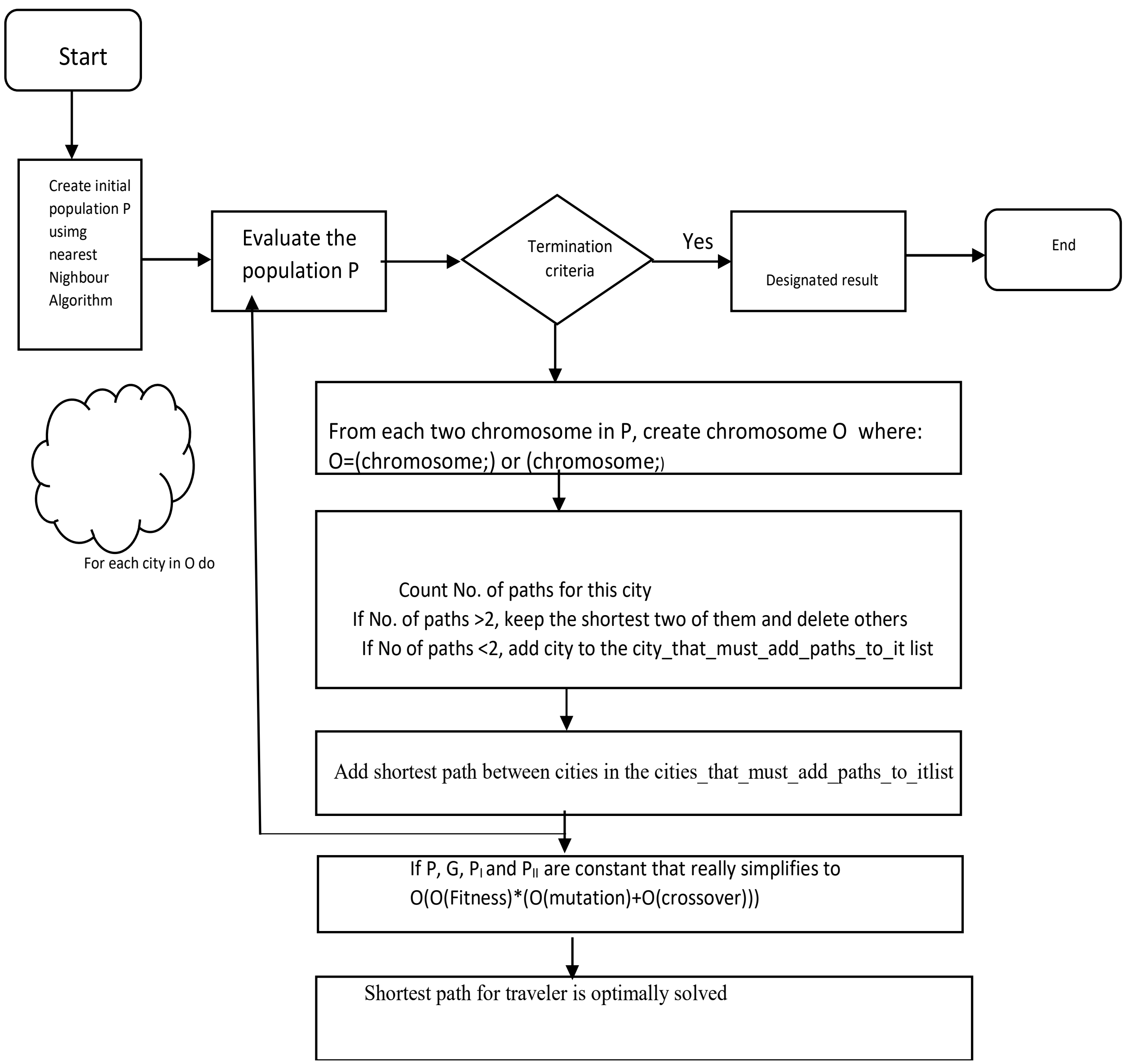

Fig 2. Traveling Sales Person Using G

4. PROPOSED GRAPHICAL MODEL FOR THE GENETIC ALGORITHM

4.1 Data Collection

In practice, it can be challenging to obtain the exact coordinates of a city or location, especially when the distance between two cities is subject to factors such as bad road networks or traffic congestion. In such cases, it may be helpful to use estimates or average values based on available data. One way to estimate the distance between two cities is to use available mapping tools such as; GPS, Google

Maps or Open Street Map can provide directions and estimated travel times based on current traffic conditions. Another approach is to use Historical Data on travel times or distance between two cities which can be collected from various sources such as; Government reports, Transportation Authorities or commercial database. For this research, the primary source of data will be Google map, this is because of its ability to give current and accurate distances between location base on current traffic condition. Construct a distance matrix for the TSP problem with 4 cities (A, B, C, D), we use the steps;

1. Define the sets of objects: {A,B,C,D}
2. Obtain the distance between each object using Google Map.

No	City	Code
1	Benin City	A
2	Ikeja	B
3	Port-Harcourt	C
4	Uyo	D

No	Code City	Distance
1	A – B	305km
2	A – C	277km
3	A – D	358km
4	B – C	579km
5	B – D	656km
6	C – D	125km

Genetic Algorithm will be used to solve the Travelling Salesman Problem (TSP), and the Implementation will be done with Java Programming Language.

4.2 Results

City Indices:
We use 0 to represent A, 1 to represent B, 2 to represent C, and 3 to represent D.
Shortest route: [0, 2, 3, 1, 0]
Minimum distance: 1363
A-B= 305, B-D=656, C-D is same as D-C=125, C-A is same as A-C=277
A – C=277, C – D=125, D- B= 656, B – A=305

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Therefore; 277+125+656+305=1363

The Shortest and best route is Benin City ⟶ P/H ⟶ Uyo ⟶ I keja ⟶ Benin City

The result of this test shows that the shortest possible path to visit each of the four (4) cities once is [0, 2, 3, 1, 0] which corresponds to the cities as: Benin City, P/H, Uyo, Ikeja, Benin City. The result of this test shows that the shortest possible path to visit each of the four (4) cities once is [0, 2, 3, 1, 0] which corresponds to the cities as: Benin City, P/H, Uyo, Ikeja, Benin City

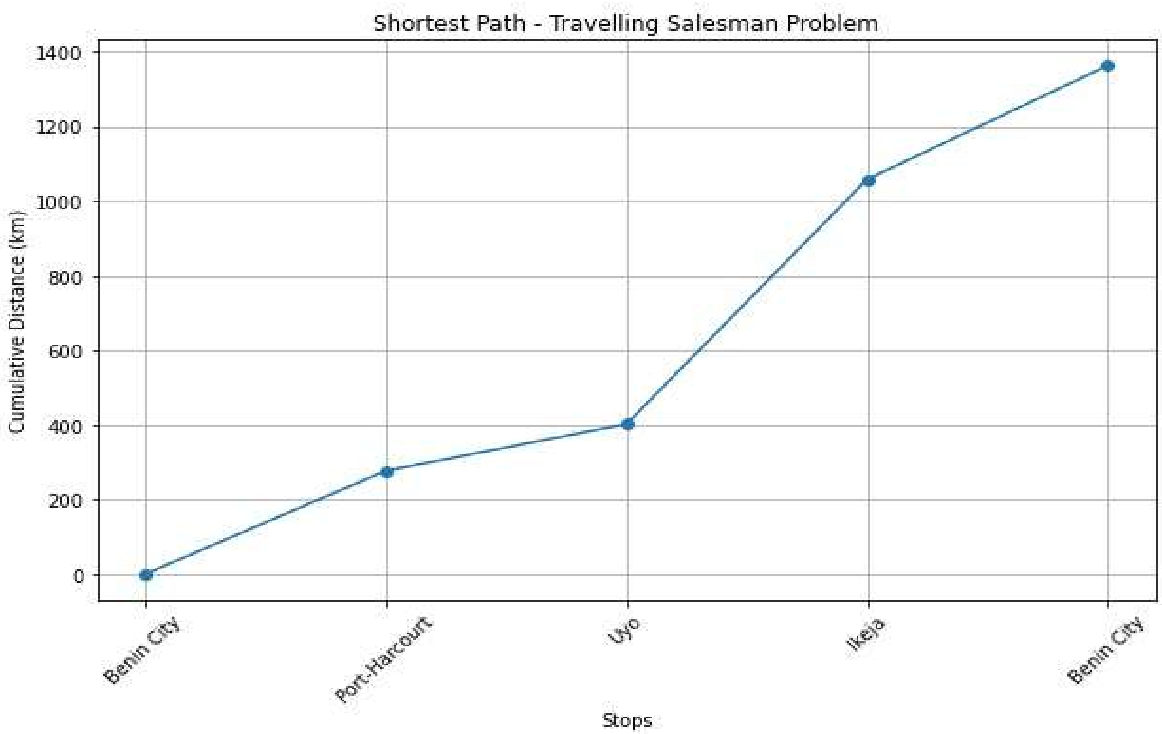

Fig 3: Shortest Path Travelling Salesman Problem

5. RECOMMENDATION

To make improvements to the software system, some work will be necessary in order to make the application more flexible for researchers or students to understand the concepts of the genetic algorithm. The future tasks involve implementation of more selection criteria and a different crossover method. This will make the application more usable. Also, the transformation of the software into an android or iPhone application will be of good future use. Since almost everyone works with a phone, this will encourage the students to play more with it.

6. CONCLUSION

This research paper presented software that solves the travelling salesman problem using the concept of genetic algorithm using java-programming language. The application produced an optimum solution to the different sets of problems

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