

A Comparative Review Between Various Selection Techniques In Genetic Algorithm For Finding Optimal Solutions

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Abstract— Genetic algorithms (GA) is an optimization search algorithm which follows the theory of "survival of the fittest" formulated by Darwin. Genetic algorithm mimics the process of natural selection where to produce every subsequent generation the individuals that have the highest fitness value among the current population are selected. This paper focuses on the selection stage and provides a comparative analysis of the different selection techniques that have been used in GA. This review also contains a brief coverage of the various study fields related to genetic algorithm along with future research directions. The most interesting genetic algorithms among the research community and their selection approaches have been selected for investigation. New as well as sophisticated researchers dealing with NP-hard problems where selection strategy plays crucial role are provided with an accurate comparison of selection techniques in light of GA's state-of-the-art applications. The implementation of well-known algorithms is shown, along with the benefits and drawbacks of each.

Keywords— Genetic Algorithm, Selection Technique, Tournament Selection, Ranked Based Selection, Truncation Selection, Optimal Solution, Roulette Wheel Selection

I. INTRODUCTION

Genetic Algorithms (GA) are stochastic, search-based optimization methods derived from the theory of evolution, genetics and natural selection that mimic Darwin's theory of "survival of the fittest" [1]. GA is widely utilized to spawn high-quality solutions for difficult problems that would otherwise be intractable in real time. Most genetic algorithm solutions go through a series of genetic operations such as mutation, crossover, and selection [2]. This theory was introduced by John Holland in unison with his students and colleagues at the College of Michigan [3].

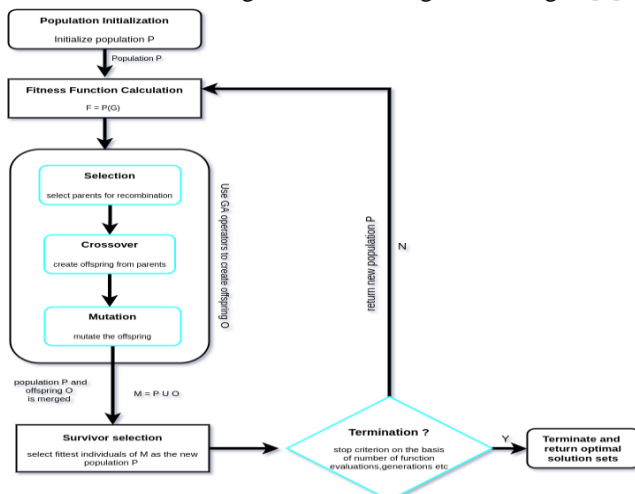


Figure 1 Framework of Genetic Algorithm

In this algorithm, first a population P, containing a randomly generated solution sets is obtained. Then each solution is represented in the most appropriate way for the problem. Example: binary representations, integer representations, real-valued representations, etc.

Then, each possible solution is tested against the problem and evaluated using a fitness function, i.e., $F=P(G)$. Followed by, a series of genetic operators namely parental selection, crossover, and mutation, are applied to the population to generate a second generation of solutions $M=P \cup O$. Biologically inspired reproduction methods are usually based on two parents, but some studies have shown that more two "parents" produce better quality chromosomes [4]. The previous two steps are repeated until an acceptable solution is found or the algorithm completes its iterations over a specified number of cycles or generations.

The selection method is a crucial part of the GA algorithm. Hence, the motivation of this paper is to provide a detailed analysis of the different selection techniques that have been experimented with in the past so as to provide an enthusiast a jump start with the most appropriate selection technique for the GA process. Therefore, the paper focuses on a comparative analysis of various selection techniques.

The GA algorithm

The steps involved in genetic algorithm can be summed up by the following algorithm [5].

```
Genetic_Algorithm()
  initialize population
  fitness calculation for populations

  while (termination criteria) do
    parent selection
    crossover with probability pc
    mutation with probability pm
    decode and fitness calculation
    survivor selection
    find best_offspring
  return best_offspring
```

Population Initialization

Population Initialization means the formation of an initial population P. Initialization can generally be done in two ways:

- Randomly initialized - the initial population is populated by using completely random solutions
- Initialization using Heuristics – the initial population is initialized with a set of known heuristics for problem [6].

The size of the initial population is usually determined by the nature of the problem, but typically a population contains several hundred or thousand possible solutions, and traditionally random initialization is used to cover the entire range of entire possible solutions. Only occasionally are solutions seeded for areas where optimal solutions are mandatory [7].

Fitness function calculation

A fitness function is used to evaluate the solution domain. It simply takes the candidate solution and produces an output that can be evaluated to check how suitable the solution is for the considered problem [8]. The following characteristics may be present in a fitness function:

- The calculation of fitness value should be sufficiently fast as it need to be repeatedly done.
- How individuals that are best suited can be generated from the given solution ought to be quantitatively measured.

The GA operators

A. Parent selection

It is the first operator applied to the population. Since natural selection is the main inspiration of this phase for the GA, in this phase of a genetic algorithm individual genomes are chosen from a population for subsequent breeding. It selects chromosomes from the population of parents to cross and produce offspring. This process determines the individuals to be chosen for mating and the number of offsprings these individuals produce. The selection strategy follows the principle 'the better is an individual; the higher is its chance of being parent.' [9]

In the selection process, the fitness value of the process solutions is used to select them. The chances of selection increases according to how high the fitness value is. After the solutions are selected, they are mated and produce new offspring. A solution with a lower than average fitness value has a lower chance of mating and will not produce any offspring [10]. So we have to choose the best selection method. Some of the selection methods are:

- Tournament Selection
- Roulette Wheel Selection
- Ranked Based Selection
- Stochastic Universal Sampling (SUS)
- Truncation Selection

B. Crossover

In a GA, to generate offspring, selected individuals of the current population are recombined and modified. In the process of crossover, two new children are created from two parent strings. This happens by copying selected bits from each of the parent. The bit at position "I" in each offspring is copied from the bit at position "I" in either parent. To indicate which parent contributes the bit at position "i", there is a string called the crossover mask. The three types of crossover operators are one-point, two-point, and uniform crossover operator [11].

C. Mutation

Mutation is the second most important operator in reproduction. Mutation operators interfere with the solution in process altering it. Such alteration is arbitrary, it does not follow any definite set of rules. The intensity of this perturbation is known as the mutation rate. Mutation rates are also known as step sizes in continuous solution spaces [12]. Mutation operators have three major requirements which are reachability, unbiasedness, and scalability.

Survivor selection

This process selects the individuals that are to be moved to the next generation and eliminates the unfit individuals. This step plays a crucial role in GA as it must be ensured that only unfit individuals are kicked out and fit individuals are correctly selected for the next generation, all this while maintaining diversity in the population [13].

The simplest way might be to kick out individuals from the population in random order, but doing so usually results in convergence issues. Hence, the following different kinds of strategies are used.

- Selection Based on Age
- Selection Based on Fitness

Termination

Termination algorithm defines whether the GA has met the termination condition. This process of evolution will continue unless and until a termination condition is fulfilled [14]. The following are common termination circumstances:

1. When the population has not improved after 'n' iterations,
2. When the number of generations reaches a specific point,
3. A solution found satisfy minimum criteria,
4. Allocated budgets reached,
5. Manual inspection,
6. Combination of the above.

This main objective of this paper is to present the workings of several selection procedures, as well as their benefits and drawbacks, as well as a comparison of them. This paper is further organized in the following way: Section II presents the prior related work completed by the researcher to employ numerous methods of selection. Section III presents different selection strategies like tournament selection, roulette wheel, ranked based selection. Section IV compares these selection strategies based on the prior study work. Finally, the conclusion and references are drawn in sections V and VI respectively.

II. PREVIOUS WORK ON SELECTION TECHNIQUE

In Genetic Algorithm, the most crucial stage is determining the appropriate selection method. Since the inception of this idea, different researchers have examined the effectiveness of GA applying various selection methods. GA performance is commonly measured by the convergence rate and the number of generations needed to reach the ideal solution. In this section, we have summarized the important prior research on various selection approaches.

Jang Sung Chun [15] first explored a unique way to use the genetic algorithm as a means of searching for optimization issues (1998). The effectiveness of the GA was determined by comparing it to evolutionary algorithms on a variety of optimization issues.

Mashohor et al. [16] contrasted three selection methodologies, including the deterministic, tournament, and roulette wheel for assessing the effectiveness of the PCB inspection system. Among the three approaches, Deterministic selection was discovered to have the capacity to provide the highest levels of fitness, computational efficiency, and precision in the fewest number of generations. The roulette wheel and tournament selection come next.

Using a variety of mathematical fitness functions, Jadaan et al. [17] weighed up the outcomes of genetic algorithm using a proportional roulette wheel and a rank based roulette wheel selection method and discovered that rank based bettered proportional in terms of the number of offspring generations needed to arrive at the best solution. They noticed rank based roulette wheel outperforms a proportional roulette wheel in terms of steadiness, speed, certainty, and robustness toward the best solutions.

Madureira [18] developed a coordinating mechanism and suggested GA as a way to solve scheduling issues that

arise in the actual world. Delivering goods on time and ensuring efficient production management are challenging issues because of how frequently dynamic circumstances change. The purpose of scheduling is to establish an optimal allocation schedule that maximizes a particular performance metric by allocating a group of machines with certain work. The order crossover operator and natural representation are utilized to encode the answers for the implementation problems. They employed the inversion mechanism as the operator for mutation. Last but not least, Madureira et al. used a collection of static scheduling strategies to solve the dynamic scheduling problem and demonstrated the viability of GA in Job-shop scheduling program.

In order to compare the effectiveness of two kind of Rank Based Selection prospect, which are Linear Ranking and Exponential Ranking prospect, with the two kind of Tournament Selection, which are 2-Tournament Selection without replacement and K-Tournament Selection with replacement, Julstrom [19] took computational time into consideration. It was discovered through investigation that Tournament Selection is favored than Rank Based Selection. The rationale is that selecting players through a series of tournaments is far quicker than sorting the population to give Rank Based probabilities.

Pandey et al. [20] differentiated three different Selection Techniques: Ranked Based, Roulette Wheel, and Tournament Selection technique. He evaluates performance of the Traveling salesman problem (TSP). It was found that Ranked Based selection performs well for the TSP problem, which is followed by Tournament selection and Roulette Wheel selection.

Zhong et al. [21] gave a comparison of selecting methods. The research looked at the Tournament and Roulette wheel selection. To carry out the experimentation, seven distinct Test Functions were considered and found that in terms of convergence, Tournament based SGA has higher efficiency than Roulette Wheel based SGA.

Champlin et al. [22] compared four selection techniques namely Roulette Wheel, SUS, Tournament selection, and Truncation selection to determine the performance of genetic sentences problem and prisoner's dilemma problem. It was found that tournament selection performs best for these two problems.

Shukla et al. [1] had compared four selection techniques namely Exponential Ranking Selection, Proportionate Roulette Wheel Selection, Linear Ranking Selection and Tournament Selection. Where it was found that Tournament Selection was determined to be better in terms of time complexity and convergence rate than other selection strategy.

Miller et al. [23] only focused on Tournament Selection on all types of data like Deterministic Environments, Noisy environments and concluded that the model was verified to

be accurate for predicting the convergence rate under a wide range of levels and tournament sizes.

III. SELECTION STRATEGY

Selection refers to the process of choosing the parents who will reproduce to produce offspring for future generations. Selection is such an important component of genetic algorithms that gaining a greater grasp of its understanding will only help improve the field [24]. The selection procedures decide who will be matched and how many children each person will have. 'The better an individual is, the greater is its likelihood of being a parent,' is the primary tenet of the selection technique. [25]. The selection operator's main goal is to promote excellent solutions and eradicate poor solutions by keeping the population size constant.

A. Roulette Wheel Selection (Fitness Proportionate Selection)

Roulette Wheel Selection is one of the early genetic algorithm selection approaches where individuals are chosen based on their proportionate probability to their fitness value. It works on the same premise as a roulette wheel. In a roulette wheel, the odd of choosing a segment is related with the magnitude of the segment's center angle. In this procedure, in accordance with their fitness values all entities are placed to a roulette wheel where the fitness values are proportionate with the amount of the sector. The likelihood of selecting a particular entity depends on how fit they are. Each individual choice represents a certain area of the roulette wheel [25]. Following that, the wheel is rolled. The entity who correlates to the point where the roulette wheel comes to a halt is chosen. The procedure is repeated until the termination requirements are met. It has the potential to overlook a population's best individuals. The major advantage of this process considers all possible individuals and preserves the diversity in the population. Its major disadvantage is that it gives excessively high value to some individuals that increases the change of loss of diversity of some lowered numbered individuals [9].

Pseudocode

```
While population size < pop_size do
  Generate Cumulative fitness, total fitness and sum of proportional fitness(sum)
  Spin the wheel pop_size times
  If Sum<r then
    Select the first chromosome,otherwise,select jth chromosome
  End If
End While
Return chromosomes with fitness value proportional to size of selected wheel selection
End
```

Table 1 Roulette Wheel Selection - Parent Selection

Chromosome	Fitness Value	Rank
Chromosome A	9.1	6
Chromosome B	4.1	4
Chromosome C	2.3	3
Chromosome D	2.1	2
Chromosome E	5.1	5
Chromosome F	1.2	1

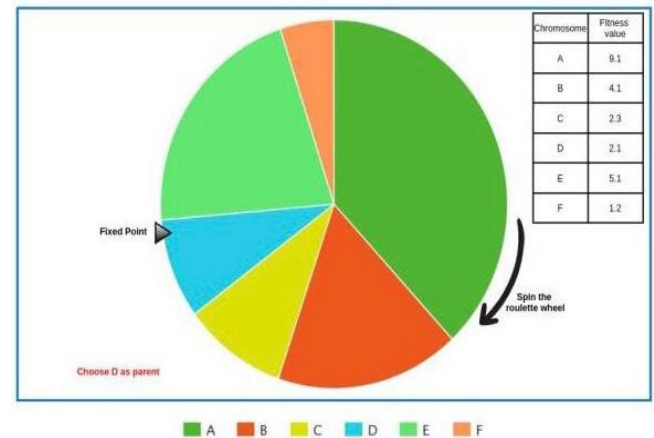


Figure 2 Roulette Wheel Selection

From fig 2, we can see that roulette wheel selection does not work on negative fitness value. Time complexity of Roulette Wheel is $O(n^2)$ steps since it needs 'n' number of turns to fill up the population of one generation [10].

B. Rank Based Selection

Ranking Selection was introduced for eliminating the certain disadvantages present in Roulette Wheel Selection. When it comes to the roulette wheel, the regions are based on the fitness value of the candidate, which means that candidates with higher fitness values have higher occurrence due to more significant regions. It means other candidates could not be selected frequently, resulting in less diversity. So, to overcome this issue, ranking process is categorized into two processes. Firstly, sorting the population and assigning the ranks in order corresponding proportionate selection. The chromosome with minimal fitness value is given rank '1' followed by the comparatively higher and so on. The top ranking is given to the chromosome having the top fitness value [26].

Pseudocode [9]

```
While population size < pop_size do
  Sort population according to rank
  Assign fitness to the individuals according to linear rank function
  Generate pop_size random number(r)
  Calculate Cumulative fitness, total fitness and sum of proportional fitness(sum)
  Spin the wheel pop_size times
  If Sum<r then
    Select the first chromosome,otherwise,select jth chromosome
  End If
End While
Return chromosomes with fitness value proportional to size of selected wheel selection
End
```

Table 2 Rank Based Selection - Parent Selection

Chromosome	Fitness Value	Rank
Chromosome A	9	6
Chromosome B	8.9	3
Chromosome C	8.95	5
Chromosome D	8.85	1
Chromosome E	8.92	4
Chromosome F	8.89	2

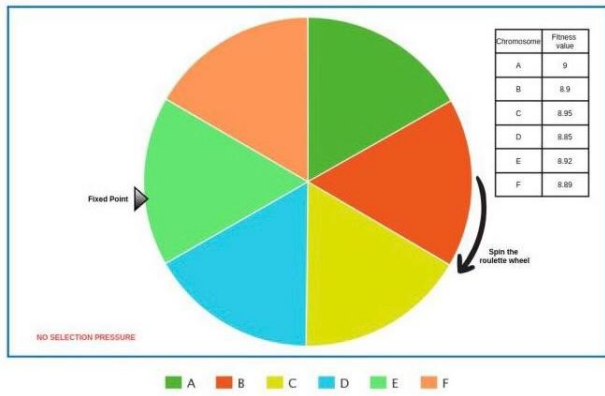


Figure 3 Rank Based Selection

Now, each region will have an equal region resulting common occurrences for all. It is advantageous when the individual in the population has a very comparable fitness value. The Ranked Based Selection have time complexity of $O(n \log n)$.

C. Tournament Selection

Tournament selection is one of the most efficient and straightforward genetic algorithm selection process. From the entire population, 'K' number of individual is chosen at random to participate in the competition. Then, these individuals compete with one another. The winner is selected for additional selection process of GA by determining the highest fitness value. It performs excellent when the tournament size is binary [27]. The tournament size is the number of individuals who are participated in every tournament set. The bigger the tournament size, the greater the possibility of losing variety. Tournament selection has a time complexity ranging from $O(K)$ to $O(K^2)$ depending upon the number of such competitions required [1].

Pseudocode [10]

```
P is population, t is tournament size
For cur=1 to mpoolno
  Begin
    Pick t individuals randomly from P
    Select best of t individuals depending on their fitness value and store in s1
    mpool(cur)=s1
    cur=cur+1
  End
```

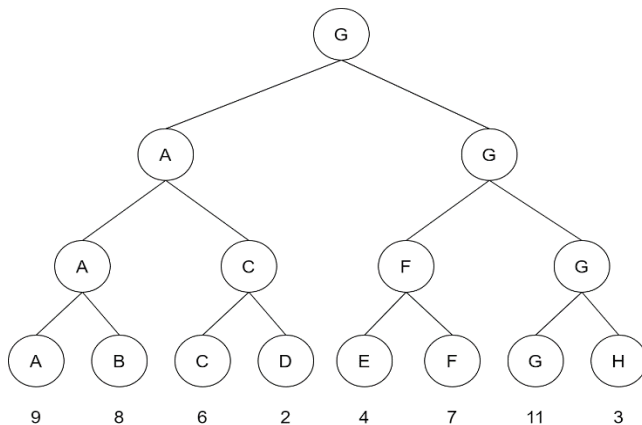


Figure 4 Tournament Selection

D. Stochastic Universal Sampling (SUS)

SUS is analogous to Roulette Wheel Selection, except that as a substitute of possessing single fixed point, it has a number of them. As a result, a single wheel spin selects all the parents. Furthermore, such a system encourages extremely fitting entities to be selected at a minimum of one time. SUS requires a single run around the list to complete after computing the total of the function values, giving it an $O(n)$ time complexity [10].

```
Set l=1, j=1
μ=F/N
While l <= mpool
  begin
    generate random number r between interval (0, μ)
    While r <= fitness[i]
      begin
        select[l]=parent[i]
        r=r+1/μ
      end
      l=l+1
    end
```

Table 3 Stochastic Universal Sampling - Parent Selection

Chromosome	Fitness Value	Rank
Chromosome A	9.1	6
Chromosome B	4.1	4
Chromosome C	2.3	3
Chromosome D	2.1	2
Chromosome E	5.1	5
Chromosome F	1.2	1

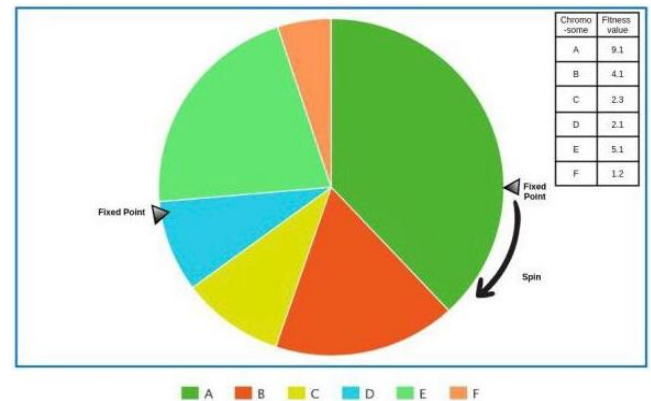


Figure 5 Stochastic Universal Sampling

E. Truncation Selection

The final and simplest selection algorithm is truncation selection. In truncation selection, the population is classified based on their fitness level and then a smaller fraction of the population is eliminated [28]. The following is the pseudo-code for truncation selection. Population sorting determines the temporal complexity of Truncation Selection. Using the optimal sorting algorithm, such as merger sort or heap sort, guarantees that the time complexity is $O(n \log n)$. As a result, Truncation selection is one of the quickest selection algorithms [29].

Pseudocode [10]

```
Input : Population P, Truncation Threshold T 0,1
Truncation(P, T, N)
Sort(P) according to fitness with worst individual at first position
For i=1 to N do
  Begin
    R= random((1-T).N,N)
    Select=P( r)
  End
```

IV. COMPARISON BETWEEN DIFFERENT SELECTION TECHNIQUES

Table 4 Comparison among various selection techniques

Citation	Published Year	Author	Factor Consider For study	Selection Technique	Observation
[20]	2016	Hari Mohan Pandey	Traveling salesman problems (10 sample)	Roulette Wheel, Ranked Based Selection, and Tournament Selection	Ranked based selection has a higher performance than roulette wheel and tournament selection.
[21]	2005	Xiaomin Hu, Jinghui Zhong, Min Gu and Jun Zhang	Normal seven test function	Roulette Wheel and Tournament Selection	Tournament Selection outperforms Roulette Wheel Selection in terms of convergence.
[22]	2018	Ryan Champlin	Genetic sentences problem	Fitness proportional, SUS, Tournament Truncation Selection	SUS fitness proportionate and truncation outperform tournament selection
[22]	2018	Ryan Champlin	Prisoner's dilemma problem	Fitness proportional, SUS, Tournament Truncation Selection	Tournament Selection perform better than other selection technique
[24]	1991	David Goldberg Kalyanmoy Deb	Time computation, Equations technique, growth ratio estimate	Fitness proportional, tournament and Ranked-based selection	Fitness proportional selection is significantly slower than other selection and tournament selection shows higher growth ratio.
[30]	2013	Tarun Varshney, Aishwary Katiyar, Pankaj Sharma	Optimum and reliable route in wired network	Roulette Wheel, Elitism, Ranked-Based and Tournament Selection	In different situations, tournament selection and rank-based selection are the best options and for convergence criteria tournament selection perform better.
[9]	2011	Noraini Mohd Razali, John Geraghty	Traveling salesman problems	Proportional Roulette Wheel, Tournament selection	Tournament selection is better suited to small-scale problems, whereas a rank-based roulette wheel can be utilized to address larger-scale problems.
[5]	2013	Denny Hermawanto	Mathematical Equality Problem	Roulette Wheel selection	Roulette wheel selection is able to solve simple Mathematical Equality Problem.
[31]	2011	Chetan Chudasama, S. M. Shah, Mahesh Panchal	Traveling salesman problems	Roulette wheel Selection, Tournament Selection and Elitism selection method.	Elitism method have produced more fit generation of population compared to Roulette Wheel and Tournament Selection.
[32]	1994	Sami Khuri, Thomas Back, Jorg Heitkotter	0/1 multiple knapsack problem	Proportional Selection	GA with proportional selection can tackle highly constrained NP-complete problems like 0/1 multiple knapsack problem.
[33]	1995	Ravindra K. Ahuja, James B. Orlin, Ashish Tiwari	Quadratic Assignment Problem	Tournament Selection	Tournament selection slightly helps in upgrading the quality of the individuals.

V. CONCLUSION

This paper provides a comparative review of GA selection techniques including an overview of GA. Among all the steps in the Genetic Algorithm, the selection strategy plays

a vital role in generating the offspring and diversifying the entire population to a new and better scope. We have contrasted different types of selection techniques to find optimal solutions for a problem. This comparative analysis concludes that Tournament Selection with the binary size is

dominant in terms of time complexity and convergence rate for most cases, followed by ranked-based selections, SUS, Roulette wheel, and Truncation Selection. Though Tournament Selection has outperformed other selection techniques most of the times, Elitism wheel method has generated very fit population generation compared to tournament and Roulette wheel in some cases. This paper can further serve as a means in reducing complexities of NP-Hard problems for upcoming researchers. Nevertheless, selection technique in GA being a vast topic to explore, the research to find the optimal solution in GA is still wide open.

REFERENCES

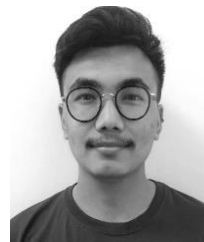
- [1] A. Shukla, H. M. Pandey, and D. Mehrotra, "Comparative review of selection techniques in genetic algorithm," in *2015 1st International Conference on Futuristic Trends in Computational Analysis and Knowledge Management, ABLAZE 2015*, pp. 515–519, Jul. 2015.
- [2] S. Katoch, S. S. Chauhan, and V. Kumar, "A review on genetic algorithm: past, present, and future," *Multimed Tools Appl*, vol. 80, no. 5, pp. 8091–8126, Feb. 2021.
- [3] J. H. Holland and J. H. Holland, "GENETIC ALGORITHMS AND ADAPTATION ABSTRACT."
- [4] R. Vankudoth, P. Shireesha, and T. R. Devi, "A Model of System Software Components Using Genetic Algorithm and Techniques International Journal of Advanced Research in Computer Science and Software Engineering A Model of System Software Components Using Genetic Algorithm and Techniques," 2016.
- [5] D. Hermawanto, "Genetic Algorithm for Solving Simple Mathematical Equality Problem."
- [6] S. Sangwan and A. Dahiya, "Literature Review on Genetic Algorithm International Journal of Research Literature Review on Genetic Algorithm," 2018.
- [7] M. Kumar, M. Husian, N. Upreti, and D. Gupta, "GENETIC ALGORITHM: REVIEW AND APPLICATION."
- [8] O. Kramer, "Studies in Computational Intelligence 679 Genetic Algorithm Essentials."
- [9] S. I. Ao and International Association of Engineers., *World Congress on Engineering : WCE 2011 : 6-8 July 2011, Imperial College London, London, U.K.* Newswood Ltd., 2011.
- [10] "Chapter 6: SELECTION 6.1 Introduction."
- [11] I. Editor, J. Parag Meht, D. M. Rat hod, L. Haldurai, T. Madhubala, and R. Rajalakshmi, "A Study on Genetic Algorithm and its Applications Related papers Effect of Genetic Algorithm on Artificial Neural Network for Intrusion Detection System IJCSE Editor A review: accuracy optimization in clustering ensemble using genetic algorithms Norwati Mustapha Detection of Cyber Attack Using Artificial Intelligence Based Genetic Algorithm With Feedback Ingestion... A Study on Genetic Algorithm and its Applications," 2016.
- [12] F. Alisherov, D. Bhattacharyya, D. M. Mukhopadhyay, M. O. Balitanas, A. Farkhod, and S.-H. Jeon, "Genetic Algorithm: A Tutorial Review A review on bio medical image processing View project software testing View project Genetic Algorithm: A Tutorial Review," 2009.
- [13] T. v Mathew, "Genetic Algorithm."
- [14] E. Elamin and E. Ali, "A Proposed Genetic Algorithm Selection Method."
- [15] Institute of Electrical and Electronics Engineers and Manav Rachna International Institute of Research and Studies, *Proceedings of the International Conference on Machine Learning, Big Data, Cloud and Parallel Computing : trends, perspectives and prospects : COMITCON-2019 : 14th-16th February, 2019*.
- [16] S. Mashohor, J. R. Evans, and T. Arslan, "Elitist Selection Schemes for Genetic Algorithm based Printed Circuit Board Inspection System."
- [17] O. al Jadaan, L. Rajamani, and C. R. Rao, "IMPROVED SELECTION OPERATOR FOR GA," 2005.
- [18] A. Madureira, C. Ramos, S. Do, and C. Silva, "A Coordination Mechanism for Real World Scheduling Problems Using Genetic Algorithms."
- [19] B. A. Julstrom, "It's All the Same to Me: Revisiting Rank-Based Probabilities and Tournaments."
- [20] H. M. Pandey, "Performance Evaluation of Selection Methods of Genetic Algorithm and Network Security Concerns," in *Physics Procedia*, Vol. 78, pp. 13–18, 2016.
- [21] Z. Jinghui, H. Xiaomin, G. Min, and Z. Jun, "Comparison of performance between different selection strategies on simple genetic algorithms," in *Proceedings - International Conference on Computational Intelligence for Modelling, Control and Automation, CIMCA 2005 and International Conference on Intelligent Agents, Web Technologies and Internet*, Vol. 2, pp. 1115–1120, 2005.
- [22] R. Champlin, "Selection Methods of Genetic Algorithms," 2018.
- [23] B. L. M. Ille R ' and D. E. Goldberg, "Genetic Algorithms , Tournament Selection, and the Effects of Noise," 1995.
- [24] D. Thierens and D. Goldberg, "Convergence Models of Genetic Algorithm Selection Schemes."
- [25] G. Gobind Singh, A. K. Sohal, S. Lata Yadav, A. Sohal, and S. Lata Yadav Asha Sohal Assistant Professor Associate Professor, "Comparative Study of Different Selection Techniques in Genetic Algorithm Congestion Control mechanism for Wireless Sensor Networks View project Load balancing with efficient energy over fog-cloud networks View project Saneh Lata Yadav Comparative Study of Different Selection Techniques in Genetic Algorithm," 2017.
- [26] K. Jebari and M. Madiafi, "Selection Methods for Genetic Algorithms Smart cities View project fuzzy clustering techniques View project Selection Methods for Genetic Algorithms," *Int. J. Emerg. Sci*, Vol.3, no.4, pp. 333–344, 2013.
- [27] F. Tan, X. Fu, Y. Zhang, and A. G. Bourgeois, "A genetic algorithm-based method for feature subset selection," in *Soft Computing*, Vol. 12, no. 2, pp. 111–120, Jan. 2008.
- [28] J. F. Croyt and M. Kimurat, "Efficiency of truncation selection* (rank-order selection/fitness potential/mutation load/viability/fitness)," 1979.
- [29] V. Ducroco and R. L. Quaas, "Prediction of Genetic Response to Truncation Selection Across Generations," *J Dairy Sci*, Vol. 71, no. 9, pp. 2543–2553, 1988.
- [30] T. Varshney, A. Katiyar, and P. Sharma, "A Comparative Analysis of Selection Schemes of Genetic Algorithm to Find an Optimum and Reliable Route in Wired Networks," *IJRIT International Journal of Research in Information Technology*, Vol.1, no. 4, 2013.
- [31] C. Chudasama, S. M. Shah, M. Panchal, and A. Processor, "Comparison of Parents Selection Methods of Genetic Algorithm for TSP."
- [32] S. Khuri, T. B. / Ick, and J. Heitkötter, "The Zero/One Multiple Knapsack Problem and Genetic Algorithms."
- [33] K. C. Tan, T. H. Lee, Y. H. Chew, and L. H. Lee, "A Hybrid Multiobjective Evolutionary Algorithm For Solving Truck And Trailer Vehicle Routing Problems."

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Sagar Phuyal received a bachelor's degree in computer science and Engineering with Deans List from Nepal Engineering College, Pokhara University, Nepal. He is currently working at Infodevelopers as Data Engineer and DBA in Nepal. He has experience of almost 3 years as Data Engineer. He is currently exploring the different concepts of Deep Learning and Machine Learning.



Aparana Pant graduated with a Bachelors Degree in Computer Science and Information Technology from Sagarmatha Collge of Science and Technology, Tribhuvan University, Nepal. She is currently working as a Software developer in Jeevee Health Pvt.Ltd. Having worked as a python developer for about a year, she has developed a keen intrest in ML and is currently exploring the the basic concepts of machine learning.

