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HYBRID SIMULATED ANNEALING: A POWERFUL APPROACH FOR OPTIMIZING THE 0-1 KNAPSACK PROBLEM

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ABSTRACT

0-1 Knapsack Problem is a well-known NP hard problem, where a set of items each with a weight and a value have to be selected to maximize the total value while not exceeding a given capacity constraint. Finding optimal solution for large instances of knapsack problem becomes computationally infeasible. Hybrid approaches, like combining genetic algorithm with simulated annealing, aim to leverage the strengths of both techniques to tackle the knapsack problem more efficiently and to improve the quality of solutions obtained within reasonable computational time. The results reveal that the average profit gained using hybrid approach outperforms the profit gained using simple genetic algorithm. This hybrid approach utilize the strengths of both algorithms, thus enhances scalability to efficiently handle complex instances of the problem. This approach provides valuable insights into algorithm design principles by showcasing the benefits of combining exploration and exploitation strategies to achieve improved optimization outcomes. Eventually, the hybrid approach presents a promising advancement in optimization algorithm with practical applications and theoretical contributions to the field.

Keywords: Combinatorial Optimization, Knapsack Problem, Memetic Algorithm, Optimization, Simulated Annealing.

1. INTRODUCTION

The optimization of combinatorial problems has long been a central focus of research in the fields of computer science and operations research. Combinatorial problems involve finding the best combination or arrangement of elements from a given set to achieve an optimal outcome based on specific criteria. Among these challenges, the Knapsack Problem (KP) stands out as one of the most well-known and challenging ones. The Knapsack Problem can be visualized as a scenario where a knapsack has a limited carrying capacity, and there is a set of items, each with its respective weight and value. The goal is to determine which items to select and place in the knapsack, aiming to maximize the total value of the chosen items while ensuring that the total weight does not exceed the knapsack's capacity. Despite its simple formulation, the Knapsack Problem is known to be NP-hard, which means that finding an optimal solution through an exhaustive search becomes impractical for large instances. As a result, traditional methods that involve exploring all possible combinations are not scalable and often fail to find high-quality solutions within a reasonable timeframe. To address these challenges and improve the efficiency of solving the Knapsack Problem, researchers have explored various optimization techniques. One approach involves combining Genetic Algorithms (GA) and Simulated Annealing (SA) into a hybrid method. Genetic Algorithms are inspired by the process of natural selection and evolution, simulating the genetic traits of potential solutions and using genetic operators like crossover and mutation to evolve better solutions over successive generations. Simulated Annealing, on the other hand, is a probabilistic optimization technique that simulates the annealing process in metallurgy. It allows the algorithm to accept "bad" moves early on to explore a wide range of solutions, gradually reducing this acceptance probability as the optimization process progresses. However, the traditional implementations of these methods may still have limitations in terms of solution quality and scalability. Hence, researchers have introduced the concept of Adaptive Simulated Annealing (ASA) into the crossover phase of the Genetic Algorithm. ASA dynamically adjusts the annealing schedule based on the algorithm's performance during optimization. This adaptive nature allows the algorithm to balance exploration and exploitation more effectively, potentially leading to improved convergence and higher-quality solutions. By combining the strengths of Genetic Algorithms and Simulated Annealing, enriched with the concept of Adaptive

Simulated Annealing, researchers aim to create a more efficient and effective hybrid approach to solve the Knapsack Problem. The objective is to explore the impact of this approach, evaluate its performance against benchmark instances, and compare it with traditional methods to understand its potential to find high-quality solutions and handle larger, more complex instances of the Knapsack Problem. The results of this research hold promise for advancing the field of combinatorial optimization and may open doors to similar hybrid approaches in tackling real-world resource allocation and decision-making problems.

The paper is structured as: Section 2 provides an overview of related research, offering insights from various researchers. In section 3, knapsack problem is described. Section 4 presents genetic algorithm. The concept of simulated annealing is discussed in section 5. The paper's methodology, which encompasses the notion of a memetic algorithm and a proposed approach, is outlined in Section 6. Results of the experiments and their analysis are presented in Section 7, followed by a summary of the findings in Section 8, concluding the paper.

2. RELATED WORK

The Knapsack Problem is a well-known and extensively researched instance of hard combinatorial optimization problem. Its goal is to find the optimal solution so that it meets the given constraints. Multiple metaheuristic optimization approaches are evaluated, including a hybrid Genetic Algorithm-Simulated Annealing technique, for solving 0-1 Knapsack Problems. Work has been done to bring together the most recent SA-based solvers for the Knapsack Problem and assess their efficacy in comparison to state-of-the-art metaheuristics in the field, in order to determine the optimal method. Each method is intended to penalize infeasible solutions while optimizing feasible ones. The experiments employ Knapsack Problems of both low and high dimensions. [14] [2] [22] [15] [9]

In order to solve hard optimization problems, GA is often utilized as a search technique. It is a probabilistic approach to solve optimization problems that seeks a global optimum solution for a variety of problems. The population evolves as a result of the genetic algorithm looping over an iteration process. Various stages which are included in each iteration such as initialization, selection, crossover, mutation, replacement are discussed. Applications of GA in the field of various combinatorial optimization problems have been discussed in detail. Different types of advantages, disadvantages of GA along with issues and challenges faced by it are described. GA has proved to be the most effective optimization methods for rapidly sampling a large solution space. [7] [6] [13] [1]

SA is a technique which uses the local search capability and employed to solve hard optimization problems. It has become a prominent technique for resolving discrete, continuous optimization problems over the past few decades. In the past decade, due to its good convergence qualities, ease of implementation, and the incorporation of hill climbing methodology to circumvent local optima has established it as a significant technique. The summarization, motivation and history of SA along-with its capability to address discrete and continuous optimization problems are discussed in detail. The convergence theory of SA and the recent advancements to analyse the performance in limited amount of time is considered. Continued research is focused on convergence and comparison of SA in terms of performance with other local search techniques. [10] [11] [8]

An overview of Memetic Algorithm is presented, with an eye toward the future of its development and its potential uses in the context of addressing particular problems and discussing certain topics. MA is concerned by utilizing all possible knowledge about a problem. The basic feature of MA is the inclusion of problem-domain knowledge. It has achieved a lot of success due to integration of different search approaches. For better convergence and optimal solution, search performance can be enhanced by using local search within GA. Researchers have directed their attention towards the practical application of memetic structures, specifically the synchronization of memes, which is a vital and defining component. A chronological sequence of past events is utilized to elucidate present advancements, with a particular emphasis on how they are applied in the fields of business and consumer analytics. [16] [4] [18] [12]

Hybrid Metaheuristics combine different metaheuristics approaches to develop a new and improved algorithm. The hybrid approach possesses best features of original approach and explores the search space effectively. Various metaheuristics approach have been merged together to solve knapsack problem efficiently. To increase the quality of the solutions produced by the knapsack-based crossover operator and the adaptive feasible and infeasible tabu search, a hybrid evolutionary search algorithm is proposed. The computational results of certain benchmark instances on multiple data sets, which are often utilised in the literature, are provided. It has been proved by the experiments that the hybrid approach is more stable and has strong convergence to solve 0-1 Knapsack Problems. [21] [17] [20]

3. Knapsack Problem

The knapsack problem (KP) is a well-known combinatorial optimization problem whose objective is to identify the optimal object among a set of objects [15]. This is a problem that has been researched for over a century, and it is one in which there is a requirement for an optimal item or a limited solution in a situation in which an exhaustive search is not possible. It is named after a situation where a fixed-size knapsack can only hold a certain number of items. The goal is to maximize the value of the items packed inside the knapsack while staying within its weight capacity, using a set of items with predetermined weights and values. Knapsack problems come in three distinct variations: 0-1 Knapsack, Fractional Knapsack, and Unbounded Knapsack. Here, the focus is on 0-1 knapsack that must be solved utilising the hybrid approach concept.

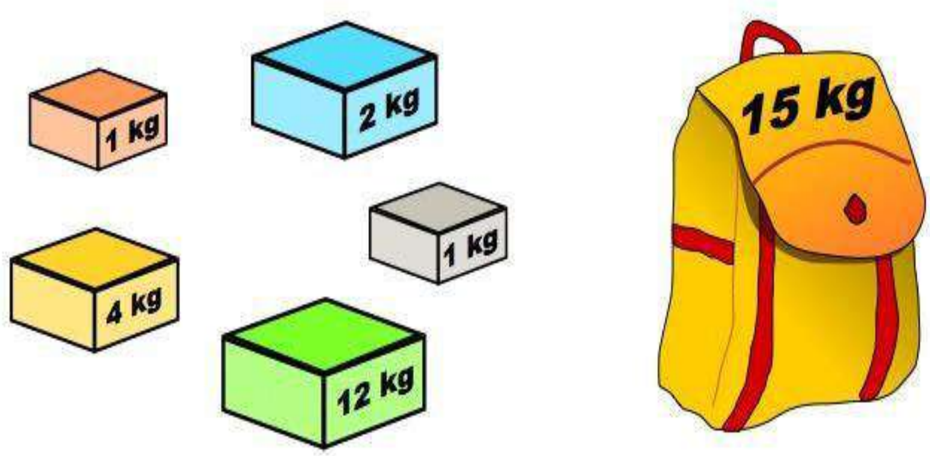

Figure 1: 0-1 Knapsack Problem

In the 0-1 Knapsack Problem, a knapsack or a bag with a particular weight capacity is provided. There are numerous objects with varying weights and values. The knapsack should be packed in a way that the combined weight of the items inside does not exceed the maximum weight capacity of the knapsack and that the total profit of the filled items is maximum.

It involves n items, where each item is characterized by a weight wi and a profit pi, and there is a maximum weight capacity W. The variable xi denotes the number of identical items i to be carried. 0–1 KP may be modelled numerically as follows:

Max $\sum_{i=1}^{n} pixi$ (1)

such that $\sum_{i=1}^{n} wixi \leq W, xi\epsilon\{0,1\}$ (2)

Due to its practical significance and NP-hard nature, considerable work has been devoted to KP, and both exact and heuristic approaches have been developed to solve this problem during the past few decades [21]. Resource allocation under budgetary limits, as well as the selection of investments and portfolios, is some real-world examples where this problem arises. It is also common in computer science, cryptography, combinatorics, applied mathematics, and complexity theory.

4. GENETIC ALGORITHM

The principles of natural selection and genetics are the basis of the heuristic search approach known as Genetic Algorithm (GA) [1]. John Holland introduced it in early 1970s. It is a method for finding exact or approximate solutions to complex optimization problems [5]. It uses a probabilistic approach to solve optimization problems that focuses on locating a global optimum solution for a number of different types of problems. This approach was developed to handle optimization problems. It is based on the biological genetic assessment process that combines selection, crossover and mutation. It is a search algorithm that comprises of population of individuals and uses the "survival of the fittest" principle. It can be regarded as a search method that can produce significantly superior solutions for combinatorial optimization problems.

GA consists of group of individuals called chromosomes. Chromosomes comprises of several genes that establish the characteristics of each individual. Within a search space, a population of individuals is formed. The fitness function of each individual is estimated to determine the ability of each individual. Then, parents are chosen according to the assigned fitness score to each individual. Those with higher fitness scores are given greater opportunities to reproduce than others. The individual with the higher fitness score is chosen. Then, the next generation is generated by mating between the selected individuals. This mechanism ultimately produces a subsequent generation that is superior to the previous generation. This entire procedure is repeated until a termination condition is achieved or predetermined generations are reached. The population evolves as a result of the genetic algorithm looping over an iteration process [6]. The following stages are included in each iteration.

Initialization: Initial population of strings with random initialization are generated. Every chromosome in GA consists of numerous genes that prescribe its characteristics.

Fitness Function: This function specifies a solution's optimality. It can be referred as evaluation function in which the input is given in terms of individuals and then the output is produced, which is the fitness score of each individual. The degree of proximity of a solution to the optimal solution of a problem determines its level of optimality. In addition, the solution is evaluated with reference to the fitness score assigned to the individuals.

Selection: In this phase, the best individuals are chosen as parents based on the fitness scores attained by fitness function. Its purpose is to choose the fitter individual to produce off-springs by following the principle of "Survival of the fittest". Selection of parents totally depends on the fitness of each individual and can be done using various selection techniques. The focus is to achieve the good chromosomes by eliminating the worst one, assuming that the population size must be stable.

Crossover: This phase plays a vital role in producing new generations of a population. It is inspired by biological reproduction between individuals. Some random crossover points are selected, and the genes between different individuals are then exchanged in a hope to obtain better genes in new generations. Then this entire process keeps revolving until better solution is achieved. In the subsequent generation, chromosomes will be produced of superior quality than those of preceding generation.

Mutation: This is a process of making random, local changes to the next generation. It is the typical way to introduce new genetic material into a population. To do this, either new genes are inserted into the off-spring or the existent are flipped. The process of mutation enables the preservation of the stochastic element inherent in the evolution of a population in order to sustain population diversity and prevent premature convergence.

Replacement: It is replacing an old population with a new one according to some replacement strategies. There are different ways to replace population, but the prevailing technique is Generational Replacement, where the newly generated population substitute the entire previous population.

Using the probability of crossover and mutation, a GA can produce optimal solutions by modifying the search process in a dynamic manner. A parallel population based search with stochastic operations is its distinguished feature. It has the ability to produce a globally optimal solution, provided that sufficient time is allotted to address a specific problem [1]. It is good at taking larger search space and navigating them to find optimal solutions. It has proven to be an enormously powerful and successful problem solving strategy. The solution produced by GA is often more efficient, elegant and more complex than a human engineer would produce. It is very helpful when precise domain knowledge is not available, as it has the ability to explore and learn from domain.

5. Simulated Annealing

The challenging hard optimization problems can be tackled with the help of a local search algorithm called Simulated Annealing (SA). Over the past decades, it has become a popular technique to address discrete, continuous optimization problems [10]. It uses the concept of hill climbing and randomness to reduce the problem of local optima. The word 'annealing' comes from the study of thermodynamics, which looks at how metals cool and anneal. The concept draws inspiration from the field of metallurgy, where the thermodynamic characteristics of materials are dictated by their temperature. It was given this name because it bears similarity to the process of physical annealing, where a crystal lattice is subjected to extremely high temperatures and then allowed to progressively cool until the optimal crystal lattice arrangement is reached. SA establishes the connection between global minima search and thermodynamic behaviour [11]. In addition to this, it offers an algorithmic method for taking use of such a connection.

SA works somewhat similar to hill climbing. The only difference is that SA chooses a random move instead of choosing the best move in every step. Its begins by randomly selecting an initial solution. Then, its neighbouring solutions are developed utilizing a set of predetermined rules. If recently produced solution shows more feasibility than the previous one, then this solution becomes the current solution. The acceptance rate of solutions of non-improving solutions is solely determined by the temperature variable, which doesn't increase with each algorithm iteration [10]. As the temperature approached zero, the frequency of hill climbing moves reduced. Therefore, the solution converges to a form where the probability of globally optimal solution is emphasized.

Adaptive Simulated Annealing (ASA) is a modification of simulated annealing, a metaheuristic optimization technique utilized for locating the maximum or minimum value of a function across its domain. ASA is a probabilistic optimization algorithm that tries to mimic the process of annealing in metallurgy. Similarly, in ASA, a solution is initially randomly generated and then gradually refined by iteratively modifying the solution to find the best solution. The main difference between ASA and standard simulated annealing is that ASA adapts the cooling schedule and step size of the search process dynamically based on the performance of the algorithm during the search. This makes ASA more efficient and effective than standard simulated annealing, especially in high-dimensional and complex search spaces. It has been effectively implemented in diverse domains, including engineering, physics, chemistry, and finance. It is particularly useful when the function to be optimized is expensive to evaluate, as it allows for efficient exploration of the search space.

For this reason, SA is more likely to find the global optimum and hence, reduce the chance of trapping in local minimum because it permits small modifications. It is used to solve various computational problems, such as TSP, SAT, VLSI routing, etc. It has been successfully applied in image recognition, machine learning and other areas of artificial intelligence.

6. METHODOLOGY

6.1 Memetic Algorithm

Though, evolutionary algorithm has the capability of exploring optimistic regions of the search space. However, they sometimes may stick in local optima. Researchers have been designed an approach to exploit the complementary advantages of both Evolutionary algorithm and local search methods, known as hybrid Evolutionary algorithm. Quite a lot, hybrid Evolutionary Algorithm is also known as Memetic Algorithm, Genetic Local Search, Lamarckian Evolutionary Algorithm, and Baldwinian Evolutionary Algorithm. MA is concerned by utilizing all possible knowledge about a problem. This inclusion of problem domain knowledge is an essential feature of MA [4]. MA has achieved a lot of success due to integration of different search approaches. Using local search within GA improves the performance of search in terms of convergence and optimal solution. The search performance is amplified due to which the issue related to genetic drift and premature convergence is reduced [18]. This hybrid approach maintains diversity in the population and converges to high quality solutions. Thus, accelerate the search towards global optima.

6.2 Proposed Approach

Memetic algorithm follows the same steps as standard genetic algorithm, with the exception that they employ a local search strategy to exploit the search space. In the proposed work, arithmetic crossover is used to generate off-springs, in which alpha value is changed using the theory of adaptive simulated annealing. The temperature and step size are calibrated to ensure comprehensive coverage of the search space with low resolution at the initial stages, followed by targeted exploration of favorable regions during the later stages. The temperature parameter in SA is set to very high in starting with the intent that algorithm moves freely in the search space. Later, the temperature is decreased gradually so that the algorithm is forced to converge at global optima. Similarly, here, alpha value decreases with each iteration in order for the system to establish equilibrium. In the initial step of GA, alpha value is set to 0.9 and this value remains constant throughout the procedure. This parameter is subsequently decremented by 0.2 at every generation until it attains a value of 0.1. When its value approaches 0.1, it is reset to the alpha value of 0.9. This procedure continues until the predetermined number of generations has occurred. Consequently, the convergence of solution to global optima can be increased and the possibility to get stuck in local minima can be reduced.

7. EXPERIMENTAL RESULTS AND DISCUSSION

7.1 Experimental Setup

To solve Knapsack Problem using proposed hybrid approach, an experimental setup has been done. To do this, an initial population is generated randomly using real encoding. Knapsack 0/1 fitness function is used to calculate fitness of the population. The randomly generated population is passed to selection phase where the best parents are selected by applying roulette wheel selection approach. Then, the selected parents are passed to crossover phase where arithmetic crossover is applied to produce offsprings. Here, the adaptive simulated annealing technique is utilized, which involves modifying the temperature and step size. It has been done by mimicking the process of annealing in metallurgy. Then, mutation is applied to maintain diversity in the population. This procedure repeats until stopping criteria is met or the predetermined number of generations is completed.

To setup the experiment, size of population in genetic algorithm is taken as 50, 100 and generations considered are 100, 150 and 200. The arithmetic crossover is applied to the selected chromosomes with a probability of 0.8 and mutation is applied with a probability of 0.2. The maximum temperature in simulated annealing is set to 200 and the temperature change is 0.80.

7.2 RESULTS AND OBSERVATIONS

Population Size =50			
Iterations	**Knapsack instances**	**GA**	**Hybrid(GA+SA)**
100	Knap_50	2060.8	2223.6
	Knap_80	2455.4	2969.2
	Knap_100	3678.2	4255.8
150	Knap_50	2029.0	2226.2
	Knap_80	2552.8	3000.0
	Knap_100	3858.0	4272.2
200	Knap_50	2116.0	2233.0

	Knap_80	2657.0	2977.4
	Knap_100	3965.2	4280.2

Table 2: Average profit gained for different knapsack instances by GA and Hybrid (SA+GA)

Population Size =100			
Iterations	**Knapsack instances**	**GA**	**Hybrid(GA+SA)**
100	Knap_50	2056.6	2225.0
	Knap_80	2448.6	2982.2
	Knap_100	3761.0	4272.0
150	Knap_50	2111.2	2239.0
	Knap_80	2566.6	3013.0
	Knap_100	3856.4	4288.4
200	Knap_50	2104.8	2237.8
	Knap_80	2645.6	3012.4
	Knap_100	3943.2	4285.2

Table 3: Average profit gained for different knapsack instances by GA and Hybrid (SA+GA)

Table 2 and Table 3 depicts average profit gained for different knapsack instances by genetic algorithm and hybrid approach of genetic algorithm and simulated annealing for population size 50 and 100 respectively.

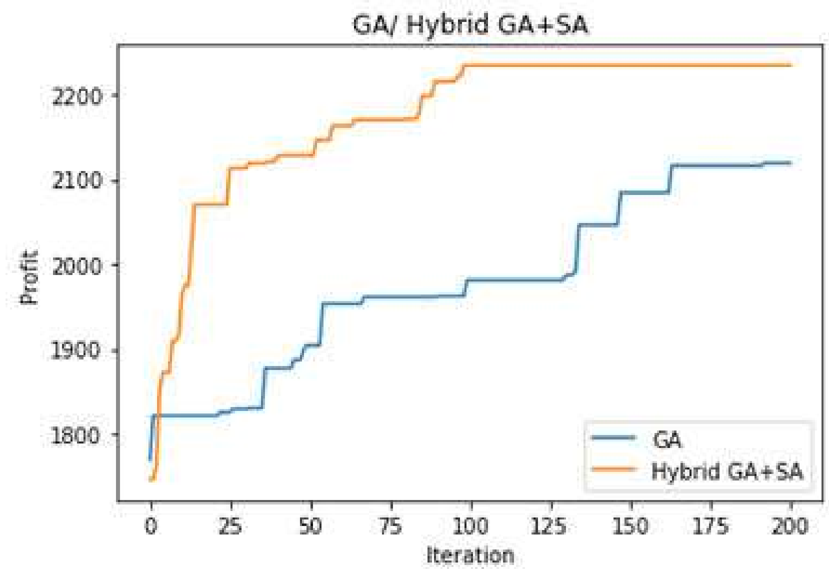

Figure 2: Profit for Knap_50 for 200 iterations (Population Size=50)

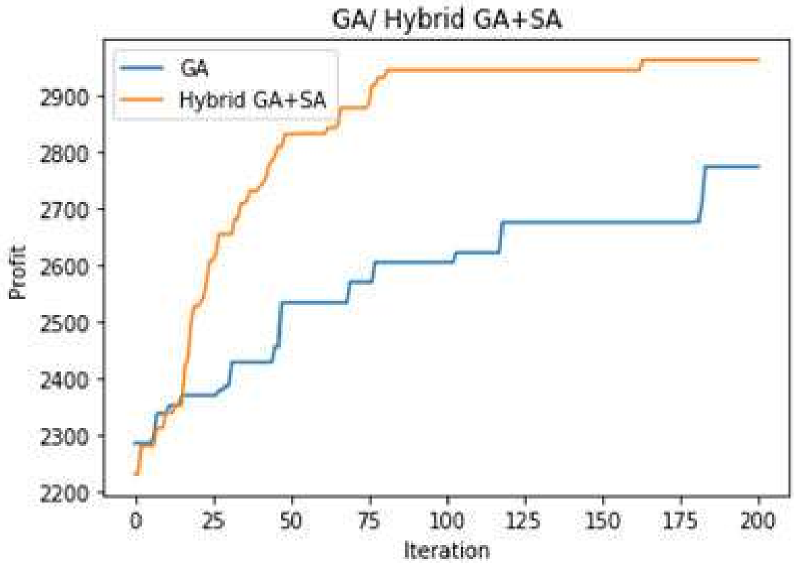

Figure 3: Profit for Knap_80 for 200 iterations (Population Size=50)

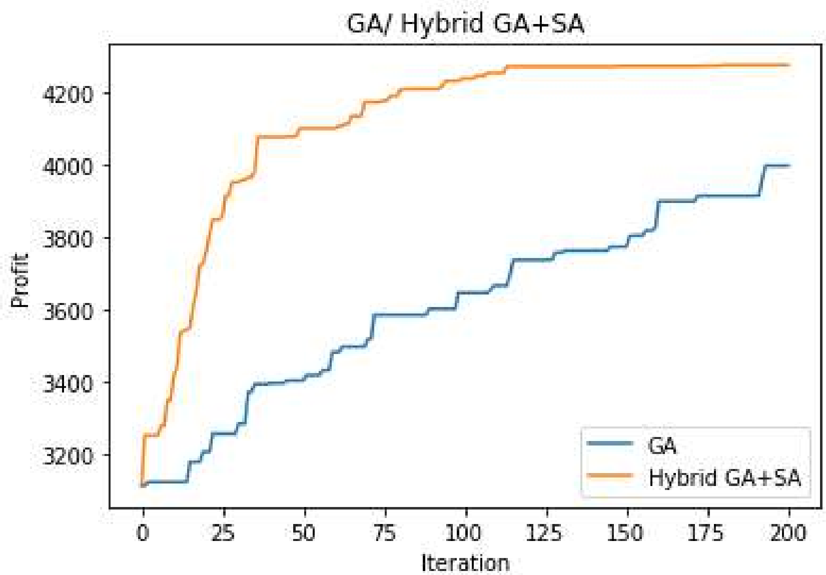

Figure 4: Profit for Knap_100 for 200 iterations (Population Size=50)

The average profit calculated for various knapsack instances is represented using graphs. Figure 2, 3, 4 illustrates profit gained for knapsack instances 50, 80 and 100 for 200 iterations respectively, when population size is 50. Similarly, in figure 5, 6, 7, the profit gained for knapsack instances is shown for population size 100.

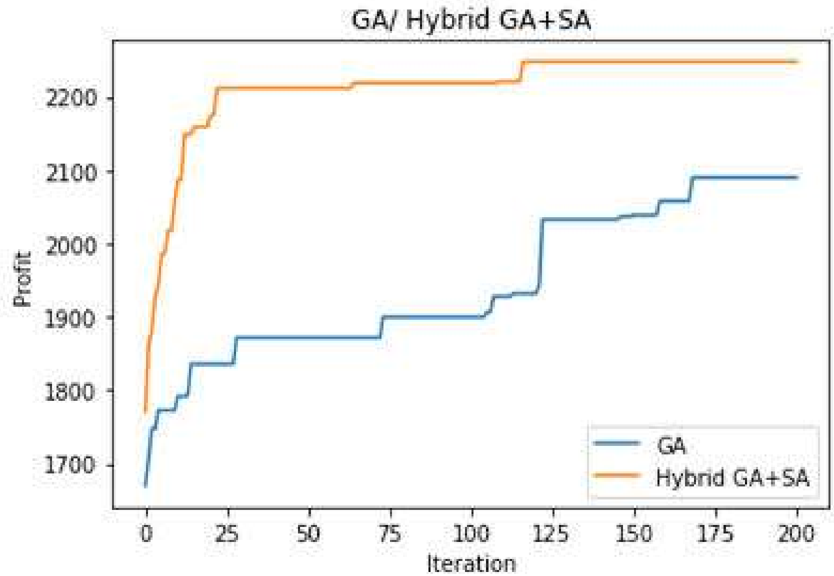

Figure 5: Profit for Knap_50 for 200 iterations (Population Size=100)

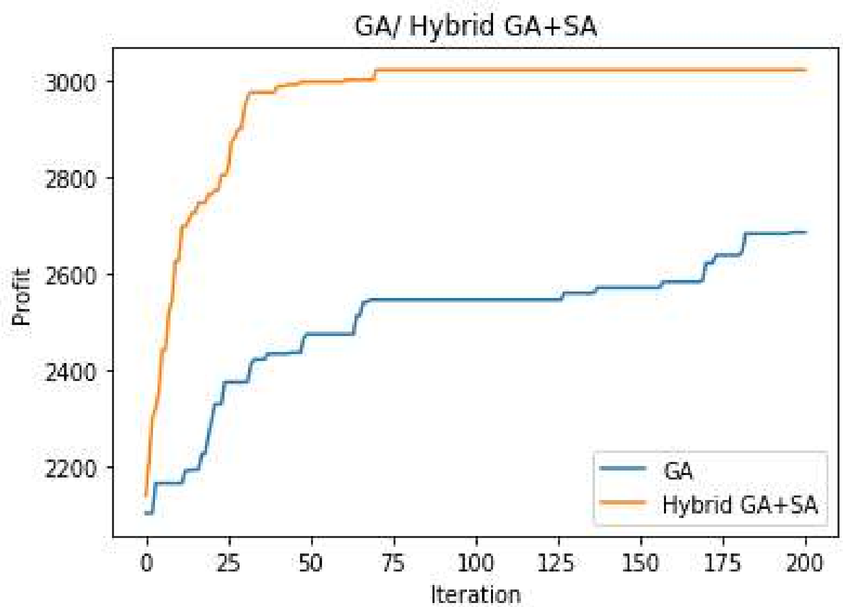

Figure 6: Profit for Knap_80 for 200 iterations (Population Size=100)

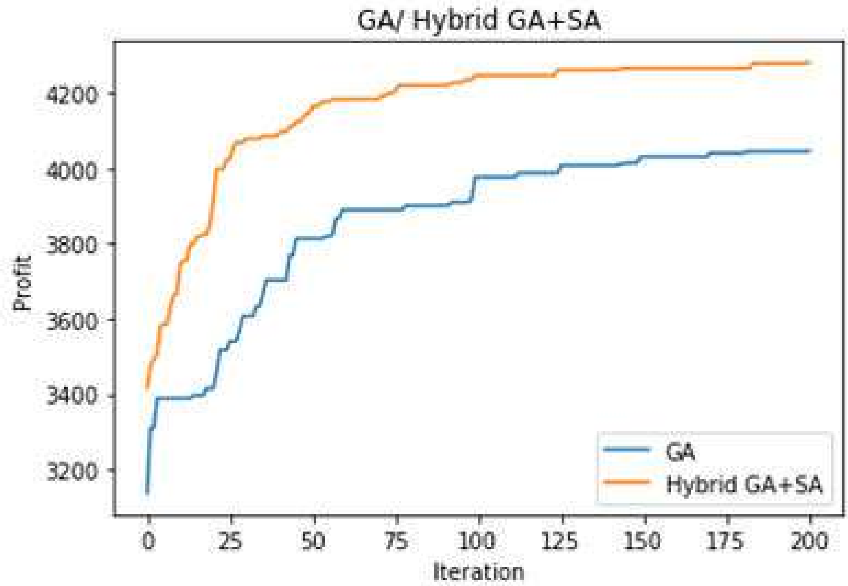

Figure 7: Profit for Knap_100 for 200 iterations (Population Size=100)

8. CONCLUSION AND FUTURE DIRECTIONS

The hybrid approach of combining simulated annealing with genetic algorithm, presents a powerful and promising solution to tackle the knapsack problem. In this paper, hybridization of genetic algorithm is done using the concept of adaptive simulated annealing, allowing for efficient exploration of the solution space and improved exploitation of promising regions. The change in alpha value used in arithmetic crossover depends on how the temperature changes over time in simulated annealing. By doing so, the stochasticity of the algorithm is reduced which force the search to converge at global optima. The findings demonstrated that the proposed memetic algorithm is superior in addressing the knapsack problem when compared to the basic genetic algorithm. The hybrid approach serves as a blueprint for addressing other challenging combinatorial optimization problems, expanding the potential for solving diverse real-world optimization challenges more effectively. The application of such a memetic approach to real-world challenges offers exciting opportunities for achieving optimal solutions in practical scenarios.

REFERENCES

[1] Katoch, S., Chauhan, S.S., & Kumar, V. (2021). A review on genetic algorithm: past, present, and future. *Multimedia Tools and Applications*, 80, 8091–8126.

[2] Ezugwu, A. E., Pillay, V., Hirasen, D., Sivanarain, K., & Govender, M. (2019). A comparative study of meta-heuristic optimization algorithms for 0 - 1 knapsack problem: Some initial results. *IEEE Access*, 7, 43979–44001.

[3] Mortazavi, A., Togan, V., & Nuhogluc, A. (2018). Interactive search algorithm: A new hybrid metaheuristic optimization algorithm. *Engineering Applications of Artificial Intelligence*, 71, 275–292.

[4] Wilson, A.J., Pallavi, D. R., Ramachandran, M., Chinnasamy, S., Sowmiya, S. (2022). A review on memetic algorithms and its developments. *Electrical and Automation Engineering*, 1, 7–12.

[5] Ankita. (2021). Travelling salesman problem using ga-aco hybrid approach: A review. *In ICDSMLA 2020: Proceedings of the 2nd International Conference on Data Science, Machine Learning and Applications*, 783, 105–113.

[6] Lambora, A., Gupta, K., & Chopra, K. (2019). Genetic Algorithm- A Literature Review. *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, 380-384.

[7] Malik, A. A study of genetic algorithm and crossover techniques. (2019). *International Journal of Computer Science and Mobile Computing*, 8, 335–344.

[8] Blum, A., Dan, C., Seddighin, S. (2021). Learning complexity of simulated annealing. *In Proceedings of the 24th International Conference on Artificial Intelligence and Statistics*, 130.

[9] Abdollahzadeh, B., Barshandeh, S., Javadi, H., Epicoco, N. (2022). An enhanced binary slime mould algorithm for solving the 0–1knapsack problem. *Engineering with Computers*, 38, 3423–3444.

[10] Rabbouch, B., Saadaoui, F., Mraihi, R.(2020). Empirical-type simulated annealing for solving the capacitated vehicle routing problem. *Journal of Experimental and Theoretical Artificial Intelligence*, 32, 437-452.

[11] Venkateswaran, C., Ramachandran, M., Ramu, K., Prasanth, V., Mathivanan, G. (2022). Application of simulated annealing in various field. *Materials and its Characterization*, 1, 1-8.

[12] Yagmur, E., & Kesen, S. E. (2021). Multi-trip heterogeneous vehicle routing problem coordinated with production scheduling: Memetic algorithm and simulated annealing approaches. *Computers Industrial Engineering*, 161, 107649.

[13] Haldurai, L. (2016). A study on genetic algorithm and its applications. International Journal of *Computer Sciences and Engineering*, 10, 139–143.

[14] Basset, M. A., Mohamed, R., & Mirjalili, S. (2020). A binary equilibrium optimization algorithm for 0-1 knapsack problems. *Computers Industrial Engineering*, 151.

[15] Moradi, N., Kayvanfar, V., & Rafiee, M. (2022). An efficient population-based simulated annealing algorithm for 0–1 knapsack problem. *Engineering with Computers*, 38, 2771–2790.

[16] Moscato, P., & Mathieson, L. (2019). Memetic algorithms for business analytics and data science: A brief survey. *Business and Consumer Analytics: New Ideas*, 545–608.

[17] Zhou, Q., Hao, J., & Wu, Q. (2021). A hybrid evolutionary search for the generalized quadratic multiple knapsack problem. *European Journal of Operational Research*, 296.

[18] Kumar, R. (2020). A survey on memetic algorithm and machine learning approach to traveling salesman problem. *International Journal on Emerging Technologies*, 11, 500–503.

[19] Muthuraman, S., & Venkatesan, V. P. (2017). A comprehensive study on hybrid meta-heuristic approaches used for solving combinatorial optimization problems. *In 2017 World Congress on Computing and Communication Technologies (WCCCT)*, 185–190.

[20] Zouari, W., Alaya, I., & Tagina, M. (2017). A hybrid ant colony algorithm with a local search for the strongly correlated knapsack problem. *In ACS14th International Conference on Computer Systems and Applications*, 11, 527–533.

[21] Lai, X., Hao, J., Glover, F., & Lu, Z. (2018). A two-phase tabu-evolutionary algorithm for the 0-1 multidimensional knapsack problem. *Information Sciences*, 436, 282–301.

[22] Li, Y., He, Y., Liu, X., Guo, X., & Li, Z. (2020). A novel discrete whale optimization algorithm for solving knapsack problems. *Applied Intelligence*, 50, 3350–3366.

[23] Zheng, Y., Lu, X., Zhang, M., & Chen, S. (2019). Optimization Problems and Algorithms, Biogeography-based optimization: Algorithms and Applications, 1-25.