
Optimizing Complex Problems Using Search Algorithms in Artificial Intelligence

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Abstract. Search algorithms are very important for artificial intelligence since they help solve hard issues by using optimization and decision-making methods. This study gives a thorough and critical look at a number of search algorithms, with a special focus on Simulated Annealing because it is flexible and works well for solving combinatorial optimization problems. This study looks at current literature in a methodical way to look at the problems that Simulated Annealing tries to solve, the methods it uses, the experiments it does, the findings it gets, and how useful they are in real life. The topic includes both positive aspects, such as algorithmic efficiency, accuracy, global optimization potential, and adaptability across different fields, as well as negative aspects, like convergence problems, parameter sensitivity, and computational complexity. This study points out areas where Simulated Annealing could be better and suggests areas for further research. It also emphasizes the possibilities of combining Simulated Annealing with other Meta heuristic methods to improve performance and use. The main goal of this in-depth study is to help researchers and practitioners choose, modify, and use the right search algorithms for the specific needs and features of different optimization issues.

Keywords: Simulated annealing, JSP, TSP, Retention Strategy, Amigobot, Search Algorithms

1 Introduction

The searching algorithms are in artificial intelligence to solve problems. For example, in most of the games these kinds of algorithms are deployed so that they can assist the users or the players in locating a precise location. A search algorithm is a tool for finding and locating a particular attribute within a data structure. It ensures many benefits such as helping to decide the searched values and allows to locate searches for algorithms which are an essential part in artificial intelligence. Basically, the use of search algorithms may find solutions to given problems [1], [2]. Thus, it is understood that the search is the generic problem-solving mechanism available in artificial intelligence.

The searching algorithms are used to check for an entity or locate an element out of some data structure. The efficiency of these algorithms is assessed as quickly as possible and mostly depends on the data structure searched. These algorithms are designed particularly to speed up or improve the efficiency of search problems [3].

Search is a versatile technique that has got a bunch of computer implementations [4]. The study focuses on assessing any of the most popular searching algorithms and the study will not concentrate entirely on the mechanics, but it also will consider the uses of applying these search algorithms and the essence of how they operate.

Simulated annealing is regarded as a modern approach in optimizing the search problems beyond the traditional methods. To tackle the combinatory optimization problems, simulated annealing technique would be utilized. The methodology is based on a solid annealing simulations model [5]. In this method, a neighboring solution is examined to see whether the original solution is stronger or not. If it is better, then the neighboring solution is selected. Otherwise, an acceptance function is derived which is dependent on certain conditions such as the worst situation in the nearby solution and how high is the current temperature [6].

The paper is structured as follows. In section II the author presents the scope of the critical analysis and its methodology which mainly focuses on the analysis for the selected papers and section III illustrates the conclusions and sets up the future work.

2 Related Work

This includes the details of the papers selected such as the title and the names of the authors, issues addressed, the approaches followed, and the results along with critical study comprising the positive and negative aspects of the papers and the possibilities for future. The most recent published papers are accessed and are assessed based on the above stated criteria.

The research paper, *Genetic Algorithm with Simulated Annealing for Resolving Job Shop Scheduling Problem* by Eulgi et al. [7] addresses the issue of the limitations in traditional genetic algorithm to solve the job shop scheduling problem. The manufacturing system's central element is job scheduling, and its primary role is to manage the industrial process's economic power. A genetic algorithm is a tool for improving scheduling problems that is dependent on genome factors.

The authors of the paper propose a hybrid approach combining genetic algorithms and simulated annealing by which they are able to come up with an algorithm by the name of Simulated Annealing Genetic Algorithm (GASA). It is understood that the algorithm is derived from the NSGA-II, which usually includes the simulated annealing for operation.

The following steps elaborate the approach followed during the study. The study begins by deciding the fundamental problem parameters, population size and time to iterate, etc. And then the individual population's fitness value is determined to find the optimum member. Next, it is tested whether the closure requirements have been fulfilled, and if so, the latest best solution is given. In addition, the undominated sorting and crowding distance is determined from the offspring. The offspring individuals have been chosen by simulated annealing according to the order value and the crowding size. The genetic algorithm is used for selection, crossover, and mutation. Through a simulated annealing process, the entities in the sample will be checked for state, whether it is stable or not regulated for the service. Otherwise, a new state is formed. Upon the successful satisfaction of the above process the procedure will be looped again by cooling down the temperature where the results are outputted. The authors have experimentally analysed the research by choosing the parameters such as generation population, population size, the probability of crossover, the probability of mutation, the coding method (floating point method) and the crossover method (pox crossover). The experiments are carried out an analysis that compare between traditional GASA and the improved GASA. The Fig.1 and Fig. 2 below shows the graphs that are generated accordingly to the experiments.

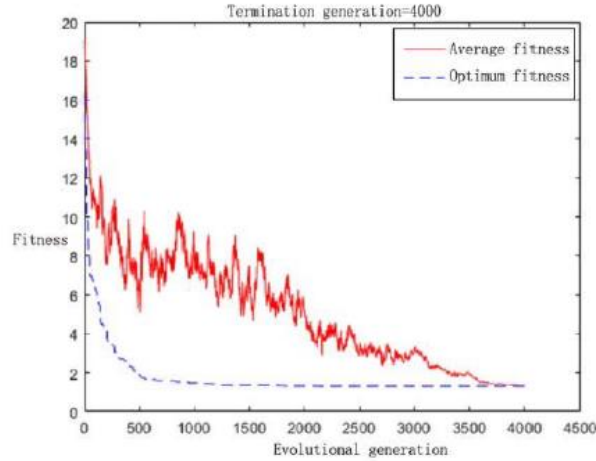


Fig. 1 Graph based on traditional GASA [7].

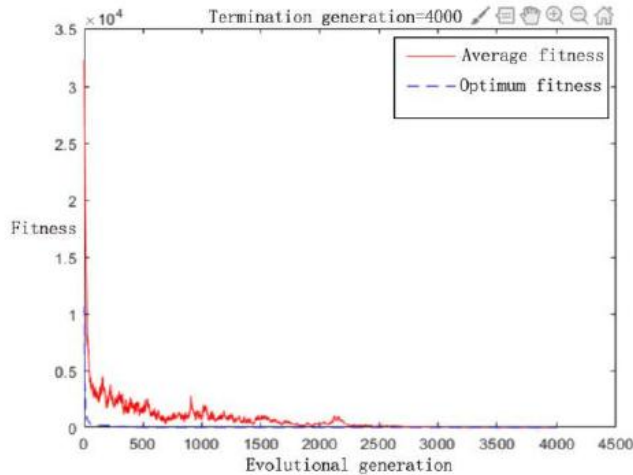


Fig. 2 Graph based on improved GASA [7].

Based on the above graphs it is understood that with reference to average fitness and optimal fitness, the GASA algorithm discussed throughout this study performed better than the traditional GASA.

Having discussed the overview of the study [7], it can be said that the paper addresses and interesting research and has a merit value in terms of problem discussed and the approach followed. The purpose of the research is (aim and objectives) is well written where the solution the authors trying to come up with seems to be effective about a hybrid approach. As the genetic algorithm and simulated annealing are combined together the study promises a faster convergence and a global search. The hybrid approach also helps in addressing the genetic algorithm's untimely convergence and simulated annealing's dimmer convergence.

Through the clearly defined methodology, the authors have described the approach in an understandable manner. The fitness value formula is described in a clear way, like wise for each step the formula is explained evidently and how they are applied to the study. The parameters considered for experimental analysis are given in sufficient, well explained fashion.

On the other hand, the paper does not clearly say what parameters were considered to set the population size and iteration times. The finding section merely describes the general results as a comparison where the authors have failed to explain in detail about the average fitness and the optimal fitness.

As a suggestion to make further improvements to the study, it can be said that the study can be further extended to combine the other genetic algorithm types with simulated annealing and overcome the deficiencies faced for the problem discussed.

The research paper, *Flocking Control of Mobile Robots via Simulated Annealing Algorithm* by Cheng & Wang [8] addresses the problem of system energy minimization due to flocking control of mobile robots where it aims to create a behaviour for the mobile robot that will enable it to evolve into a flock-centring state. The behaviour of a herd of birds or the swarming behaviour of insects is referred to as flocking. Separation, coordination, and stability are the three basic behaviours that it normally requires.

The paper follows the approach of defining a control method for flocking problem where at each sampling period, the simulated anneal algorithm searches for the desired position for each robot with the least amount of energy in a finite amount of time. And finally, a motion control law is created to guide the robots to the desired position. In this paper, simulated annealing is used to find the smallest solution to a cost positive function that is used to control the flocking state. Also, the simulated annealing is used as a flocking control law designer in this study.

This paper proposes a system for controlling the flocking problem of mobile robots by setting a problem formulation which aims to create a behaviour for the mobile robot. The assumptions considered while setting up the problem are that each robot perceives its neighbouring position, and the monitoring can be done only to robot's velocity. Once the problems are formulated, the preliminaries such as defining the position vector, defining the sum of all cost by adding the cost function of a single robot and defining the total cost function of all robots are set up. Then the methodology creates the flocking control method and the motion control method based on the pseudo code of simulated annealing algorithm. The Fig. 3 show the algorithm derived based on the simulated annealing's pseudo code.

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Input: Objective Function  $F(X)$ 
Output: Optimal Solution  $X^*$ 
1 Initialize  $T, T_{min}, \alpha$  and  $N$ 
2 Randomly Generate a solution  $X$ 
3  $X_{best} \leftarrow X$ 
4 while  $T < T_{min}$  do
5   for  $i = 1 : N$  do
6      $X_{new} \leftarrow neighbor(X)$ 
7     if  $\Delta E < 0$  then
8        $X \leftarrow X_{new}$ 
9        $X_{best} \leftarrow X$ 
10    else
11      if  $\exp(-\frac{\Delta E}{K_B T}) > Rand()$  then
12         $X \leftarrow X_{new}$ 
13   $T \leftarrow \alpha T$ 
14   $X^* \leftarrow X_{best}$ 
15 return  $X^*$ 

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Fig. 3 Algorithm derived based on the pseudo code of simulated annealing [8].

Five amigobots are tested to evolve into a herd. As a realistic test prototype, amigobot can only track the robot speed and heading angle. The simulated annealing algorithm is used to build a single action for each robot while flocking can be built by itself. The result shows that the five robots have balancing and flock centering features. Stabilized trajectories were seen in amigobots involving balanced neighboring interactions and stable movement.

From the issue addressed, methodologies and the experimental analysis of the study [8], it is clear that the study meeting its purpose has evidently compared the newton method with the simulated annealing to show that the second one performs better in terms of time used for computation and the speed taken for convergence. The method suggested through this paper seems to be applicable to any cost function beyond the traditional methods. Also, the approach can be implemented to any other robots which makes the research a significant one to be considered.

Besides these there are certain drawbacks as well that could be senses from the study conducted. Amigobot is used for research but it is uncertain if other agent types can also work using the same approach followed for problem formulation and experiments. Moreover, the technical data (details) of the amigobots used for the study are not specified. As a consideration for future, the author would like to suggest that the methodology can further focus on implementing the mechanism for hindrance prevention and a desired motion to goal approach.

The research paper, *Route Optimization of Airplane Travel Plans Using the Tabu-Simulated Annealing Algorithm to Solve the Traveling Salesman Challenge 2.0*. by Ahmad et al. [9] focuses on the use of travelling salesman problem (TSP) in air plane travel path (plan) problem. The authors have conducted this research as a part of a competition that was held during 2008. The competition is based on travelling salesman challenge (TSC) 2.0.

The approach for solution begins with forming the initial route by arbitrarily selecting the city as the initial route. Then the Optimal solution is generated by implementing Tabulated Simulated Annealing Algorithm. Within this step there are several other procedures conducted that include, a low-grade heuristic is being employed after obtaining the initial solution using the city swapping technique (based on the number of cities). And this creates a temporary solution. The tabu-simulated annealing process is applied to the temporary solution achieved. If the temporary solution is superior to the original, the temporary solution is approved as a new solution. The Boltzmann equation would be used to solve if the temporary solution is worse than the initial solution. If the Boltzmann equation value is greater than the random value, the temporary solution is regarded as a new solution. If the temporary solution is poorer from the original response the low-grade algorithm response is used to oversee the temporary alternative. If the expense of a temporary solution is less than the costing of the initial solutions, it may be regarded as a latest solution. Finally, the parameters are experimented. The Fig. 4 shows the algorithm parameters that are considered for experiments.

The results based on the experiment conducted shows that the suggested optimization algorithm can solve the problem and exceeds the high drift algorithm, that is, the improvement from the initial solution measures 48.54% when compared 41.33% at the beginning.

Parameters	Description
LLH	Number of low level heuristic used
T_0	Initial temperature of simulated annealing algorithm
T_1	Final temperature of simulated annealing algorithm
cr	Cooling Rate
TL	Length of list of tabu search algorithm solutions

Fig. 4 Algorithm parameters [9].

With the background information regarding the research [9], it can be understood that the methodology to find the solution uses a hybrid approach that consists of simulated annealing and tabu search. Right selection of algorithms for the methodology brings out a positive sense towards the study. For example, the tabu-annealing simulated improves the population variety in gene representation and enhances the search process. But the results of this study's parameter adjustments may influence algorithm efficiency by that way an optimal solution will not be guaranteed.

As a suggestion it can be said that the study can focus more towards maintaining the parameters at an optimal level so that the parameter changes or the parameters with the greater values do not affect the solution.

The research paper, *Optimization of Plant Light Source Based on Simulated Annealing Particle Swarm Optimization Algorithm* by Cui et al. [10] focuses on addressing the issue of unequal lighting of plantation emission spectra in crop manufacturing.

The authors use the simulated optimization of the LED array by the annealed particle swarm and model the improved array. The principle of simulated annealing with amplification and Gaussian mutation is presented in these algorithms. The steps of the methodology used in the study can be explained as follows. The research first initializes the swarm particle. Next, each particle's objective value function is calculated. Then after the optimal locations (both individual and global) are updated. Then the simulated annealing neighborhood looks for the optimum value of particles. With these the individual and the global search locations are updated again the looping continues.

The tests are conducted through a software that enables optical simulation in which the optimized LED array has been simulated with the aim of checking the homogeneity, consequently augmenting the LED sources of lighting in the farm. The findings showed that, in rectangle arrangements, the algorithm used to conduct the research would maximize the lighting properties LED and enhance the lighting homogeneity.

With the above given overview and summary for the study [10], it is understood that the study is favorable towards the algorithm suggested in the study helps to achieve the greater uniformity in the plant nursery illumination. Also, the optimized algorithms target in getting cleared of local minima and provide enhanced speed of convergence with a higher accuracy. However, it is understood that certain important constraints for the study are not properly mentioned or included. For example, the authors have stated the plant cultivation is merely a general fact instead they have failed to address on which plant types or cultivation crops they research can be implied. Because it is known that the light intensity and illumination range of each plant varies.

As a suggestion for future, one could argue that the approach will be considered a better one when the setup is made to varied LED configurations.

The research paper, *Application of simulated annealing particle swarm optimization in underwater acoustic positioning optimization* by Li et al. [11] addresses the issue of acoustics positioning in underwater. The issues caused by time delay, velocity, measurements errors are all considered while trying to find a solution to this problem. The approach to the study covers the concept of the average method of arithmetic optimization, the theoretical analysis of the iteration method and theoretical analysis of the optimization of particulate swarm based on simulated annealing.

The RMS (Root Mean Square) of the three methods is simulated and assessed in this paper using the SNR (Signal-to-noise ratio). The simulated annealing particle swarm optimization (SA-PSO) algorithm had shown to be more effective in finding the observed objective.

Provided the summary on the study conducted [11], it is observed that the research paves the way to real time simulations, faster calculations and simple in processing yet much effective. Oppositely, the study also demands a complexity in terms of computing. Therefore as suggestion for future possibilities it can be stated that the algorithm can be further optimized using any other relevant, appropriate algorithms to provide a simpler computing.

3 Methodology

In this study simulated annealing algorithm has been employed for numerical optimization. It is well know that an effective and broad way of optimization is simulated annealing (SA). In the presence of huge numbers of local optima, it is helpful to locate global optima. Simulated annealing leverages rather than the energy of a material, the objective function of optimization. The figures shown below illustrates the methodology adopted by the algorithm.

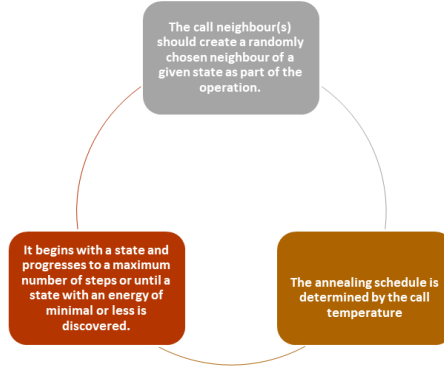


Fig. 5 Simulated Annealing Algorithm

Simulated Annealing:

- Let $s = s_0$
- For $k = 0$ through $k_{\max}$ (exclusive):
 - $T := \text{temperature}(k / k_{\max})$
 - Pick a random neighbour, $s_{\text{new}} := \text{neighbour}(s)$
 - If $P(E(s), E(s_{\text{new}}), T) \geq \text{random}(0, 1)$:
 - $s := s_{\text{new}}$
- Output: the final state s

Fig. 6 Simulated Annealing Algorithm – Pseudo code [12]

The global minimum of the numeric function $\mathbf{X} \rightarrow \mathbf{X}^2$ is found by implementing the simulated annealing using python. It includes defining the function to minimize, the interval, the cost function, the neighbor, acceptance probability and the temperature. When defining the neighbor (random), the $\mathbf{X}$ is moved little bit (either left or right). And for the acceptance probability there is a condition checked which says whether new cost is less than the cost. If the conditions passes then it returns the acceptance probability.

4 Results and Discussion

In this study the numerical optimization of a function is carried out. The annealing is repeated for a maximum number of thirty steps where the temperature, state, cost and the new state and new cost is generated. The Table 1 below illustrates, the temperature (T), state (S), cost (C), new state (NS) and new cost (NC) for few considered steps out of the thirty steps.

Table. 1 Evolution of states and cost using annealing

STEP NO.	T	S	C	NS	NC
0/30	1	-1.87	-6.49	-1.87	-6.49
5/30	0.833	-1.95	-7.44	-1.85	-6.35
11/30	0.633	-2.26	-11.5	-1.91	-6.97
17/30	0.433	-2.49	-15.4	-2.32	-12.6
23/30	0.233	-3.35	-37.5	-2.86	-23.3
29/30	0.0333	-4.18	-73.2	-4.1	-68.8

The figures given shows the visualized steps that are given as graphs showing the evolutions of states and cost of the simulated annealing.

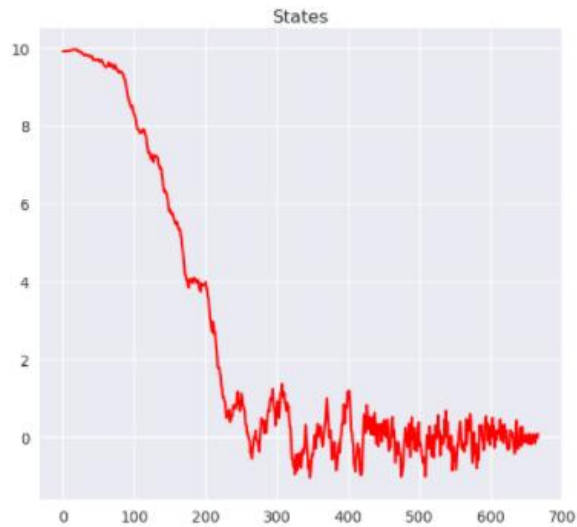


Fig. 7 Evolution of states of the simulated annealing

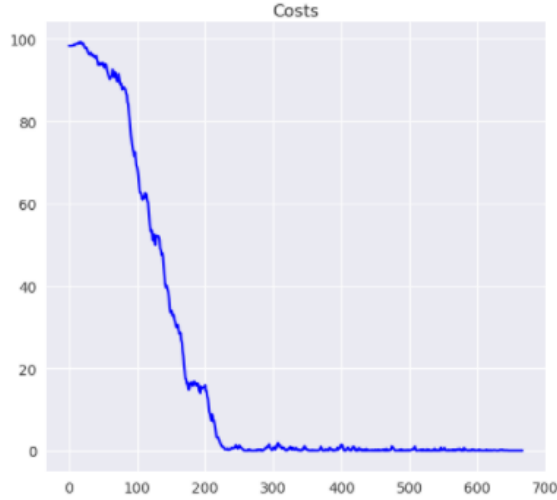


Fig. 8 Evolution of costs of the simulated annealing

5 Conclusion

This paper provided an extensive critical analysis of search algorithms, emphasizing Simulated Annealing due to its prominence in solving complex optimization problems within artificial intelligence. Through a thorough analysis and comparison of previous academic research, it was determined that Simulated Annealing offers a number of noteworthy benefits, such as the capacity to search globally, successfully avoid local optima, and adapt to a variety of problem domains. The thorough analysis of a few chosen recent articles revealed a number of effective uses, from robotics and work scheduling to travel and LED plant lighting optimization, illustrating the algorithm's versatility and wide range of applications.

But the study also found important shortcomings that call for more investigation. The lack of specific experimental circumstances, sluggish convergence rates in some situations, computational complexity, and the susceptibility of results to parameter settings were all recognized as problems. These drawbacks highlight the necessity of meticulous parameter adjustment, open experimental designs, and precise methodology explanations in order to guarantee reproducibility and future development.

Future studies should investigate hybrid algorithmic approaches that combine Simulated Annealing with other metaheuristics such as Genetic Algorithms, Particle Swarm Optimization, Tabu Search, and Ant Colony Optimization in order to overcome these restrictions. In complicated real-world situations, such hybrid approaches have shown promise in improving convergence speed, cutting down on computation time, and boosting the robustness and dependability of solutions.

Furthermore, to lessen the need for manual tweaking and improve generalizability across many applications, future research could potentially examine the incorporation of machine learning techniques to automatically find the ideal algorithm parameters. These algorithms' scalability to manage bigger and more dynamic datasets and problem domains, as well as their real-time application, offer encouraging opportunities for more research.

In summary, even though Simulated Annealing has proven to be a highly effective search optimization technique in artificial intelligence, further research and development are still required. To optimize the performance of search algorithms, it is advised that future research prioritize thorough and open experimental reporting, investigate innovative hybrid

approaches, and take use of developments in computational intelligence. This will make it possible to apply Simulated Annealing and related approaches more broadly and sophisticatedly, which will ultimately help solve more difficult real-world optimization problems.

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