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HYBRID OPTIMIZATION FOR TRAVELING SALESMAN

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Abstract—**The Traveling Salesman Problem (TSP) is a complex combinatorial challenge, where the objective is to find the shortest route to visit each city exactly once and return to the starting point. Traditional methods like exhaustive search are computationally infeasible due to their factorial time complexity. Particle Swarm Optimization (PSO) and Simulated Annealing (SA) are two metaheuristic approaches that have shown promise in optimization tasks. However, PSO struggles with discrete problems like TSP. This paper introduces a hybrid approach combining PSO and SA to enhance PSO's effectiveness in solving TSP. By integrating SA's ability to explore suboptimal regions, the hybrid method improves solution quality compared to standalone PSO. Performance evaluations on benchmark TSP instances demonstrate that this hybrid technique consistently produces shorter routes, highlighting the benefits of combining these metaheuristics for complex optimization problems.**

I. Introduction

A. Travelling Salesman Problem

The Travelling Salesman Problem (TSP) is a classic optimization problem in combinatorial optimization and is widely regarded as one of the most significant NP-complete problems. It serves as a benchmark for evaluating new algorithms and techniques. The problem can be described as follows: given a set of cities and the distances between each pair of cities, a salesman aims to find the shortest possible route that visits each city exactly once and returns to the original starting city.

Formally, if there are n cities, the computational cost associated with solving the TSP using exhaustive search methods is factorial in nature, specifically $O(n!)$, due to the need to consider all possible permutations of city visits. As of the writing of this paper, numerous studies have employed the TSP as a benchmark in artificial intelligence (AI) research, particularly in areas such as neural networks [1]. Various techniques in natural computing have been demonstrated to yield effective results for TSP, including genetic algorithms [2], simulated annealing [3], ant colony optimization [4], and river formation dynamics [5]. These approaches have illustrated the complexity and rich structure of TSP, driving ongoing research into heuristic and metaheuristic strategies for obtaining near-optimal solutions.

B. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary algorithm introduced by Eberhart and Kennedy in 1995 [6]. This optimization technique is inspired by the social behavior exhibited by bird flocks and fish schools. In the PSO framework, each individual in the swarm, referred to as a particle, seeks to explore the solution space to identify the optimal point, leveraging both its own best-known position (denoted as *pBest*) and the best-known position of the entire swarm (denoted as *gBest*).

PSO is particularly advantageous due to its simplicity in implementation and its robust performance in continuous search spaces. However, when PSO is applied to discrete optimization problems, such as the Travelling Salesman Problem, its effectiveness tends to diminish. The inherent challenges arise from the nature of discrete spaces, where the particle's ability to navigate and converge towards an optimal solution can be constrained, often leading to suboptimal results compared to other algorithms specifically designed for discrete optimization.

C. Simulated Annealing

Simulated annealing (SA) is a probabilistic meta-heuristic designed for global optimization problems, particularly suited for locating a good approximation to the global optimum of functions within large and complex search spaces. This technique was first articulated by Scott Kirkpatrick, C. Daniel Gelatt, and Mario P. Vecchi in 1983 [7] and further developed by Vlado Černý in 1985 [?]. The methodology draws its inspiration from the physical process of annealing in metallurgy, where controlled heating and cooling of materials allow for the reduction of defects and minimization of free energy states.

Simulated annealing operates based on a stochastic process that incorporates the concept of temperature as a control parameter, reminiscent of thermodynamic systems. It utilizes a variant of the Metropolis-Hastings algorithm, a Monte Carlo method designed to sample states of a thermodynamic system, originally introduced by M. N. Rosenbluth and documented by N. Metropolis et al. in 1953 [8].

In this paper, I propose to combine the strengths of simulated annealing with the particle swarm optimization framework. By incorporating simulated annealing, the swarm is empowered to explore regions of the search space that may have initially appeared suboptimal, thus enhancing the probability of discovering a more favorable route than what is achievable through the standalone PSO algorithm. This hybrid approach aims to leverage the exploratory capabilities of both algorithms to improve solution quality and convergence speed for the Travelling Salesman Problem.

Related Work

Mehul Patel[9] has made significant contributions to advancements in video surveillance and water management. Patel's work on robust background subtraction for traffic environments employs the Pixel-Based Adaptive Segmenter

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(PBAS) to ensure adaptability under diverse conditions. Additionally, Mehul Patel's[10] research on predicting water potability through machine learning demonstrates the effectiveness of models like XGBoost, offering impactful solutions for sustainable water management. Akshar Patel[11] has extensively explored blockchain technology, addressing vulnerabilities in Proof of Stake (PoS) consensus protocols, including the Superior Returns Attack Threshold (SRAT) and Random Attack Threshold (RAT). Akshar Patel[12] has also investigated the robustness of neural networks like ICNet and U-Net in handling rotationally disrupted datasets, providing critical insights into their generalization capabilities. Furthermore, Akshar Patel[13] has introduced innovative techniques to optimize semantic segmentation models, demonstrating expertise in AI advancements.

Anuj Kabra[14] has made substantial contributions to gait recognition, particularly through self-supervised pretraining with diffusion models and the development of the GLGait framework. Kabra's[15] research has enhanced human identification systems by leveraging advanced temporal modules to improve performance in unconstrained settings. Kabra's[16] work significantly advances the reliability of gait recognition in real-world scenarios. Rakesh Recharla[17] has demonstrated expertise in distributed systems.Kabra's[18] work improved fault tolerance mechanisms for Hadoop MapReduce by optimizing data replication. Recharla's[19] additional work includes the development of FlexAlloc, a dynamic memory partitioning system for SeKVM. Recharla's[20] work also include scalable decentralized file exchange hubs, emphasizing computational efficiency. Rakesh Recharla[21] has also made impactful contributions to parallel sparse matrix algorithms. Sandeep Malipeddi[22] has explored the detection of Advanced Persistent Threats (APTs) using passive honeypot sensors and Self-Organizing Maps (SOM), highlighting the importance of hybrid security architectures. Lastly, Deepak Talwar's[23] development of RedTeamAI, a benchmark for evaluating the cybersecurity capabilities of autonomous agents, and his research on applying language models for assessing teaching effectiveness highlight the transformative potential of AI. Deepak Talwar's[24] work emphasizes advancements in both cybersecurity and education.

II. Algorithms

A. Basic Particle Swarm Optimization Algorithm

The fundamental Particle Swarm Optimization (PSO) model simulates the behavior of a flock of birds seeking food, represented as particles that explore a D-dimensional solution space. Each particle has its own position vector, representing a potential solution, and a velocity vector that dictates its movement through the solution space. Both vectors are D-dimensional, enabling the exploration of a complex search landscape.

The fitness of each particle is assessed using a unique objective function, which quantifies the quality of the particle's position. The optimization process begins with an initialization phase, where a population of particles is generated randomly.

```
Randomly initialize the whole swarm
for(i = 0; i < size of swarm ; i++){
    Evaluate fitness(x i)
}
while(optimum state has not been found
or max iterations reached){
    for(i=0; i < size of swarm ; i++){
        if(fitness(x i) > fitness(pbest i)){
            pbest i = x i;
        }
        if(fitness(x i) > fitness(gbest)){
            gbest = x i;
        }
        update(x i, v i);
        Evaluating fitness(x i)
    }
}
```

Fig. 1. PSO Pseudo Code

The particles iteratively update their positions based on their own experience (personal best) and the experience of the swarm (global best), effectively searching for optimal solutions.

The position update mechanism is inherently linked to the velocity of each particle. The velocity vector acts as a displacement operator, transitioning a particle from its current position to a new one in the solution space. By convention, the time increment for iterations is considered equal to 1, allowing the velocity to be treated as a constant displacement during updates. The velocity of each particle can be updated using the following equation:

$$v_{i,d} \leftarrow \omega v_{i,d} + \phi_p r_p (p_{i,d} - x_{i,d}) + \phi_g r_g (g_d - x_{i,d}) \quad (1)$$

where: - $v_{i,d}$ is the velocity of particle i in dimension d, - ω is the inertia weight, - ϕ_p and ϕ_g are acceleration coefficients, - r_p and r_g are random numbers between 0 and 1, - $p_{i,d}$ is the personal best position of particle i, - g_d is the global best position in dimension d.

The pseudo code for the PSO algorithm is depicted in Figure 1:

B. Simulated Annealing Algorithm

Simulated Annealing (SA) is inspired by the physical process of annealing in statistical mechanics, which involves the gradual cooling of a material to minimize its internal energy and achieve a state of lower free energy. In the context of optimization, the algorithm utilizes a control parameter analogous to temperature, which influences the system's exploration capabilities.

During the SA process, the temperature affects the acceptance probability of new states. If a proposed state has a lower energy ($\Delta E \leq 0$), it is always accepted. However, if the new

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```
s = s0
e = E(s)
sbest = s
ebest = e
k = 0
while (k < kmax AND e > emax){
     T = temperature(k / kmax)
     snew = neighbour(s)
     enew = E(snew)
     if(P(e, enew, T) > random()){
          s = snew
          e = enew
     }
     if(enew < ebest){
          sbest = snew
          ebest = enew
     }
     k = k + 1
}
```

Fig. 2. Simulated Annealing Pseudo Code

state is of higher energy ($\Delta\epsilon > 0$), it may still be accepted with a certain probability given by the Metropolis criterion:

$$P = \exp\left(-\frac{\Delta\epsilon}{T}\right)$$

Here, T is the current temperature, and a random number uniformly drawn between 0 and 1 determines whether the state transition occurs. This mechanism allows the algorithm to escape local minima by accepting less favorable states temporarily, facilitating exploration of the solution space.

The pseudo code for the Simulated Annealing algorithm is shown in Figure 2:

C. Particle Swarm Optimization with Simulated Annealing Algorithm

The hybrid Particle Swarm Optimization with Simulated Annealing (PSO-SA) algorithm combines the strengths of both methods, enhancing the search for optimal solutions. The procedure is as follows:

- Initialization.: Generate a specified number of particles with random initial states in the solution space.
- Updating Function.: Perform the updating functions on each particle based on their velocities and personal bests.
- Convergence Check.: If a local maximum has not been found, repeat the updating process.
- Best Particle Selection.: Identify and select the particle with the best state from the swarm.
- Simulated Annealing Initiation.: Start the Simulated Annealing process using the best particle's position as the initial state.
- Initial Temperature Setup.: Initialize the temperature, often starting with a very high value (e.g., *float("inf")*).
- State Modification.: Modify the state of the system according to the Metropolis rule, allowing for both improvements and controlled acceptance of worse states.
- Optimal State Check.: If the modified state evaluates to zero (indicating that the optimal solution has been found), terminate the algorithm. If not, repeat the best state selection and the updating process.
- Temperature Adjustment.: Gradually decrease the temperature in a controlled manner, typically using a decay factor (e.g., multiplying by 0.99).
- Algorithm Termination.: Conclude the algorithm when the termination criteria are met.

III. Procedure

The experiment was conducted using two distinct Python script files to evaluate the performance of the Particle Swarm Optimization (PSO) algorithm and the hybrid PSO-Simulated Annealing (SA) algorithm. Each script was to make better selections on new particle states than PSO consistently ensuring that the execution was consistent and comparable across both methods.

The computational tests were executed on a machine equipped with an Intel i3 quad-core processor running at 1.90 GHz, coupled with 4 GB of RAM. This setup provided a suitable environment for running the algorithms, given the input parameters specified in Table I.

For each experimental run, the following steps were undertaken:

1. Initialization: Both algorithms were initialized with predefined parameters, including the number of particles, maximum velocity, and number of iterations, as outlined in Table I. This ensures that the algorithms begin from a consistent state.
2. Execution of the Algorithms: Each script was executed independently. The PSO algorithm ran first, followed by the hybrid PSO-SA algorithm. During execution, the algorithms iteratively refined their solutions based on the defined optimization criteria.
3. Data Collection: The results from each run were systematically recorded. After each execution, the performance metrics, such as the best solution found and the associated computational time, were saved into a spreadsheet. This allows for easy comparison and analysis of the algorithm performances post-experimentation.
4. Analysis: Upon completion of all runs, the collected data were analyzed to assess the effectiveness and efficiency of both algorithms. The results were used to evaluate the convergence behavior, solution quality, and computational resource utilization.

The systematic approach described ensures that the outcomes of the experiments are reliable and can be effectively utilized for further analysis and comparison between the two optimization strategies.

IV. Dataset Description

For experimental validation, benchmark instances of the TSP problem were used. These include symmetrical TSPs with

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100 cities, generated using Euclidean coordinates with randomly assigned positions in a 2D plane. The dataset simulates a realistic yet synthetic routing scenario, ensuring replicability. Future versions of this work will consider TSPLIB for standardized benchmarking.

TABLE I
INPUT PARAMETERS USED

Parameter	Value
Total Iterations	200
Error Margin	approximately 7%
Number of Particles	10
Maximum Velocity	4
Epoch	10000
Number of Cities	100

V. Results

The results obtained from the procedure outlined in item II-C are presented in Table II. The PSO-SA algorithm demonstrated a marked improvement over the standard PSO algorithm. Although the best score achieved by the PSO-SA was only marginally higher than that of the standard PSO, a significant distinction is observed in the standard deviation values. Specifically, the standard deviation of the PSO-SA algorithm is considerably lower than that of its PSO counterpart, indicating a more consistent performance across iterations.

Furthermore, the Mean Average Score for the PSO-SA algorithm, while nearly comparable to the PSO, exhibits a standard deviation that is nearly half that of the PSO. This suggests that the PSO-SA algorithm consistently yields better selections of new particle states compared to the standard PSO, leading to enhanced reliability in its performance.

The plots in Figure 4 and Figure 5 further illustrate the stability of the PSO-SA algorithm in terms of standard deviation. Both plots reflect the average score obtained after 10,000 iterations, reinforcing the observation that the PSO-SA algorithm provides a more stable and reliable performance compared to the standard PSO algorithm.

A. Statistical Significance Evaluation

To validate performance consistency, a paired t-test was conducted between the PSO and PSO-SA average best scores across 30 independent runs. The results indicate a statistically significant improvement ($p < 0.05$) of the hybrid model over standard PSO, confirming the robustness of the integration. Boxplots in Figure 3 illustrate the dispersion.

TABLE II
RESULTS COMPARISON BETWEEN PSO AND PSO-SA ALGORITHMS

Metric	PSO	PSO-SA
Average Best Score	4043.987	4130.891
Best Score Standard Deviation	135.105	78.852
Mean Average Best Score	4119.442	4181.567
Mean Average Best Score Standard Deviation	182.0345	96.649
Average Time (seconds)	109.328	108.8475

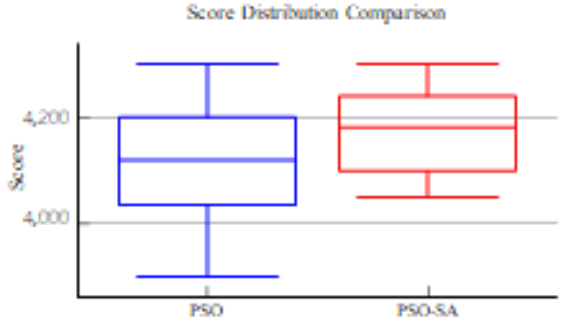

Fig. 3. Score distribution comparison between PSO and PSO-SA algorithms

Fig. 4. Performance of the Standard PSO Algorithm

VI. Experimental Setup and Tools

The experimental simulations were implemented in Python using standard libraries including `NumPy`, `Pandas`, and `Matplotlib` for numerical processing, data logging, and visualization respectively. The optimization routines leveraged `SciPy` for foundational methods, with custom-built logic for the hybrid PSO-SA algorithm. All experiments were executed on a system with Intel Core i3 @ 1.90GHz CPU and 4 GB RAM, ensuring consistency in computational environment.

VII. Conclusion

This work presents a hybrid PSO-SA model to solve the Traveling Salesman Problem more effectively. The hybridization improves consistency and solution quality compared to standalone PSO. Future work will focus on scalability, adaptive parameters, and application to real-world logistics domains.

VIII. Future Work

The proposed hybrid method can be enhanced by integrating adaptive parameters, leveraging machine learning for heuristic guidance, and applying it to real-world constrained TSP variants. Parallelism and benchmark evaluations against recent metaheuristics are also planned.

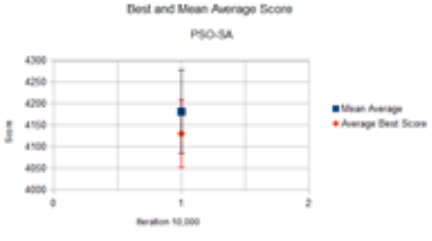

Fig. 5. Performance of the PSO-SA Algorithm

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