Hybrid Evolutionary Algorithm for Travelling Thief Problem

Phase 1
Group No: 64
GUIDE: Ms. Anisha Radhakrishnan
Review 1

SL NO.	Roll No	Name
1	CB.EN.U4CSE21105	Anwesha B
2	CB.EN.U4CSE21117	Manvish D
3	CB.EN.U4CSE21138	Surya N
4	CB.EN.U4CSE21148	Chaitanya R

Date: 28/09/2024

GUIDE’S APPROVAL MAIL

AR **Anisha Radhakrishnan (CSE)**

To: Rudraraju Chaitanya Varma - [CB.EN.U4CSE21148]

The presentation has been approved

Thank you

With Regards ,
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Date: 28/09/2024

INTRODUCTION

Definition: A problem combining elements of the Travelling Salesman Problem (TSP) and the Knapsack Problem.

Objective: Maximize the total value of items while minimizing travel costs.

Constraints: Limited carrying capacity for items.

Trade-off: Balancing travel costs vs. item values.

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MOTIVATION

Real-World Impact: TTP mirrors real challenges like **delivery services, where optimizing both routes and loads can save money, fuel,** and help the environment.

Complexity: Solving TTP perfectly in real-time is difficult due to its complexity, and traditional methods are too slow or inefficient. That's why smarter approaches are needed.

LITERATURE SURVEY - 1

YEAR	TITLE	AUTHOR	DESCRIPTION	METHODOLOGY	LIMITATIONS
2020	Hybrid Evolutionary Algorithm for Travelling Thief Problem	• Neeraj Pathak • Rajeev Kumar	Hybrid Evolutionary Algorithm that combines local search and mutation techniques to solve the Travelling Thief Problem, showing strong results on small instances.	• Combines evolutionary operators and local search heuristic • Uses domain knowledge to handle the interdependency between TSP and KP.	It doesn't fully evaluate the Hybrid Evolutionary Algorithm's performance on larger Travelling Thief Problem instances or versions with varied Knapsack components.

LITERATURE SURVEY - 2

YEAR	TITLE	AUTHOR	DESCRIPTION	METHODOLOGY	LIMITATIONS
2022	Evolutionary approaches with adaptive operators for the bi-objective TTP	• Roberto Santana • Sidhartha Shakya	An adaptive evolutionary algorithm for solving the bi-objective TTP, which combines the TSP and the Knapsack Problem for finding optimal solution.	• MOEV • MOEVAdapt • AOS	The MOEVAdapt algorithm may take time to stop using an operator that initially worked well but later declines in performance, causing it to be overused due to past success.

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LITERATURE SURVEY - 3

YEAR	TITLE	AUTHOR	DESCRIPTION	METHODOLOGY	LIMITATIONS
2024	Reinforcement Learning-Based Multi-start Neighborhood Search for Solving the Travelling Thief Problem	• TaoWu, • HuachaoCui, • TaoGuan, • YuesongWang • Yan Jin	**Uses Reinforcement Learning To Solve TTP By Improving Both The Traveling Path and the Items Picked During the Journey.**	**The Algorithm Creates An Initial solution then Improves it with Reinforcement Learning-Based Neighborhood Search, Followed by Post-Optimization.**	**The algorithm needs a lot of adjustments and computing power, while setting up the reinforcement learning part correctly.**

LITERATURE SURVEY - 4

YEAR	TITLE	AUTHOR	DESCRIPTION	METHODOLOGY	LIMITATIONS
2019	A Specialized Evolutionary Approach to the bi-objective Travelling Thief Problem	• Maciej Laszczyk,Paweł • B.Myszkowski	**TTP using two algorithms, NSGA-II and NTGA, which handle both Fast Travel and High Item Value.**	Focusing on Genetic Algorithms with Custom Operators for TTP.	Genetic algorithms can be slow for large problems and may struggle to find the best solutions. They might settle for good but not the optimal results.

LITERATURE SURVEY - 5

YEAR	TITLE	AUTHOR	DESCRIPTION	METHODOLOGY	LIMITATIONS
2023	A comparative study of evolutionary approaches to the bi-objective dynamic Travelling Thief Problem	• Daniel Herring • Michael Kirley • Xin Yao	**Explores dynamic multi-objective optimization challenges and the need for realistic benchmarks in the dynamic Travelling Thief Problem.** **.**	Utilizes benchmark evaluations, seeding strategies in evolutionary algorithms, and performance metrics to assess solutions.	Highlights the lack of real-world complexity capture and insufficient exploration of dynamic characteristics in existing studies.

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LITERATURE SURVEY - 6

YEAR	TITLE	AUTHOR	DESCRIPTION	METHODOLOGY	LIMITATIONS
2022	[Evolutionary Diversity Optimisation for The Traveling Thief Problem]	• Adel Nikfarjam • Aneta Neumann • Frank Neumann	Introduces a bi-level evolutionary algorithm for maximizing diversity in solutions to the Traveling Thief Problem (TTP).	Employs a two-tiered approach with crossover and optimization methods, measuring diversity using an entropy-based metric.	leading to longer run times and higher resource consumption.

LITERATURE SURVEY - 7

YEAR	TITLE	AUTHOR	DESCRIPTION	METHODOLOGY	LIMITATIONS
2024	Solves biobjective traveling thief problems using multiobjective reinforcement learning.	• G. Santiyuda • R. Wardoyo • R.Pulungan	Solves biobjective traveling thief problems using multiobjective reinforcement learning.	Uses Deep Q-Network for MORL agent, learns to balance profit and distance.	May struggle with large problems, choice of reward function and weight learning, and dynamic environments.

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LITERATURE SURVEY - 8

YEAR	TITLE	AUTHOR	DESCRIPTION	METHODOLOGY	LIMITATIONS
2017	Solving the Bi-objective Traveling Thief Problem with Multi-objective Evolutionary Algorithms	• Julian Blank • Kalyanmoy Deb • Sanaz Mostaghim	The Bi-objective TTP optimizes a thief's route to minimize travel distance and maximize item value.	Multi-objective Evolutionary Algorithms (MOEAs) evolve diverse solutions through selection, crossover, and mutation to find Pareto optimal routes.	High computational complexity Parameter sensitivity Scalability issues with larger instances

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SUMMARY OF LITERATURE SURVEY

The Traveling Thief Problem (TTP) has inspired various optimization approaches.

- **Hybrid Evolutionary Algorithm:** Combines local search and mutation; performs well on small instances but lacks evaluation on larger problems.
- **MOEVAdapt:** Utilizes adaptive operators for bi-objective TTPs but may over-rely on early successful operators.
- **Multiobjective reinforcement learning:** Employs deep Q-networks to balance profit and travel distance but struggles with scalability.
- **Multi-objective evolutionary algorithms:** Generate diverse Pareto solutions but face high computational complexity and scalability issues.
- **Genetic algorithms:** Show promise but experience slow performance on larger instances.
- **Reinforcement learning-based multi-start search:** Enhances initial solutions but requires significant computational resources.

श्रद्धावान् लभते ज्ञानम्

Evolutionary Algorithms On TTP

Advantages:
Global exploration
Avoid local optima

Disadvantages:
Slow convergence
Sensitive to parameter settings
Lack fine-tuning

Reinforcement Learning On TTP

Advantages:
Learn from experience
Dynamic adaptation
Real-time decision-making

Disadvantages:
Exploration-exploitation balance
Sample inefficiency
Difficult reward function design

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RESEARCH GAP

Existing models primarily rely on either Evolutionary Algorithms (EAs) or Reinforcement Learning (RL), with limited exploration of hybrid approaches combining both. Research on how to effectively merge these techniques to optimize both the knapsack selection and travel routing aspects of the problem remains underdeveloped.

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Evolutionary Algorithm + REINFORCEMENT LEARNING = Better Solution?

Broad Search Capabilities

Fine-Tuning

Optimizing both travel efficiency and item selection for higher quality outcomes

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PROBLEM STATEMENT

To investigate and analyze the integration of Evolutionary Algorithm with Reinforcement Learning for optimizing the Traveling Thief Problem (TTP).

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MODULE DESCRIPTION

Module 1 - Evaluation of Evolutionary Algorithms

- Review and implement multiple evolutionary algorithms known for their effectiveness in solving the TTP.
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- Assess these algorithms using the benchmark dataset to identify their performance in terms of solution quality and computational efficiency.

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MODULE DESCRIPTION

Module 2 - Integration of Reinforcement Learning:

- Following the evaluation of evolutionary algorithms, research and implement reinforcement learning strategies tailored for the TTP.

- These strategies will be applied to enhance the performance of previously identified evolutionary algorithms, focusing on optimizing both travel routes and item selection.

MODULE DESCRIPTION

Module 3 - Compare and Analyze Results

- Compare the performance of evolutionary algorithms and reinforcement learning strategies.

- Identify the best-performing algorithm overall, considering factors such as computational efficiency, solution quality, and adaptability.

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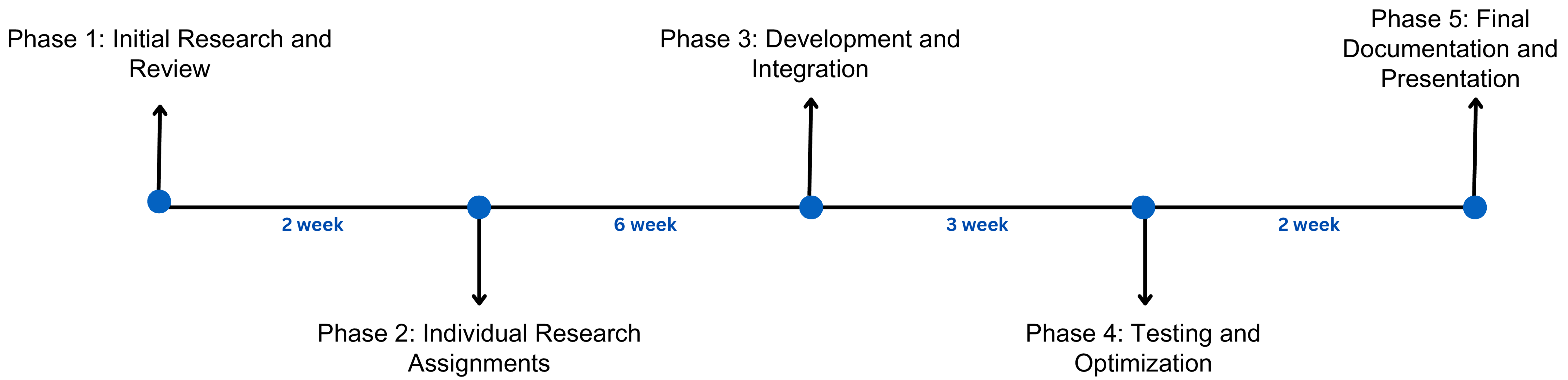
TIMELINE



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WORKFLOW

Phase	Duration	Tasks	Responsible
Phase 1: Initial Research and Review	1 week	- Conduct literature review on TTP methodologies. - Document findings and prepare Review 1.	All Members
Phase 2: Individual Research Assignments	2 weeks	- CB.EN.U4CSE21105: Documentation and dataset preparation. - CB.EN.U4CSE21117: Research RL algorithms. - CB.EN.U4CSE21138: Investigate EA algorithms. - CB.EN.U4CSE21148: Start integration of components.	All Members
Phase 3: Development and Integration	6 weeks	- Develop individual components. - Integrate RL and EA into a cohesive framework. - Test with sample datasets.	All Members
Phase 4: Testing and Optimization	3 weeks	- Conduct testing of the integrated solution. - Optimize parameters for performance. - Analyze results.	All Members
Phase 5: Final Documentation and Presentation	2 weeks	- Prepare final documentation detailing methodologies and results.	All Members

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SAMPLE DATASET

Node Coordinates

Index	X	Y
1	565.0	575.0
2	25.0	185.0
3	345.0	750.0
...	...	...
52	1740.0	245.0

Dimension: 52 nodes (cities)

Number of Items: 153

Knapsack Capacity: 12,513 units

Speed Range: Minimum speed = 0.1, Maximum speed = 1.0

Renting Ratio: 1.07

Items Section

Index	Profit	Weight	Assigned Node Number
1	101	1	2
2	202	2	3
...	...	...	...
153	694	594	52

ROLE OF EACH TEAM MEMBER

SL NO.	Roll No	Name
1	CB.EN.U4CSE21105	• Literature Survey - 1 & 2 • TimeLine, Flow Chart, Dataset
2	CB.EN.U4CSE21117	• Literature Survey - 5 & 6 • Research Gap, Problem Statement
3	CB.EN.U4CSE21138	• Literature Survey - 3 & 4 • Advantages & Disadvantage
4	CB.EN.U4CSE21148	• Literature Survey - 7 & 8 • Module Description

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[2] G. Santiyuda, R. Wardoyo, and R. Pulungan, "Solving biobjective traveling thief problems with multiobjective reinforcement learning," in 2024 IEEE Congress on Evolutionary Computation (CEC)*, pp. 1-8, doi: 10.1109/CEC48979.2024.111751.

[3] Blank, Julian, Kalyanmoy Deb, and Sanaz Mostaghim. "Solving the Bi-Objective Traveling Thief Problem with Multi-objective Evolutionary Algorithms." In 9th International Conference on Evolutionary Multi-Criterion Optimization - Volume 10173, EMO 2017, pp. 46-60. Berlin, Heidelberg: Springer-Verlag, 2017. URL: https://www.julianblank.com/_static/research/emo17-thief.pdf

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[5] Laszczyk, M., & Myszkowski, P. B. (2019, September). A specialized evolutionary approach to the bi-objective travelling thief problem. In 2019 Federated Conference on Computer Science and Information Systems (FedCSIS) (pp. 47-56). IEEE.

[6]Herring, D., Kirley, M., & Yao, X. (2024). A comparative study of evolutionary approaches to the bi-objective dynamic Travelling Thief Problem. Evolutionary Computation, 84, 101433.

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[7] Nikfarjam, A., Neumann, A., & Neumann, F. (2022, July). Evolutionary diversity optimisation for the traveling thief problem. In Proceedings of the Genetic and Evolutionary Computation Conference (pp. 749-756).

[8] Wu, T., Cui, H., Guan, T., Wang, Y., & Jin, Y. ReinforceNS: Reinforcement Learning-based Multi-start Neighborhood Search for Solving the Traveling Thief Problem.