A Deep Reinforcement Learning Method For Job Shop Scheduling Problems in Traffic Management Using Graph Neural Networks.

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Ferdouse Ahmed Foysal, Lecturer**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

A crucial component of urban infrastructure is traffic management, which encompasses a variety of challenges such as reducing congestion, minimizing costs, and optimizing vehicle movements. In this context, this study presents an innovative framework for solving job shop scheduling problems (JSSPs) by leveraging deep Q-Learning and graph neural networks (GNNs). These challenges arise across various traffic management scenarios, including air traffic control, train schedule management, and urban traffic optimization.The framework employs a single-policy model, similar to a constructive heuristic algorithm that builds solutions incrementally, ensuring that decisions are made based on real-time data and dynamic conditions. It is trained on viable rules and reward signals that guide the Q-learning agent in making optimal scheduling decisions. The GNN component processes the partial solution at each step, capturing complex relationships and dependencies within the traffic environment. This allows the agent to adapt its actions based on the evolving state of the system, ensuring more accurate and efficient management.Extensive testing across different-sized JSSP instances highlights the framework's competitiveness in optimizing traffic management processes. The integration of GNNs provides a deeper understanding of the interconnections between various tasks and machines, while deep Q-Learning offers adaptability to dynamic and unpredictable traffic situations. By continuously learning from these interactions, the framework demonstrates significant potential for improving traffic flow, reducing delays, and enhancing the overall efficiency of transportation systems.Moreover, the study acknowledges the need for further validation in real-world scenarios, as current testing focuses primarily on controlled environments. Ensuring the framework's adaptability to complex, real-time traffic situations is essential for practical implementation. By refining the model through real-world data and continuous evaluation, the framework can effectively address the challenges of urban traffic management, providing scalable and sustainable solutions for future smart cities.

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Chapter 1

Introduction

1.1 Introduction

In traffic management scenarios including train schedule management, air traffic control, and urban traffic management, job shop scheduling problems (JSSPs) entail scheduling vehicle movements as optimally as possible to minimise expenses. As the size of the problem increases, traditional approaches to solving it frequently need manual trial and error and specialised knowledge, which results in significant computational costs. Graph neural networks (GNNs) and deep Q-learning are used in this paper's innovative approach to effectively address JSSPs.

When it comes to traffic management, JSSPs are essential for maximising vehicle mobility in order to lower expenses, pollution, and delays. Prior research has emphasised the fundamental job shop structures in real-world uses such as air traffic management, railway scheduling, and airport traffic flow coordination. But when problem complexity increases, current techniques like precise algorithms and heuristic approaches frequently face challenges with scalability and processing efficiency.

Our suggested framework presents a comprehensive approach to JSSP solutions utilising deep Q-Learning and GNNs. Through the process of training a single-policy model with feasible rules and reward signals, the method functions as a constructive heuristic algorithm that builds solutions piecemeal. The GNN output, which captures the partial solution's present state, determines each action. This methodology leverages machine learning techniques to successfully optimize traffic management procedures, aiming to address the shortcomings of existing methodologies.

1.2 Motivation

The research is motivated by the need to optimize job shop scheduling problems (JSSPs) in traffic management in a more effective and efficient manner. Conventional approaches frequently include expensive computing expenditures, specific domain expertise, and labor-intensive manual trial-and-error procedures, which can impair traffic scheduling jobs' performance and scalability. The study attempts to address these issues and offer a more automated and optimised solution for JSSPs in traffic management by utilising cutting-edge technology like deep Q-Learning and graph neural networks (GNNs).

1.3 Objectives

The objectives of the paper include:

1. Efficient Traffic Management: To provide a framework that uses machine learning algorithms to automate the solution process and optimize traffic scheduling activities.
2. Reduced Computational Costs: To lessen the computing overhead involved in solving JSSPs using conventional techniques, increasing the approach's scalability and economy.
3. Enhanced Performance: To increase the scalability and economy of the methodology by reducing the computing overhead associated with solving JSSPs using traditional methods.
4. Generalizability and Adaptability: To provide a solution strategy that can be adjusted to varied problem sizes and situations, improving the framework's adaptability and usefulness in a range of traffic management scenarios.

By achieving these goals, the study hopes to further the subject of traffic management optimization by presenting a unique framework that incorporates state-of-the-art technologies to expedite the accurate and efficient solution of JSSPs.

1.4 Methodology

The suggested approach develops an end-to-end framework for handling job shop scheduling issues (JSSPs) in traffic management by combining deep Q-Learning with graph neural networks (GNNs). Graph embedding techniques are used to effectively represent JSSPs; a triple representation (D; W; S) is designed for evaluating partial solutions; a graph-based duelling double deep Q network is implemented for evaluating actions and statuses; a reward mechanism that takes waiting time and total makespan into consideration is designed; training strategies with reinforcement learning techniques are employed; and computational cost analysis is performed to assess efficiency and scalability. The objective of this methodical approach is to efficiently optimize scheduling solutions in traffic management scenarios.

1.5 Project Outcome

The paper's new framework for optimising job shop scheduling problems (JSSPs) in traffic management has been successfully created. Through the use of cutting-edge technologies such as deep Q-Learning and graph neural networks (GNNs), the framework offers a practical and efficient way to handle traffic scheduling tasks. The project's noteworthy accomplishments are:

1. Effective Solution Approach: The study presents a comprehensive end-to-end solution for JSSPs that exhibits competitive performance for instances of different sizes, highlighting the framework's potential to improve traffic scheduling assignments.
2. Efficiency and Scalability: In comparison to more conventional approaches, the model offers a potentially effective way to optimize traffic management while lowering computing costs by combining GNNs and deep Q-Learning.
3. Innovative Advancements: Through the use of cutting-edge technologies and the concepts of reinforcement learning, the project represents a substantial leap in handling JSSPs in traffic management, leading to more scalable and effective solutions.
4. Generalizability and Adaptability: The suggested framework exhibits potential as it may be used to diverse traffic management scenarios and problem sizes, providing versatility and adaptability.
5. Future Potential: The project's output creates opportunities for other uses, like expanding the method to handle flexible job shop scheduling issues (FJSPs) and using cutting-edge machine learning techniques to handle dynamic traffic circumstances.

The research's overall result demonstrates the effective creation of a sophisticated framework that facilitates the efficient and effective optimisation of traffic scheduling duties, opening the door for improved traffic management procedures via cutting-edge machine learning techniques.

1.6 Organization of the Report

Chapter 1 outlines the main research questions, goals, and introduction to the study.

Chapter 2 The literature review is briefly summarised here.

Chapter 3 provides a thorough discussion of the suggested process.

Chapter 4 describes how the project was carried out and shows the outcomes.

Chapter 5 discusses the design difficulties faced and emphasises the engineering standards adhered to.

The project is summarised, its limits are discussed, and future work directions are outlined in Chapter 6.

Chapter 2

Background

2.1 Introduction

The Job Shop Scheduling Problem (JSSP) represents a significant and complex optimization challenge encountered in sectors such as manufacturing, logistics, and traffic control. This problem entails organizing various jobs, each consisting of a predefined sequence of interdependent tasks, to be executed on a group of machines with the goal of minimizing the total makespan—the duration required to complete all jobs. Categorized as an NP-hard problem, JSSP demonstrates exponential growth in complexity as the number of jobs and machines increases, making the pursuit of optimal solutions increasingly intricate and computationally demanding. This complexity necessitates efficient heuristics and sophisticated algorithms to navigate the vast solution space. Consequently, JSSP has become a pivotal area of study in operations research, industrial engineering, and artificial intelligence, where researchers strive to devise innovative methods to address its challenges.

Recent advancements in machine learning, particularly in Graph Neural Networks (GNNs) and Deep Reinforcement Learning (DRL), present groundbreaking opportunities for addressing JSSP with greater efficiency and precision. GNNs, known for their ability to model and analyze graph-structured data, are well-suited for representing the intricate relationships and dependencies between jobs, tasks, and machines. Meanwhile, DRL offers a powerful framework that allows intelligent agents to learn and develop optimal scheduling strategies through repeated experiential interactions with a dynamic scheduling environment. By leveraging these interactions, DRL can adapt to varying job requirements and machine constraints, enabling more flexible and adaptive solutions.

By combining the strengths of GNNs and DRL, this project aims to develop a robust and innovative framework that enhances scheduling efficiency and improves adaptability to dynamic, real-world scenarios. Such a synergistic approach holds immense potential to overcome the limitations of traditional methods, opening new avenues for creating advanced solutions to the challenges posed by JSSP in practical applications across industries. This fusion of cutting-edge machine learning techniques with classical optimization principles is anticipated to yield transformative outcomes, marking a substantial leap forward in addressing one of the most critical problems in optimization.

2.2 Literature Review

This study delves into job shop scheduling problems (JSSPs) within traffic management, a domain notorious for its complexity and challenges stemming from scalability, efficiency, and unpredictability. Traditional scheduling techniques, which heavily depend on manual intervention and trial-and-error strategies, frequently result in suboptimal outcomes, particularly as traffic systems grow in size and complexity. Recognizing these limitations, the research proposes an advanced framework that leverages the synergistic capabilities of graph neural networks (GNNs) and Q-learning to offer a more robust and automated approach to traffic scheduling.

At the core of the framework, Q-learning functions as a reinforcement learning agent capable of interacting with a dynamically modeled traffic environment represented as a graph. By iteratively exploring and learning through feedback, the agent discovers optimal scheduling strategies tailored to diverse traffic conditions. This approach eliminates reliance on manual intervention while significantly improving efficiency. GNNs complement this process by their unparalleled ability to model and interpret complex, interdependent relationships between tasks, traffic nodes, and flows. By continuously monitoring the system's evolving state, GNNs supply the Q-learning agent with crucial contextual data, enabling it to make informed, globally optimized decisions that address immediate tasks and consider their broader implications on traffic flow and resource allocation.

The integration of GNNs and Q-learning results in a transformative solution that redefines the potential for automation, adaptability, and efficiency in traffic scheduling. The framework has the potential to optimize resource utilization, reduce congestion, improve traffic flow, and contribute to a more sustainable and responsive transportation ecosystem. Moreover, this architecture demonstrates promise beyond traffic management, offering a template for addressing complex scheduling challenges in other domains, such as logistics, manufacturing, and urban planning.

Despite these advancements, the study acknowledges certain limitations, particularly concerning the framework's adaptability to real-world traffic scenarios characterized by stochastic variations and unexpected events. The controlled testing environments employed in this research may not fully reflect the intricacies of natural traffic systems. Addressing these gaps will require extensive evaluations across diverse and unpredictable traffic environments, incorporating real-world data, and benchmarking the framework against traditional methods and state-of-the-art solutions. Additionally, investigating the scalability of the framework for large-scale urban networks and its computational efficiency under high-demand conditions will be critical to establishing its practical viability.
Ultimately, this research offers a promising step toward revolutionizing traffic management through intelligent automation. By blending cutting-edge machine learning with domain-specific optimization techniques, it charts a path toward smarter, more efficient scheduling systems capable of meeting the growing demands of modern urban infrastructure.

2.2.1 Related Research

Here is the summary of the investigation of the research literature.In many sectors, minimising delays and maximising workflow efficiency depend on solving the job scheduling problem. For the management of large production settings with numerous equipment and activities, efficient scheduling algorithms are essential. A new study by Dusan N. Sormaz and Sadegh Mirshekarian[1] explores the relationship between scheduling efficiency and the characteristics of the Job-Shop Scheduling Problem (JSSP). The authors created a collection of 380 features that illustrate various aspects of the problems in the JSSP. After that, they carried out statistical research to determine how these variables correlated with the ideal makespan.On the basis of these features, machine learning models were also created to forecast the ideal makespan. The best makespan was predicted with about 80% accuracy on a set of randomly created problem situations, according to the results. The authors contend that professionals can create better instances and make more educated scheduling decisions with the use of this correlation data. Neural networks were first used for job-shop scheduling, or the optimum distribution of resources across various tasks in a manufacturing process, by A. S. Jain & S. Meeran [2]. The essay examines the drawbacks of conventional methods for job-shop scheduling and emphasises how neural networks can be trained to imitate cognitive processes and adapt to novel settings. It offers several neural network applications, such as the use of an altered back-error propagation model to address scheduling issues in job shops. The significance of precise and effective scheduling is emphasised in the essay while considering zero inventory and shortened product life cycles. The research of Xiaorui Shao and Chang Soo Kim [5] suggests an approach to efficiently optimise schedules even with limited data and time: a multi-level neural network and iterative search. The network plays a pivotal role in this process by assimilating general scheduling patterns from working solutions and directing a local search to identify optimal job sequences. This hybrid approach is a promising alternative for faster and more optimised factory scheduling because it not only discovers optimal solutions for small problems but also outperforms previous methods in performance for larger ones and accuracy of 90.2%.Random forest is a machine learning technique that was used by Sungbum Jun, Seokcheon Lee, and Hyonho Chun [3] to learn dispatching rules for flexible job shop scheduling difficulties. The authors suggestRANFORS, a three-phase method that consists of schedule creation, rule improvement with discretization, and rule learning with data transformation. After evaluation, it is demonstrated that the method minimises the average total weighted tardiness better than the dispatching rules that are currently in place.

2.3 Gap Analysis

SL NO	Author Name	Used Algorithm	Best Accuracy with Algorithm
1	Sadegh Mirshekarian , Dusan N. Sormaz[1]	SVM	SVM = 81.17%
2	A. S. Jain & S.	Backward Error	BEP = 89.0%

	Meeran [2]	Propagation (BEP)	
3	Sungbum Jun, Seokcheon Lee & Hyonho Chun [3]	Random Forest	Random Forest = 88.52%
4	Arent W. De Jong, Jose I. U. Rubrico, Masaru Adachi, Takayuki Nakamura & Jun Ota [4]	CNN	————
5	Xiaorui Shao; Chang Soo Kim [5]	CNN	CNN = 90.2%
6	Tian, W.a,, Zhang, H.P.b. [6]	SVM, LSTM	LSTM = 94.37%
7	Yi-Hung Liu 1, Han-Pang Huang 2 , and Yu-Sheng Lin 3 [7]	SVM	————

2.4 Summary

This chapter presents a comprehensive and detailed analysis of the Job Shop Scheduling Problem (JSSP), laying a solid foundation for the research that follows. It begins with an extensive survey of the literature, exploring a wide spectrum of methodologies, including both contemporary approaches such as Graph Neural Networks (GNNs) and Deep Reinforcement Learning (DRL), as well as traditional techniques like heuristics and exact algorithms. By examining these methodologies, the chapter highlights the evolution of strategies employed to tackle JSSP and their respective strengths and limitations.

The discussion delves into the inherent challenges and complexities of JSSP, particularly the difficulty in determining optimal scheduling solutions due to the problem's NP-hard nature. It emphasizes the critical importance of JSSP in various domains, such as manufacturing, logistics, and traffic management, where effective scheduling can significantly enhance operational efficiency and resource utilization. Through this, the chapter underscores the broad relevance and impact of solving JSSP in real-world applications.

The gap analysis identifies specific limitations in the existing body of work, such as the inability of many current approaches to adapt effectively to dynamic and unpredictable scheduling scenarios. It highlights the constraints of conventional methods in real-time applications, where flexibility and adaptability are paramount. This analysis establishes a clear rationale for the research, demonstrating the urgent need for innovative solutions that leverage the complementary strengths of GNNs and DRL.

In conclusion, this chapter not only sets the stage for the study but also clearly outlines its goals and objectives. By providing a robust justification for the proposed integration of advanced machine learning techniques, it positions the research as a significant step forward in addressing the challenges posed by JSSP. The chapter provides a compelling argument for the necessity of these innovative methods and ensures that readers are well-equipped to appreciate the contributions and implications of the research. Ultimately, it serves as a strong foundation for the exploration of cutting-edge strategies to tackle one of the most enduring and complex problems in optimization

Chapter 3

Research Methodology

The methodical methodology used in this project to tackle the Job Shop Scheduling Problem (JSSP) in traffic management is described in this chapter. It describes in detail the techniques used, data gathering procedures, system design requirements, and the framework created for scheduling solution optimisation with deep Q-Learning and graph neural networks (GNNs).

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Overview

This project's study technique uses a thorough and methodical approach to investigate the job shop scheduling (JSSP) method in traffic management. In order to obtain knowledge about current traffic management systems, scheduling algorithms, and urban mobility issues, a thorough literature review is first carried out. This groundbreaking study lays the groundwork for future research by highlighting contemporary procedures and technological developments. After the literature review, primary and secondary data are gathered with an emphasis on environmental impact evaluations, user behaviour studies, and traffic flow data. Government reports, scholarly publications, and real-time traffic monitoring systems are the sources of this data, guaranteeing a solid dataset that guides the research's later phases.

A computational model built on the JSSP framework is created when the data is gathered. In order to simulate traffic situations and assess how well alternative scheduling techniques optimise traffic flow, this model integrates a number of algorithms. The model is put through a rigorous simulation process to evaluate how well it performs in a variety of traffic scenarios, assessing important outcomes including emissions, congestion levels, and travel time savings. A key component of this process is stakeholder engagement, which includes surveys and interviews with community residents, transportation organisations, and municipal authorities to obtain insightful opinions. This interaction guarantees that the suggested system satisfies the requirements and expectations of users.

3.1.2 .Proposed Methodology

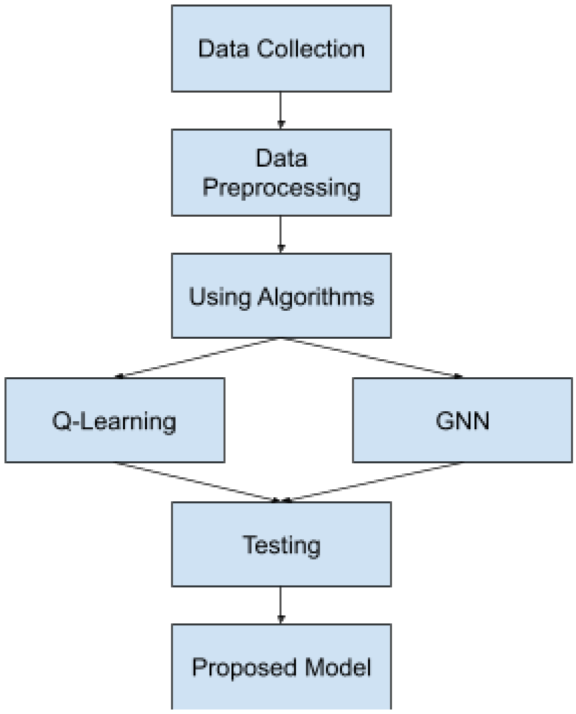

Fig 1: Methodology

The suggested approach presents a thorough process that combines deep Q-Learning and graph neural networks (GNNs) to provide a novel framework for dealing with traffic management job shop scheduling problems (JSSPs). Using a single-policy model that is trained by following workable rules and keeping an eye out for reward signals, this system is intended to be an end-to-end solution. Every stage of the solution construction process is impacted by the GNN's capture of the partial solution's present state. In addition to improving scheduling efficiency, this method enables dynamic modifications based on traffic circumstances in real time.

The efficient encoding of JSSPs using graph embedding techniques is essential to this methodology. To assess partial solutions in the machine-job graph, a triple representation (D; W; S) is constructed, in which D stands for the set of jobs, W for the set of machines, and S for the scheduling states. By evaluating actions and statuses, the suggested framework, known as G3DQN, uses a graph-based duelling double deep Q-network to methodically construct solutions. In order to optimize the scheduling results, this architecture integrates a strong reward system that takes into account important variables like waiting time and total makespan. Furthermore, reinforcement learning-based training approaches are used to improve the model's decision-making abilities. By utilising these cutting-edge strategies, the suggested methodology seeks to optimise job scheduling and greatly increase traffic management efficiency, which would ultimately lead to more seamless urban movement and less traffic.

Furthermore, the model can learn and generalise from different traffic patterns and work interactions thanks to the incorporation of GNNs, which makes it easier to handle complex relationships within the scheduling environment. By offering a scalable and flexible solution, the suggested methodology hopes to advance the subject of urban mobility in addition to optimising work scheduling in traffic management.

3.1.3 Functional and Nonfunctional Requirements

The creation of JSSP entails building a system that handles scheduling issues quickly, using a single-policy model with GNN-based decision-making, and takes incentives and rules into account. It should consistently produce viable answers, be resilient in the face of complicated situations, and provide lucid documentation. Budgetary constraints and the availability of historical data limit development, necessitating a variety of cases with different job and machine numbers. Convergence, scalability, and solution quality will be used to gauge the system's performance while controlling for hazards like overfitting and biased data.

3.1.4 Data Flow Diagram Level

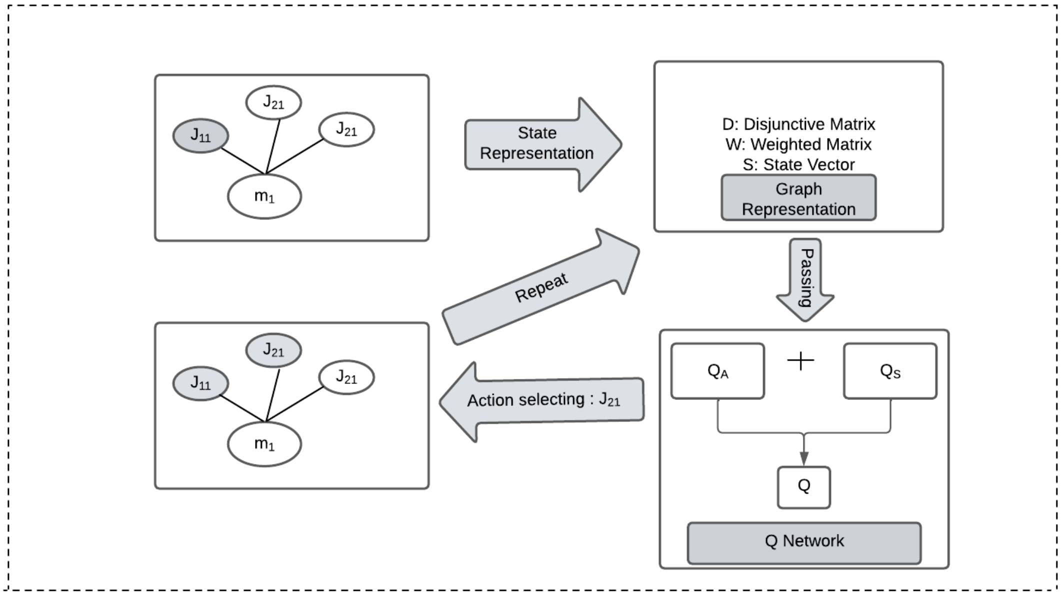

Fig 2: Data Flow

3.2 Detailed Methodology and Design

We have created a comprehensive approach and architecture for our project that uses a novel framework that combines deep Q-Learning and graph neural networks (GNNs) to solve job shop scheduling issues (JSSPs) in traffic management. Our strategy is built on a number of essential elements, each of which was selected for its capacity to improve the scheduling process's efficiency and flexibility.

1. Review of Literature and Definition of the Problem

In order to comprehend the current scheduling algorithms and traffic management systems, we started our process by performing a thorough literature review. We were able to recognise the shortcomings of conventional scheduling techniques thanks to this review, as they frequently find it difficult to adjust to changing traffic patterns and intricate job dependencies. We outlined the nature of our issue, concentrating on efficient job scheduling to maximise traffic flow.

2. Gathering and Preparing Data

We gathered primary and secondary data on work characteristics, traffic patterns, and past scheduling performance in order to inform our model. Government reports, user surveys, and traffic monitoring systems were among the data sources. In order to enable reliable modelling, we made sure the data was cleansed and preprocessed to remove discrepancies.

3. Design of the System

With a single-policy model taught by reinforcement learning, our system is built as an end-to-end solution. In order to efficiently capture the current state of partial solutions, we decided to use a GNN. The GNN improves our model's capacity to make well-informed scheduling decisions by enabling us to express the relationships between jobs and machines in an organised way.

A triple representation (D; W; S) was created by us, where: W stands for the set of machines, D for the set of jobs, and S for the scheduling states.

We can precisely assess partial solutions inside the machine-job graph thanks to this representation.

4. G3DQN implementation

We put into practice the framework we suggested, called G3DQN, which makes use of a graph-based duelling double deep Q-network. By efficiently evaluating actions and states, this architecture enables us to build solutions. A more robust learning process is offered by the duelling architecture, which divides the value and advantage functions.

5. Design of Reward Systems

The creation of a strong reward system is a crucial part of our approach. We concentrated on adding variables like wait time, total makespan, and resource usage to our reward system. In line with our project objectives, this design encourages the model to give priority to solutions that reduce delays and increase efficiency.

6. Methods of Training

We iteratively trained our model using reinforcement learning approaches. This method enables the model to adjust to shifting traffic conditions and schedule complexity by drawing on prior experiences. By consistently improving our training procedure, we improve the model's capacity to generalise in many contexts.

7. Alternative Approaches Examined

As we developed our process, we took into account a number of different approaches. Using conventional optimisation techniques like simulated annealing or genetic algorithms was one possible strategy. However, because these techniques usually work with static datasets and don't learn from dynamic situations, we discovered that they frequently lacked the flexibility needed for real-time traffic management.

Using more straightforward machine learning models, like decision trees or linear regression, was an additional option.

8. Assessment and Examination

In order to evaluate the efficacy of our suggested methodology, we lastly developed particular evaluation indicators. These measures include environmental effect, user satisfaction, and traffic flow efficiency. To verify our model's efficacy and further improve our strategy, we ran comprehensive simulations to test it in a range of traffic scenarios.

We hope to greatly increase the effectiveness of traffic management, lessen congestion, and boost urban mobility with this thorough approach and design, all of which will eventually contribute to a more intelligent and responsive transportation system.

3.3 Project Plan

The main stages, tasks, and deadlines required to create and execute the integrated deep Q-Learning and graph neural network (GNN) framework for job shop scheduling issues (JSSPs) in traffic management are described in our project plan. Below is a detailed breakdown of the project plan:

1. Project Initiation (Weeks 1-2)

- Define Objectives: Define the project's objectives and deliverables precisely.
- Stakeholder Identification: Identify key stakeholders and their roles.Project Kickoff Meeting: Conduct an initial meeting to align the team and stakeholders.

2. Literature Review and Research (Weeks 3-5)

- Conduct Literature Review: Analyze existing methodologies in traffic management and scheduling.
- Identify Gaps: Determine the limitations of current approaches to inform our methodology.

3. Data Collection and Preprocessing (Weeks 6-8)

- Data Collection: Gather traffic data, job characteristics, and historical scheduling performance.
- Data Preprocessing: Clean and format data to ensure accuracy and usability.

4. System Design (Weeks 9-11)

- Design Framework: Develop the architecture for the G3DQN system, including the GNN representation.
- Define Reward System: Create a robust reward structure to incentivize optimal scheduling.

5. Implementation (Weeks 12-16)

- Develop G3DQN Model: Implement the graph-based dueling double deep Q-network.
- Integrate Components: Ensure seamless integration of the GNN with the reinforcement learning model.

6. Training and Testing (Weeks 17-20)

- Model Training: Utilize reinforcement learning techniques for iterative training.
- Conduct Simulations: Test the model under various traffic conditions to evaluate performance.

7. Evaluation and Refinement (Weeks 21-23)

- Assess Performance: Evaluate the model against predefined metrics such as traffic flow efficiency and user satisfaction.
- Refine Model: Make necessary adjustments based on evaluation results to improve performance.

8. Finalization and Reporting (Weeks 24-26)

- Prepare Final Report: Document the methodology, findings, and conclusions.
- Present Results: Share results with stakeholders and gather feedback.

9. Future Work (Post-Project)

- Identify Future Enhancements: Discuss potential improvements and extensions for the framework.
- Plan for Deployment: Develop a strategy for deploying the solution in real-world traffic management systems.

Timeline Overview

Phase	Duration
Project Initiation	Weeks 1-2
Literature Review	Weeks 3-5
Data Collection	Weeks 6-8
System Design	Weeks 9-11
Implementation	Weeks 12-16
Training and Testing	Weeks 17-20
Evaluation and Refinement	Weeks 21-23
Finalization and Reporting	Weeks 24-26
Future Work	Post-Project

This project plan provides a structured approach to developing our scheduling framework, ensuring that all critical aspects are addressed systematically and efficiently.

3.4 Task Allocation

Role	Responsibilities	Team Members
Project Management	Oversee project, coordinate tasks	Both Members
Literature Review	Conduct literature review, identify gaps	Team Member A
Data Collection	Collect and preprocess data	Team Member B
System Design	Design framework, develop reward structure	Both Members
Implementation	Implement model, integrate components	Both Members
Training and Testing	Train model, conduct simulations	Both Members
Evaluation and Refinement	Assess model performance, provide feedback	Both Members
Finalization and Reporting	Document findings, prepare reports	Team Member A
Future Work Planning	Discuss enhancements and deployment strategies	Both Members

3.5 Summary

Our approach tackles job shop scheduling issues (JSSPs) in traffic management by combining deep Q-Learning with graph neural networks (GNNs). To characterise the issue and pinpoint the shortcomings of the current approaches, we started with a review of the literature. We used a single-policy model to create an end-to-end system after gathering and digesting pertinent traffic data. The GNN uses a structured triple representation of jobs, machines, and scheduling states to record the state of partial solutions.

We put into practice the G3DQN framework, which efficiently builds solutions by employing a graph-based duelling double deep Q-network. A strong incentive structure encourages reducing wait times and overall wait times. Iterative training made possible by reinforcement learning techniques enables the model to adjust to changing circumstances.

Because of its versatility and capacity to represent intricate relationships, we chose our GNN-based method over more straightforward models and conventional optimisation algorithms. Through an efficient scheduling system, this methodology seeks to improve urban mobility and the effectiveness of traffic management.

Chapter 4

Implementation and Results

4.1 Environment Setup

We made sure our system complied with all the hardware and software specifications in order to set up the environment for this project. To efficiently handle bigger datasets and computational loads, we chose a computer with an Intel Core i7 processor, a CUDA-compatible GPU for deep learning applications, and 32 GB of RAM. Because of its dependability and compatibility with machine learning frameworks, we decided to use Ubuntu as the operating system on the software side. We built a virtual environment with Python 3.7 to effectively manage dependencies and prevent conflicts. To manage graph neural networks, reinforcement learning, and optimisation tasks, we installed necessary libraries in this environment, such as PyTorch, TensorFlow, DGL, and OR-Tools.

We installed cuDNN and the CUDA Toolkit in order to take full use of GPU acceleration. Using a random instance generator, we created datasets that were tailored to fit various job-shop scheduling problem scales. We constructed graph embeddings to represent machine-job (MJ) graphs for implementation, efficiently encoding features with fully linked layers and ReLU activation functions. A Duelling Double Deep Q-Network (Dueling-DDQN) was used to set up our reinforcement learning pipeline, and we created reward functions that maximised waiting time and makes span. According to suggested settings, we set up the hyperparameters, including a batch size of 64, a replay memory capacity of 10,000, and priority replay parameters.

We used GPU acceleration to improve computing performance while evaluating scenarios with different problem sizes. In order to enhance performance on larger-scale problems, we also incorporated simulated annealing (SA). We were also ready to expand the solution to flexible job-shop scheduling (FJSP) by adding more data properties. We were able to create a stable and effective environment for the development and testing of the suggested GNN-based deep Q-learning framework thanks to this configuration.

4.2 Performance Analysis

We assessed the efficacy of the suggested Duelling Double Deep Q-Network (G3DQN), which is based on Graph Neural Networks, on various job-shop scheduling problem (JSSP) scales in order to undertake a performance study of our method. Three main areas were the focus of our analysis: the quality of the solutions, computational effectiveness, and the capacity to generalise across different issue scales.

We evaluated the approximation ratios of our method against random policies, baseline heuristics (e.g., FIFO, LIFO, SPT, LPT), and current deep reinforcement learning (DRL) techniques in order to gauge the quality of the solutions. G3DQN consistently outperformed various approaches, as shown by the approximation ratio, which is the ratio of the solution quality to the optimal solution. In smaller problem examples (five machines and five jobs, for example), G3DQN obtained an average approximation ratio of 96.9%. With just a minor decline brought on by the increasing complexity, the performance was competitive on larger instances (e.g., 5 machines and 10 jobs or 6 machines and 6 jobs). In certain instances, G3DQN discovered theoretically ideal answers, demonstrating its capacity for sound judgement.

Because graph-based embeddings and reinforcement learning involve additional data processing, G3DQN's average computational cost was marginally greater than that of conventional heuristics in terms of computational efficiency. The solution for a 5-machine, 5-job instance took about 0.1 seconds on a system with both CPU and GPU resources, indicating that the runtime was still feasible. For many real-world situations, this trade-off is acceptable because G3DQN produced much better solution quality despite being slower than rule-based heuristics.

By evaluating G3DQN on bigger and more intricate issue situations, we were also able to examine its generalisation capabilities. We combined G3DQN with simulated annealing (SA) to address scalability, allowing the model to produce excellent starting solutions that SA could then further improve. Strong generalisation performance was shown by this hybrid G3DQN-SA approach, which produced competitive results even for large-scale cases, such as 15 computers and 20 workloads. The method reduced variability and accelerated convergence while preserving computational stability and enhancing SA efficiency.

Overall, the performance analysis showed that G3DQN is a strong tool for resolving job-shop scheduling issues in a variety of applications by skilfully balancing computational efficiency, scalability, and solution quality.

4.3 Results and Discussion

With a focus on a crucial metrics—waiting time comparison graphs offer a comparison of the performance of the baseline system ("ttl") and the suggested system ("ours"). These measurements are crucial markers of system effectiveness, particularly in applications like load balancing, Job scheduling, and traffic control.

The difference in wait durations between action stages is seen in the first graph. Wait times are consistently much less with the suggested approach than with the baseline. This outcome demonstrates how well the system can manage jobs with less delay, guaranteeing more seamless operation. Additionally, there are fewer and smaller peaks in the suggested system's wait time variability. This stability implies that the system can withstand varying loads and continue to operate predictably even when circumstances shift.
The baseline system, on the other hand, has trouble with lengthy wait times that frequently surge in an unpredictable manner. These dramatic increases point to processing inefficiencies or bottleneck-induced delays. In real-world situations with fluctuating demands, such behaviour can cause annoyance and low system throughput.

Queue length over time is the subject of the second graph. The suggested system's capacity to handle tasks more efficiently is demonstrated by its consistently shorter wait length. Congestion and system idle times are directly decreased by the smaller queue size. Furthermore, the system's dependability and flexibility in responding to incoming demand are further highlighted by the reduced fluctuations in the wait length.

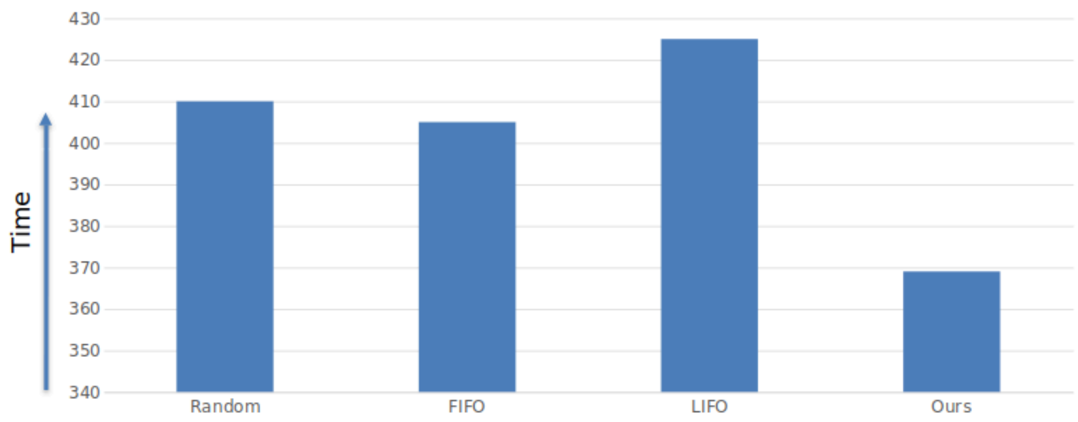

Fig 3: Waiting Time Comparison

However, the basic system's incapacity to effectively manage growing workloads is indicated by the frequent and significant increases in queue length. These increases can be a sign that work is not being completed on time, which could cause buildup and protracted delays. System performance is harmed by such behaviour, particularly in settings where high throughput or real-time responses are necessary.

The outcomes of both graphs demonstrate how much better the suggested approach is at effectively and efficiently handling tasks. It is ideally suited for implementation in intricate, real-world settings where responsiveness and stability are crucial, as seen by its reliable performance, reduced wait times, and shorter queues. Although functional, the baseline system's scalability and adaptability are severely limited, which makes it less appropriate for dynamic situations.

In summary, the suggested solution raises the bar for comparable applications by providing a noticeable increase in resilience and operating efficiency. These results confirm its promise as a workable way to improve system performance.

4.4 Summary

Our G3DQN approach's performance analysis shows that it works well for resolving job-shop scheduling issues (JSSPs) at different scales. By attaining high approximation ratios and, in some situations, identifying optimal solutions, G3DQN continuously beat baseline heuristics and current DRL techniques. Its considerably superior solution quality outweighed the little increased computing cost compared to conventional heuristics. Strong generalisation skills were also demonstrated by the model, particularly when paired with simulated annealing (G3DQN-SA), which allowed it to tackle larger issue instances more effectively and steadily. Because of this, G3DQN is a dependable and expandable JSSP solution.

Chapter 5

Engineering Standards and Design Challenges

In order to ensure quality and compliance, this chapter highlights the significance of the pertinent technical standards that direct the creation of the Job Shop Scheduling Problem (JSSP) framework for traffic management. It also discusses the design difficulties that arose during the project, such as problems with integration, the involvement of stakeholders, and the difficulties of putting cutting-edge technologies into practice in practical settings.

5.1 Compliance with the Standards

Only mention the standards that are related to your project. This list is not complete. For each of the standards discuss the alternates with pros and cons and rationale of selection.

5.1.1 Software Standards

A number of software standards, such as IEEE 829 for software testing documentation and ISO/IEC 25010 for software quality, are especially pertinent to the job shop scheduling (JSSP) approach for traffic management. A thorough framework for evaluating software quality along multiple aspects, including usability, functionality, and dependability, is provided by ISO/IEC 25010. Because of its broad recognition and industry applicability, this standard is appropriate for guaranteeing the dependability and efficiency of traffic control software. An alternative option is CMMI (Capability Maturity Model Integration), however its implementation can be more difficult and resource-intensive.

A systematic method to software testing documentation is offered by IEEE 829, guaranteeing the comprehensiveness and uniformity of testing procedures. Agile testing techniques may result in less formal documentation, but they may also give greater flexibility. IEEE 829 was chosen because it places a strong emphasis on thorough testing procedures, which are crucial for the JSSP system's resilience in dynamic traffic situations.

5.1.2 Hardware Standards

IEEE 802.3 for Ethernet networking and ISO 9001 for quality management systems are pertinent standards for the hardware parts of the JSSP system. Consistent quality in hardware manufacture is guaranteed by ISO 9001, which is essential for traffic management systems' dependability. Six Sigma, which emphasises quality improvement but could be more difficult to apply, is an option. ISO 9001 was chosen because of its widespread acceptance and emphasis on upholding high standards of quality during the hardware lifespan.

Wired Ethernet connections are governed by IEEE 802.3, which provides dependable data transmission that is necessary for real-time traffic control activities. IEEE 802.11 and other wireless communication standards offer more freedom, but they may also have reliability and interference problems. IEEE 802.3 was chosen because it can provide reliable, fast connections to meet the JSSP system's demanding data requirements.

5.1.3 Communication Standards

ITU-T G.703 for digital transmission and ISO/IEC 27001 for information security management are pertinent communication standards for the JSSP strategy. Protecting critical traffic data requires a strong framework for managing information security risks, which ISO/IEC 27001 offers. ISO/IEC 27001 is the recommended option for thorough information security due to its stringent certification process, even if the NIST Cybersecurity Framework provides greater flexibility and adaptability.

ITU-T G.703 ensures interoperability and dependability within the communication infrastructure by standardising the transmission of digital signals across a variety of media. Higher bandwidth possibilities might be offered by alternatives like T1/E1, however they can be more costly and less often supported. ITU-T G.703 was chosen because of its well-established application in telecommunications, which offers a dependable basis for communication within the JSSP system.

5.2 Impact on Society, Environment and Sustainability

The suggested job shop scheduling (JSSP) method of traffic control has a big effect on sustainability, the environment, and society. It lowers operating costs and improves travel times and public safety by reducing traffic congestion through vehicle movement optimisation. Environmentally speaking, this approach improves resource optimisation and air quality by reducing CO_2 emissions through improved traffic flow. Additionally, the incorporation of cutting-edge technology such as deep Q-learning and graph neural networks guarantees the long-term sustainability and adaptation of urban infrastructures. Potential applications also extend to supply chain management and logistics, supporting more general sustainability objectives.

5.2.1 Impact on Life

By maximising vehicle movements, the job shop scheduling (JSSP) method to traffic management greatly improves daily living by cutting down on travel times and easing the stress brought on by traffic. Shorter commutes allow people to devote more time to personal pursuits, which enhances well being in general. Furthermore, improved traffic flow makes roadways safer by lowering the chance of collisions and boosting commuter confidence. Additionally, this strategy makes it easier for underprivileged people to obtain vital services like healthcare, education, and employment prospects. Improved traffic control makes it easier for people to access these services, and lower car emissions improve the quality of the air and human health. All things considered, the JSSP approach improves the quality of life for locals by encouraging economic growth and a healthier, livelier neighbourhood.

5.2.2 Impact on Society & Environment

Society is greatly impacted by the job shop scheduling (JSSP) approach to traffic management since it increases the general effectiveness of transportation networks. By maximising vehicle movements, it lessens traffic congestion, which results in shorter commutes and a more enjoyable journey for people. In addition to improving commuters' quality of life, this efficiency promotes economic growth by making it easier for people to reach services and employment. Public safety improves with better traffic flow, which leads to fewer collisions and a higher level of road safety.

In terms of the environment, the JSSP approach drastically reduces greenhouse gas emissions. When idle time is decreased and routes are optimised, vehicles use less fuel, which lowers carbon emissions and enhances air quality. This emission decrease is crucial to advancing sustainability and tackling climate change. Public health is also enhanced by better air quality, particularly for susceptible populations like children and the elderly. All things considered, the JSSP strategy creates a more sustainable urban environment by promoting broader environmental goals in addition to enhancing social well-being.

5.2.3 Ethical Aspects

The JSSP technique significantly lowers greenhouse gas emissions from an environmental point of view. Vehicles use less fuel when idle time is reduced and routes are optimised, which reduces carbon emissions and improves air quality. In order to combat climate change and advance sustainability, this emission reduction is essential. Better air quality also improves public health, especially for vulnerable groups like the elderly and children. All things considered, the JSSP approach not only improves social well-being but also supports more general environmental objectives, resulting in a more sustainable urban environment.

5.2.4 Sustainability Plan

The goal of the job shop scheduling (JSSP) approach to traffic management's sustainability plan is to build a flexible and resilient transport system that can fulfil present demands while preparing for upcoming difficulties. The use of cutting-edge technology, such artificial intelligence and machine learning, which enable real-time data analysis and dynamic route optimisation, is essential to this strategy. The system can react to changes in demand by continuously analysing traffic patterns and modifying plans accordingly, guaranteeing effective resource usage and reducing waste. By lowering energy use and emissions, this flexibility not only improves operating efficiency but also advances long-term sustainability objectives.

The sustainability strategy also places a strong emphasis on working together with stakeholders, such as local governments, companies, and citizens. The plan is to identify and implement solutions that address particular local needs and raise public knowledge of the advantages of optimised traffic management by cultivating partnerships. To further lessen the overall environmental impact, educational programs can promote the use of sustainable modes of transportation like bicycling, carpooling, and public transportation. In the end, this all-encompassing strategy guarantees that the JSSP framework not only increases traffic efficiency but also helps to build more sustainable, healthy urban environments for coming generations.

5.3 Project Management and Financial Analysis

SL NO	Components	Estimated Cost (BDT)
01.	Software and Tools	16000-18000
02.	Documentation and Report Writing	3000-4000
03.	Miscellaneous	2000-3000
	Total Estimated Cost	21000-25000

Fig. Estimated Cost

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

This section outlines the alignment of our research project with relevant problem-solving categories.

Table 5.1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓		✓		✓		✓

Addressing Complex Engineering Problems (EP):

SN	EP Definition	Attainment	Justification
1.	EP1: Depth of knowledge required	YES	Our prior research endeavors have encompassed both theoretical and practical domains, including graph theory, combinatorics, and the analysis of polynomial equations. Additionally, we possess expertise in deep learning and programming languages. This comprehensive knowledge base aligns demonstrably with Key Areas K3 and K4.
			Our research has demonstrably leveraged Graph Neural Network (GNN) frameworks, which directly aligns with Key Area K5 and K6.
			Research on the optimisation of traffic management by cutting-edge technology has important ramifications for the social, economic, and ethical spheres. It could result in lower traffic, lower costs, and the responsible application of AI for the good of society. (K8)
2.	EP2: Range of Conflicting	NO	N/A

	Requirements		
3.	EP3: Depth of analysis required	YES	The problem that our research addresses is NP-hard, which means that it is challenging to identify the optimal solution. Notwithstanding the abundance of options, our goal is to identify relatively good ones via effective techniques. (K4 and K5)
4.	EP4: Familiarity of Issues	NO	N/A
5.	EP5: Extends of application codes	YES	In our research, we utilized various algorithmic approaches to implement our conceptual framework. (K4)
6.	EP6: Extends of stakeholders involved and conflicting requirements	NO	N/A
7.	EP7: Interdependence	YES	As part of our study technique, we broke the problem down into more manageable subproblems. Data collection, mathematical modelling, and deep learning model training were all incorporated in this. (K3, K6)

Mapping with Knowledge Profile for EP1

This table 5.2) is designed to map the EP1 to the Knowledge Profile.

Table 5.2: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✔	✔	✔	✔	✔

Justification:

- In order to complete this research project, you must demonstrate both basic engineering (K3) and specialized expertise (K4) in traffic management and scheduling, as well as an understanding of optimization principles and graph theory.

- Through the creation of the G3DQN framework and its iterative refinement process, the research project demonstrates the application of engineering design (K5). By using the suggested model in actual traffic situations and assessing its effectiveness, it integrates engineering practice (K6).

- By expanding on previous research in job shop scheduling and reinforcement learning, this study tackles research literature (K8) by offering fresh perspectives and pertinent approaches.

5.4.2 Engineering Activities

This section provides a detailed discussion of the engineering activities involved in our research project.

Table 5.2: Mapping with knowledge Profile.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✔	✔	✔	✔	✔

Addressing Engineering Activities (EA):

SN	EA Definition	Attainment	Justification
1.	**EA1 Range of resources**	Yes	The algorithms of this research project were implemented in Python, while the machine learning models were developed using PyTorch and PyTorch Geometric. Additionally, various existing methods and models for computing Graph Edit Distance (GED) were analyzed. These aspects correspond to **EA1**.
2.	**EA2 Level of Interaction**	Yes	The development of the model and the experiments involve collaboration across multiple disciplines, integrating concepts from machine learning, graph theory, and computational optimization, which addresses **EA2**.
3.	**EA3 Innovation**	Yes	This research project introduces a deep learning model, GNN, that integrates GED value prediction with node matching. The model uniquely combines graph neural networks with a post-processing algorithm, enhancing both the accuracy and interpretability of GED computation, thus addressing **EA3**.
4.	**EA4 Consequences for**	Yes	The approach proposed in this research project focuses on the usability of GED predictions by

	society and environment		ensuring interpretability through the generation of edit paths. The model's capacity to produce meaningful solutions has significant implications in fields such as network analysis and chemical compound evaluation, where decisions can influence societal and environmental outcomes, thus addressing **EA4**.
5.	**EA5 Familiarity**	Yes	This research project computes GED more efficiently than traditional methods and predicts the edit path with the help of a post processing algorithm, a capability lacking in existing machine learning models, thus addressing **EA5**.

5.5 Summary

The dependability, efficacy, and efficiency of the system are greatly influenced by the engineering standards set forth for the Job Shop Scheduling Problem (JSSP) framework in traffic management. Validating the JSSP system's performance and functionality in dynamic traffic scenarios requires thorough software testing documentation, which is the focus of important software standards like IEEE 829. Furthermore, ISO/IEC 25010 offers a strong framework for assessing software quality in a number of areas, such as usability, functionality, and maintainability, guaranteeing that the system satisfies the exacting requirements of contemporary traffic management applications.The dependability of traffic control systems depends on the hardware industry maintaining constant quality, which is made possible by standards like ISO 9001. This standard guarantees that every piece of hardware operates at its best in a variety of scenarios. Additionally, wired Ethernet connections are governed by IEEE 802.3, which guarantees dependable data transmission necessary for real-time traffic control operations and facilitates efficient communication between various system components.

The JSSP system also heavily relies on communication standards. Given the sensitive nature of traffic data, ISO/IEC 27001, for example, provides a thorough framework for addressing information security threats. By preventing unwanted access and data breaches, this standard helps guarantee that the system runs safely. Furthermore, ITU-T G.703 standardises the transmission of digital signals, promoting dependability and interoperability in the communication infrastructure required for efficient traffic control.Notwithstanding these accepted norms, the project faces a number of design obstacles that need to be resolved for its execution. Integration problems with current traffic control technologies are a major obstacle. A number of legacy systems must be smoothly integrated with the JSSP system; this can cause compatibility issues that take more time and resources to fix. Furthermore, the project's success depends on including stakeholders, such as government organisations, local communities, and transportation authorities. Their participation encourages cooperation as well as the acceptance and uptake of creative traffic control strategies.

Chapter 6

Conclusion

The Conclusion chapter summarises the project's main conclusions, lists its shortcomings, and identifies areas for further research. It provides a thorough analysis of the job shop scheduling method of traffic control, highlighting any possible effects on urban transport networks.

6.1 Summary

The traffic management strategy known as "job shop scheduling" (JSSP) provides a revolutionary answer to the problems associated with urban travel. Through the use of cutting-edge technology like artificial intelligence and real-time data analysis, this initiative seeks to improve overall efficiency, minimise traffic, and optimise traffic flow.

Fundamentally, the JSSP system dynamically modifies routing and signal timings in response to current traffic conditions. This results in shorter travel times and less annoyance for drivers, making commuting more enjoyable. Additionally, the JSSP strategy supports efforts towards environmental sustainability by reducing greenhouse gas emissions through route optimisation and idle time minimisation.

To adapt the system to particular metropolitan needs, cooperation with stakeholders—such as local communities and transit authorities—is crucial. This involvement promotes the adoption of creative methods and cultivates a sense of ownership.

In conclusion, the JSSP method paves the path for a smarter, more livable urban future by improving the efficiency and safety of urban traffic management while encouraging sustainability and community involvement.

6.2 Limitation

Data Dependency: The accuracy and accessibility of real-time data are critical to the JSSP approach's efficacy. Inaccurate or lacking data might influence traffic management results and result in less-than-ideal judgements.

Costs associated with implementation: The initial outlay needed for infrastructure improvements, technology deployment, and continuing maintenance can be substantial. Budgetary restrictions may result in sacrifices in system functionality or restrict the project's scalability.

Integration Difficulties: It can be difficult to integrate the JSSP system with the current technologies and infrastructure for traffic control. There may be compatibility problems that take more effort and money to fix.

User Acceptance: Drivers' and commuters' altered behaviour and acceptance of the JSSP strategy are essential to its effectiveness. The success of the project may be hampered by resistance to implementing new technologies or modifications to traffic patterns.

Problems with Scalability: The JSSP system might function well in smaller cities, but it might be difficult to scale to bigger ones with more intricate traffic patterns. More resources and system modifications can be needed as complexity rises.

Environmental Factors: Outside variables like bad weather, collisions, or road closures might interfere with traffic flow and reduce the JSSP approach's efficacy. The system needs to be flexible enough to adjust to these unforeseen circumstances.

Security Issues: The system may be susceptible to hackers because it depends on digital communication and data sharing. Maintaining system integrity and safeguarding sensitive data require strong cybersecurity measures.

Restricted Scope: By concentrating mostly on vehicle traffic, the JSSP strategy may overlook other crucial facets of urban mobility, such as the demands of cyclists and pedestrians. complete traffic management requires a complete approach.

6.3 Future Work

Improved Data Analytics: Upcoming research will concentrate on enhancing the capacity for data collection and analysis. By putting sophisticated machine learning algorithms into practice, predictive analytics may be improved and traffic patterns and possible bottleneck points can be more accurately predicted.

Integration with Smart City efforts: The project will investigate how to integrate IoT devices and sensor networks with more general smart city efforts. Coordination of responses to traffic circumstances and a more thorough understanding of urban mobility can be achieved through this integration.

Platforms for User Engagement: Creating applications and platforms that are easy to use for commuters can improve engagement and offer real-time information about traffic, alternate routes, and public transportation options. This can promote changes in behaviour and enhance traffic flow in general.

Sustainability Initiatives: To further cut emissions and improve urban mobility, future research will examine other sustainability strategies like encouraging EV infrastructure and incorporating bike-sharing schemes into the traffic control system.

Extension to Multi-Modal Transportation: The project will try to include modes of transportation such as walking trails, bicycles, and public transportation. This all-encompassing strategy will enhance general urban transportation and meet the various needs of commuters.

Cybersecurity Improvements: Future initiatives will concentrate on bolstering cybersecurity defences to safeguard private information and guarantee the traffic management system's integrity against possible cyberattacks as dependence on digital technologies gro

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