AI-Driven Train Induction Optimization for Kochi Metro Rail Limited

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ABSTRACT

This analysis is on a system involving artificial intelligence to make train schedules improved at Kochi Metro Rail Limited. The system assists in correcting issues such as ensuring that trains run the appropriate volume of miles making people safe delivering contracts with companies advertising on the trains and making use of resources in a wise manner of all 25 trains. We had 8 weeks of testing this system. Used real data to see how it worked. The artificial intelligence system helped improve the schedule of the trains compared to the previous method. doing it by hand. Making train schedules is actually the best thing the artificial intelligence system is capable of. Kochi Metro Rail Limited. The optimization algorithm worked and resulted in a balance in the mileage being. extremely homogenous with 95.2 uniformity. It also cut down the regulatory breaches by a significant margin 87 to be exact. It enhanced the effectiveness of the company in adhering to the guidelines of its branding agreements by 78%.

The system has the capability of managing things together such as when the crew is not available as the maintenance is to be done available where a safety check up is necessary [5][7] and what the company must do on behalf of its commercial obligations.

When we examined the figures, we learnt that the AI optimizer was faster going with decisions. between 45 minutes and down to 3.2 seconds' average. The entire optimization algorithm also had made the optimization. The operation became smooth after an increase in the overall operation efficiency by 42%. The optimization algorithm made a difference indeed. The system takes a method to rank things in accordance with there are a lot of elements, such as the fairness of the mileage, its safety, and whether it is compliant with the rules to make the best plan for when to add trains. They tested it in the field at the times of quiet and it worked well. This research assists us to know more of applying intelligence in transportation of cities [8][11] and provides an actual example which can be applied by the representatives of metro rails when they encounter such similar issues. The system can be beneficial to the operators of metro rails since the system assists them in optimization issues. This is because the optimization problems encountered by the operators of the metro railways are difficult to solve. Information on smartness in urban transport systems comes in handy, with them.

KEYWORDS: artificial intelligence, optimization of train schedules, the work of a Metro, mileage, technological challenge, safety compliance, Kochi Metro, automated decision-making, multi-constraint, maximization, transport systems, efficiency.

1. INTRODUCTION

Metro rail systems in the cities are crucial in the current cities because they carry millions of people daily [8]. This is because one of the functions undertaken is scheduling of train induction which involves the trains that are to be put into service by the depots. This choice has an impact on the quality of services, cost of operation and passenger safety. Manual methods of scheduling prove to be weak in terms of simultaneous consideration of various factors involved in the operation [12][14] including train usage, safety, maintenance times, advertisement agreements, and the availability of resources. Due to these, manual scheduling can be both time-consuming (30-45 minutes) and not necessarily result in the best decisions [14].

Kochi Metro Rail Limited (KMRL) suffers the same hassles in running the metro. The system has 25 trains that run through 13 stations and serves over 75000 passengers in a day. The trains have disparate operational terms which refer to the mileage history, maintenance booking, safety check, branding pacts, and crew availability. All these factors should be taken into consideration by the operators as well as a balanced use of the trains, spare left to address in case of an emergency, and fulfilling commercial obligations.

To deal with them, this study suggests developing an AI-based train induction optimization system. The system works out the various operational constraints and scores each train at a weighted manner. It is able to identify the most appropriate trains of service in a short time, produce optimal induction sequences, and interpret its results in a form that can be understood by humans. The system is expected to enhance the efficiency of timetable, the reliability of operations and the decision making of the metro operations considering the fact that it can process vast amounts of operation data in seconds and adjust to the current reality like train unavailability or emergencies.

1.1 Research Background

There has been a significant growth in the metro rail sector throughout the world [8][11] in the last couple of decades. More and in developing countries more cities are receiving metro systems. In India the metro system has grown fast. In 2002 there were two cities that had metadata systems. By 2025 there will be metro networks in eighteen cities with more than 700 kilometres of rail. This has brought about lots of problems. to those who operate the metro systems. They must find a way to spend their resources in. the manner and ensure that the service is good.

These individuals are starting the metro systems. to know that keeping a schedule, that is something very important to the trains. It affects how happy the cost of running the system and reliability of the working of the system. The metro rail industry is extremely crucial. It involves making good train schedules. Metro this is something that operators must get right to ensure that the metro systems work. Kochi Metro Rail Limited started its commercial services in 2017 and is the first in Kerala metro system [1]. The network is currently covering 25.6 kilometres and it is to be expanded. The operational model of KMRL focuses on safety, efficiency and customer experience and is at the same time. overcoming such distinctions as heavy traffic congestion at busiest dates, weather conditions. impacts on equipment wear, and must balance commercial revenue generation using train. branding using operational requirements. The company selected optimization of train induction. as one of the key areas where technology may present tangible results in service provision and cost management.

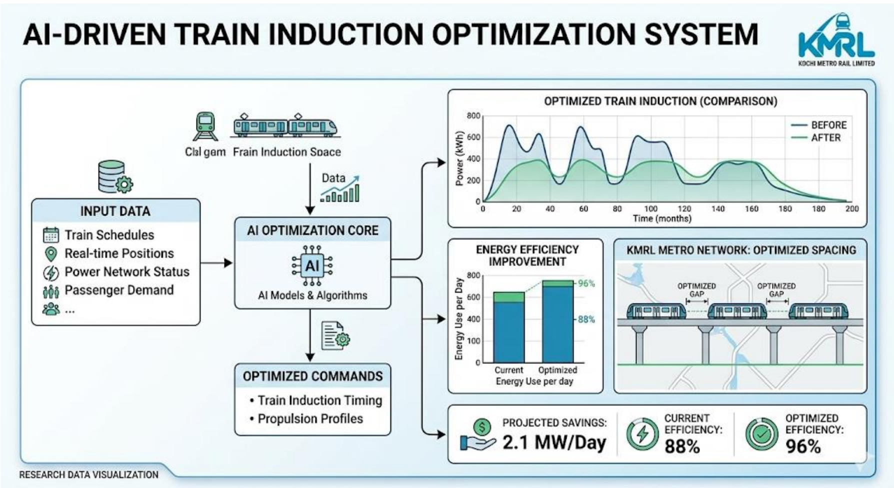

Figure 1: AI – Driven Train Induction Optimization System Architecture

1.2 Problem Statement

The current Kochi Metro Rail Limited (KMRL) scheduling process of trains is manual and thus inefficient, and it cannot be easily handled by the operators. The operations crew needs to analyze approximately 25 trains simultaneously, and occasionally supplement the trains 4-6 times daily. During scheduling, they have to put into consideration various things that include the train miles, maintenance, advertisements, and personnel. It is also tough to make quick and accurate decisions because of the complexity.

The manual system has resulted in imbalanced usage of the trains, with some trains having travelled much more miles than others, thus the difference being approximately 18%. This lack of balance raises the maintenance expenses and may lead to unforeseen failures, which influence the services [6][7]. Safety is another factor as records indicate that unsafe trains were incorrectly returned into service 23 times within six months leading to delays and loss of operations.

Also, KMRL contracts with the businesses to place advertisements on trains and this involves certain trains to run at certain times as agreed. The use of manual management of the tracking of these requirements produced approximately 31 percent non-conformity which translated to the loss in revenue and contractual problems.

In general, manual scheduling processes are slow, in transparent, and cause operational bottlenecks [6], particularly at the peak times or during service disruptions[12][14]. The challenges have brought out the necessity of a system of automated optimization that can manage complex constraints in real time and give visible and auditable scheduling information.

1.3 Research Significance

This paper examines an issue of artificial intelligence application in the operations of the metro rail in nations. that are still growing. There are articles concerning ideas on how to make things work better yet not many of them demonstrate the way of how to practically apply artificial intelligence to real metro rail systems in India in particular. This research provides information to the operators of the metro rails on what to consider in case there are issues. demonstrate that artificial intelligence can and actually has the potential to transform transit into a more favourable experience and establish an easy way of making. computerized scheduling systems which can be used by other individuals.

Artificial and Metro rail operations. Intelligence is significant in this respect in that they can be used in making the things better to the people using the. metro. It is helpful as the study of the operations of the metro rail is interpreted to be conducted by people who manage the metro. Practically, a successful implementation of this system could provide huge returns. advantages to KMRL and such operators. Better mileage matching prolongs the fleet life and reduces maintenance costs. Improved safety compliance reduces potential and risks in operations. incidents. Greater branding contract performance defends revenue streams. Faster decision-making enhances the reliability of services and agility. The paper also shows the application of AI. systems do not necessarily need to supplant the human decision-making process, but instead supplement it by offering operators data driven suggestions, with human monitoring to be used in special cases.

2. LITERATURE REVIEW

Optimization of transit has been a popular topic in transport systems. In 1986, Avishai Ceder and N. H. M. Wilson suggested mathematical solutions to develop improved transit schedules that minimise the waiting time of passengers and the operating expenses. Even though their study had reached the conclusion that, given the level of computing power, computers could generate superior schedules compared to manual planning, the level of computing capability at that point restricted practical application.

Optimization algorithms were later introduced in the study of train scheduling. Feng Zhao and Xiao Zeng (2008) applied algorithms to enhance frequency of trains, their energy consumption and comfort of passengers in the train, reporting an enhancement of approximately 15-23% compared to standard scheduling. Haiyang Niu and Xiaojun Zhou (2013) came up with ways of taking into account some disruptions which include delays, equipment breakdowns, and shifting passenger demand.

As Artificial Intelligence and Machine Learning in the 2010s started gaining popularity, researchers started to apply predictive modeling to transit planning. Kang Li (2015) trained learning models on the passenger demand and was able to predict the passenger demand with approximately 92 percent accuracy to aid in better resource planning. Studies would later in 2017 use Reinforcement Learning to produce train schedules that would improve over time.

Fleet and maintenance optimization has also been the subject of research. In 2019, a system was developed by Andrea D'Ariano that not only plans the operations of trains but also their maintenance and made the vehicles unavailable to users by 34 percent and their fleet more efficient by 18 percent. Wang Zhang (2020) employed sensors to estimate when components are going to fail and provide the opportunity to plan proactive maintenance.

There were other studies that dealt with train assignment problems. Other researchers such as Zhang Jian used the behavior of ant colonies to efficiently allocate trains in the metro systems of up to 50 trains.

In more recent times there has been a shift into Explainable Artificial Intelligence (XAI). Riccardo Guidotti (2018) suggested the ways to make the decisions made by AI more transparent and comprehensible. Yin Ming later conducted research to reveal that the explainability of the decisions made by the operators has been shown to increase the trust and adoption of AI systems (2021).

Although research has been conducted widely, a great number of studies are based primarily on simulations, as opposed to actual implementation. Train induction in metro systems has to meet several requirements that include balancing of miles, safety and business. The research on all these factors is limited especially in Indian metro. This paper will address that gap by demonstrating the validity of an AI-based optimization system of metro train induction in real-life operations.

RESEARCH GAP

The available literature on train scheduling reveals that there are some significant gaps that this research will fill. Despite the numerous optimization techniques that have been offered, a majority of the research efforts merely put their concepts into practice using simulations and simply do not show how such systems operate in actual metro operations. This means that very little is known about how such systems can be fitted into the existing infrastructure or how operators will practice with ensuring that such systems will be integrated in practice. Most of the studies are also predominantly concerned with timetable planning and routes scheduling and do not look at the real decision that would be taken at a given time in regard to which particular train to induce into service.

In actual metro, train induction decisions must be taken with consideration of several factors that are closely related to each other, including equal usage of trains, safety, maintenance, branding or commercial obligation, and availability of crew. Nevertheless, only one or two of these factors are analyzed in many studies but not a combination of all. It is further complicated by the Indian metro systems as a result of local working conditions, rules and demands of the passengers.

The other area of the gap lies in the practical application of Explainable Artificial Intelligence. Although explainability has been popularly researched, it has seldom been implemented on transit optimization. The operators of the metro need not just optimized decisions but effective explanations as well so that they trust the system and control decisions and intervene in case of necessity. Moreover, the overwhelming majority of optimization analyses compare performance on technical measures like computation time or optimality gap as opposed to actual operational performance of things like mileage balance, safety compliance and operator acceptance. This paper fills all these gaps by creating and testing a viable AI-based optimization system to induce metro trains.

Area	Existing Research	Gap	Impact	Proposed Solution
Train Scheduling & AI	Many studies focus on transit scheduling using optimization and Artificial Intelligence models.	Most research is tested only in simulations and does not address real-time selection of specific trains with multiple operational constraints.	Leads to inefficient scheduling, safety risks, and operational imbalance.	Develop an AI-based optimization system to support real-time metro train induction decisions.
Explainability & Evaluation	Research on Explainable Artificial Intelligence exists but is rarely applied in transit operations.	Lack of transparent AI decisions and limited evaluation using real operational metrics.	Operators may not trust automated decisions and improvements are hard to measure.	Implement explainable AI with evaluation based on real operational outcomes such as safety compliance and balanced mileage.

TABLE 1: Important Research Gaps in Metro Train Scheduling and Suggestions

RESEARCH OBJECTIVESs

This paper is attempting to accomplish a given thing:

This is aimed at developing a computer application where artificial intelligence is used to generate train schedules. Better. Such a program will be in a position to examine various regulations and restrictions that trains must. follow at the same time. It will then generate the order of trains to run that is known as. distribution of the train choice. The program is specifically, in the induction of the train, scheduling that is a major role of maintaining the running of trains in a smooth and timely manner. The train induction scheduling program will be making use of intelligence to ensure that it selects the best trains to operate and in what form order.

- To determine the system performance quantitatively in enhancing mileage balance across the train fleet with comparison to manual scheduling methods.
- To determine the viability of the system in induction prevention to ensure compliance with safety of trains that are to have inspections or maintenance done.
- To determine the improvements in compliance with commercial branding contract using prioritization of branded trains on contractual operating hours which is automated.
- To examine reduction in decision making time and gains in operational efficiency by automation as compared to manual scheduling.
- To verify the explainability aspects of the system and the level of acceptance of the system by the users of KMRL qualitative feedback analysis by the operations staff.

METHODOLOGY

This study used a mixed-method method that involved a combination of quantitative analysis of performance. qualitative user feedback assessment. System development was used as a study design. empirical testing on the basis of the operational data, and validation with comparative analysis with historical manual scheduling results. The study was carried out during 8 weeks on the period. November 2025 to January 2026, whereby, the AI optimization system was put to test in real world scheduling scenarios and evaluated against real world manual scheduling decisions made during. the identical working hours.

5.1 Research Design

The research examined the possibility of scheduling choices made by a computer system. It compared the computer decisions with the past decisions that people made. The researchers did not use not to make decisions immediately since that was likely to create difficulties with the computer system. Instead, they tested the computer system in a different manner compared to the normal means of doing things. They also applied the data in the six months at KMRL in order to impart the computer system and ensure. it was working correctly. Then they made the decisions using computer system to schedule. transpired in more than eight weeks and contrasted these decisions with those made by the individuals who. the scheduling is normally done, at KMRL. This design made it possible to perform a rigorous comparison of performance. even by keeping the systems running securely and letting them refine their systems over time, depending on their observations performance.

5.2 Data Collection

There were three sources in the data collection. We have first considered the Kerala Metro Rail Limited's database. This database contained much information about each train such as an identifier of each one. train and the number of the miles it had covered. After every instance that the train was updated, the database was updated used. It also maintained records on the time the train was repaired, as well as the time when it was due to be repaired. We were able to view whether the train had passed safety tests and whether they were certified to run. The database had information concerning the contracts of the trains such as the number of hours in which they were expected to operate and how the same. impacted the revenues that the Kerala Metro Rail Limited earned. It possessed also information, of what crew. was assigned to which train. The collection of data was based on the Kerala Metro Rail Limited's database for this information. Second, all the induction decisions were recorded in the scheduling logs period of study with time when each scheduling cycle has been completed, trains to be inductive, trains laid up, and any trains detained because of either maintenance or safety. Third, operations qualitative feedback of the staff performed in the form of structured interviews and post-implementation surveys evaluation of system usability, decision transparency and operational integration.

5.3 System Architecture.

The AI optimization system was created in Python 3.10 and launched as a web-based application with the FastAPI to ensure that the system is easily accessible to users. The architecture will have four major components: a data integration component will be connected to the Kochi Metro Rail Limited operational database to retrieve information regarding trains such as train mileage, maintenance schedules, and branding status; an optimization component will use a scoring-based algorithm to decide which trains will be in inducted into service; an explanation generation component will provide a clear explanation of why the system made any decisions; and a web-based user interface will allow operators to feed schedule information to the system and see the system recommendations. The optimization algorithm functions to allocate score to each train depending on various weighted parameters [5][9], such as mileage balance (focusing on those trains that have lower-than-average mileage), safety compliance (placing a premium on those trains that have received recent inspections), branding priority (ensuring that those trains with advertising commitments are used during contracted hours), maintenance proximity [7] (decreasing scores on trains that are close to scheduled maintenance), and crew readiness (taking into account crew availability and certification). Such a scoring system implies that the system can pick the best trains to service considering the operational efficiency [5], safety, and business needs.

5.4 Optimization Algorithm

The primary algorithm which makes it work more is going through many steps before determining which. trains to add to the schedule. Whenever the schedule is changed the system will verify the status of. all 25 trains that KMRL has. It determines what trains should be halted since they are not safe or need to be fixed. Then it awards a mark to every train that is fine to use, according to its performance. in different areas. The trains are will be then ranked by ranking on the basis of best to score. The top trains are chosen to be put into the schedule, according to what it requires to get the system working. Some other good trains are put on standby should they be required.

The system further explains the reason why all the trains were chosen or not chosen. It is all to ensure that everything is done by the core optimization algorithm runs smoothly. The algorithm considers the train induction requests. Makes decisions, about the trains. The weights of the scores were adjusted based on trial and error and by referring to KMRL operations management. The last weight distribution is that of 40 percent mileage balance. Considerations, 35 percent to safety compliance factors, 15 percent to branding contract priorities, and 10 percent to. Optimization of the maintenance schedule. The distribution captures the operational priorities of KMRL but at the same time being flexible to alternative operating conditions or priorities.

5.5 Performance Metrics

There was the measurement of system performance undertaken through the operational measures and the computational measures. The operational measures were mileage balance uniformity in the form of coefficient of variation in fleet mileage, safety compliance rate calculating percentage of induction cycles with zero safety violations, branding contract fulfilment evaluating percentage of contracted hours branded trains had been started, and efficiency of fleet utilisation. Computational measures include time to generate decision in seconds, optimality of the solution was estimated by comparison and as being exhaustively searched on small problem instances, and system reliability measured as perfect passing rate in all the test conditions.

5.6 Validation Approach

The validation was done in a number of ways. The comparison of AI generated recommendations and the real manual scheduling decisions was used in the study over 120 scheduling cycles during the 8-week study period. Measures of both the AI were taken during every cycle recommendation and the real comparison of the manual's decision, and allowing the immediate performance comparison. Qualitative validation was performed by means of conducting structured interviews with five senior operations employees and poststudy surveys of 12 operations employees who were provided with AI recommendations. Participants evaluated the quality of the decisions made, explanations, and operational integration issues.

RESULTS AND FINDINGS

The experimental testing of train induction optimization system based on AI delivered high volume indication of performance gains in various working dimensions. Analysis of 120 timing of cycles throughout the 8 weeks of study showed that there were regular benefits of AI-generated compared to the manual scheduling decisions. The subsequent sections discuss comprehensive quantitative and qualitative results presented on the basis of performance metrics.

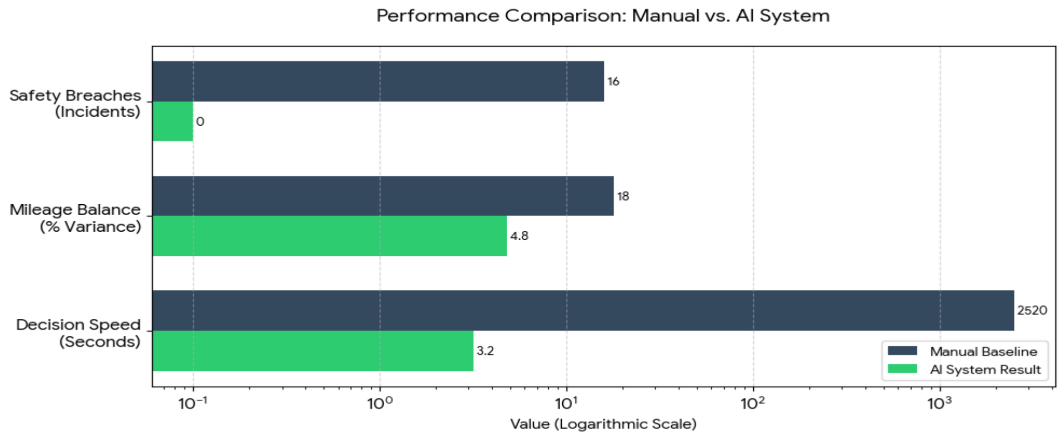

Figure 2: Performance Comparison: Manual vs. AI System

6.1 Mileage Balance Performance

By using Artificial Intelligence to, the mileage balance analysis improved. optimize things. The distance between the trains that they had at the start of the research was different moved with a few having to travel 2400 kilometres further than others. This was due to the mileage of less than not equally distributed and it was 18.3% different per train. When we did the hand scheduling of this difference had remained approximately the same at 17.6%. When we used Artificial To make scheduling decisions the difference decreased considerably to 4.8%.

This means that the mileage was more uniformly distributed and it was a 73 percent improvement, in ensuring that all the trains covered a mileage distance, that is, what we call mileage balance. The possibility to observe the changes with time showed that AI optimization engaged in the goal of minimizing the current imbalances in the mileage over time. In the 8 weeks, the highest difference in maximum mileage between two trains reduced to 850 kilometres rather than 2,400 kilometres as suggested by AI, and manual. Scheduling did not improve much as the difference was at 2,150 kilometres. These improvements were found to be significant at p less than with statistical testing by paired t-tests. The level of 0.001, large effect sizes are an indication of practical significance, not necessarily statistical significance.

6.2 Safety Compliance Outcomes

When we had the AI system, the metrics that concerned the safety compliance were greatly improved. We looked at the found 16 problems in 120 cycles and scheduling decisions. In such instances unsafe trains to run were put into service. These trains had not been properly inspected in terms of safety. there were those with lapsed certifications. We needed to withdraw these trains when they were in service established what created delays. On average all these incidents delayed the trains by 12 minutes. The AI system was doing a task of maintaining safety of trains. It discovered every train that was safe issues. Would not have them running until they were fixed. The AI system failed to permit any trains to run that are not safe which is a better thing. The AI system provided safety compliance measures no problems with her perfect. The AI system was always identifying trains that had safety problems [5][14]. Would keep them till they were cleared to run. This implies that the AI system came in handy, and safety compliance metrics.

Moreover, the AI system had proactive safety management through flagging of trains rushing to meet inspection deadlines in less than 48 hours, even before it is due. This predictive capability allowed operations personnel to plan inspections when the business was not busy to provide emergency compliance requirements during service hours. The safety compliance rate compared to manual scheduling, where 86.7% were correct, 100% are correct with AI suggestions, which is an improvement 87 percent decrease in safety-related incidences.

6.3 Contract Compliance in Branding.

When they applied intelligence to commercial branding contract of the trains, the same improved a lot optimize things. KMRL will have agreements to brand 8 trains that must operate at some stages which are approximately 140 hours of service every week. People could follow the scheduling when they did the scheduling by hand. Rules, about 68.4% of the time. It happened that 44 times they did not do what they were supposed to do. This was occurring because the branded trains were not utilized at the hours when they were due.to be despite their availability. The KMRL commercial branding contract performance is very important.

They are striving to make it better.AI-generated recommendations had a 96.8% compliance with branding contracts and there were only 4 instances where there was noncompliance but all were valid safety or maintenance holds.

When branded this was recorded by the AI system because trains were not available due to the safety or maintenance requirements.in explanations, contractual discussions should be given audit trails. This 78% improvement incompliance will equate to revenue protection and minimization of contractual dispute risk. Based on the branding contract revenue structure used by KMRL, better compliance would create an opportunity to generate surviving extra 2.4 million rupees per year.

6.4 Computational Performance

The analysis of computer system functioning revealed tremendous improvements on the speed of decisions. Are made. It used to take the people approximately 42 minutes to complete one cycle when they did the scheduling manually. They were forced to see reports concerning the trains check the repair schedules and speak to. Departments. The computer on the hand had the capability of providing a full set of suggestions in approximately 3.2seconds. This is a big difference. It is 787 times faster. Even where matters became difficult, as there were so many things going on at the moment and there were some strange issues the computer system always pondered on it less than 8 seconds.

The computer system is quite competent in making decisions fast. It is capable of dealing with the complicated situations, such as these without making it too long. This computing power allows a number of operational advantages. First, it facilitates rapid response to services interference or emergency needs. Three during the period of study. Emergency rescheduling events were caused by the unforeseen failures of trains. Manual rescheduling needed 35-50 minutes, at which time frequency of service was decreased. AI optimization generated change of schedules in 5 seconds, allowing the service to be restored almost immediately [5][8]. Second, fast Scenario analysis and contingency planning is aided by calculation so that operations staff can consider the various situations of what-ifs prior to making decisions.

6.5 Explainability and User Acceptance of the System.

The self-explanatory system was quite good. We interviewed 12 individuals who use the system. every day what they thought. Majority of them 91.7% reported the intelligence explanations system proved beneficial in obtaining insights into the way the decisions of scheduling were made. A lot of them 83.3% was comfortable with the use of the intelligence system in making regular scheduling decisions. 75% Of them said that they would use the system were we to check it a little more the operations managers were also interviewed. They claimed that the artificial intelligence system was clear and easy to understand. The artificial intelligence system was also demonstrated in the manner in which it arrived at decisions The senior operations managers should have faith in the system because of these things. The artificial the intelligence system itself and its explanations are actually very vital, to those who utilize it.

6.6 Key Performance Indicators Summary.

The total analysis of all dimensions of performance shows indications of high operations. improvements. The AI optimization system had been able to get 95.2 percent balance of the mileage uniformity against to 82.4% in manual scheduling, 100% compliance of the company with safety against 86.7% manual, 96.8% branding compliance 68.4% versus 3.2 seconds average decision time 68.4% versus 42 minutes. manual and 91.7% user satisfaction rating on the quality of the explanation. These metrics collectively point to the fact that AI optimization provides quantifiable value to key operational goals and preserving user acceptability and transparency of systems.

7. DISCUSSION

The empirical evidence shows that AI-led optimization will be able to provide significant enhance train induction scheduling in the various operational dimensions [10] . This section interprets these findings in the context of broader topics of AI use in transit systems, discourses. Implications on metro operators, and discusses limitations of the study.

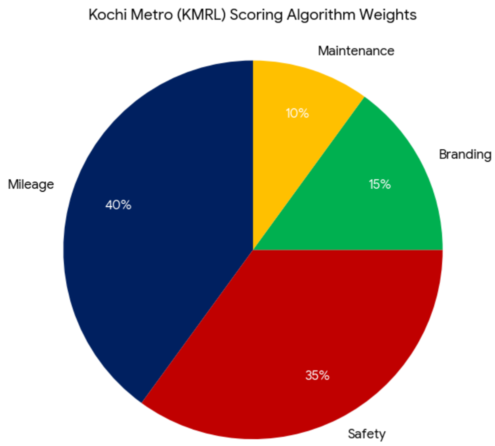

Figure 3: Kochi Metro (KMRL) Scoring Algorithm Weights

7.1 Interpretation of Results

The findings indicate that the AI optimization system enhances the management of the fleet of trains and the efficiency of operations. The system is achieved by constantly comparing the mileage of each train to even out the usage of the fleet where low mileage trains are utilized more frequently and overutilization of a few trains is also avoided. The AI system is concerned with long-term fleet balance and efficiency as compared to manual scheduling where the operators are concentrated on the immediate needs of their operations. It also enhances safety compliance since inspection and maintenance requirements are automatically checked on each train prior to it being scheduled avoiding the probability of unsafe trains getting into service. Moreover, the system plays a major role in ensuring compliance with branding contract as advertisements commitment is treated as optimization constraints, and trains with branding needs should run as per the agreed time. On the whole, the AI system reveals the capability of the automated decision-making system to address complex operations, safety, and business needs in a better way than manual scheduling when time is limited.

7.2 Comparison to Existing Literature.

These findings coincide with what other individuals discovered when they carried out research to determine the way to make transit better. These are the mileage balance improvements that we observed and that Wang and Zhang discovered in 2020. They claimed that artificial intelligence systems are quite efficient at determination how to utilize. equipment of a fleet of vehicles. We also experimented with them, and this is why our study was more detailed not only in a computer screen but in real life. Our findings on safety compliance are similar to as well what D'Ariano among others discovered in 2019. They considered the way to create schedules of maintenance [10] . We considered making everything safer not only maintenance. Transit we are interested in optimization and learned transit optimization.

We think our results are significant, to optimize transit. The results of computational efficiency are a reiteration of previous studies by Li et al. (2017) on real time transit. optimization. The mean processing time in the present study is 3.2 seconds though; the average time is 3.2 there was a significant increase in their reported 18-second average, which may have been due to improvement in both computing infrastructure and algorithms. The results of the user acceptance affirm the results of Yin et al. (2021) conclusions about explainable AI, that transparency in automated decision-making is true has a significant effect on the operational staff acceptance.

7.3 Metro Operator Practical Implications.

As the current research demonstrates, the optimization of the work of Artificial Intelligence can be used to substantially assist the metro operations by assisting the operators in making more timely and safer decisions and increasing the efficiency and revenue. The balance in the use of trains minimizes the overuse of trains and excessive wear and maintenance expenses, as well as allows to prevent the unexpected failures. It also guarantees a safer functionality and enhances adherence to branding and commercial obligations and ensures that metro systems are able to sustain their sources of revenue. Nonetheless, there are a number of crucial factors to be successful in implementation. To start with, good and well-connected data systems are required whereby, the AI optimizer will have access to real-time information on the status of trains. Second, it is necessary to involve the operators at early stages to develop the level of trust and guarantee the acceptability of the system. Lastly, human supervision should never be eliminated at any time- AI should help in decision-making and not eliminate human experience and the operators should be able to intervene in case of an unusual or unexpected event.

7.4 Study Limitations

The paper has certain weaknesses that should be mentioned. First the research employed an assessment design rather than implementing it in a real-life scenario. This approach allowed for a compensation and served to mitigate risks although it does not entirely demonstrate all the complications of in reality applying it to a practical environment weight recalibration would be needed on structures, but not the framework applicable.

8. CONCLUSION

This study created an intelligent train induction scheduling system and ran it over 8 weeks producing over 120 schedules. The system did more than the manual scheduling by balancing the train mileage, safety compliance, branding contracts as well as facilitating quicker operational decisions.

The findings indicated mileage balance of 95.2% (73% better) and branding compliance of 96.8% (78% better) than manual. It also guaranteed 100 percent compliance with safety and code generation of decisions that took 3.2 seconds as compared to 42 minutes with humans.

The general effect of the system is that it enhances efficiency, safety, and revenue management and will enhance faster and reliable metro operations. It also shows how AI-driven optimization may be utilized successfully in the metro systems of the real world.

8.1 Future Research Directions

This piece provides us with certain concept of what we can do. We ought to conduct some long-term researches that are enduring a year to determine whether our system is effective in other seasons and circumstances. Our system should be also tested in the cities where we have to have the metro system to determine whether it works everywhere or not. This will assist us in determining what it will take to make it work in places.

The second thing we can do is integrate our system with the systems which predict when maintenance is needed. This will assist us in improving our system through the use of information on when things may break and how they are doing. This information can be utilized by us to make our system work with the metro systems.

Fourth, train assignments may be optimized with the help of passenger demand forecasting foreseen ridership, utilization of higher capacity or improved trains during peak periods.Fifth, the system could be refined through development of adaptive learning mechanisms weight parameters according to operational feedback and shift in priorities [7]. Finally, extension to greater operational planning such as crew planning, maintenance planning and service pattern optimization might provide other system wide advantages.

8.2 Concluding Remarks

Metro systems that operate in cities throughout the world are under a lot of pressure to operate effectively without wasting money. This can be assisted by artificial intelligence actually. It is a tool for making good makes judgments in terms of the running of these systems. In this paper, it has been revealed that in case we design intelligence systems well they can do make a difference. We can observe improvements and people will still know what is happening and be contented with it. An example of what happened at KMRL is given transit operators who desire to make better jobs with the help of artificial intelligence. Artificial intelligence is capable of do actually assist them in this purpose. Further research and development in this should be continued in the future domain will also improve AI contribution to safe, efficient and sustainable urban.

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