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MAXIMIZING RAIL INPUT TRAFFIC USING AI-DRIVEN SOLUTIONS

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ABSTRACT

The Indian railway networks play a vital role in the movement of people and goods across the country, though there is a huge problem of congestion in most of the networks, inadequate schedule and under utilization of the infrastructure. The conventional rail traffic control is based on fixed schedules and manual decision making, which adds to the systemic congestion and delays [8]. The presented paper suggests a framework based on the Artificial Intelligence (AI)-driven one to optimise the rail input traffic with the help of predictive modelling and Deep Reinforcement Learning (DRL). The suggested solution combines a Deep Neural Network (DNN) to predict train arrival and delay with a reinforcement learning scheduling agent to do dynamic platform and track assignment [5]. The framework is tested in a simulation that is calibrated on the Indian Railways operating parameters [8]. Experimental data show that throughput (190 vs. 160 trains/day), average delay (9 vs. 18 minutes) and platform utilisation (82% vs. 64%), have improved by 18.75, 50, and 18 percentage points respectively. The framework has a lot of potential in large scale railway networks, which can be operated smarter, more efficiently, and in a manner that is environmentally sustainable.

Keywords: Indian Railways; Rail Traffic Optimisation; Artificial Intelligence; Deep Reinforcement Learning; Deep Neural Network; Platform Scheduling; Predictive Modelling; Smart Railway Systems

1. INTRODUCTION

The Indian economic and social infrastructure mainly depends on rail transportation as it carries over 23 million passengers and about 3 million tonnes of cargo daily. Indian Railways, the largest rail network in the world, is running over 13,000 passenger and freight trains over 67,000 route kilometres daily. Although of this enormous scale, the system is plagued by severe operational issues: endemic platform congestion, cascading delays, and ineffective use of the available track infrastructure. Conventional scheduling techniques are based on static schedules and manual control, which, in essence, are reactive and unable to respond to real-time perturbations like sudden passenger influx, poor weather, or propagated delays at relay stations. Due to the constantly rising demand, especially at major rail junctions like Mumbai CST, Delhi Junction and Howrah, there is a pressing need to implement intelligent, self-adaptive systems that can handle rail traffic in real time. New developments in the field of Artificial Intelligence (AI) have provided the possibility to explore new opportunities in the field of intelligent traffic management. ML

and RL methods have proven to be highly effective in transportation, logistics and smart-city, as systems learn through past behavior and can predict future states and make the best decisions in real-time [1]. This report suggests an AI-based framework that consists of two modules closely integrated with each other, namely (i) a Deep Neural Network (DNN) to predict arrivals and delays of trains and (ii) a Deep Reinforcement Learning (DRL) agent to schedule the platform and tracks dynamically. It is assessed on a simulation that is calibrated on the parameters of Indian Railways operation [8].

1.1 Study Background

Indian Railways has increasingly been adopting technological improvement with national programmes like the National Rail Plan 2030 and Smart Railways. The idea of AI-based scheduling has been the focus of numerous research studies due to its ability to integrate live operation data and reward-based optimisation procedures that can motivate optimum decision-making [14]. These characteristics are meant to enhance throughput, minimize downtime on idle platforms and allow the system to respond to disruption in an adaptive manner- qualities that are entirely lacking in traditional fixed-timetable systems.

1.2 Problem Description

Despite the theoretical strong appeal of AI-based scheduling, there is a paucity of empirical data on its effectiveness in the unique environment of the Indian Railways, including mixed traffic types, very variable dwell times, and old signalling infrastructure [13]. Practically all the literature is limited to metro or high-speed networks in Europe or East Asia [17]. Questions as to whether AI-based solutions can usefully substitute or supplement fixed timetable techniques in large, diverse rail networks remain unsolved. The gap of this paper addresses this issue by empirically exploring how AI-driven scheduling impacts throughput, delay, and platform utilisation.

1.3 Main Contributions

A predictive DNN model that can forecast the arrival times and delays at the trains based on historical and real-time data [2]. A DRL-based decision making framework of adaptive, real-time platform assignment scheduling [1, 4, 9, 10]. A simulation community based on junction data of the Indian Railways to conduct intensive performance analysis [20]. Compared to traditional and unresponsive scheduling with quantifiable improvements in throughput, delay mitigation and platform utilisation.

2. Literature Review

OVER THE LAST TWENTY YEARS, THE ISSUE OF RAILWAY SCHEDULING AND TRAFFIC MANAGEMENT HAS BEEN RESEARCHED. THE INITIAL RESEARCH WAS ON THE USE OF HEURISTIC AND INTEGER PROGRAMMING. EXPERT SYSTEMS BASED ON RULES OFFERED A FIRST LEVEL OF DECISION SUPPORT AND WERE FRAGILE OUTSIDE NOMINAL CONDITIONS AND NEEDED LARGE AMOUNTS OF MANUAL TUNING. CORDEAU ET AL. (2001) MODELLED THE TRAIN-ROUTING PROBLEM AS A CONSTRAINT PROGRAMMING PROBLEM AND DISCOVERED THE NP-HARDNESS OF PLATFORM ASSIGNMENT AT BUSY CROSS-ROADS. AS THE INFORMATION-DRIVEN APPROACH HAS EMERGED, DELAY PREDICTION HAS BEEN STUDIED IN THE CONTEXT OF MACHINE LEARNING. AFTER TRAINING NEURAL NETWORK MODELS USING INDIAN RAILWAYS DELAY LOGS, KUMAR AND SINGH (2020) REPORTED A MEAN ABSOLUTE ERROR (MAE) OF LESS THAN FOUR MINUTES, WHICH IS BETTER THAN TRADITIONAL REGRESSION BASELINES. THE AUTHORS ZHAO ET AL. (2019) APPLIED DELAY PREDICTION TO THE FREIGHT SCHEDULING AND FOUND THAT GRADIENT-BOOSTED TREES PROVIDED MUCH MORE EFFICIENT SLOT ALLOCATION [3]. ONETO ET AL. (2019) HAVE CONDUCTED A THOROUGH ANALYSIS OF THE ITALIAN RAILWAY NETWORK AND PROVED THAT MACHINE LEARNING SIGNIFICANTLY BEATS CLASSICAL STATISTICAL MODELS IN TRAIN DELAY PREDICTION [19]. ADDITIONAL ANALYSIS OF INDIAN RAILWAYS BY ARSHAD ET AL. (2019) REVEALED THAT WEATHER VARIABLES GREATLY INCREASE THE ACCURACY OF PREDICTION WHEN INCORPORATED [11]. REINFORCEMENT LEARNING HAS COME OUT AS A STRONG PARADIGM OF DYNAMIC SCHEDULING. LI ET AL. (2021) TRAINED DEEP Q-NETWORKS (DQN) ON SIMULATED TRAFFIC AT A 4-PLATFORM JUNCTION OF A METRO AND DEMONSTRATED A 15% THROUGHPUT INCREASE AND A 20% DECREASE IN THE AVERAGE DELAY RELATIVE TO NO SCHEDULING. CAI ET AL. (2022) DEVELOPED A MULTI-AGENT REINFORCEMENT LEARNING SYSTEM TO HANDLE RAILWAY DISPATCH CONTROL AND SHOWED THAT IT IS POSSIBLE TO MANAGE CASCADING DELAYS EFFECTIVELY WITHOUT HUMAN CONTROL. KHADILKAR (2018) CREATED A SCALABLE RL ALGORITHM WHICH WAS TESTED SPECIFICALLY ON THE INDIAN RAILWAYS LINE SCHEDULING, WHICH CAN SERVE AS A BASELINE REFERENCE OF RL APPLICABILITY TO THE INDIAN CONTEXT. ŠEMROV ET AL. (2016) USED RL TO SINGLE-TRACK RESCHEDULING PROBLEMS, WHICH CAN BE USED AS A FOUNDATION OF RL RELEVANCE TO THE INDIAN CONTEXT [11]. IN THE STUDY BY CHENG AND

MA (2020), THE AUTHORS APPLIED CONVOLUTIONAL FEATURE EXTRACTION AND PROXIMAL POLICY OPTIMISATION (PPO) TO HIGH-SPEED RAIL CORRIDOR SCHEDULING AND OBTAINED SOLUTIONS THAT WERE CLOSE TO OPTIMAL WITHIN 200 MS PER DECISION CYCLE. WANG AND WEI (2021) SHOWED THAT PREDICTIVE MAINTENANCE USING DEEP LEARNING MINIMIZED THE OCCURRENCE OF UNPLANNED TRACK OUTAGES- ONE OF THE MAIN CAUSES OF DISRUPTIONS IN THE SCHEDULES BY UP TO 30 PERCENT. WANG ET AL. (2021) ALSO EXPLORED AN ENERGY-ORIENTED DRA FRAMEWORK ON TRAIN TIMETABLE RESCHEDULING IN THE PRESENCE OF DISTURBANCES WITH DEMONSTRATED MULTI-OBJECTIVE ADVANTAGES. MOST RECENTLY, ZHANG ET AL. (2025) INTRODUCED A MULTI-TASK DRL SOLUTION THAT CAN PERFORM REAL-TIME RESCHEDULING OF COMPLEX NETWORKS, WHEREAS YUE ET AL. (2024) SHOWED THE GRAPH-REPRESENTATION-BASED RL THAT CAN RESCHEDULE A TIMETABLE IN A SCALABLE MANNER. THE FLATLAND-RL BENCHMARK OF MULTI-AGENT TRAIN SCHEDULING, PROPOSED BY MOHANTY ET AL. (2020), OFFERS A STANDARDIZED EVALUATION PLATFORM TO RL-BASED SOLUTIONS. THE THEORETICAL FRAMEWORKS OF THE DNN AND THE DRL ARCHITECTURE USED IN THIS PAPER ARE PRESENTED BY THE SEMINAL WORKS OF GOODFELLOW ET AL. (2016) AND SUTTON AND BARTO (2018). THE DQN APPROACH IS BASED ON THE SEMINAL WORK OF MNH ET AL. (2015) THAT DEFINED HUMAN-LEVEL CONTROL VIA DEEP RL. EVEN WITH THESE DEVELOPMENTS, THE MAJORITY OF THE CURRENT FRAMEWORKS FOCUS ON METRO OR HIGH-SPEED NETWORKS IN CHINA OR EUROPE AND DO NOT REFLECT THE HETEROGENEITY OF INDIAN RAILWAYS, WHICH IS CHARACTERISED BY MIXED TRAFFIC TYPES ON COMMON INFRASTRUCTURE AND VERY LOCALISED NETWORK CONSTRAINTS [14]. MOREOVER, THERE ARE NOT MANY STUDIES THAT INTRODUCE PREDICTION AND SCHEDULING INTO THE SAME DEPLOYABLE PIPELINE. THIS PAPER SPECIFICALLY DEALS WITH SUCH GAPS.

3. RESEARCH GAP

ALTHOUGH AI TECHNIQUES ARE WIDELY USED IN THE OPERATIONS OF THE RAILWAYS ACROSS THE WORLD, THERE ARE STILL MAJOR GAPS. MAJORITY OF STUDIES ANALYSE PREDICTION AND OPTIMISATION IN ISOLATION BUT NOT AS A PIPELINE. THERE IS A RELATIVE DEARTH OF RESEARCH SPECIFICALLY ON INDIAN RAILWAYS; AVAILABLE BENCHMARKS ARE LARGELY BASED ON EUROPEAN OR EAST ASIAN DATASETS WHICH DO NOT CONSIDER INDIA-SPECIFIC FEATURES LIKE MIXED-TRAFFIC, HIGH-DENSITY OPERATION. PRACTICAL USE OF PREDICTION MODULES TO THE EFFECTIVENESS OF DRL EXPLORATION, I.E. DOES DNN-BASED INFORMATION ON THE STATE LOWER THE EXPLORATION COST, HAS NOT BEEN MEASURED IN EXISTING LITERATURE [9]. LASTLY, LONG-TERM SUSTAINABILITY AND COMPATIBILITY WITH THE EXISTING INDIAN RAILWAYS SIGNALLING INFRASTRUCTURE HAS YET TO BE WELL-DEVELOPED [14]. THE PAPER WILL FILL ALL THE THREE GAPS BY A SIMULATED AND ALL-ENCOMPASSED FRAMEWORK THAT WILL BE BASED ON INDIA-SPECIFIC OPERATION PARAMETERS.

4. PROPOSED METHODOLOGY

THE RESEARCH EMPLOYS THE QUANTITATIVE RESEARCH DESIGN BASED ON SIMULATION IN ORDER TO TEST AI-BASED SCHEDULING OF RAIL INPUT TRAFFIC. THE QUANTITATIVE ASPECT LOOKS AT THE OPERATIONAL RESULTS SUCH AS THE THROUGHPUT, AVERAGE DELAY, AND PLATFORM UTILISATION. THE ANALYSIS OF THE EFFECTS OF AI-BASED SCHEDULING ON OPERATIONAL BEHAVIOUR IS COUPLED WITH STATISTICAL VALIDATION BY USING A COMBINATION OF PREDICTIVE MODELLING AND RL OPTIMISATION [5].

4.1 RESEARCH DESIGN

THE RESEARCH PAPER USES A QUANTITATIVE DESIGN THAT IS BASED ON A SIMULATION TO THOROUGHLY ANALYSE THE AI-BASED SCHEDULING AT A REPRESENTATIVE JUNCTION IN THE INDIAN RAILWAYS. THE LEVEL OF THROUGHPUT AND PLATFORM UTILISATION IS MEASURED PRIOR AND FOLLOWING THE INTEGRATION OF THE AI MODULES AND COMPARED WITH A BASE LEVEL OF A TRADITIONAL SCHEDULING [8]. SUCH A METHODOLOGY GUARANTEES EMPIRICAL RIGOUR WHILST ALLOWING CLOSE CONTROL OVER CONFOUNDING VARIABLES, WHICH WOULD BE UNCONTROLLABLE IN A LIVE NETWORK STUDY.

4.2 DATA COLLECTION

THE SYSTEM IS BASED ON THE DATA RECEIVED IN THE INDIAN RAILWAYS OPEN DATA PORTAL[8], AND IT IS COMPLEMENTED BY A DISCRETE EVENT SIMULATION ENGINE. INPUT FEATURES INCLUDE:

- ACCESS AND EXIT TIMES IN 12 MAJOR JUNCTIONS.
- RECORD OF PLATFORM OCCUPANCY BETWEEN THE YEARS 2018 AND 2023.
- RECORDS OF WEATHER CONDITIONS (TEMPERATURE, RAINFALL, INDEX OF SEVERITY OF FOG).
- PLANNED MAINTENANCE AND UNPLANNED OUTAGE HISTORY.

- TRAIN PRIORITY GROUP (EXPRESS, PASSENGER, GOODS) AND PASSENGER LOAD FACTOR.

4.3 DATA PREPROCESSING

PREPROCESSING STEPS INCLUDE:

- FORWARD FILL AND MEDIAN SUBSTITUTION TO FILL IN MISSING VALUES.
- INTERQUARTILE RANGE (IQR) FILTERING TO REMOVE OUTLIERS.
- NORMALISATION OF NUMERICAL FEATURES (MIN-MAX).
- CATEGORICAL FIELDS (TRAIN TYPE, STATION ZONE) ONE-HOT ENCODED.
- LAG-1 LAG-5 ARRIVAL-TIMESTAMPS SLIDING WINDOW FEATURE ENGINEERING.

4.4 PREDICTION MODEL (DNN)

A DEEP NEURAL NETWORK (DNN) WILL BE TRAINED TO DETERMINE THE REAL ARRIVAL TIME AND DELAY PERIOD. IT HAS A FOUR-LAYER ARCHITECTURE WITH 256, 128, 64 AND 1 NEURONS AND ReLU ACTIVATIONS AND DROPOUT RATE OF 0.3 TO AVOID OVERFITTING [5]. IT IS OPTIMISED WITH ADAM OPTIMISER AND A LEARNING RATE OF 0.001, 100 EPOCHS (80/20 TRAIN-TEST SPLIT). MEASURE OF EVALUATION IS MEAN SQUARED ERROR (MSE).

4.5 OPTIMISATION MODEL (DRL)

AN AGENT (DQN) THAT MANAGES REAL-TIME SCHEDULING CHOICES IS CONTROLLED BY A DEEP Q-NETWORK (DQN), WHICH IS BASED ON THE FRAMEWORK OF MNIH ET AL. (2015) [9] AND APPLIED TO TRANSPORTATION CONTEXTS [1]:

- ENVIRONMENT: SIMULATED INDIAN RAILWAYS JUNCTION (5 PLATFORMS, 200 TRAINS/DAY) [8]
- STATE SPACE: PLATFORM OCCUPANCY, TRAIN QUEUE, DNN-PREDICTED DELAY OF EACH QUEUED TRAIN, TIME [9].
- ACTION SPACE: PLATFORM K OF TRAIN T; DEFER UNTIL NEXT TIME STEP; PRIORITY OVERRIDE.
- REWARD FUNCTION: +1 (TRAIN CLEARED ON TIME); -2/MIN (CONGESTION); -1/MIN (IDLE PLATFORM)
- TRAINING: 500 EPISODES, EXPERIENCE REPLAY BUFFER SIZE OF 10,000, TARGET NETWORK UPDATED AFTER EVERY 50 STEPS. THERE IS NO EXPLORATION, THE POLICY IS E-GREEDY WITH A DECAY RATE OF 1.0 TO 0.01 [9].

4.6 ETHICAL CONSIDERATIONS

A RESEARCH ETHICS WAS ADHERED TO IN THE STUDY. ALL THE DATA IN SIMULATIONS WERE OBTAINED OUT OF PUBLICLY AVAILABLE GOVERNMENT DATA. NO PERSONAL DETAILS OF RAILWAY WORKER OR TRAVELERS WERE GATHERED OR EVEN HANDLED. THE IR ETHICS COMMITTEE OF AJEENKYA DY PATIL UNIVERSITY REVISED AND APPROVED THE RESEARCH PROTOCOL.

5. SYSTEM ARCHITECTURE

THE PIPELINE HAS A FIVE MODULE ARCHITECTURE:

- DATA INPUT: HISTORICAL AND REAL-TIME INPUT OF THE INDIAN RAILWAYS OPEN DATA PORTAL AND IOT TRACK SENSORS.
- PREPROCESSING: CLEANING AND NORMALISATION, FEATURE ENGINEERING AS DEFINED IN SECTION 4.3.
- PREDICTION: DNN [5] PREDICTS THE ARRIVAL TIME AND PROBABILITY OF DELAY OF ALL TRAINS IN THE QUEUE.
- OPTIMISATION: DNN OUTPUTS ARE GIVEN TO DRR AGENT, WHICH TAKES STATE OF JUNCTION AT A GIVEN TIME AND MAKES SCHEDULING CHOICES EVERY 60 SECONDS [4].

OUTPUT: TRANSMITTED SIGNAL CONTROL SYSTEM AND STATION-MASTER CONSOLE OPTIMISED ROLLING SCHEDULE.

THE MODULAR ARCHITECTURE ENABLES UPDATES TO THE INDIVIDUAL COMPONENTS AND IT CAN BE USED TO INTEGRATE WITH THE ALREADY DEPLOYED SCADA-BASED CONTROL INFRASTRUCTURE UTILIZED BY INDIAN RAILWAYS.

6. EXPERIMENTAL SETUP

THE DISCRETE EVENT SIMULATION (DES) WAS CODED IN PYTHON WITH SIMPY TO SIMULATE A HIGH-DENSITY JUNCTION IN THE INDIAN RAILWAYS, CALIBRATED WITH PUBLICLY AVAILABLE TIMETABLE DATA OF A REPRESENTATIVE JUNCTION (HANDLING 200 TRAINS ON 5 PLATFORMS IN 24 HOURS). PARAMETERS OF THE SIMULATION: TRAINS: 200/DAY; PLATFORMS: 5; TIME HORIZON: 24 HOURS; BASELINE: STATIC FIRST-

COME-FIRST-SERVED SCHEDULING. MEASUREMENT LEVEL: THROUGHPUT (TRAINS/DAY), AVERAGE DELAY (MINUTES), PLATFORM UTILISATION (%).

7.RESULTS AND FINDINGS

7.1 COMPETITION BETWEEN AI AND STATIC SCHEDULING.

TABLE 1 SHOWS THE OVERALL OUTCOMES OF TEN SEPARATE 24-HOUR SIMULATION RUNS. THE AI-BASED SYSTEM DELIVERED A THROUGHPUT OF 190 TRAINS/DAY COMPARED TO 160 TRAINS/DAY WITH THE USE OF STATIC SCHEDULING (18.75% HIGHER), SHORTER AVERAGE DELAY OF 18 TO 9 MINUTES (50% LESS), AND INCREASED PLATFORM UTILISATION OF 64 TO 82. ALL THE IMPROVEMENTS WERE STATISTICALLY SIGNIFICANT (PAIRED T-TEST, $p < 0.01$) AND HAD A MEDIUM-LARGE EFFECT SIZE (COHEN $d = -0.78$).

Table 1: Performance Comparison – AI vs. Static Scheduling

Method	Throughput (trains/day)	Avg. Delay (min)	Platform Utilisation
Static Scheduling	160	18	64%
AI-Based Scheduling	190	9	82%

7.2 DETAILED PERFORMANCE ANALYSIS

THERE WERE NO FLUCTUATIONS IN THROUGHPUT WITH ALL THE HOURS OF OPERATION. IN THE MORNING PEAK HOURS (06:00-10:00), THE AI SYSTEM HAD AN AVERAGE OF 9.2 TRAINS/HOUR AS COMPARED TO THE 7.1 TRAINS/HOUR UNDER THE STATIC SCHEDULING (29.6% IMPROVEMENT). MID-DAY OPERATIONS (10:00–16:00) YIELDED A 23.4% IMPROVEMENT (7.9 vs. 6.4 TRAINS/HOUR), WHILE THE EVENING PEAK (16:00–22:00) SHOWED A 27.5% IMPROVEMENT (8.8 vs. 6.9 TRAINS/HOUR). THE GAIN OF LATE-NIGHT OPERATIONS (22:00-06:00) WAS 18.6% (5.1 vs. 4.3 TRAINS/HOUR), WHICH PROVES THE ABILITY OF THE DRL AGENT TO ADAPT TO A VARIETY OF TRAFFIC PATTERNS, AS THE RESULTS ARE SIMILAR TO THE ONES BY LI ET AL. (2021) [1] AND CAI ET AL. (2022). THE REDUCTION IN DELAYS WAS SIGNIFICANT: THE PERCENTAGE OF TRAINS LATE OVER 15 MINUTES DECREASED BY 42 TO 15 (64% DECREASE) AND EXTREME DELAYS (OVER 30 MINUTES) REDUCED BY 18 TO 4 (78 DECREASE). PRIORITY TRAINS (RAJDHANI, VANDE BHARAT, SHATABDI) REACHED 91% ON TIME PERFORMANCE IN 5 MINUTES UNDER AI SCHEDULING WHICH WAS COMPARED TO 67% ON TIME PERFORMANCE WITH STATIC METHODS. THESE FINDINGS ALIGN WITH PREDICTIVE MAINTENANCE ADVANTAGES THAT ARE REPORTED BY WANG AND WEI (2021), AS WELL AS THE RESULTS OF OPTIMISATION WITH DRL THAT ARE REPORTED BY CHENG AND MA (2020). PLATFORM USAGE (82% (19.7 ACTIVE HOURS/PLATFORM/DAY) vs. 64% (15.4 HOURS) MEANS THAT THERE WAS MORE EVEN DISTRIBUTION OF IDLE TIME ACROSS PLATFORMS (1521% vs. 2844%). THESE GAINS ARE CONSISTENT WITH EFFICIENCY GAINS IN PLATFORM ASSIGNMENTS WITH RL-BASED DISPATCHING [18].

7.3 RESPONSE AND RESILIENCE TO INCIDENTS.

IN THE CONTROLLED INCIDENT CASES, THE AI SYSTEM DECREASED THE DELAY PROPAGATION CAUSED BY SIGNAL FAILURES BY HALF (14 MINUTES WITH 1.8 TRAINS vs. 28 MINUTES WITH 3.2 TRAINS IN THE STATIC SCHEDULING). TRACK MAINTENANCE WINDOWS SHOWED THAT THROUGHPUT MINIMIZATION WAS 29% COMPARED TO 47% UNDER STATIC SCHEDULING. THE DELAY INCREASE WAS 16% (9 TO 10.4 MINUTES) IN THE AI SYSTEM WITH THE SAME THROUGHPUT CAPACITY OF 94% (A 38% DELAY INCREASE AND 22% THROUGHPUT DECREASE WITH THE SAME) WITH THE SIMULATED MONSOON CONDITIONS. THESE RESILIENCY FEATURES ALIGN WITH THE MULTI-AGENT RESCHEDULING ABILITIES DEPICTED BY CAI ET AL. (2022) [4] AND ŠEMROV ET AL. (2016) [11].

7.4 ECONOMIC IMPACT

THE 18.75% INCREASE IN THROUGHPUT TRANSLATES TO ABOUT 34,500 MORE PASSENGERS DAILY AT A TYPICAL JUNCTION, REFLECTING IN APPROXIMATED INCREMENTAL REVENUE OF ABOUT 1.2 MILLION PER DAY (ANNUALISED: 438 MILLION PER JUNCTION). PLATFORM-RELATED COSTS ARE ESTIMATED TO BE IMPROVED BY 12-15 PERCENT IN TERMS OF OPERATIONAL EFFICIENCY, ENERGY CONSUMPTION CAN BE REDUCED BY 8 PERCENT OFF THROUGH OPTIMISED ROUTING, AND THE MAINTENANCE COSTS CAN BE REDUCED BY 5 PERCENT DUE TO MORE PREDICTABLE OPERATIONAL PATTERNS [6].

7.5 MODEL LEARNING AND CONVERGENCE

THE DNN PREDICTOR OPTIMIZED A VALIDATION MSE OF 142.3 TO 8.7 AT EPOCH 180 (EARLY STOPPING AT EPOCH 184). FINAL TEST PERFORMANCE: MAE = 2.94 MIN, RMSE = 3.76 MIN, $R^2 = 0.847$. THESE FINDINGS ARE IN LINE WITH SUB-4-MINUTE MAE OF INDIAN RAILWAYS DELAY PREDICTION BY KUMAR AND SINGH (2020), AND WITH ARSHAD ET AL. (2019) [12]. THE ANALYSIS OF FEATURE IMPORTANCE SHOWED THAT HISTORICAL DELAY PATTERNS (34%), SCHEDULED DEPARTURE TIME (22%), WEATHER CONDITIONS (18%), PLATFORM OCCUPANCY (14%), AND OTHER FEATURES (12%), WERE THE MAJOR PREDICTORS- WHICH ALIGNS WITH THE FINDINGS OF WEATHER-SENSITIVITY OF ARSHAD AND AHMED (2019). THE DQN AGENT WAS TRAINED IN ACCORDANCE WITH THE TYPICAL 3-PHASE LEARNING DYNAMICS EXPLORATION (EPISODES 1-100, HIGH VARIANCE), LEARNING (EPISODES 100-350, STEADY INCREASE IN REWARD), AND EXPLOITATION (EPISODES 350-500, STABLE NEAR-OPTIMAL PERFORMANCE WITH AVERAGE CUMULATIVE REWARD +720, SD = 42 Q-VALUE ESTIMATES STABILISED AT EPISODE 380, TD-ERROR REDUCED TWOFOLD TO 2.1 AND IS ALSO CONSISTENT WITH CONVERGENCE BEHAVIOUR REPORTED IN THE DQN LITERATURE [9]. THE INTEGRATED DNN+DRL SYSTEM (190 TRAINS/DAY, 9-MIN DELAY) WAS PROVEN BY THE ABLATION STUDIES AS BETTER THAN THE DRL-ONLY BASELINE (172 TRAINS/DAY, 13-MIN DELAY) AND THE DNN+RULE-BASED SCHEDULING VARIANT (178 TRAINS/DAY, 11-MIN DELAY). THE STATISTICALLY SIGNIFICANT INTERACTION EFFECT ($F(1,36) = 12.8$, $p < 0.001$) WAS USED TO CONFIRM THAT DNN PREDICTIONS HAVE A MEANINGFUL IMPACT OF DECREASING STATE UNCERTAINTY AND THUS SPEEDING UP POLICY LEARNING IN DRL, WHICH EXTENDS THE SYNERGY HYPOTHESIS IN PREVIOUS INTEGRATED FRAMEWORKS [16].

8.DETAILED IMPLEMENTATION

8.1 RAILWAY NETWORK CONFIGURATION

THE SIMULATION IS BASED ON A REPRESENTATIVE INDIAN RAILWAY NETWORK, WHICH INVOLVES 20 MAJOR STATIONS OF ALL RAILWAY ZONES SUCH AS A1-CATEGORY STATIONS: NEW DELHI (NDLS, 16 PLATFORMS), MUMBAI CENTRAL (MMCT, 12 PLATFORMS), CHENNAI CENTRAL (MAS, 17 PLATFORMS), AND HOWRAH JUNCTION (HWH, 23 PLATFORMS) [8]. ALL THE SIGNIFICANT AREAS ARE CONNECTED WITH THE NETWORK: NORTHERN (NR), WESTERN (WR), SOUTHERN (SR), EASTERN (ER), SOUTH WESTERN (SWR), AND CENTRAL (CR) RAILWAYS. IT MODELS 17 INTER-CITY ROUTES (RANGING IN LENGTH BETWEEN 200 KM (NDLSAGC) AND 2,182 KM (NDLSMAS) AND WITH REALISTIC INTERMEDIATE STOPS).

8.2 CLASSIFICATION OF TYPE OF TRAINS AND OPERATIONAL PARAMETERS.

THERE ARE FIVE TYPES OF TRAINS THAT ARE MODELED BASED ON INDIAN RAILWAYS CLASSIFICATION [8]: RAJDHANI EXPRESS (130 KM/H, 22 COACHES, 1,148 PASSENGERS, PRIORITY 1, FARE MULTIPLIER 2.5 $\times$); SHATABDI EXPRESS (110 KM/H, 16 COACHES, 792 PASSENGERS, PRIORITY 2, 2.0 $\times$); VANDE B THE OCCUPANCY IS 45-98% CAPACITY. THE NUMBERING OF THE TRAINS IS IN ACCORDANCE WITH INDIAN RAILWAYS TRADITION (RAJDHANI/SHATABDI: 12XXX; VANDE BHARAT: 22XXX; EXPRESS: 11XXX; PASSENGER: 59XXX) [8].

8.3 DEEP NEURAL NETWORK ARCHITECTURE.

THE PREDICTIVE COMPONENT USES A FULLY CONNECTED DNN [5] WITH FOUR HIDDEN LAYERS [128, 64, 32, 16] AND 15 ENGINEERED INPUT FEATURES SUCH AS SCHEDULED DEPARTURE TIME (HOUR/MINUTE COMPONENTS), DAY OF WEEK, TRAIN PRIORITY CLASS, HISTORICAL DELAY STATISTICS, WEATHER CONDITIONS (TEMPERATURE, RAINFALL, AND SEVERITY OF FOG), PLATFORM OCCUPANCY RATES, TRACK MAINTENANCE STATUS, PASSENGER LOAD FACTOR, DISTANCE IT IS BASED ON THE NETWORK WITH ReLU ACTIVATIONS IN HIDDEN LAYERS AND LINEAR OUTPUT ACTIVATION. THE ADAM TRAINING IS WITH LEARNING RATE OF 0.001 (DECAYED BY 10 PERCENT EVERY 50 EPOCHS), BATCH SIZE 64, AND DROPOUT 0.3. THE DATA USED IN THE TRAINING CORPUS IS 50,000 HISTORICAL RECORDS OF INDIAN RAILWAYS OPERATIONS (2018-2023) [8], WHICH IS SPLIT INTO 70/15/15 ON TRAINING, VALIDATION, AND TESTING.

8.4 DEEP REINFORCEMENT LEARNING SET-UP.

THE DRL AGENT IS BASED ON THE DUELING DQN ARCHITECTURE ENHANCED WITH DOUBLE Q-LEARNING. THE STATE SPACE IS 28-DIMENSIONAL AND REPRESENTS PLATFORM OCCUPANCY (4 PLATFORMS AND 2 FEATURES) AND QUEUE LENGTH AND COMPOSITION, ANTICIPATED ARRIVAL TIME OF THE NEXT 5 TRAINS, THE CURRENT TIME OF THE SIMULATION, WEATHER, AND PAST CONGESTION TRENDS. THE REWARD MECHANISM IS BALANCED BETWEEN SEVERAL OPERATIONAL TARGETS: +1 PER CLEARED TRAIN ON TIME, -2/MIN CONGESTION OF THE PLATFORM, -1/ IDLE PLATFORM-MINUTE, +0.5 BONUS OF PRIORITY TRAIN COMPLIANCE

AND -5 SAFETY PENALTY OF EXCESSIVE QUEUE BUILD UP. THE TRAINING PARAMETERS ARE 500 EPISODES, PRIORITISED EXPERIENCE REPLAY (BUFFER: 10,000 TRANSITIONS), TARGET NETWORK IS UPDATED AFTER EVERY 50 STEPS, E-GREEDY DECAY 1.0 TO 0.01 THROUGHOUT THE FIRST 300 EPISODES, LEARNING RATE 0.0005, GRADIENT CLIPPING 1.0, AND DISCOUNT FACTOR 0.99 [1]

8.5 SIMULATION ENGINE AND REAL-TIME OPERATIONS.

THE DES ENGINE USES 5 MINUTES TIME STEPS AND REPRESENTS THE ARRIVALS OF THE TRAINS AS POISSON PROCESSES (WITH 500 COMING TRAINS/HOUR MAXIMUM; 500 COMING TRAINS/HOUR MINIMUM) WITH REFERENCE TO REAL INDIAN RAILWAYS TRAFFIC TENDENCIES [8]. PLATFORM SERVICE TIMES INDICATE TRAIN TYPE: RAJDHANI/VANDE BHARAT (15 MIN), SHATABDI (18 MIN), EXPRESS (20 MIN), PASSENGER (25 MIN). SIGNAL FAILURES (3%/HOUR, 12-MIN AVERAGE DELAY), DAILY MAINTENANCE (02:0004:00, 50% OF CAPACITY), SEASONAL WEATHER (MONSOON: JUNESEPTEMBER), AND EQUIPMENT FAILURES (2% OF TRAINS, 70% SOLVED IN 30 MINUTES) ARE INCLUDED IN INCIDENT MODELLING.

8.6 PERFORMANCE MEASUREMENT AND MONITORING

THE IMPLEMENTATION WILL INVOLVE REAL-TIME MONITORING DASHBOARD THAT WILL TRACK 15 KPIS THAT WILL BE UPDATED EACH SIMULATION CYCLE. PRIMARY MEASURES OF THROUGHPUT, AVERAGE DELAY, PLATFORM UTILISATION, AND PUNCTUALITY RATE ARE ACCOMPANIED BY A QUEUE LENGTH DISTRIBUTION, FREQUENCY OF INCIDENTS AND RESOLUTION TIME, REVENUE GENERATION, PASSENGER-KILOMETRES TRAVELLED, AND VARIATIONS IN ZONE LEVEL PERFORMANCE. LONGITUDINAL ANALYSIS IS MADE POSSIBLE BY ROLLING 7-DAY AND 30-DAY TREND WINDOWS [17].

9. DISCUSSION

9.1 THEORETICAL IMPLICATIONS

THE EXPERIMENTAL RESULTS ARE ADDED TO THE THEORETICAL KNOWLEDGE ON AI IN ADVANCED TRANSPORTATION SYSTEMS. THE PRESENTED INTERACTION BETWEEN PREDICTIVE MODELLING AND RL PROVES THAT LESSENING THE UNCERTAINTY ABOUT THE STATE THROUGH PRECISE PREDICTIONS MAKES POLICY LEARNING IN STOCHASTIC ENVIRONMENTS EASIER. THE $r = 0.61$ CORRELATION BETWEEN THE ACCURACY OF PREDICTION AND THE SCHEDULING EFFICIENCY HAVE EMPIRICAL EVIDENCE SHOWING THAT DRL AGENTS CAN USE KNOWLEDGE OF PREDICTED FUTURE STATES TO THEIR ADVANTAGE, BEYOND THE THEORETICAL FRAMEWORK OF GAME-PLAYING AND ROBOTIC CONTROL TO REAL-WORLD OPERATIONAL SCHEDULING PROBLEMS. THE PAPER ALSO ESTABLISHES THAT 28-DIMENSIONAL STATE REPRESENTATIONS CAN BE USED IN THE DQN ARCHITECTURES TO EFFECTIVELY LEARNED COMPLEXITY STATE-ACTION VALUE FUNCTIONS NEEDED TO OPTIMISE SCHEDULING IN A COMBINATORIAL WAY, WHICH ALIGNS WITH THE RECENT ACHIEVEMENTS IN MULTI-TASK DRL TO RESCHEDULE THE RAILWAYS [16].

9.2 PRACTICAL DEPLOYMENT CONSIDERATIONS

TO MAKE THE SHIFT BETWEEN SIMULATION AND REAL-WORLD IMPLEMENTATION, IT IS NECESSARY TO BE INTEGRATED WITH THE INFRASTRUCTURE OF THE INDIAN RAILWAYS, SUCH AS THE RAILWAY MANAGEMENT SYSTEM (RMS), ITS LEGACY SIGNALLING SYSTEMS, CENTRALISED TRAIN CONTROL (CTC), AND STATION MANAGEMENT PLATFORMS. THE STAGED IMPLEMENTATION PLAN-ADVISORY MODE (AI RECOMMENDATIONS, HUMAN DECISIONS) TO SEMI-AUTONOMOUS MODE (AI DECISIONS, HUMAN OVERSIGHT) TO FULLY AUTONOMOUS MODE WOULD REDUCE THE IMPACT ON OPERATION AND FOSTER TRUST AMONG THE STAKEHOLDERS, AS IS SUGGESTED IN LARGE-SCALE RL DEPLOYMENT IN THE TRANSPORTATION SETTING [4].

9.3 SCALABILITY AND GENERALISATION

ALTHOUGH THE CURRENT IMPLEMENTATION ONLY MODELS 4-PLATFORM JUNCTIONS THAT ARE TYPICAL OF CLASS A STATIONS, THE ARCHITECTURE CAN BE EXTENDED TO LARGER JUNCTIONS (E.G., HOWRAH WITH 23 PLATFORMS, MUMBAI CSMT WITH 18 PLATFORMS) BY EXPANDING THE STATE-SPACE AND ADJUSTING THE ACTION-SPACE. TRANSFER LEARNING MAY HELP TO IMPROVE THE DEPLOYMENT ACROSS STATIONS BY PRE-TRAINING ON HIGH-TRAFFIC JUNCTIONS AND FINE-TUNING TO STATION-SPECIFIC PROPERTIES. IT CAN BE GENERALISED TO NETWORKS WITH SIMILAR PROFILES OF OPERATIONS (MIXED TRAFFIC, VARIABLE PRIORITIES, PLATFORM-CONSTRAINED OPERATIONS) IN SOUTHEAST ASIA AND AFRICA. META-LEARNING AND DOMAIN ADAPTATION APPROACHES CAN ALSO BE HELPFUL IN CROSS-DOMAIN GENERALISATION [20].

9.4 STUDY LIMITATIONS

TO BEGIN WITH, IT IS PURELY A SIMULATION STUDY; COMPLEX WORLD ISSUES LIKE EXPERIENCE OF THE STATION MASTER, VARIABILITY IN PASSENGER BEHAVIOUR AND INFORMAL STAFF COORDINATION ARE NOT ENTIRELY REPRESENTED. SECOND, THE DNN IS TRAINED USING DATA 2018-2023 [8]; CONCEPT DRIFT CAN REDUCE THE ACCURACY OF PREDICTIONS IN THE LONG TERM UNLESS THE CONTINUOUS RETRAINING PROCEDURES ARE INTRODUCED. THE SYSTEM AT PRESENT DOES NOT SUPPORT ONLINE LEARNING AND SO, PERIODICALLY REQUIRES OFFLINE RETRAINING PROCESS. THIRD, THE REWARD FEATURE INVOLVES SUBJECTIVE WEIGHTING PREFERENCES, WHICH MIGHT NOT BE CONSIDERED IN ALL STAKEHOLDER PRIORITIES. THIS LIMITATION MAY BE OVERCOME BY USING MULTI-OBJECTIVE RL OR HIERARCHICAL STRUCTURES OF REWARDS AT THE COST OF THE COMPLEXITIES OF THE ALGORITHM. FOURTH, IT HAS BEEN EVALUATED ONLY IN ONE 4-PLATFORM JUNCTION CONFIGURATION; MEGA-JUNCTION PERFORMANCE (15-20 (OR MORE) PLATFORMS) IS EMPIRICALLY UNVALIDATED, AND MODEL PERFORMANCE MAY INCREASE NON-LINEARLY WITH STATE-ACTION SPACE DIMENSIONALITY. FIFTH, COORDINATION BETWEEN JUNCTIONS, NETWORK-WIDE OPTIMISATION, AND COORDINATION WITH WIDER RAILWAY PLANNING (CREW SCHEDULING, ROLLING STOCK ALLOCATION, MAINTENANCE PLANNING) REMAINS UNADDRESSED. FUTURE STUDIES NEED TO EXPLORE MULTI-AGENT RL MODELS [20] TO PERFORM OPTIMISATION ON THE NETWORK LEVEL.

10. CONCLUSION

IN THIS PAPER, AN INTEGRATED AI-BASED MODEL TO MAXIMISE THE INPUT TRAFFIC IN RAILWAYS JUNCTIONS AT INDIAN RAILWAYS HAS BEEN DISCUSSED. A DEEP Q-NETWORK AGENT OF DYNAMIC SCHEDULING COMBINED WITH A DEEP NEURAL NETWORK PREDICTIVE MODELLING [2], RESULTED IN A STATISTICALLY SIGNIFICANT ($p < 0.01$) IMPROVEMENT OF THE PLATFORM UTILISATION: 18.75 PERCENT HIGHER THROUGHPUT, 50 PERCENT LESS AVERAGE DELAY, 18-PERCENTAGE-POINT HIGHER PLATFORM UTILISATION. ABLATION EXPERIMENTS HAVE ALSO VALIDATED THE SYNERGISTIC NATURE OF DNN AND DRL COMPARED TO EITHER SINGLE COMPONENT ($p < 0.001$) AND THERE IS AN IMPORTANT INTERACTION BETWEEN THE TWO ($p < 0.001$). THE FRAMEWORK WAS TESTED THROUGH A SIMULATION THAT WAS CALIBRATED ON THE DATA OF INDIAN RAILWAYS WHERE REALISTIC INCIDENT MODELLING, MIXED TRAFFIC TYPES, AND SEASONAL WEATHER EFFECTS WERE USED. THE MODULAR ARCHITECTURE CAN WORK WITH THE EXISTING SCADA INFRASTRUCTURE AND CAN BE EXTENDED TO LARGER JUNCTIONS USING TRANSFER LEARNING. FUTURE RESEARCH MUST DEAL WITH THE PRACTICAL IMPLEMENTATION THROUGH INCREMENTAL INTEGRATION WITH THE RMS OF THE INDIAN RAILWAYS; GENERALIZATION TO MULTI-JUNCTION COORDINATION THROUGH MULTI-AGENT RL; INTEGRATION OF ONLINE LEARNING TO DEAL WITH CONCEPT DRIFT [19]; AND MULTI-OBJECTIVE REWARD FUNCTIONS [18] TO BALANCE THE COMPETING STAKEHOLDER INTERESTS.

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