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COST, TRANSIT TIME, AND GHGS EMISSIONS MINIMISATION OF FREIGHT TRAINS: APPLICATION OF Q-LEARNING AND GENETIC ALGORITHM

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Abstract: The purpose of this research is to address the multi-objective problem of minimising overall cost, transit time, and CO2e emissions in Pakistan's railway system. A multi-objective problem is designed using integer linear programming and reinforcement learning. This study is generally applied to transportation network design and planning challenges that need balancing various objectives. Integer linear programming is used to design a multi-objective problem, and reinforcement learning is used to identify the shortest path for a railway network. Pareto front solutions are also generated using the genetic algorithm. Using the Q-learning method, we estimated and analysed the cost, time, and greenhouse gas emissions of current and future railway networks. According to our findings, the shortest railway track connecting Pakistan's provinces of Punjab and Sindh outperforms the current railways (Fareed Express) in terms of cost, time and emissions. A cost, transit time, and CO2e emission reduction of 13% is possible when compared to the existing railway line.

1 Introduction

Freight mobility is crucial to a country's competitiveness, growth, and regional integration at the global scale. A well-developed transportation system provides for efficient and cost-effective freight transit from origin to destination. To handle such freight operations, numerous modes of transportation are provided, including road, railway, aviation, and pipelines. However, the two principal modes of inland cargo movement in the country are highway and railway [1,2]. The train has a particular benefit over transportation in terms of long-distance and large-scale traffic activities. Furthermore, rail transit causes less damage to the environment than truck transportation [3,4]. The railway transportation network of a country facilitates trade and commerce, reduces transportation costs and congestion on crowded roadways, and promotes regional integration and infrastructure development [5]. The demand for rail freight is a critical part of railroad operations. Rail freight transportation networks are created in the same manner that companies create demand for labour, power, and other resources. Freight transportation is generally viewed as an input to a company's manufacturing process, and it is obtained from demand for goods that are produced in different locations. Demand for rail freight transportation is influenced by a variety of factors, including economic activity and cost [6,7]. The primary goal of freight rail transportation demand analysis is to identify the principal elements that influence rail freight demand so that rail transportation strategy and demand management may be implemented. Policymakers, transportation planners, public agencies, and transportation operators can utilise empirical elasticity studies to analyse alternative policy choices for restricting future rail freight transport expansion, modal switch, or decarbonization. Furthermore, making policy decisions such as price control, subsidies, and taxes requires an accurate assessment of the empirical rail freight transport demand model.

Along with the importance of rail demand, international multi-echelon freight networks become intermodal transport when many modes of transportation are joined. These networks are made up of a variety of highly linked logistical networks, each having its own transit times, distances, operating costs, and transportation emissions. One of the most challenging tactical and operational challenges is the network infrastructure architecture [7]. Service network design formulas create the transportation plan to guarantee that the logistics chain runs smoothly, that demand is met, and that profitability is maintained. This is done through network-wide operations planning, which includes choosing and organising transportation services, integrating terminal activities, and regulating material movement across the logistics system [8]. The network design issue, on the other hand, is one of the most challenging problems in combinatorial optimisation [9] and The issues are caused by the system's unique interplay of parts and competing needs. This tactical-based decision issue includes the supply chain design, mode and storage selection, route description, and route elements to be employed such as shipping frequency and the number of intermediate transhipment locations, distribution assignment along the routes, and terminal operations. Because of the system's unique interplay of components and conflicting criteria, difficulties occur. The design of the distribution network, mode and capacity selection, route definition, and route characteristics to be employed, such as transportation frequency and the number of intermediaries [10-12].

For the distribution networking, the Pakistan Railway (PR) was established in 1861 as a state-owned Pakistani enterprise based in Lahore. It is responsible for organizing and operating passenger locomotive services, as well as regulating railway firms, industries, and allied organisations, and reports to the Ministry of Railways. The PR encourages passenger and freight travel across the United States. It links the country's hinterland to coastal and dry ports (Karachi and Bin-Qasim). It also makes revenue by carrying various commodities such as petroleum oil, corn, coal, fertiliser, limestone, industrial and imported products, and so on. The Pakistan railway's effectiveness has deteriorated over time as resources have been diverted to the expansion of the road network. As a result, its proportion of inland passenger traffic has decreased from 41% to 10%, while its part of freight traffic has decreased from 73% to 4% [13]. Recognises the significance of rail for transportation, Pakistan's government has set a goal of increasing rail's share in the country's Vision 2025 from 4% to 20% [14]. Rail freight transport is measured in total tonnes (millions) and ton-kilometres (millions). In 1997-98, PR transported 5.97 million tonnes and 4447.3 million ton-kilometres of freight, which has now increased to 7.23 million tonnes and 6187.3 million ton-kilometres after a decade. The majority of the success throughout this time period may be attributed to PR's development programmes aimed at improving its services [5]. However, following 2008, the performance of public relations began to degrade, particularly between 2010 and 2013. Because of ageing infrastructure, a shortage of locomotives, and a lack of rolling stock, PR has had the biggest difficulty throughout this time period. As a result, the number of freight trains departing ports each day has decreased from 96 to just one per day [5]. Furthermore, between 2010 and 2013, the number of terrorist attacks against PR increased dramatically [15]. As a result, PR's freight volume dropped from 7.23 million tonnes in 2007-08 to 1.01 million tonnes in 2012–13, as well as from 6187.3 to 419.3 million ton-kilometres. Since then, PR has used a number of strategies to boost rail freight transportation (for example, boosting freight trains from ports, strengthening dry ports, and so on [16]. As a result, rail freight increased dramatically in tonnes and ton-kilometres in 2016-17, reaching 5.63 tonnes and 5031 ton-kilometres, respectively. As a result, Figure 1 shows data on CO2e emissions from 1960 to 2018.

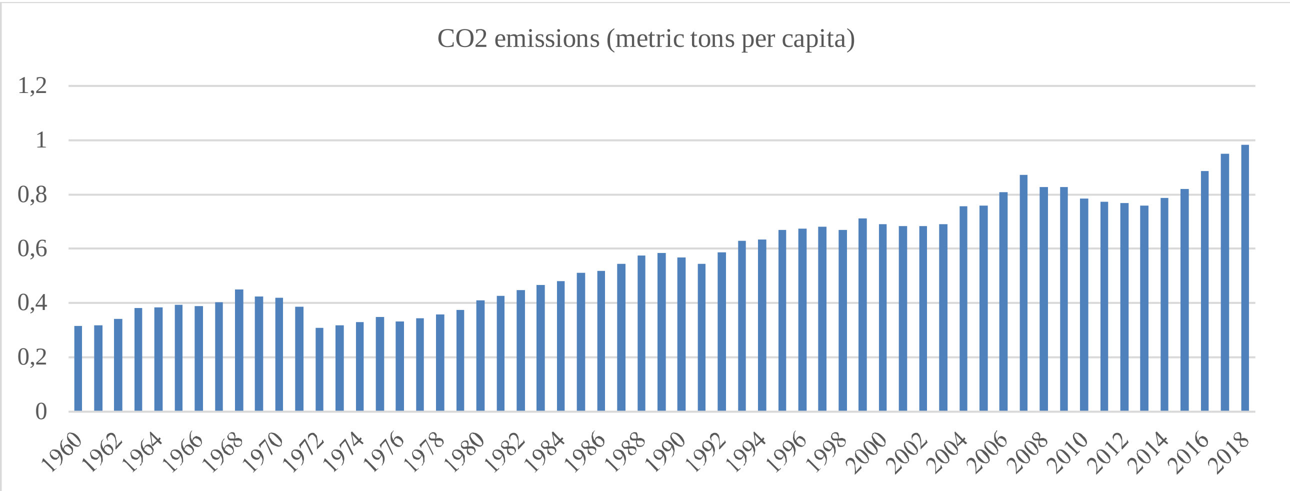

Figure 1 CO2 emissions data of Pakistan (metric tons per capita)
Source: [29]

With the increase in the demand of railway freight distribution, there has been a steady increase in reliance on fossil fuel-derived energy over the last century, resulting in increased CO2e emissions [17,18]. Transportation is deeply ingrained in all social functions, including medical logistics, raw materials, consumable products, technology products, energy sources, and a wide range of other human activities. As a result, the transportation industry is a major source of CO2e emissions [19], mainly due to growing infrastructure development and global transportation demand It also contributes to air pollution by releasing particles into the atmosphere from both stationary and mobile sources [20]. It's important to note that railway transportation is expected to expand significantly in the near future [21], All modes of transportation, including construction, maintenance services, operation, and decommissioning, must cut carbon footprints at all phases of their life cycles [22,23].

A literature review on CO2e emissions from railway maintenance finds that real activity-based monitoring and estimation are restricted and lacking in detail, and that the results are impossible to check due to the use of broad assumptions. Because of data limitations and previously published studies, assumptions have been made about railway resurfacing machinery's fuel usage and track-processing rates. They properly proposed that more research on the technology's fuel usage and CO2e emissions be conducted in order to confirm their findings [24].

In our research, first of all, we looked at the shortest path (SP) of a rail network for passenger and freight transportation. The findings can be applied directly to the railway system. To overcome our challenge, we used an ILP model. To accomplish our objective of reducing path length, travel/transit time, and CO2e emissions, we used Q-learning and a genetic algorithm. The key distinction between our research and the investigations proposed by [25] are shown in Table 1.

Table 1 Research gaps

Research framework	[25]	Our research
Model formulation	Integer linear programming	Integer linear programming
Solution algorithm	MONET	Q-learning and genetic algorithm
Research region	Anonymous case study	Lahore-Karachi (Pakistan)
Objectives	Minimisation of path length and travel time	Minimisation of path length, travel time, and CO2e emissions

Using a multiobjective genetic algorithm, we propose the first study in Pakistan to identify the SP and provide a trade-off between cost, time, and CO2e emissions. This study helps decision-makers, policymakers, freight forwarders, importers, and exporters in Pakistan in lowering transportation costs, completing green orders, and delivering goods promptly. Second, this research will assist freight forwarders in providing clients with door-to-door delivery at the lowest possible transportation cost. The following are the research's main contributions:

1. Modelling of integer linear programming (ILP) problem for Pakistani transportation level considering the cost, time, and CO2e emissions in the SP distribution network;
2. To find the SP for railway network between two capital cities of Pakistan by applying the Q-learning algorithm;
3. To solve the multi-objective optimisation problem by creating Pareto fronts to the trade-off between path length, travel time, and CO2e emissions generated by the genetic algorithm;
4. To analyse the railway networks by applying real-world data for the multi-objective optimisation problem.

This paper has been split into five sections. Section 2 shows crucial technical information on the description of real-life problems. This section also provides details for the solution methodology of the problem and details of the assumption about the ILP transportation problem. Section 3 presents the parameters and preliminary data applied in the calculations & solution methodology. Section 4 provides results and discussion. This section also compares and proposes the multi-objective problem concerning the existing railway network. Lastly, Section 5 provides the conclusions and some additional developments and implications for studies.

1.1 Problem statement

This section provides the definition and design of the multi-objective optimisation problem of minimising travel costs, travel time, and CO2e emissions by formulating an integer linear programming problem.

1.1.1 Problem definition

In this study, we formulated our problem as a multiobjective integer linear problem, with the major and secondary functions being the minimisation of overall cost and time for cargo transfers in the nodes. In addition, the carbon emissions rate function is considered as a third goal. The primary goal of this topic is to minimise the adverse consequences of road transportation, which result in high carbon emissions and fuel consumption for logistics systems, while also meeting consumer expectations concerning transit times. In the problem, passenger and freight trains between Lahore and Karachi carry passengers and cargo simultaneously.

The suggested model takes into account network design for transportation in Pakistan; nonetheless, several assumptions for real-life scenarios are provided. For example, the proposed path is based on the existing path's work, passenger and freight trains are considered as one train due to the lack of a separate freight train, a single railway track is chosen, speed is constant for both trains, emissions factors and transit time calculations are the same.

2 Methodology

2.1 Model

One of the most efficient techniques to solving the SP problem is to use various heuristic algorithms. The standard single-source shortest path (SSSP) model is used as a foundation for developing an ILP model. Let us consider, G = (V, E) where the directed network of railway transport for the passenger is a set of V nodes, and E is a set of arcs {(a, j) ….(m, n)} with d_ij shows the travel distance on nodes (i, j). The SP from source s to destination t is fixed by the set of arcs, which produces SP based on applied factors like the distance of arc d_ij. The formulation of the model in the form of a linear program is given below.

Notations

i, j	set of nodes $(i, j = 1, \ldots, I)$
$c_{ij}, k \in \{1,\ldots,r\}$	for each iteration $k = 1,\ldots, r$
V	finite set of nodes on a directed graph where $G = (V, E)$
E	finite set of edges on directed graph where $G = (V, E)$
s	source node $s \in V$
t	destination node where t $\in$ $t \in V$
c_{ij}	cost on the edges as $i \in V$, and $j \in V$
t_{ij}	time on the edges as $i \in V$, and $j \in V$
$CO_{2_{ij}}$	CO2e on the edges as $i \in V$, and $j \in V$
ed_{ij}	an edge from vertex $i \in V$, and $j \in V$
S	the current state of an agent.
A	the current action selection according to the policy.
S'	the next state of the agent where it ends up.
A'	for the estimation of the Q-value, the next possible best action of the agent.
R	the current reward in response to the current action after interacting with the environment.
r	the discounting factor for future rewards with values between greater than 0 and less than or equal to 1.
α	step length for the estimation of $Q(S, A)$.

$$\text{Min } f_1 = \left(\sum_{(i,j)\in V} c^1{}_{ij} ed_{ij}, \ldots, \sum_{(i,j)\in V} c^r{}_{ij} ed_{ij} \right) \tag{1}$$

$$\text{Min } f_2 = \left(\sum_{(i,j)\in V} t^1{}_{ij} ed_{ij}, \ldots, \sum_{(i,j)\in V} t^r{}_{ij} ed_{ij} \right) \tag{2}$$

$$\text{Min } f_3 = \left(\sum_{(i,j)\in V} CO_2{}^1{}_{ij} ed_{ij}, \ldots, \sum_{(i,j)\in V} CO_2{}^r{}_{ij} ed_{ij} \right) \tag{3}$$

s.t.

$$\sum_{j\in V} ed_{sj} - \sum_{j\in V} ed_{js} = 1 \tag{4}$$

$$\sum_{j\in V} ed_{tj} - \sum_{j\in V} ed_{jt} = -1 \tag{5}$$

$$\sum_{j\in V} ed_{ij} - \sum_{j\in V} ed_{ji} = 0 \quad \forall i \in V\{s,t\} \tag{6}$$

$$\sum_{(i,j)\in V} c^1{}_{ij} \le C \tag{7}$$

$$\sum_{(i,j)\in V} t^1{}_{ij} \le T \tag{8}$$

$$\sum_{(i,j)\in V} CO_2{}^1{}_{ij} \le CO_2 \tag{9}$$

$$ed_{ij} \in \{0,1\} \qquad \forall (i,j) \in E \tag{10}$$

Equation (1) shows the minimisation of the total path length of the railway network from the source node s to the destination node t. Equation (2) depicts the minimisation of the total travel time in the railway network. Equation (3) defines the minimisation of the CO2e emissions in the railway network. Equation (4) shows one edge that should be leaving the node s, which must not be on the cycle. Equation (5) indicates that one edge must be entering the node t, which should not be on the cycle. Equation (6) ensures the conservation of the flow of the constraints. Equation (7) shows that the cost of each arc should not be exceeded by the total cost in the SP network. Equation (8) indicates that the time of each arc should not be exceeded by the total cost in the SP network. Equation (9) presents that the CO2e of each arc should not be exceeded by the total cost in the SP network.

2.2 Solution methodology

We used two different solution algorithms in this investigation. The first is the Q-learning algorithm proposed by [26]. Secondly, we generated Pareto front solutions generated by genetic algorithm [27] to trade-off cost, transit time, and CO2e emissions. Figure 2 shows the selected nodes in the railway network for the SP problem (source node: 0; destination: 30).

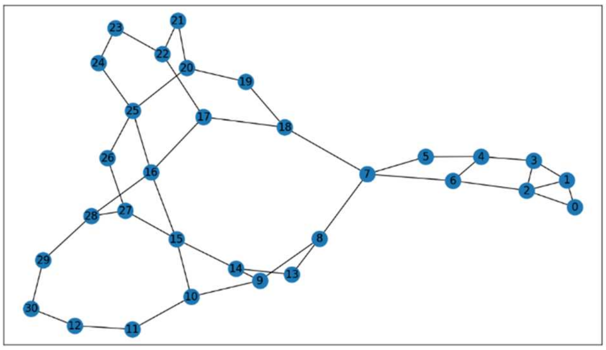

Figure 2 Selected nodes in the railway network for the SP problem (source node: 0; destination: 30)

2.3 Reinforcement learning

Reinforcement learning is a simplified model of the learning process in which a learning agent continuously interacts with its environment and learns to produce the best solution over time. The learning agent meets a range of scenarios in its surroundings throughout the learning phases. State refers to all of the situations that an agent encounter. During each stage, the agent chooses from a list of authorised activities, earning variable rewards and punishments. In whatever state, the agent is rewarded the most for optimal behaviour. Figure 3 depicts the reinforcement learning process and the agent's interaction with the environment.

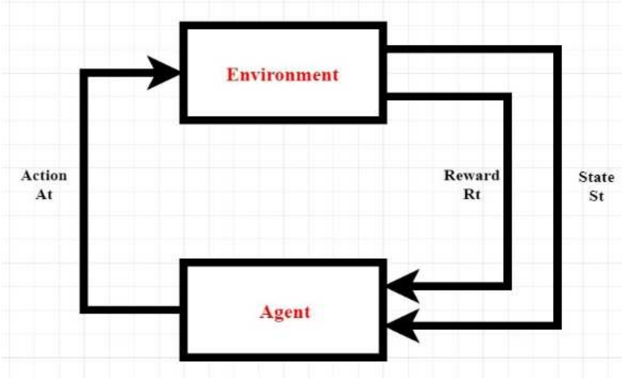

Figure 3 Deep reinforcement learning

Q-learning is a fundamental form of reinforcement learning which uses Q-values to improve the behaviour of the learning agent. We define the value of Q for actions A and states' S. Q(S, A) provides the estimation of taking action A at various states S and this estimation is iteratively calculated by following the temporal difference update rule.

An agent progresses through different states S in the course of its actions, starting from the starting state and progressing to the subsequent states based on its actions and interactions with the environment. As indicated in Table 2, at each state or transition, an agent performs action A, receives a reward or punishment from the environment, and advances to the next state. This process is finished when the episode is completed and no additional transitions are feasible. The temporal difference rule can be represented as follows:

$$Q(S,A) \leftarrow Q(S,A) + \alpha\big(R + rQ(S',A') - Q(S,A)\big) \quad (11)$$

When the agent interacts with the environment, the update rule of estimating the Q-value is applied.

Q-learning algorithm pseudocode

begin
    Initialisation:
        $\underset{m*n}{Q}(s_t, a_t) \leftarrow \{0\}$, (n states and m actions)
        for (each episode):
Set s_t ← a random state from the states set S;
while ($s_t \neq$ Goal state)
Choose at in s_t by using an adequate policy ∈-greedy, etc.);
Act at, and receive reward/penalty and s_t+1;
Update $Q(s_t, a_t)$ using equation 11
$s_t \leftarrow s_t + 1$;
end-while
        end for
end

Table 2 Reward matrix

(12, 11) (0, 1) (1, 0) (1, 3) (3, 1) (3, 4) (4, 3) (4, 5) (5, 4) (13, 14) (14, 13) (14, 15) (8, 13) (15, 14) (9, 14) (5, 7) (15, 16) (16, 15) (15, 10) (16, 17) (17, 16) (17, 18) (7, 18) (18, 19) (19, 20) (20, 19) (20, 21) (21, 20) (21, 22) (22, 21) (22, 23) (23, 22) (23, 24) (24, 23) (24, 25) (25, 24) (16, 25) (17, 22) (25, 26) (26, 25) (25, 20) (26, 27) (27, 26) (27, 15) (28, 16) (27, 28) (28, 27) (28, 29) (29, 28) (29, 30) (30, 29) (30, 12) (12, 30)

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2.4 *Genetic algorithm*

GA leverages the premise of the presence of the fittest cross-breeding population to construct a robust search strategy. To that goal, the solutions with a finite population that are based on the defined problem are first kept. Second, from current populations, new populations are generated by prioritising solutions and rating them based on their fitness values, followed by cross-breeding of the fittest to produce the best-optimised offspring. The GA algorithm operates solely on the fitness value and has no other knowledge. Generations generate solutions, and weaker ones are weeded out since they have no progeny. The stronger solutions, on the other hand, remain and mix parental qualities to form new families, and the cycle repeats. In this work, the generated mathematical model with GA application is written as M-files in MATLAB software.

- The evaluation of the target population as a whole.
- Best and fittest parents chosen from a population.
- Creating a new generation by combining the children of two parents.
- New generation mutation.
- If the operation doesn't end, go back to the best-found individual in the current population.

Multi-objective genetic algorithm pseudocode

Begin
$t = 0$
Initialise the chromosome population $P(g)$;
Calculation of initial population fitness $P(g)$;
While not termination criteria do
$g := g + 1$;
Select $P(g+1)$ from $P(g)$;
Crossover $P(g + 1)$;
Mutate $P(g + 1)$;
Evaluate $P(g + 1)$;
End While
Result output to an external archive
End

2.5 *Computational experiments*

This part explains the original data utilised for the model, as well as a basic summary of the real-world cases and their relevance to this research. A few design and operation assumptions for railway networks are also mentioned.

We used data from Google Maps and Railway Pakistan for location, distances, links between cities, vehicle capacity, transfer time, fuel consumption, and the total number of nodes in this analysis. Existing rail movements are also taken into account in our research. We assumed that the rail speed is constant. CO2e emissions are calculated based on the same parameters and emission factors proposed by [28]. The railway emission factor is derived using the average rail fuel consumption (litres diesel/revenue ton-kilometre) from the Railway Association of Canada's locomotive emissions monitoring programme in 2015. The emission factor used to calculate CO2e emissions in our study's existing and planned shortest rail path is 15.2g CO2e emissions/ton-km. Figure 4 shows the existing railway path between Lahore, Punjab and Karachi, Sindh. Figure 5 shows the proposed path of railways.

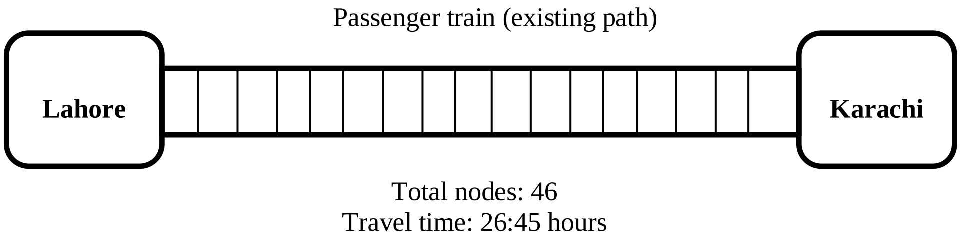

Figure 4 Existing railway path between Lahore, Punjab and Karachi, Sindh

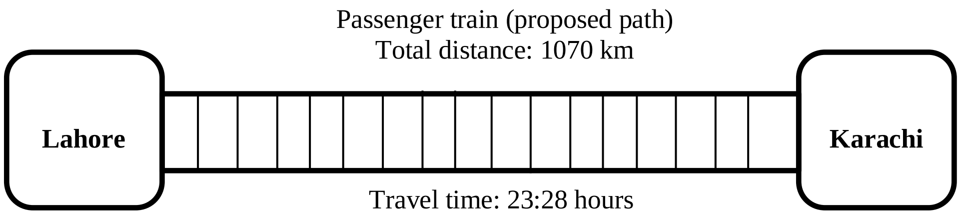

Figure 5 Proposed rail track for SP

3 Results and discussion

We examined our ILP model in different cases in this section. The focal differences between the cases are the cost of the path, travel time, and CO2e emissions in the railway network from Lahore to Karachi. We obtained the SP first by using Q-learning. Secondly, we applied a genetic algorithm and compared the results of our problem. The ILP model is performed on a system with Intel Core I5 2520 M CPU with a 2.50 GHz dual-core processor and 4.00 GB of RAM. Figure 6 shows the propsed shortest path generated by Q-learning algorithm.

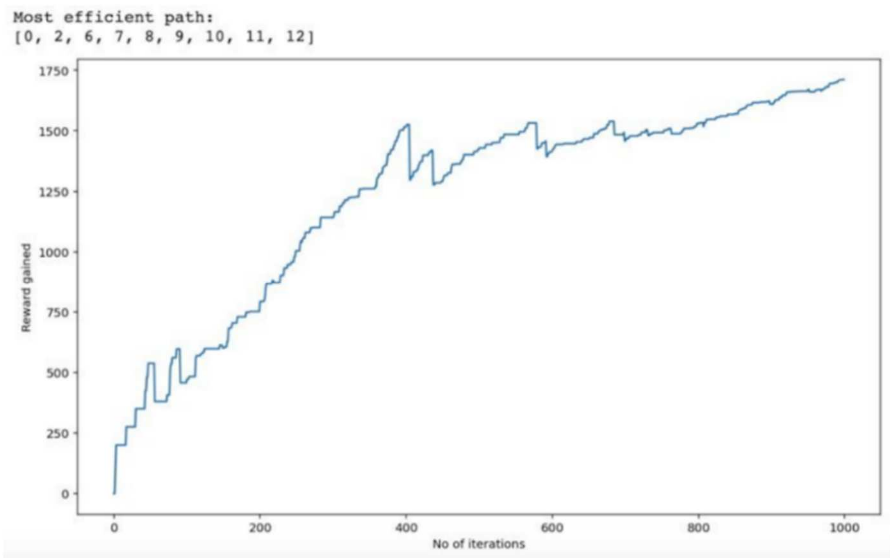

Figure 6 The proposed SP from Lahore to Karachi using RL

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3.1 Case 1 - existing rail track

In this case, the operation begins at 6:45 a.m. at the Lahore railway station (LRS) and ends at 5:00 a.m. at the Karachi railway station (KRS), traversing a total distance of 1214 kilometres and stopping at 46 nodes. The train has a daily capacity of 1000 passengers, with 12 AC and 14 economy class coaches. The passenger/freight train (Fareed express) travels from LRS to KRS in 26 hours and 45 minutes. For the calculation of CO2e emission, we used the railway emission factor proposed by [28]. Based on path length (existing track and proposed track developed by Q-learning) and constant weight carried by train, the CO2e calculations are done. The method covers the following aspects:

Cargo features: container count or goods weight.

Route features: CO2e emissions per tonne-kilometre.

According to this emission factor, the total CO2e emissions from this method are 18.45 kgs-CO2e emissions/ton-km, where one km-ton emission equals 15.2 g CO2e emissions. Table 3 also shows the overall length of the existing passenger rail route.

Table 3 Selected nodes and distances to find the shortest path

Shortest path train	Nodes	Distance
Lahore	0	0
Sharqpur	1	27
Raiwind	2	38
Haripur	3	119
Chunian	4	87
Kamalia	5	216
Hujra Shah	6	126
Jampur	7	481
Sahiwal	8	170
Ghotki	9	692
Rohri	10	749
Khanpur	11	380
Kot Samba	13	81
Tranda	14	483
Rahim Yar Khan	15	587
Goth Jooro	16	506
Sadikabad	17	606
Mirpur Mathelo	18	683
Ghotki	19	692
Rohri	20	749
Mahrabpur	21	833
Bhiria Road	22	867
Padidan	23	874
Nawabshah	24	933
Shahdadpur	25	980
Tando Adam	26	1022
Hyderabad	27	1044
Kotri	28	1066
Landhi	29	1201
Drigh Road	30	1199
Karachi Cantt	12	1208

3.2 Case 2 - proposed SP

Figure 5 shows the graphical illustration of the proposed shortest path. In this operation, we propose the shortest railway course from Lahore (Punjab) to Sindh to reduce travel costs, time, and CO2e emissions. Our activity begins at 6:45 a.m. at LRS and concludes at 3:28 a.m. at Karachi Railway Station. For existing and projected routes, we used the same criteria (capacity of train, speed, type of fuel, starting time, CO2e emission factor). The whole length of the passenger train's chosen route is shown in Table 3. The findings of the Q-learning algorithm suggest that the total distance of the railway track is 1070 km, as shown in Figure 6, which illustrates the proposed shortest path. Total time and CO2e emissions are 23 hours 28 minutes and 16.18 kgs CO2e/ton, respectively.

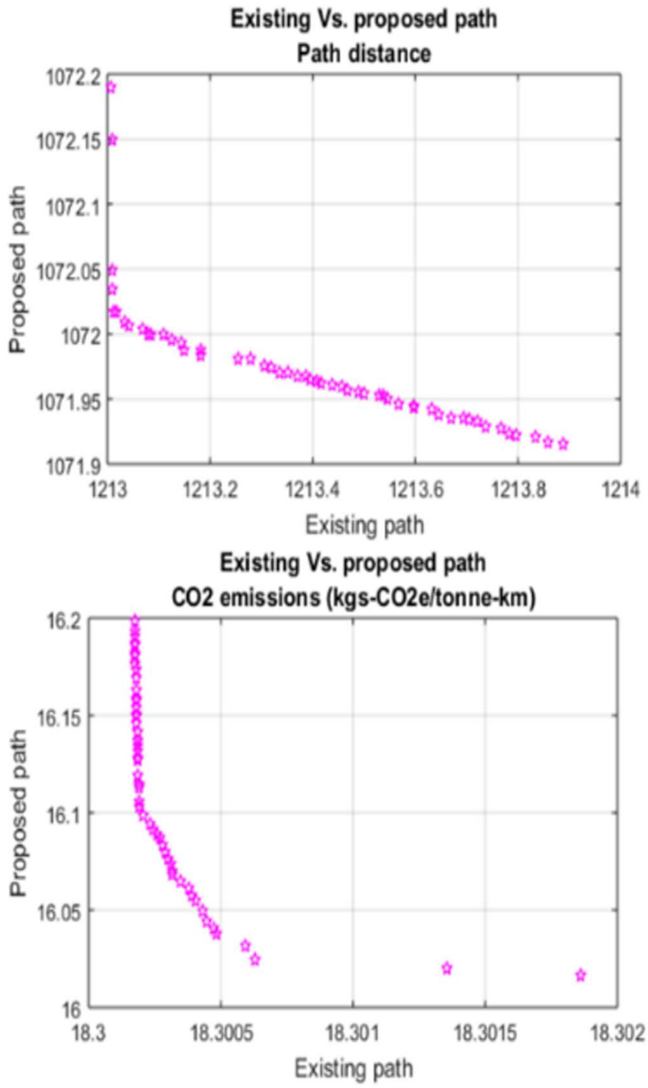

Figure 7 Existing and proposed path distance and CO2e emissions in rail network

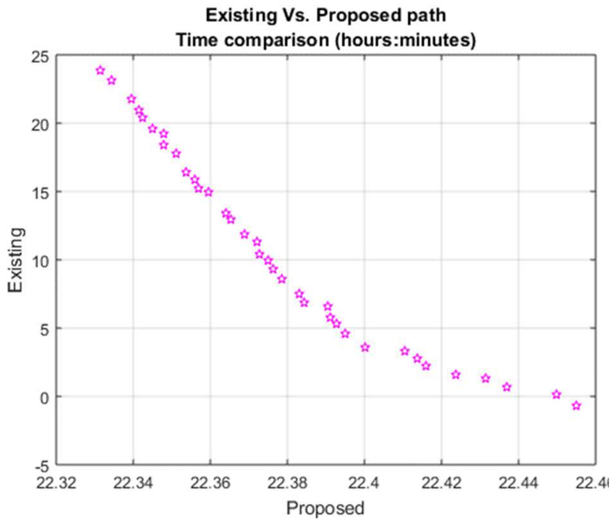

Figure 8 Existing and proposed total travel time in the rail network

The total path lengths and CO2e emissions in existing and prospective rail tracks between the Punjab and Sindh provinces are depicted in Figure 7. Figure 8 depicts the total travel time comparison between current and proposed rail routes, while Figure 9 depicts the savings in terms of travel time, path length, and CO2e emissions by comparing existing and proposed railway pathways. Our analysis shows that the proposed railway network is better than the existing railway network.

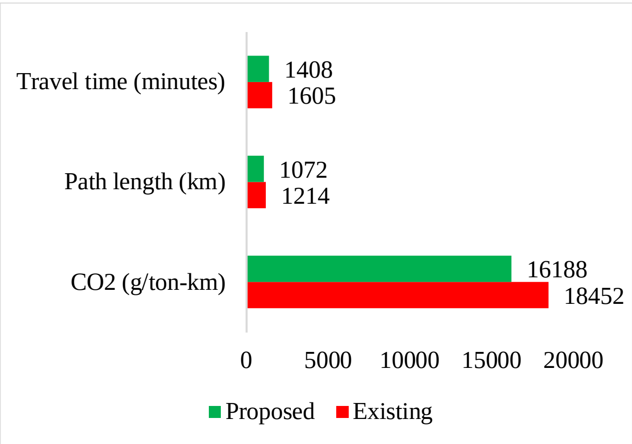

Figure 9 Savings in total time, path length, and CO2e emissions

4 Conclusion

To formulate the problem, we employed integer linear programming. In this study, we used two algorithms: Q-learning and genetic algorithms. We employed reinforcement learning, specifically a Q-learning method. We used Pakistan's railway network to find the quickest path to execute the Q-algorithm.

- First, we calculated the SP between Pakistan's Punjab and Sindh provinces and created Pareto front solutions by applying multi-objective optimisation to the SP and existing path data.
- The Pareto front solutions presented help decision-makers and practitioners arrange their transportation more strategically.
- The results of multi-objective optimisation indicate that adopting the proposed SP to Pakistan's railway network would result in savings of 13% in path length, total travel time, and CO2e emissions.
- Furthermore, the scope of this study could be broadened by investigating multi-modal shortest path for passenger and freight movements in Pakistani transportation and logistics operations.

Conflict of interest

The author of this paper declare that he has no financial or personal ties that could have influenced their work, and they have nothing to hide.

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