IMPROVING INTERCITY CONNECTIVITY FOR COMMERCIAL TRANSPORTATION USING MACHINE LEARNING OPTIMIZATION

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Abstract—

Improving connectivity between different cities requires design of highly efficient route planning models that can incorporate, analyze & optimize multiple routing parameters. These models analyze parameters that include city-to-city distance, road quality, toll booths, type of goods, capacity of vehicles, probability of accident on route, and intermediate hop quality. Combination of these parameters is given to an application-specific routing model that minimizes route delay, while maximizing driver comfort and reducing probability of route accidents. Existing planning models utilize linear techniques for intercity route planning; thus, they consider only a limited number of parameters due to their reduced computational capabilities. To improve this efficiency, a novel intercity connectivity optimization model for transportation of goods & heavy materials is proposed in this text. The proposed model is able to capture & analyze parameters including route quality, distance between hops, quality of hopping destination, accident probability on route, vehicle capacity, total toll cost, and vehicle density to estimate driving quality, approximate travel time, and risk of accidents. To perform this task, the proposed model utilizes a particle swarm optimization (PSO) model, that assists in performance-based route selection. The model initially generates a random set of solutions for given route, and then optimizes them via cognitive and social learning phases. These optimizations are tested on Intercity Bus Atlas dataset, Intercity Bus Working Group dataset, Intercity bus dataset, & Rio Vista Delta dataset, and parametric evaluation in terms of routing delay, accident probability, driver experience, and cost of routing was evaluated w.r.t. different routes. This performance was compared with various state-of-the-art approaches, and it was observed that the proposed model showcased 9.7% lower routing delay, 6.5% lower accident probability, 15.8% better driver experience, and 8.3% lower routing cost. This performance was observed to be consistent across different vehicle and route types with minimum reconfiguration & modifications, which makes the model highly scalable for a large number of scenarios. Due to these improvements, the proposed model was observed to be applicable for a wide variety of application deployments.

Keywords: Public, transportation, intercity, vehicle, planning, route, capacity, toll, driver, experience, density, accidents

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I. Introduction

Modeling intercity transit & logistics management systems is a multidomain task that involves application-specific data collection, preprocessing, feature extraction from this data, pattern analysis, and post-processing operations. These tasks are designed depending upon the application for this the model is being deployed. For instance, model design for heavy goods logistics will involve selection of routes with minimum level of congestion, and moderate road quality, while model design for food stuff logistics requires superior road quality, with moderate to low level of congestion. A typical intercity modeling method [1] that utilizes clustering, feature extraction & selection, cross validation with parameter tuning, comparison of data with temporal information for travel delay estimation is depicted in *Fig.1*, which can be used for multiple intercity route modeling applications.

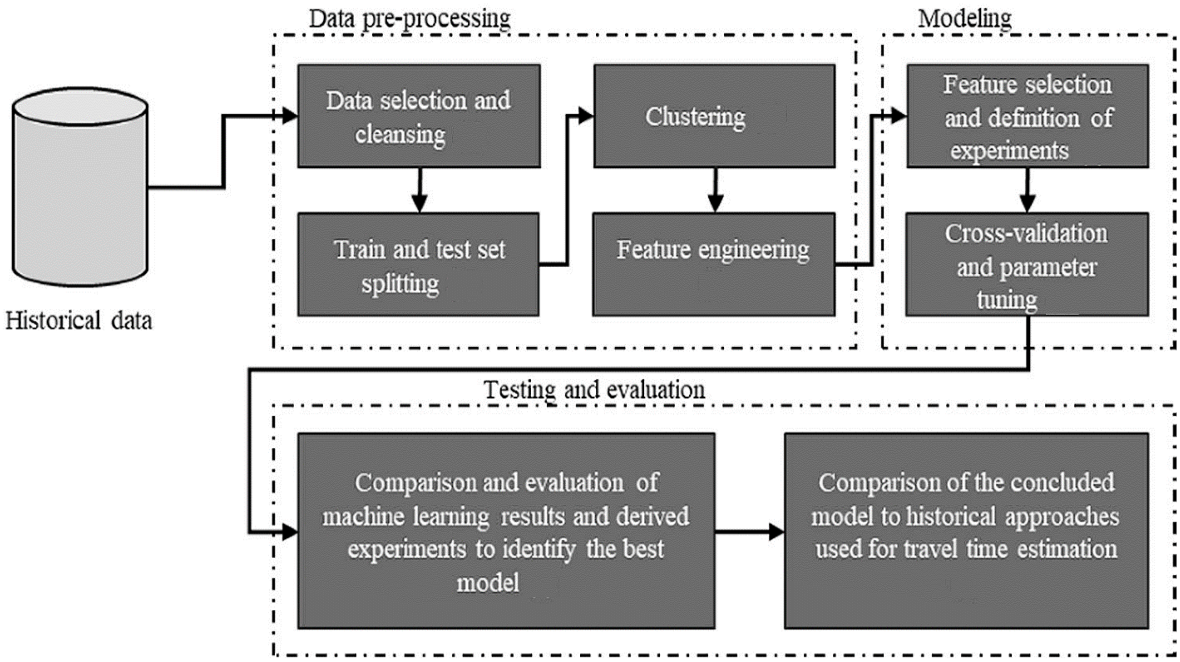

Fig. 1. Design of a typical intercity logistics modeling method

From this flow, it can be observed that feature extraction, selection, and comparison with temporal data blocks must be designed with higher efficiency than other blocks, because they control travel time estimation & drive quality improvement. Other blocks like clustering, feature selection, & cross validation are used for fine tuning the drive performance, and can be implemented if computational resources are available with the processing unit [2, 3, 4]. This observation is validated from the next section, wherein different intercity path modeling models are reviewed, and their characteristics are discussed in terms of nuances, advantages, limitations and future research scopes. Based on this review, it was observed that existing models use linear techniques for route planning; thus, they consider only a limited number of parameters due to their reduced computational capabilities. To overcome this limitation, section 3 discusses design of a PSO based intercity connectivity optimization model for transportation of goods & heavy materials. The proposed model formulates driver experience, as a fitness function, which includes city-to-city distance, cost of passing through toll booths, quality of road, type of goods, probability of accident on route, vehicle capacity, and intermediate hop quality. Performance of this model is evaluated in terms of routing delay, accident probability, driver experience, and routing cost in section 4, where these parameters are compared with various state-of-the-art approaches for performance validation. Finally, this text concludes with some interesting observations about the proposed model, and recommends methods to further improve its performance.

II. Literature Review

A wide variety of system models are available for low complexity, and high efficiency intercity routing. These models assist in reducing point-to-point routing distance, while improving driver experience by consider road quality, fuel consumption, etc. For instance, work in [5, 6] propose models for intercity bus routing for stochastic demands, and intercity bus terminal &inner-city toll road development for specific areas. These models have limited scalability, thus cannot be used for wider areas. To extend this model for railway networks, work in [7] proposes a novel low complexity multimodal alternative service management & infrastructure maintenance method to improve routing performance. This efficiency & scalability is further improved via the work in [8] that proposes an ant colony optimization (ACO) model for intercity travel optimizations.

Application of such models is depicted in [9], wherein intercity transportation for China is optimized via machine learning based models. A case study of such routing is depicted in [10], wherein innovative approaches for demand estimation in intercity bus services for rural environments is studied, and analyzed. Another ACO based model that uses bi-objective optimization (BO ACO) for emergency dispatching &routing is discussed in [11], wherein multiple mode networks. This model is capable of low delay, and high efficiency routing for vehicles between different cities. An optimum use case of this model is discussed in [12], wherein joint fleet sizing & planning charging systems for electric vehicles (EVs) using machine learning approaches is discussed. Similar approaches are discussed in [13, 14], wherein future thin-haul air mobility demand during routing, and eVTOL air shuttle design for rapid intercity transports is proposed. An application specific model for this approach is depicted in [15, 16], wherein intercity traffic flow pattern is evaluated using linear classification (LC) models via traffic patterns, and travel delay optimizations. Thus, it can be observed that very few models are capable of considering multiple intercity routing metrics, which limits their scalability when applied to real-time networks. To improve this performance, next section proposes design of PSO model for efficient intercity routing via driver experience improvement. Performance of this model is evaluated w.r.t. various state-of-the-art methods for validation & control under different scenarios.

Design of the proposed PSO model for efficient intercity routing via driver experience improvement

Based on the literature review, it can be observed that existing models utilize a limited number of parameters while path planning, which limits their scalability for large-scale intercity modeling application scenarios. To improve this efficiency, a novel PSO based model is discussed in this section, which assists in low-complexity, and high-performance driver experience-based path planning & control. Overall flow of the model is depicted in *Fig 2*, wherein city-to-city distance, cost of passing through toll booths, quality of road, type of goods, probability of accident on route, vehicle capacity, and intermediate hop quality are used for evaluation of final path.

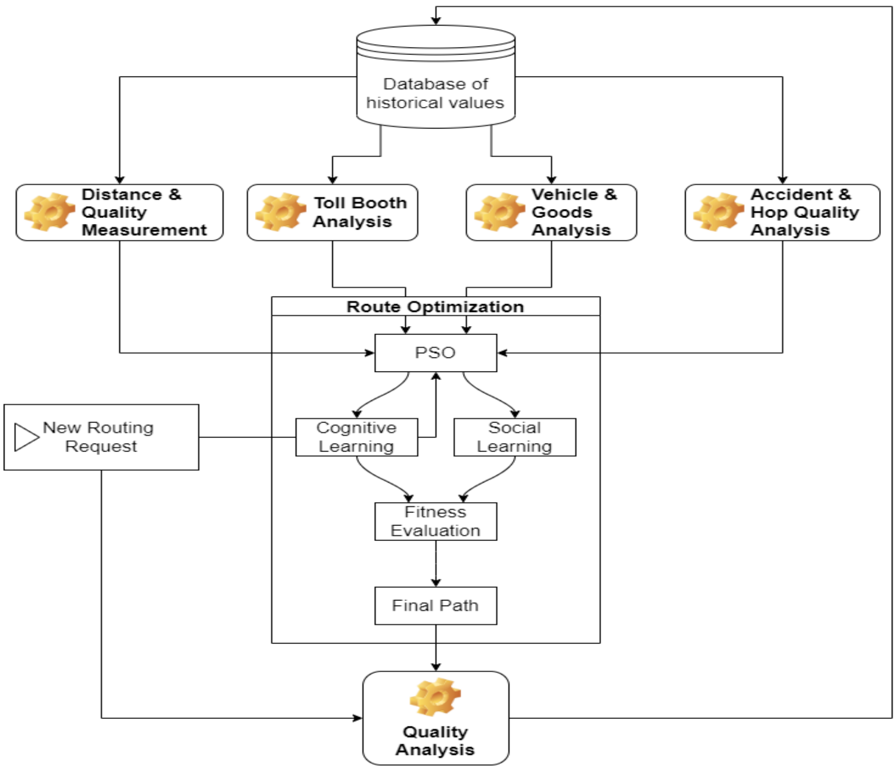

Fig. 2. Overall flow of the proposed model

From the flow, it can be observed that historical dataset of node location, node speed, toll booth locations, their fares, road quality, vehicle types, etc. are stored & updated regularly by central authorities.

Using this data, a PSO based model is trained to serve routing requests. This model requires source city & destination city as inputs, and based on these inputs it evaluated multiple on-road parameters. These parameters include, reference distance between source & destination, which is evaluated via equation 1,

$$d_{ref} = \sqrt{(x_s - x_d)^2 + (y_s - y_d)^2} \quad (1)$$

Where, x, y, s & d represents cartesian location of cities & ID of source & destination cities respectively, while d_{ref} represents reference distance between these cities. Based on this distance evaluation, distances between all cities from source & destination are evaluated. Let these distances be represented by $d_{s,i}$&$d_{i,d}$, where i indicates ID of the reference city. All cities which satisfy equation 2, are grouped as on-route cities ($List_{route}$).

$$d_{ref} > d_{s,i} \& d_{ref} > d_{i,d} \& d_{ref} < (d_{s,i} + d_{i,d}) \quad (2)$$

Based on this group of cities, road quality *(Q_r)*, number of toll boots (N_t), cost of each toll booth (C_t), accident probability for each route (A_p), and number of driver performance enhancement entities on the hop (N_{dp}) parameters are extracted from the database. These values combined with vehicle capacity (V_c), and Goods capacity (G_c) via the PSO model, which works using the following process,
Initialize PSO parameters,
Number of iterations (N_i)
Number of particles (N_p)
Error tolerance threshold (E_{th})
Maximum number of hops required by driver (Max_{hop})
Initialize each PSO particle via the following process, Select a random number of intermediate hopping cities via the following process,
Generate a random number of hops via equation 3,

$$P_h = random(1, Max_{hop}) \quad (3)$$

For each hop in 1 to P_h select a random city via equation 4,

$$City_{sel} = random(1, List_{route}) \quad (4)$$

This city is selected such that distance between source to the next hop reduces overall trip distance.
Based on these cities, evaluate particle velocity via equation 5, and mark these velocities as local best for each particle.
Find the minimum velocity via equation 6, and mark it as global best for the current set of particles.

$$\mathrm{P_v} = \sum_{i=1}^{P_h} \frac{\begin{pmatrix} \frac{d_{i,i+1}}{d_{ref}} + \frac{Max(RQ)}{RQ_{i,i+1}} + \\ \sum_{j=1}^{N_t} \frac{C_{t_j}}{N_t} * Max[\cup C_t]^{-1} + A_p + \\ N_{dp} * Max[\cup N_{dp}]^{-1} \end{pmatrix}}{P_h} * \frac{G_c}{V_c} \quad (5)$$

$$G_{best} = Min\left[\bigcup_{i=1}^{N_p} P_{v_i}\right] \quad (6)$$

This velocity is evaluated for each particle, and then the following process is evaluated for each iteration in 1 to N_i Evaluate new particle velocity via equation 7,

$$New(P_v) = r * P_v + c_{cog} * [P_v - P_{best}] + c_{socail} * [P_v - G_{best}] \quad (7)$$

Where, $r, c_{cog}, \& c_{social}$ represents a random velocity variable, cognitive learning factor, and social learning factor respectively.

Using this new value of P_v add or subtract city IDs from the current list of routes.
Evaluate error threshold for each particle via equation 8,

$$E_t = \frac{New(P_v) - P_v}{Max(New(P_v), P_v)} \quad (8)$$

Terminate the iteration if $E_t < E_{th}$, else go to next particle
Equate $P_v = New(P_v)$, and evaluate G_{best} via equation 6 for each iteration.
At the end of the final iteration, select particle with minimum value of velocity, and use the selected hops for intercity routing & logistics.

Based on these hops a final path is traced, and drivers are informed about it. While traversing the path, a feedback mechanism is activated, which assists drivers to update about their current trip status. Based on this feedback mechanism, following results are gathered from the driver,
Location of the driver ($L_{current}$)
Number of accidents spotted at the current location ($A_{current}$)

Accelerometer status for the current hop (Acc_{trip})

Based on these values, a feedback metric is evaluated, which assists in updating the current database. This feedback metric consists of updated accident probability on road ($A_{updated}$), and new road quality status (New_{road}), which are evaluated via equation 9 and 10 as follows,

$$A_{updated} = A_{previous} + \frac{A_{current}}{A_{total}} \quad (9)$$

Where, $A_{current} = -1$, if no accidents were recorded, while $A_{previous}$&A_{total} represents previously stored probability of accidents, and total number of accidents recorded for the current route & road. Similarly, new road quality is evaluated via equation 10, as follows,

$$New_{road} = Old_{road} + \sum_{i\in(X,Y,Z)}^{N} \frac{Acc_i - Prev(Acc_i)}{Max(Acc_i, Prev(Acc_i)) * N} \quad (10)$$

Where, $Old_{road}, Acc, \& Prev(Acc)$ represents previous road conditions, current accelerometer readings on the road, and previous accelerometer readings recorded for the road. These values are updated in the database for continuous road quality measurements improvement. Based on these updated values newer evaluations for road planning are done, which assists in improving quality of hop selection, and driver experience. This model was evaluated on various datasets, and their results were compared with various state-of-the-art methods. These results can be observed from the next section of this text.

III. Results & Performance Evaluation

The proposed intercity routing model is capable of improving route quality selection by integrating multiple road-level, infrastructure-level, vehicle-level, and goods-level parameters. To validate performance of the proposed model, the model routing delay (D), accident probability (AP), driver experience (E), & routing cost (C) were compared with ACO [8], BO ACO [11], and LC [15].

This performance was evaluated for Intercity Bus Atlas dataset, Intercity Bus Working Group dataset, Intercity bus dataset, & Rio Vista Delta dataset, which are available with Open Source Licensing. All these datasets were combined to form a total of 1000 city points, which were evaluated for 25 different drivers, with 400 different routing requests. A total of 100k requests were used from this set, and were divided in a ratio of 70:30, wherein 70% records were used for training the PSO model, while remaining 30% were used for evaluation & validation purposes. Based on this simulation setup, parametric evaluation of average routing delay (D) in minutes was tabulated in Table I as follows,

TABLE I. ROUTING DELAY COMPARISON FOR DIFFERENT MODELS

Requests	**D (mins.) ACO [8]**	**D (mins.) BO ACO [11]**	**D (mins.) LC [15]**	**D (mins.) PSO**
500	150.6	126.4	145.8	108.9
1000	160.9	132.9	154.6	115.5
2000	175.8	135.8	164.0	129.8
5000	192.3	176.4	194.1	145.6
7500	196.4	198.3	207.7	156.8
10k	200.8	226.5	224.9	175.0
15k	230.5	259.4	257.8	202.3
20k	265.8	304.8	300.3	218.4
25k	262.7	311.6	302.3	226.9
30k	277.4	337.5	323.6	242.4
35k	292.1	363.4	345.0	257.9
40k	306.8	389.3	366.3	273.3
45k	321.5	415.2	387.7	288.8
50k	336.1	441.1	409.1	304.3
55k	350.8	467.0	430.4	319.8
60k	365.5	492.9	451.8	335.3
65k	380.2	518.8	473.1	350.8
70k	394.9	544.7	494.5	366.3
75k	409.6	570.6	515.9	381.7
80k	424.2	596.5	537.2	397.2
85k	438.9	622.4	558.6	412.7
90k	453.6	648.3	579.9	428.2
100k	468.3	674.1	601.3	443.7

Based on this evaluation & *Fig.3*, it was observed that the proposed model had 8.5% lower delay than ACO [8], 19.2% lower delay than BO ACO [11], and 15.4% lower delay than LC [15], which makes it useful for high-speed intercity routing applications.

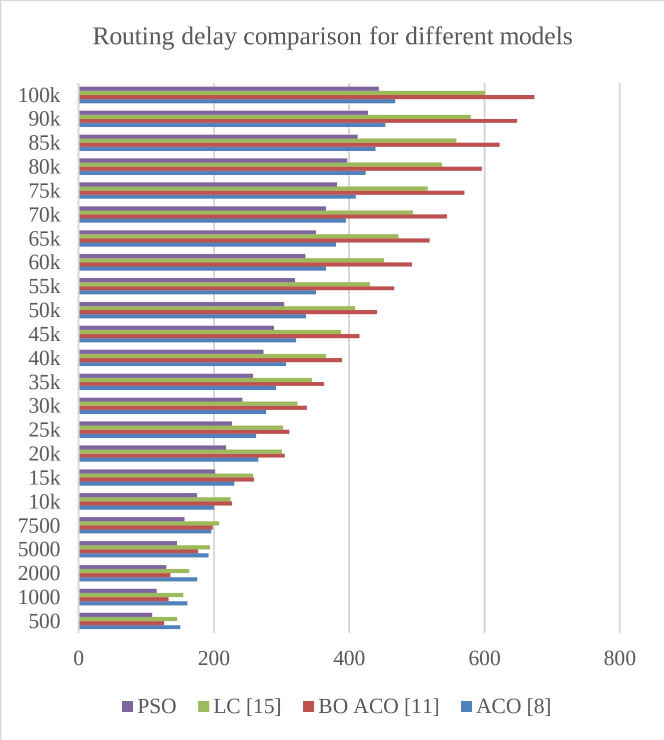

Fig. 3. Routing delay performance for different models

The main reason for reduction in delay, is the use of continuous update mechanism, which assists in finding shortest path with better driver experience, and minimum number of accidents. Similar evaluation was done for accident probability (AP), and tabulated in Table II as follows,

TABLE II. ACCIDENT PROBABILITY COMPARISON FOR DIFFERENT MODELS

Requests	AP ACO [8]	AP BO ACO [11]	AP LC [15]	AP PSO
500	3.01	2.53	2.92	2.18
1000	3.22	2.66	3.09	2.31
2000	3.52	2.72	3.28	2.60
5000	3.85	3.53	3.88	2.91
7500	3.93	3.97	4.15	3.14
10k	4.02	4.53	4.50	3.50
15k	4.61	5.19	5.16	4.05
20k	5.32	6.10	6.01	4.37
25k	5.25	6.23	6.05	4.54
30k	5.55	6.75	6.47	4.85
35k	5.84	7.27	6.90	5.16
40k	6.14	7.79	7.33	5.47
45k	6.43	8.30	7.75	5.78
50k	6.72	8.82	8.18	6.09
55k	7.02	9.34	8.61	6.40
60k	7.31	9.86	9.04	6.71
65k	7.60	10.38	9.46	7.02
70k	7.90	10.89	9.89	7.33
75k	8.19	11.41	10.32	7.63
80k	8.48	11.93	10.74	7.94
85k	8.78	12.45	11.17	8.25
90k	9.07	12.97	11.60	8.56
100k	9.37	13.48	12.03	8.87

Based on this evaluation & *Fig.4*, it was observed that the proposed model had 0.8% lower accident probability than ACO [8], 5.3% lower accident probability than BO ACO [11], and 4.6% lower accident probability than LC [15], which makes it useful for highly safe intercity routing applications.

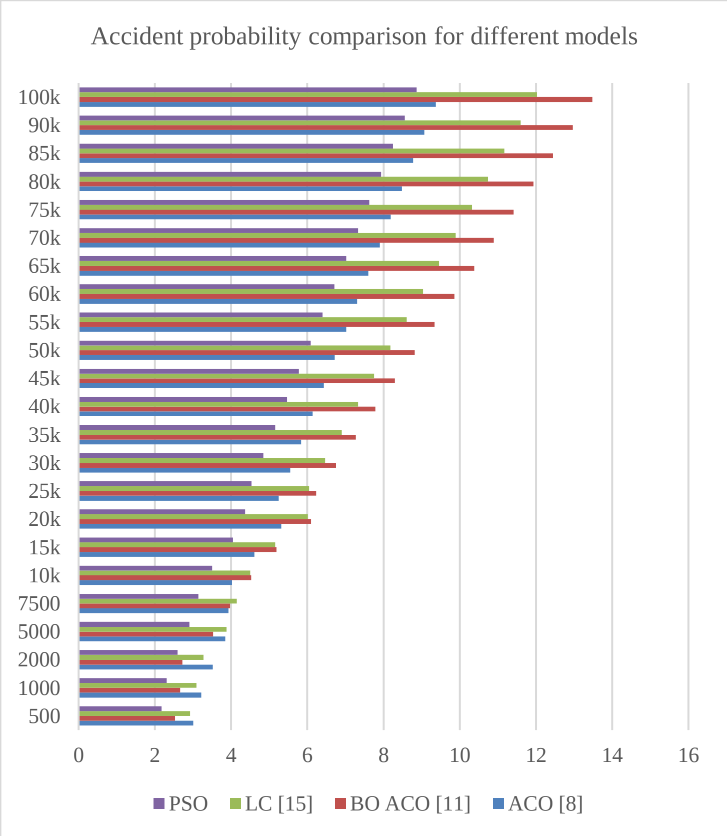

Fig. 4. Accident probability comparison for different models

The main reason for reduction in accident probability is the use of continuous update mechanism with accident inclusion in PSO model, which assists in finding shortest path with better driver experience, and minimum number of accidents. Similar evaluation was done for driver experience in terms of ratings collected during routing process and tabulated in Table III as follows,

TABLE III. DRIVING EXPERIENCE COMPARISON FOR DIFFERENT MODELS

Requests	E (%) ACO [8]	E (%) BO ACO [11]	E (%) LC [15]	E (%) PSO
500	80.08	76.27	79.42	90.82
1000	81.35	77.43	80.60	91.34
2000	82.94	77.91	81.71	92.30
5000	84.40	82.99	84.54	93.13
7500	84.73	84.87	85.56	93.62
10k	85.06	86.75	86.66	94.29
15k	86.98	88.43	88.36	95.06
20k	88.71	90.16	90.01	95.42
25k	88.58	90.37	90.08	95.59
30k	89.19	91.11	90.73	95.87
35k	89.73	91.74	91.30	96.12
40k	90.22	92.29	91.81	96.34
45k	90.67	92.77	92.26	96.54
50k	91.08	93.20	92.67	96.71
55k	91.45	93.58	93.03	96.87
60k	91.79	93.91	93.36	97.02
65k	92.11	94.22	93.66	97.15
70k	92.40	94.49	93.93	97.27
75k	92.68	94.74	94.18	97.38
80k	92.93	94.97	94.42	97.48
85k	93.17	95.18	94.63	97.58
90k	93.39	95.37	94.83	97.66
100k	93.59	95.55	95.01	97.75

Based on this evaluation & *Fig.5*, it was observed that the proposed model had 4.3% better driver experience than ACO [8], 2.2% better driver experience than BO ACO [11], and 2.5% better driver experience than LC [15], which makes it useful for high-speed & high efficiency intercity routing applications.

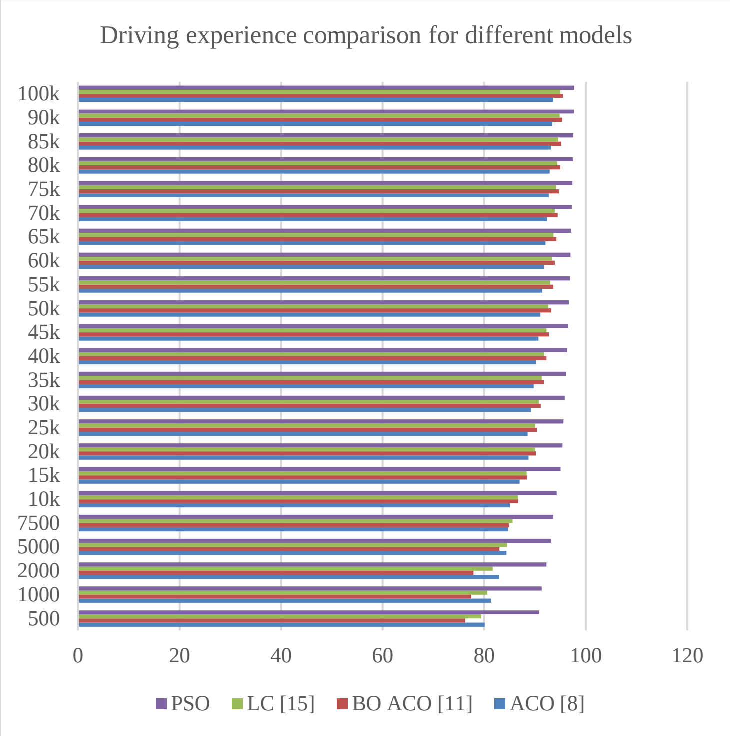

Fig. 5. Driving experience comparison for different models

The main reason for improvement in driver experience is the use of continuous update mechanism with accident reduction, toll charge reduction & distance minimization, which assists in finding shortest path with better driver experience, and minimum number of accidents. Similar evaluation was done for routing cost in terms of delay needed to find the routing path, and tabulated in Table IV as follows,

TABLE IV. ROUTING COST COMPARISON FOR DIFFERENT MODELS

Requests	**C (ms) ACO [8]**	**C (ms) BO ACO [11]**	**C (ms) LC [15]**	**C (ms) PSO**
500	86.77	76.33	84.64	60.13
1000	91.38	79.07	88.56	63.24
2000	98.19	80.30	92.79	70.05
5000	105.87	98.47	106.70	77.71
7500	107.80	108.70	113.17	83.17
10k	109.88	122.14	121.37	92.10
15k	124.06	138.08	137.32	105.66
20k	141.20	160.37	158.16	113.69
25k	139.70	163.73	159.12	117.92
30k	146.88	176.57	169.69	125.67
35k	154.10	189.46	180.29	133.45
40k	161.34	202.39	190.93	141.23
45k	168.61	215.36	201.60	149.03
50k	175.89	228.35	212.29	156.84
55k	183.20	241.37	223.00	164.66
60k	190.51	254.41	233.73	172.49
65k	197.84	267.46	244.47	180.32
70k	205.19	280.53	255.23	188.15
75k	212.54	293.61	265.99	196.00
80k	219.90	306.71	276.77	203.84
85k	227.27	319.81	287.56	211.69
90k	234.65	332.92	298.35	219.55
100k	242.04	346.04	309.15	227.40

Based on this evaluation & *Fig.6*, it was observed that the proposed model had 10.8% lower routing cost than ACO [8], 25.6% lower routing cost than BO ACO [11], and 20.6% lower routing cost than LC [15], which makes it useful for high-speed intercity routing applications. The main reason for reduction in cost, is the use of PSO, which assists in finding shortest path with better driver experience, and minimum number of accidents. Due to such a high performance, the proposed model is capable of being deployed for a wide variety of real-time intercity routing applications.

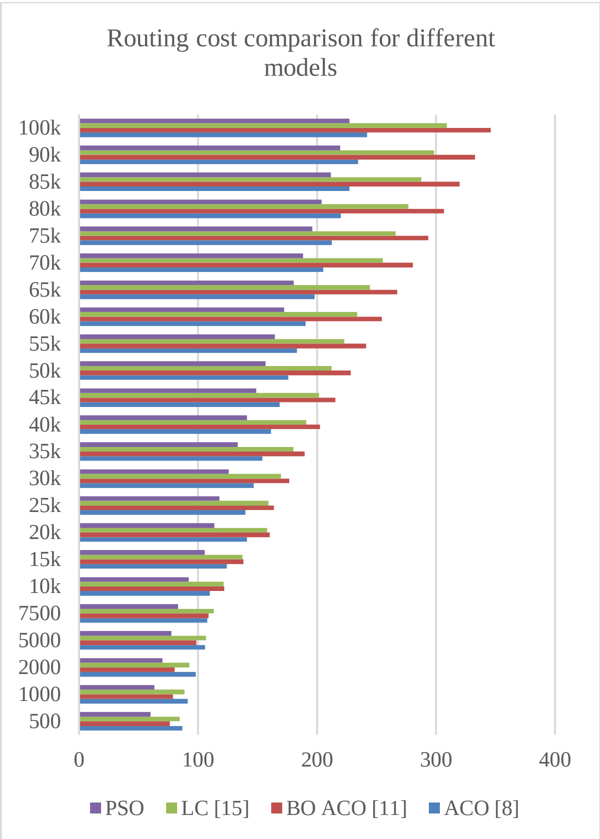

Fig. 6. Routing cost comparison for different models

IV. Conclusion and Future Work

The proposed intercity logistics model uses a combination of PSO with continuous database updates for improving quality of goods transfer between different geological points. Due to use of PSO, the model is capable of reducing the routing delay by had 8.5% when compared with ACO [8], 19.2% when compared with BO ACO [11], and 15.4% when compared with LC [15], thus making it highly useful for a wide variety of low-delay routing applications. Due to use of continuous update mechanism, the proposed model is able to reduce accident probability by 0.8% when compared with ACO [8], 5.3% when compared with BO ACO [11], and 4.6% when compared with LC [15], thus making it useful for safe-driving applications. Moreover, the model is also capable of improving driver performance by 4.3% when compared with ACO [8], 2.2% when compared with BO ACO [11], and 2.5% when compared with LC [15], thus making it useful for highly scalable deployments. Due to such a wide improvement in intercity routing performance, the proposed model is highly useful for a wide variety of routing applications. In future, researchers can integrate deep learning models in place of PSO, for further enhancing its real-time performance. Moreover, researchers can validate the model on larger datasets, for further estimating its long-term performance capabilities.

V. Acknowledgment

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VI. References

1. Li, S.; Liang, Y.; Wang, Z.; Zhang, D. “An Optimization Model of a Sustainable City Logistics Network Design Based on Goal Programming” *Sustainability* 2021, *13*, 7418.
2. Runze Qi, Jinghu Pan, Rong Zhang, "Comparison of Intercity Travel Network Structure during Daily Time and Holiday in China", *Complexity*, vol. 2021, Article ID 2193782, 15 pages, 2021.
3. Zhang, Rong & Pan, Jinghu & Lai, Jianbo. (2021). Network Structure of Intercity Trips by Chinese Residents under Different Travel Modes: A Case Study of the Spring Festival Travel Rush. Complexity. 2021. 1-19. 10.1155/2021/1283012.
4. Andisheh Ranjbari, Mark Hickman & Yi-Chang Chiu (2020) A network design problem formulation and solution procedure for intercity transit services, Transportmetrica A: Transport Science, 16:3, 1156-1175,
5. Yan, Shangyao & Chi, Chin-Jen & Tang, Chinghui. (2006). Intercity bus routing and timetable setting under stochastic demands. Transportation Research Part A: Policy and Practice. 40. 572-586. 10.1016/j.tra.2005.11.006.
6. Ayuningtyas, Kardina & Frazila, Russ & Wibowo, Sony & Farda, Muhammad. (2019). Network Analysis of Intercity Bus Terminal and Inner-City Toll Road Development – The Case of Bandung City. International Journal of Sustainable Transportation Technology. 2. 8-18. 10.31427/IJSTT.2019.2.1.2.
7. Scheduling multimodal alternative services for managing infrastructure maintenance possessions in railway networks,

8. Beed, R, Roy, A, Sarkar, S, Bhattacharya, D. A hybrid multi-objective tour route optimization algorithm based on particle swarm optimization and artificial bee colony optimization . *Computational Intelligence*. 2020; 36: 884– 90 9.
9. Zhu, Zhenran & Zhang, Anming & Zhang, Yahua, 2018. "Connectivity of intercity passenger transportation in China: A multi-modal and network approach," Journal of Transport Geography, Elsevier, vol. 71(C), pages 263-276
10. Mattson, Jeremy. "Innovative Approach to Estimating Demand for Intercity Bus Services in a Rural Environment." (2016).
11. E. Liu and J. Wang, "Bi-objective Optimization of Emergency Dispatching and Routing for Multi-mode Network Using Ant Colony Algorithm," 2020 IEEE 5th International Conference on Intelligent Transportation Engineering (ICITE), 2020, pp. 513-517, doi: 10.1109/ICITE50838.2020.9231463.
12. H. Zhang, C. J. R. Sheppard, T. E. Lipman and S. J. Moura, "Joint Fleet Sizing and Charging System Planning for Autonomous Electric Vehicles," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 11, pp. 4725-4738, Nov. 2020, doi: 10.1109/TITS.2019.2946152.
13. Y. Paproth, F. Adam, V. Stich and A. Kampker, "Model for future thin-haul air mobility demand in Germany," 2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), 2020, pp. 1-8, doi: 10.1109/ICE/ITMC49519.2020.9198496.
14. J. Xiao, N. Salk and K. Haran, "Conceptual Design of an eVTOL Air Shuttle for Rapid Intercity Transport," 2020 IEEE Power and Energy Conference at Illinois (PECI), 2020, pp. 1-8, doi: 10.1109/PECI48348.2020.9064631.
15. Zhuo, L., Chen, Z., Wu, C. *et al.* Deriving intercity human flow pattern and mechanism based on cell phone location data: case study of Guangdong Province, China. *Comput.Urban Sci.* 2, 4 (2022).
16. Ghamami, Mehrnaz & Kavianipour, Mohammadreza & Zockaie, Ali & Hohnstadt, Laura & Ouyang, Yanfeng. (2020). Refueling infrastructure planning in intercity networks considering route choice and travel time delay for mixed fleet of electric and conventional vehicles. Transportation Research Part C: Emerging Technologies. 120. 102802. 10.1016 /j.trc.2020.102802.
17. "Mitigation of Blackspots on Highways by the Application of Safe System Approach", Dinesh K.Yadava,Sujesh D.Ghodmare, Naveen Kumar, Materials Today: Proceedings, Elsevier, https://doi.org/10.1016/j.matpr.2021.11.042, online 19 November 2021
18. Sujesh D. Ghodmare, Akshay Gulghane,An attempt for sustainability evaluation considering implementation of rapid transit system,Materials Today: Proceedings, 2022,ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2022.01.262.(https://www.sciencedirect.com/science/article/pii/S2214785322002942)
19. "Transportation Planning Using Conventional Four Stage Modeling", Sujesh D. Ghodmare, Geetanjali Yadav (2021), Turkish Journal of Computer and Mathematics EducationVol.12 No.12 (2021), 2891-2897, Published online: 23 May 2021
20. "Application of the multi attribute utility technique with its for sustainability evaluation of emerging metropolitan city of Nagpur", International Journal of Civil Engineering and Technology(2019), EID: 2-s2.0-85060924119, Sujesh D. Ghodmare, Preeti Bajaj, B. V. Khode
21. "Feasibility Study on Widening of Roads as Per Traffic Survey", Manisha P. Gupta, S. D. Ghodmare, Dr. B. V. Khode. (2021). Design Engineering, 2021(04), 210 - 217. Vol 2021: Issue 04