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# AN INTELLIGENT TRANSPORTATION SYSTEM FOR SMART CITIES UTILIZING MACHINE LEARNING TECHNIQUES BASED ON VEHICLE NETWORKS

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**Abstract**
Vehicle navigation must undergo a paradigm change in light of the dynamic and linked character of smart cities. Conventional static path design causes congestion, inefficiency, and environmental harm since it cannot change with the ever-evolving urban terrain. In this new paradigm, real-time vehicular path planning—powered by ubiquitous data and intelligent systems—emerges as a crucial tool for optimizing traffic flow. The core of real-time path planning in smart cities is explored in this abstract. We examine how integrating cutting-edge technologies such as artificial intelligence (AI), sensor networks, and vehicle-to-everything (V2X) communication enables cars to modify their routes in response to traffic conditions dynamically, changes in the dynamic infrastructure, and even outside influences. The overwhelming amount of data, the requirement for quick decision-making, and the intricate relationships in the urban environment. The abstract will discuss several planning methods and point out their advantages and disadvantages in navigating this dynamic environment, ranging from graph-based optimization to reinforcement learning.
**Keywords:** Machine Learning, Intelligent Systems, Environmental

## I. Introduction

By 2050, 66-70% of people on Earth are predicted to live in cities, posing hitherto unheard-of difficulties in terms of resource management, environment management, and security. Numerous nations are creating smart city [6] programs to address these issues by maximizing resource utilization and minimizing environmental impact through technology. Artificial intelligence (AI) [5], machine learning (ML) [1], and deep reinforcement learning (DRL) are becoming more and more significant in intelligent transportation, and these technologies are being applied to create new approaches to smart cities. Smart cities also require the generation, administration, and use of energy. Our cities' electrical grids, or "smart grids," can run more reliably and efficiently with the application of big data analytics. A major obstacle to vehicle routing and the larger transportation, distribution, and logistics sector in smart cities is figuring out the shortest path [13] between two places within road networks. In a variety of transportation applications using actual road networks, choosing the right route planning algorithm from the plethora suggested in the literature is crucial [14]. This complexity results from the fact that dynamic factors, such as traffic jams, sporadic events, and meteorological conditions, can significantly affect how well an applied machine learning (ML) model performs in these networks. As such, machine learning (ML) must be automatically expanded to take into account these dynamic elements, ensuring that the shortest path is adapted. Road network locations present a major obstacle to vehicle routing and the larger transportation, distribution, and in logistics sector. In a variety of transportation applications using actual road networks, choosing the right route planning algorithm from the plethora suggested in the literature is crucial [14]. This complexity results from the fact that dynamic factors, such as traffic jams, sporadic events, and meteorological conditions, can significantly affect how well an applied machine learning (ML) model performs in these networks. As such, machine learning (ML) must be automatically expanded to take into account these dynamic elements, ensuring that the shortest path is adapted.

Car navigation systems are one of the main uses of Intelligent Transportation Systems (ITS) [4]. These systems use computerized road map databases and data from the Global Positioning System (GPS) to provide information about traffic conditions in tourist areas and suggest the best routes to destinations. The software components of automobile navigation systems must function in real-time

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or dynamic network contexts, where road conditions fluctuate over time, to fully realize their benefits. Dynamic road network algorithms have to adjust to these modifications by revising the chosen path to preserve its best qualities in the altered circumstances.
Because carbon emissions are closely related to resource efficiency, public health, environmental health, and the general sustainability of metropolitan regions, they are significant in smart cities. Reducing carbon emissions is in line with the larger objectives of building habitable, resilient, and ecologically friendly communities.
The interrelated parts of the machine learning-based Optimizing Green Routing system in Smart Cities are shown in Figure. 1. By integrating smart city infrastructure and using machine learning to make adaptable and environmentally friendly routing decisions, connected vehicles
add data to the system.

### 1.1. Motivation and Contribution

To combat climate change, safeguard the environment, maintain air quality and human health, and advance a sustainable and resilient future, carbon emissions must be managed and reduced. Our effort is motivated by the need to address the pressing environmental and sustainability issues posed by modern urbanization. As cities grow, so do issues like air pollution, traffic congestion, carbon emissions, and energy consumption, all of which hurt the quality of life for residents. The advent of Smart Cities offers an opportunity to reconsider and enhance transportation infrastructure, particularly through the application of cutting-edge technologies such as the Internet of Vehicles (IoVT).
The primary contribution of this work lies in developing and applying a sophisticated ML-based green routing system within the IoVT framework. Integrating predictive analytics used in multiple linear regression this machine learning model allows the system to continually learn and adapt, making informed routing decisions prioritizing minimizing carbon emissions and energy consumption. This adaptability distinguishes the proposed system from conventional multipath routing methods, offering a more responsive and sustainable solution for urban transportation.

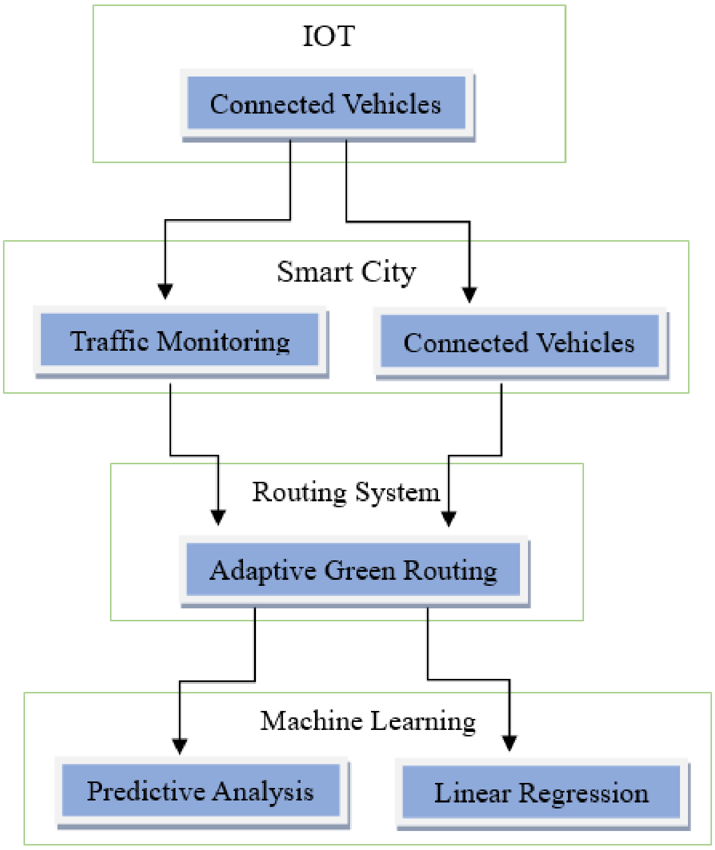


Figure. 1: Work Flow of Green Path Planning for IoVT.

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## II. Literature Survey

Cities are currently grappling with intricate challenges associated with socio-economic development and improving quality of life. The term" smart city" has emerged as a strategic response to address these multifaceted challenges. The foundational elements of urban development in smart cities are rooted in Internet and broadband network technologies [10], which serve as the backbone for providing various e-services. Smart cities fundamentally rely on Internet technology, facilitating seamless access and interaction with diverse devices. Examples include cameras for video surveillance, sensors monitoring air pollution, actuators, and devices for traffic monitoring.

The accessibility to the Internet not only enables real-time connectivity [3] but also fosters the development of a myriad of applications capable of harnessing the vast volume of data generated by these devices. This proliferation of data gives rise to the creation of innovative services for the benefit of citizens, businesses, and public administration alike. Therefore, the integration of Internet technology [2] plays a pivotal role in the evolution of smart cities, ushering in a new era of interconnectedness and service delivery. Numerous algorithms addressing travel route selection have been published, each with its distinct characteristics. The Dijkstra algorithm, while straightforward, operates by identifying the shortest path on a road map. Although simple to implement, its drawback lies in its computational intensity, resulting in slow performance due to an extensive number of numerical operations. Recognized as an optimal algorithm within the labeling method category, Dijkstra offers accuracy but at the expense of efficiency [8]. The derivation of Dijkstra's approach introduces a heuristic function to optimize route exploration. This algorithm substantially reduces computational operations by leveraging heuristic insights, enhancing operational speed [12].

The author employing a multipath [9] approach in a routing model aligns more closely with the global trend of infrastructural development. In light of the various connecting pathways accessible between each node, empirical studies indicate that this strategy yields superior outcomes compared to a singular path between nodes in a two-dimensional (2D) framework. In this paper [11], the author tackles the issue of eco-friendly communication in 6G-enabled extensive Internet of Things (IoT) devices by adopting a cluster-based data dissemination approach in the network. The author introduces an innovative Hybrid Whale-Spotted Hyena Optimization (HWSHO) algorithm, synthesizing the Whale Optimizer Algorithm (WOA) with the exploitation capabilities of the Spotted Hyena Optimizer (SHO).

**Algorithm 1** Optimal Path Selection based on Carbon Emissions

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**Input:** Graph $G$ representing the road network, Start node $s$, End node $t$
**Output:** Optimal path from $s$ to $t$ based on carbon emissions
Initialize empty priority queue $PQ$
Initialize distance array $dist[]$ with $\infty$ for all nodes
Initialize carbon emission array $emission[]$ with 0 for all nodes Set $dist[s] \leftarrow 0$ and $emission[s] \leftarrow 0$
Insert $(s,0)$ into $PQ$
**while** *PQ is not empty* **do**
    $(u,d) \leftarrow$ extract minimum element from $PQ$
    **foreach** *neighbor v of u* **do**
        $w \leftarrow$ weight of edge $(u,v)$ $e \leftarrow$ carbon emission of edge $(u,v)$
        **if** $dist[u]+w < dist[v]$ **then**
            $dist[v] \leftarrow dist[u]+w$ $emission[v] \leftarrow emission[u]+e$ Insert $(v,dist[v])$ into $PQ$
        **end**
    **end**
**end**
Reconstruct the optimal path from $s$ to $t$ using $dist[]$ and $emission[]$

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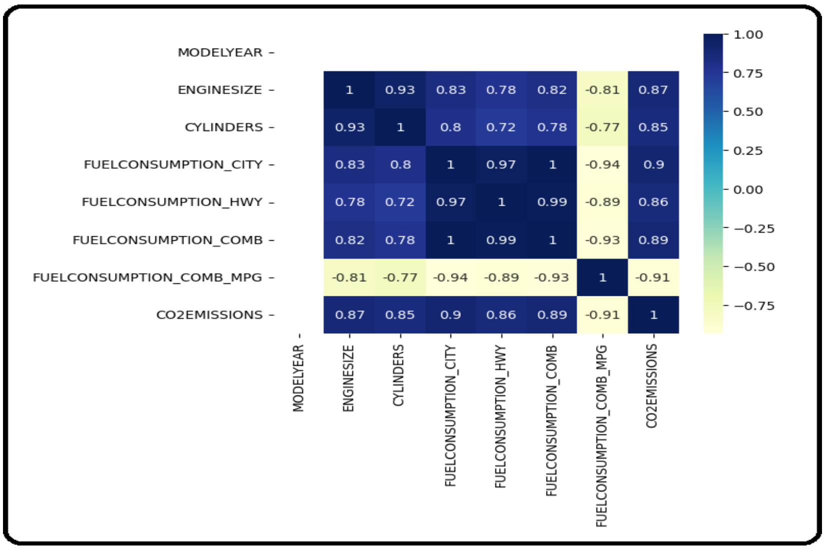
This article [7] critically examines established annual-based carbon accounting methodologies, emphasizing emerging real-time carbon emission technologies and their pre-vailing application trends. Additionally, a framework for the latest near-real-time carbon emission accounting technology, poised for widespread adoption, is introduced.

This Algorithm 1 is used for finding the shortest path in a graph with weighted edges. The weight of each edge represents the travel time or distance, and the carbon emission of each edge is taken into account during the path selection process based on machine learning. The priority queue efficiently selects the node with the minimum distance at each step that contains the minimum carbon emission-enabled route. The algorithm outputs the optimal path from the start node *s* to the end node *t* based on both travel distance and carbon emissions.

## III. Result and Discussion

Figure. 2 shows the heatmap of the particular dataset. The dataset contains the attribute model make, model, vehicle class, engine size, cylinders, transmission, fuel type,

Figure. 2: Hitmap of the dataset




| Model Objective | multipath | single path (1$^{st}$ path) |
|---|---|---|
| path | 0(2) -6(0)- 8(1)-7(1)- 5(0)- 2(1)-9(0)- 1(0)- 3(1)- 4(2)-0 | 0(0)-6(0)-7(0)-9(0) -8(0)-4(0)-5(0) -3(0)-1(0)-2(0)-0 |
| travel distance (km) | 191 | 203 |
| travel cost (INR) | 1791 | 1815 |
| travel time (minute) | 1095 | 1146 |
| additional time (minute) | 301 | 311 |
| total time (minute) | 1576 | 1637 |
| Total Carbon Emission | 2974 | 3019 |

In Table 1, the optimal results are given below multipath and single path. Here, we are taking ten nodes, including the depot. Every path starts with the depot in the model objective path 0(2) represents the Node, and which route will take means 0$^{th}$ node via 2$^{th}$ route in multipath. In a single path, every route is the 0$^{th}$ route. Here, we consider total travel distance, travel cost, travel time, additional time of every node, and carbon emissions. This is the optimal path result. Figure. 3 shows the result comparison amongmultipath and single paths.

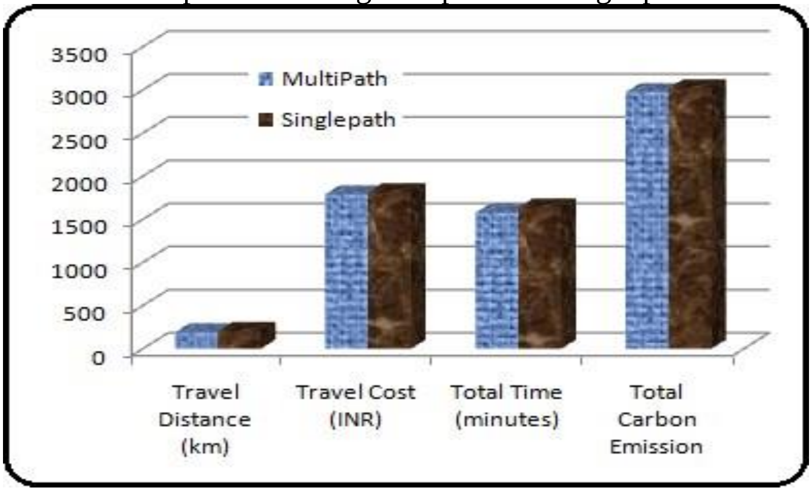


Figure. 3: Result comparing multipath and single path

## IV. Conclusion

There is great potential for the Internet of Vehicular Things (IoVT) in Smart Cities when a machine learning-based multipath green routing system is implemented. The study concentrated on using machine learning algorithms to optimize vehicle routes to reduce carbon emissions while considering the dynamic nature of traffic and environmental factors. According to the findings, the suggested approach successfully reduced carbon emissions and trip times while increasing traffic routes' general effectiveness. The system's adaptability to shifting traffic patterns and environmental conditions was proved by integrating machine learning models with real-time data from the Internet of Things (IoT). The multipath strategy makes smart cities' transportation networks more resilient to unforeseen circumstances and traffic jams.

This paper's future lies in the development of more advanced machine learning algorithms that can adjust carbon emissions to shifting traffic patterns and more accurately represent the intricate dynamics of IoV networks. Reinforcement learning is included to proactively learn from its interactions with the environment and provide real-time, optimal routing options. Think about aspects like security and privacy, in addition to energy efficiency, while choosing routing paths. For this study, standardized protocols are being developed to help vehicle makers and other network providers achieve interoperability.

## References

1. Limon Barua, Bo Zou, and Yan Zhou. Machine learning for international freight transportation management: a comprehensive review. *Research in Transportation Business & Management*, 34:100453, 2020.
2. Leo-Paul Dana, Aidin Salamzadeh, Morteza Hadizadeh, Ghazaleh Heydari, and Soroush Shamsoddin. Urban entrepreneurship and sustainable businesses in smart cities: Exploring the role of digital technologies. *Sustainable Technology and Entrepreneurship*, 1(2):100016,2022.
3. Alexandre Dolgui and Dmitry Ivanov. 5g in digital supply chain and operations management: fostering flexibility, end-to-end connectivity, and real-time visibility through the internet- of everything. *International Journal of Production Research*, 60(2):442–451, 2022.
4. Ali Gohar and Gianfranco Nencioni. The role of 5g technologies in a smart city: The case for the intelligent transportation system. *Sustainability*, 13(9):5188, 2021.
5. Lakshmi Shankar Iyer. Ai-enabled applications towards intelligent transportation. *Transportation Engineering*, 5:100083, 2021.
6. Ayca Kirimtat, Ondrej Krejcar, Attila Kertesz, and M Fatih Tasgetiren. Future trends and current

state of smart city concepts: A survey. *IEEE Access*, 8:86448–86467, 2020.
7. Zhu Liu, Taochun Sun, Ying Yu, Piyu Ke, Zhu Deng, Chenxi Lu, Da Huo, and Xiang Ding. Near-real-time carbon emission accounting technology toward carbon neutrality. *Engineering*, 14:44–51, 2022.
8. Min Luo, Xiaorong Hou, and Jing Yang. Surface optimal path planning using an extended dijkstra algorithm. *Ieee Access*, 8:147827–147838, 2020.
9. Somnath Maji, Samir Maity, Debasis Giri, Oscar Castillo, and Manoranjan Maiti. A multi-path delivery system with random refusal against online booking using type-2 fuzzy logic-based fireworks algorithm. *Decision Analytics Journal*, 6:100151, 2023.
10. Diego F Paredes-Páliz, Guillermo Royo, Francisco Aznar, Concepción Aldea, and Santiago Celma. Radio over fiber: An alternative broadband network technology for IoT. *Electronics*, 9(11):1785, 2020.
11. Sandeep Verma, Satnam Kaur, Mohammad Ayoub Khan, and Paramjit S Sehdev. Toward green communication in 6g-enabled massive internet of things. *IEEE Internet of Things Journal*, 8(7):5408–5415, 2020.
12. Ningkang Yang, Lijin Han, Changle Xiang, Hui Liu, Tian Ma, and Shumin Ruan. Real-time energy management for a hybrid electric vehicle based on heuristic search. *IEEE Transactions on Vehicular Technology*, 71(12):12635–12647, 2022.
13. Zhihui Yang, Huiwen Xia, Fuwen Su, Jiayu Zhao, and Fan Feng. Application of genetic al-algorithm in modeling of shortest path problem. In *2020 Chinese Automation Congress (CAC)*, pages 3447–3450. IEEE, 2020.
14. Dongqing Zhang, Stein W Wallace, Zhaoxia Guo, Yucheng Dong, and Michal Kaut. On scenario construction for stochastic shortest path problems in real road networks. *Transportation Research Part E: Logistics and Transportation Review*, 152:102410, 2021.