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Original Paper

Use of Energy-Efficient Routing Algorithms for Green Transportation

Arun Kumar Singh

School of MCS, PNG University of Technology, Lae, Papua New Guinea.

arun.singh@pnguot.ac.pg

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Abstract - The faster development of urban structures accompanied by the growth of transportation infrastructure has given rise to important questions concerning energy use and ecology. Sustainable transportation, which, at its core, suggests a lack of harm to the environment, is now a hot topic of discussion. This paper focuses on the optimization of energy use in the transportation system using energy-efficient routing algorithms. Intending to address factors including traffic information, vehicle power consumption, and influence on the environment, these algorithms and models are expected to help achieve low carbon society, high fuel economy, and environmentally conscious transportation systems. The evaluation of several routing options is presented to determine the effect of these routing approaches on energy-efficient and eco-friendly objectives. Due to the emerging awareness of environmental consciousness, green transportation solutions are receiving increased attention; routing algorithms should also address energy efficiency. They are used to improve the routing of these vehicles and minimize the consumption of fuel, carbon emissions, and expenses incurred. This paper mainly analyses several energy-efficient routing algorithms for green transportation, such as Dijkstra, A star search Algorithm and Ant Colony Optimization Algorithm. Its effectiveness is based on real-world considerations of the specifications of these algorithms and how they can accommodate the traffic conditions, the kind of vehicles involved, and how energy is consumed are also discussed. Moreover, we assess the strategic usage of GPS and IoT to improve the effectiveness of these algorithms by supplying real-time data to support the adaptation of good routing methods. The experience of reporting on urban environments has also shown effectiveness in reaching goals of energy efficiency and decreasing travel time and emission rates. The results of this study support the need for multi-attribute design optimization strategies that consider energy consumption, cost, and building service quality. Finally, the study calls for increased use of energy-efficient routing algorithms as a plausible strategy in focalizing sustainable transportation systems. Through these algorithms, municipalities and logistic companies can support green conservation as the efficiency of operations is improved. This paper can be used as a starting point for researchers and students who focus on the issue in question.

Keywords - Energy efficiency, Routing algorithms, Green transportation, Sustainable mobility, Eco-routing.

1. Introduction

1.1. Background

Transportation is among the major causes of global emissions of greenhouse gases or compound gases. With the expansion of cities, mobility needs also rise consequently, which will require more energy. The old style of routing is most likely to choose the path that takes the least amount of time and space and does not consider the environmental cost that comes with fuel consumption. In response, there is the development of green transportation systems, which involves optimizing routes used by the vehicle, the time spent by the vehicle in the transport system, fuel rates, and environmental impacts. Transportation is a major world energy consumer and an important source of GHG emissions, responsible for approximately one-quarter of the total energy consumption and over oneseventh of carbon dioxide emissions. With the enhancement of the Living Charter and the increase in the urbanization rate and population growth, the need to transport goods and persons increases and presses on the environment and the economy. These issues have necessitated the search for sustainable solutions, of which green transportation is a thrust area. Green transportation refers to the amelioration of the effects of transport systems on the environment through improvement of efficiency, use of non-conventional energy and decreased emission [1, 2]. The authors further suggest that one approach toward attaining sustainable transport is through efficient energy routing algorithms. Conventional ESP routing metrics involve some basic parameters such as delay and hop count, and energy consumption and emissions are neglected. However, energy-efficient routing algorithms are designed to consider the energy consumption of the vehicles, the fuel cost and carbon emission level. These algorithms use data on current traffic situations, road networks, power 'templates' for vehicles in use, and environmental parameters to discover the paths that require minimum energy.

This change in the routing approach is attributed to two factors that have environmental and economic implications. From an environmental perspective, energy efficiency reduction is a key activity that leads to emission reduction, climate change, and general improvement of the urban atmosphere. Self-organizing routing commonly implies cost savings, for example, in fuel consumption, increased lifetime of vehicles, and maintenance requirements for transport infrastructure [3, 4].

1.2. Motivation

Eco-routing algorithms, which can be described as energy-efficient routing algorithms, appear as a powerful paradigm for minimizing energy consumption in transportation. There is an acute need for such algorithms because of the emergent requirements for reducing emissions and energy consumption and utilizing inventions in transportation systems. The worsening effects of climate change, which are mainly informed by high carbon emissions and consumption of hydrocarbons, have socialized transport systems. The transportation sector is one of the most important energy-demanding industries that creates a huge impact on the emission of air pollutants and global climate change.

As the world population expands and grows more urbanized, city streets are growing crowded and filled with cars; hence, there is a need for improved and sustainable transportation solutions that will help solve these effects on the natural environment while at the same time making it easy, fast and convenient for the users. Energy-efficient routing algorithms have become a viable solution to this problem. Conventional routing solutions that are built on such criteria as distance or time have no regard for environmental impact in terms of fuel and emissions. Thus, learning from GPS, knowing that the car is waiting in traffic or moving uphill or along a non-optimal and smooth route, the driver wastes a lot of energy and contributes to increased carbon emission and fuel consumption. As societies around the world shift toward eco-friendly technologies and smart city growth, achieving efficiency in transportation systems is not only a requirement but a benefit [5].

The motivation to explore and develop energy-efficient routing algorithms stems from several key factors:

1.2.1. Environmental Imperative

Cutting down transport emissions is essential to meeting international climate goals, including those in the Paris Accord. By applying energy efficient or optimum energy routing, road transport emissions can be reduced directly by this long-standing approach of utilizing the optimum path length to improve fuel economy or energy savings and hence limit the expulsion of CO_2 and other hazardous gases.

1.2.2. Economic Benefits

From the consumer and business points of view, energy-efficient routes are profitable since they save fuel. When it comes to intra-fleet optimization, the smallest of the enhancements can translate into enormous savings throughout the operation. Likewise, for users of Electric Vehicles (EV), efficient use of energy can go a long way in shaving much-needed miles off the battery life of the vehicle as well as the frequency in which the EV has to be recharged, which in effect, gives the driver much more flexibility when using the electric instead of the conventional vehicles.

1.2.3. Technological Advancements

With the emergence of smart cities, big data understanding, and connected vehicles, more effective algorithms for routing can now provide far more intelligent real-time solutions. This means that through sensors, GPS systems and traffic data problem-solving algorithms, energy-efficient algorithms can adjust their ROUTES in relation to current traffic conditions, road topography and even weather, making green transport far more viable today than it used to be.

1.2.4. Increased Adoption of Electric Vehicles

As the number of EVs increases on the road, controlling energy needs more effectively becomes important. Contrary to I.C. engine vehicles, EVs have fixed battery capacity and hence the driving range and need much attention when it comes to energy utilization. Cost-efficient routing schemes, in particular, can contribute significantly to the increase of the driving range of EVs, particularly if the necessary recharging facilities are still insufficiently developed in the urban environment.

1.2.5. Sustainability Goals in Urban Planning

Closely related, governments and policy-makers are increasingly emphasizing the application of green solutions in the transportation sector, which falls under sustainable development strategies. Local authorities are laying down measures that would decrease the release of greenhouse gases and encourage the use of sustainable means of transportation. Thus, it can be stated that the goals of energy-efficient routing algorithms indeed match the overall policy targeting the minimization of the environmental costs of road transportation.

1.3. Research Goals

The primary objective of this research is the design, assessment, and improvement of energy-efficient routing algorithms for effectively minimizing energy consumption and Greenhouse gas emissions in the prevailing transport systems. To achieve environmentally friendly transportation, this research seeks to develop routing approaches that reduce travel time and distance while optimizing energy consumption [6].

To achieve this goal, the research will address the following specific objectives:

1.3.1. Algorithm Development

Propose energy-aware routing strategies that depend not only on the type of vehicle, internal combustion engine vehicles, hybrids, and electric vehicles but also on the road conditions, traffic flow, and physical characteristics of the route, such as incline and climate. The algorithms will then be compared to conventional routing techniques in order to estimate the decrease in fuel consumption and pollution.

1.3.2. Comparative Analysis

Compare various methods to achieve energy-efficient routing, including modified Dijkstra's based routing algorithms, energy-based heuristics incorporated with A* search Algorithms, and bio-inspired techniques like Ant colony optimization and genetic algorithms. The purpose is to know which system is better suited for application to match the transport situations and vehicle types.

1.3.3. Simulation of Real-World Scenarios

The real-world transportation networks and urban traffic environments can be emulated to evaluate the effectiveness of the suggested routing algorithms. In the simulations, weather and light conditions will be added, and they will cover different areas, such as urban and suburban/rural areas with different levels of traffic, road types, and different environmental conditions.

1.3.4. Impact on Electric Vehicle Range Optimization

Examine the precise advantages of the algorithms in detail by exploring how energy-efficient routing can further the driving range of EVs, minimize the rate of recharging and provide real-time battery optimization.

1.3.5. Environmental and Economic Impact

The impact of embedding energy efficiency in routing algorithms for the transportation network will call for the measurement of decreases in fuel usage, CO2 emissions, and operational costs for the fleet.

1.3.6. Scalability and Real-Time Adaptation

As the developed routing algorithms have to be easily scalable for different large-scale transportation systems, they are required to make changes in real time depending on the traffic data, road conditions and the changing environment. This will entail attempting to establish how real-time data analysis and machine learning can be used in highly iterating the routes.

This study aims, therefore, to help achieve these objectives and thereby further the improvement of sustainable green transport systems by offering workable, cost-effective strategies for decreasing the impact of road transport on the environment without compromising its performance. Finally, the study intends to contribute to a shift towards improved urban mobility based on optimized energy consumption pathways as fundamental in smart transportation systems [7].

2. Energy Consumption in Transportation Networks

2.1. Energy Factors in Transportation

The use of energy in the transportation system depends on the following factors, most of which positively correlate with the efficiency and environmental effects of the different modes of transport. It is important to have an appreciation of these elements when fashioning systems that would support energy-efficient transport, especially in relation to environmentally enhanced transport systems [8, 9].

Here are the key energy-related factors that impact transportation:

2.1.1. Vehicle Type and Fuel Efficiency

Depending on the type of vehicle and its fuel economy, the comprehensive energy consumption of transport is quite different. Specific categories include Internal Combustion Engine Vehicles (ICEVs), Hybrid Vehicles (HEVs) and Electric Vehicles (EVs) for which energy requirements differ.

- Internal Combustion Engine Vehicles (ICEVs): Automobiles that use the conventional systems of gasoline or diesel engines are normally less economical when compared to new moderate automobiles, particularly on the rates of densities of urban traffic. Their energy consumption is a function of the size of the engine, weight, aerodynamics, and operation conditions.
- Hybrid Electric Vehicles (HEVs): Blend an internal combustion engine with an electric motor to enhance fuel economy. They are more energy efficient than ICEVs, especially when performing acceleration in and out of traffic lights. The electric motor and the ICE can interact to operate either one, depending on which one is most efficient.
- Electric Vehicles (EVs): EVs rely on one or more electric motors for power and, therefore, do not emit anything through a tailpipe. The power they use is expressed in kilowatt-hours km or per mile, and the factors affecting efficiency are the size of the battery, the regenerative brake, types of roads and conditions usually in Metro.

Energy conservation and emissions are important concerns for fuel and engine technologies; therefore, the use of energy-efficient routing is essential to take full advantage of these vehicle types by directing them to the most efficient routes relative to their energy characteristics.

2.1.2. Traffic Conditions and Congestion

Traffic conditions significantly impact energy consumption, as vehicles consume more fuel when idling or moving in stop-and-go traffic. ICEVs burn more fuel in congested conditions due to frequent acceleration and deceleration, while EVs deplete their battery reserves faster.

- Congestion**:** In highly congested areas, energy usage increases as vehicles spend more time idling and require more fuel or battery power to regain speed after stopping.
- Traffic Flow**:** Smooth traffic flow minimizes fuel consumption by allowing vehicles to maintain consistent speeds, reducing the need for acceleration and braking, which are energy-intensive.

Energy-efficient routing algorithms take traffic conditions into account, allowing vehicles to avoid congested routes and reduce energy consumption [10].

*2.1.3***.** *Road Topography*

The work found that the topography of the road network has a significant influence on energy consumption in transportation. Loose gradients alter the energy needed in ferrying a car to a given place or transporting a car with a large weight or one that has less engine prowess.

- Hills and Inclines: Any object with an engine needs more energy to start moving uphill, so vehicles use more energy to move up hills. This is particularly the case with large car models, especially heavy-duty trucks and other vehicles of a large size. Electric vehicles equally suffer from a very short battery life whenever they encounter inclines.
- Downhill Driving: Downward gradients not only help to save energy; indeed, where the car is equipped with regenerative braking– as is common among EVs and HEVs– it can actually benefit. This transforms kinetic power into electrical power and stirs it in the battery, enhancing energy density in a general way.

Some routing algorithms centre on the road gradients; hence, they can cause directions requiring less energy by avoiding steep grades or utilizing maximum brake energy recovery capability during descents.

2.1.4. Looking at the Speed and the Acceleration Patterns

Speed, acceleration and deceleration rate directly influence energy use in a vehicle. Higher speeds result in higher fuel consumption because of resistance; at the same time, slow speed, like in slow-moving traffic jams, also consumes a lot of fuel.

- Highway vs. City Driving: Most highways are stretch-free, meaning powering through them at moderate speeds is relatively energy-friendly compared to city power surges from activities such as halting traffic signals or congestion points.
- Acceleration: Jagged movement is less efficient than smooth movement since it takes more fuel to go at a fast pace than it does to go at a slow pace. Hence, the more fluently a certain route can be negotiated without many abrupt acceleration, the better its energy efficiency will be.

There are routing algorithms that are power-aware to ensure that vehicles travel at the right speeds on the road without much staking or acceleration zones.

2.1.5. Weather Conditions

This paper aims to review how weather can affect energy consumption in transportation in several ways. Nowadays, climate conditions, including rainfall, snowfall, or high-speed winds, can affect the working of vehicles and energy consumption.

- Cold Weather: Cold temperatures lead to greater energy losses in ICEVs, as cold engines take longer to warm up. For EVs, the reduced battery range results from some fundamental problems associated with cold weather, in which more energy is necessitated to keep the cabin warm and manage battery temperature.
- Rain and Snow: Wet or icy roads add to the rolling resistance and control; more energy is needed to restore speed and traction on the roads.
- Wind: Some months indicated that headwinds could enhance gasoline intake because of biomass acceleration shocks, which improve aerobic opposition, whereas tailwinds could decrease vitality utilization by boosting car motility.

Weather-responsive algorithms can be used to prevent drivers from using routes that are likely to be affected by bad weather, hence enhancing energy utilization.

2.1.6. Vehicle Load and Occupancy

For this reason, energy consumption is influenced by the weight of the vehicle plus that of the load it is pulling. Large loads use more fuel to move and maintain motion than smaller loads do, and thus, long-distance travel is more efficient with the loads.

- Cargo Weight: Indeed, in this mode of transport, the freight's weight greatly influences fuel consumption. Large trucks have the propensity to use even more fuel than smaller ones, especially when over slopes.
- Passenger Occupancy: More passengers or luggage consume more energy in operation, heating, ventilation, and air conditioning. However, carpooling or ridesharing can mean that global energy utilization per passenger is lower as it is additionally cost-effective.
  Due to the optimization of routes, it can reduce energy consumption by vehicle load routing algorithms with a focus on freight or delivery vehicles.

2.1.7. Urban Infrastructure and Smart Transportation Systems

Another factor affecting energy consumption is the layout of cities and the usage of such innovative transport solutions. Measures that include signal timings at a particular intersection, exclusive corridors for public or electric cars, and intelligent traffic systems will improve energy efficiency.

- Smart Traffic Management: Strategies including smart signals and observations in traffic can go a long way in improving traffic flow and the times needed to get back on the road, decreasing energy use.
- Dedicated Lanes: For vehicles that can save energy in certain conditions, electronic vehicle lanes, High Occupancy Vehicle (HOV) and bus lanes help improve traffic flow.

Intelligent transportation systems where real-time information feeds into the routing equations can boost energy-efficient transport by factoring infrastructure conditions and adjusting the route accordingly.

2.1.8. Energy Source and Fuel Type

The type of energy selected to fuel a vehicle, whether gasoline, diesel, electricity, hydrogen or biofuels, dramatically impacts energy use and the environment in the matter of transportation [11].

- Electric Vehicles (EVs): On their part, EVs are considered to be more energy efficient than gasoline-engine vehicles since electric motors draw less power to turn into energy to ensure motion. However, sources of electricity like coal, hydro, and solar that are used for lighting systems play a major role in pollution.
- Biofuels and Hydrogen: Biofuels or Hydrogen can be used as cleaner products compared to gasoline and diesel. However, their energy efficiency is therefore subject to the production and distribution technique employed.

Optimized energy-efficient routing algorithms specific to fuel or energy employed in the vehicles also assist in the enhancement of fuel efficiency, thus reducing the effects of environmental pollution. Understanding the energy factors present in the transportation system can then facilitate efficient routing of vehicles for optimal performance and the least energy consumption so that improvement in green transport efficiency could be realized [12].

2.2. Challenges in Green Transportation

The topic of Green transportation is an important area of research, and this paper seeks to highlight some of the challenges that accompany the use of green transport systems. All these are technological, infrastructural, economic and social barriers that need to be overcome to create sustainable transport systems [13]. Below are the key challenges that need to be overcome to realize the potential of green transportation fully:

2.2.1. High Initial Costs and Economic Barriers

This paper has identified some of the major challenges explored earlier, including the high initial cost needed to implement green technologies in the vehicle sector and the transport infrastructure sector.

- Electric Vehicles (EVs) and Hybrid Vehicles: COMPARED TO conventional ICE vehicles, the cost of manufacturing electric vehicles and hybrid vehicles is comparatively high in the initial years primarily because of the cost of the state-of-the-art battery. The FMCV impedes consumers since although the TC lowering is made through optimization of fuel and maintenance costs, the initial cost is higher.
- Public Transport and Infrastructure Development: Moving to green public transport involves massive restructuring by shifting from conventional buses to electric ones or switching from regular rails to high-speed rails. Numerous policy-makers, including the central and local governments, have limited funds and other legislative priorities restricting the speed at which green transport infrastructure facilities are built.
- Economic Incentives and Policies: Lack of or ineffective tax credits, subsidies, rebates, or other economic motivators contribute to the difficulty of getting people to shift towards green transit modes. Few areas have the conditions in place that would make sustainability in transportation operations financially viable.

2.2.2. Limited Charging and Refueling Infrastructure

There is still a struggling infrastructure for electric and other alternative fuel vehicles, limiting the movement to better and more sustainable transport.

- Charging Infrastructure for EVs: It is true that the use of electric vehicles is gradually increasing. However, these vehicles charge infrastructure, which is still a relatively rare occurrence, especially in remote and rural areas, commodities. These include longer charging times than the very short refuelling time of gasoline engine vehicles.
- Hydrogen Refueling Stations: FCEVs are a highly effective green automobile technology, but refuelling stations are very limited and costly to install.
- Biofuel Availability: While biofuels offered are environmentally friendly, reducing emissions in traditional engines, they also present certain problems in their production and distribution and lack of access to fuelling stations, primarily in the regions outside large cities.

The problem mainly arises because consumers are unwilling to make the initial transition towards low-emission vehicles because of the existing range issues or refuelling convenience.

2.2.3. The Issues that Render or can Result in Range Anxiety and the Performance of Vehicles

So, the psychological barrier that locally affects the perception towards EVs is range anxiety, especially with electric cars.

- Battery Limitations: The current battery technology reduces the range of usual electrically powered cars more than their gasoline-equivalent. While battery technology is constantly advancing, range concerns can always be an issue for longer-distance travellers or someone in an area with limited charging options.
- Performance in Extreme Weather Conditions: A common disadvantage of using EV batteries is that they are particularly vulnerable to ocean temperatures, and therefore, short-range batteries mean that driving will be

limited in extremely cold or hot conditions. In the same way, hydrogen fuel cells and biofuel systems could run differently in different climates, which impacts their durability.

- Energy-Efficient Routing: However, the current state and implementation of these routing algorithms in minimizing energy consumption and coverage are still scarce and not well known to the public; thus, the following concerns can be expected.

2.2.4. Slow Technological Advancement and Standardization

Although green transportation technologies are developing faster and better, slow technological growth and non-standard systems hamper their development and deployment.

- Battery Technology and Charging Times: Even now, numerous problems exist, such as long charging times, limited battery cycle life, problems in manufacturing, etc. Fast-changing technologies are not currently widespread, and the application of this type of charging implies large investments in infrastructure.
- Standardization of Charging Systems: The absence of one-size-fits-all charging equipment and connectors may result in challenges for electric vehicle users. In some countries and areas, different producers apply different chargers, preventing the construction of a uniform network.
- Hydrogen and Biofuel Technology: Hydrogen fuel cell vehicles and biofuel systems are relatively less advanced than EVs, and challenges include the storage and transport of hydrogen and improvements in the proper production of liquid fuels.

2.2.5. Thus, the Environmental and Resources Constraints

In a rather paradoxical fashion, the creation of green transportation technologies may also carry out other environmental and resource-linked effects that pose challenges to extensive sustainability objectives [14].

- Lithium and Rare Earth Metals: Far from being green, electric vehicle batteries contain lithium, cobalt and rare earth metals that have a horrendous ecological impact during extraction. Exploiting these materials can destroy the natural environment, cause water pollution, and cause suffering for people in the territories where these materials originate.
- Energy-Intensive Manufacturing: Many electric vehicles, hydrogen fuel cell vehicles, and other green technologies also need much power input, a big part of which is from conventional energy sources. This, in turn, reduces the net environmental advantage when shifting to green transport means.
- Recycling and Disposal of Batteries: The disposal and recycling of such batteries also offer their unique challenge. Techniques used currently and traditional practices in recycling lithium-ion batteries are not perfect; thus, there is potential for massive waste management issues if recycling is not handled well.

2.2.6. Consumer Awareness and Behavior

However, customer awareness and consumer behaviour barriers affect green transportation adoption even though environmental and economic benefits accrue.

- Lack of Knowledge: Few people know that there is a cost-saving potential connected with green transport or the consequences of its usage for the environment. Basic information on the relevance of green transportation that may be acquired through information sharing and promotion is usually lacking.
- Resistance to Change: Consumers may be unwilling to switch to green transportation because it is perceived as inconvenient, unfamiliar with green Technologies, or culturally attached to gasoline-consuming vehicles.
- Reluctance to Adopt Public Transport: Public transportation is the most efficient in energy utilization, but users experience flexibility deficiency compared to personal cars. Changing the population's mindset and offering the right policy incentives needed to move away from car ownership to public transport will take a massive turn.

2.2.7. Policy and Regulatory Challenges

This means that sufficient availability of green transportation highly relies on supportive policies and regulations, but most of the regions still lag In-laws.

- Inconsistent Policies: Lack of policies or fragmented policies between regions and countries is a significant challenge for manufacturers and consumers. For example, diverse emissions regulations, fuel taxes, and subsidies for green technologies are not favourable for businesses to deploy green transportation solutions at the international level.
- Regulatory Hurdles for New Technologies: Technological innovations that include self-driving electric cars and bikes sharing economy companies, including ride-hailing drones for delivery service channels, are usually constrained by regulatory hurdles limiting their growth and adoption.
- Lack of Comprehensive Green Transport Policies: Few regions actually have holistic plans for green transport, which include vehicle technology, infrastructure, and city planning. The lack of these policies also limits the implementation of common synergistic frameworks for developing green transport systems.

2.2.8. Urban Planning and Infrastructure Limitations

Current urban design and modern transport systems present constraints to the achievement of green transport solutions.

- Urban Sprawl: Most cities have been established with car-oriented transportation systems, which hinder the adoption of public transport, cycling or walking-friendly corridors. Urban expansions mean reliance on personal vehicles becomes deeper and the shift to green mobility becomes unreachable.
- Retrofitting Existing Infrastructure: Converting the existing infrastructure for utilization by electric or hydrogen-driven vehicles is a capital-intensive affair. Installing charging points along the roads, painting some specific roads for EVs or HOVs only, and increasing public transport capacity are costly investments that need long-term planning.
- Lack of Integration with Smart Transportation Systems: Generally, the effectiveness of green transport systems hinges on the viable application of smart features inherent or adopted by smart cities, including the approaches used in traffic management and route optimization. Unfortunately, the infrastructure needed for such integration does not exist in many cities across the world.

3. Energy-Efficient Routing Algorithms

3.1. Traditional Routing vs. Eco-Routing

The conventional rout-ing algo-rithms, including Dijkstra and A*, are mostly used to minimize the travel time or distance. However, they do not consider the efficiency of energy integration. On the other hand, eco-routing algorithms focus on reducing energy consumption by taking into account factors such as vehicle energy, road slope, traffic signals, and recoveries in the case of vehicles equipped with regenerative brakes, including EVs in the current research [15, 16].

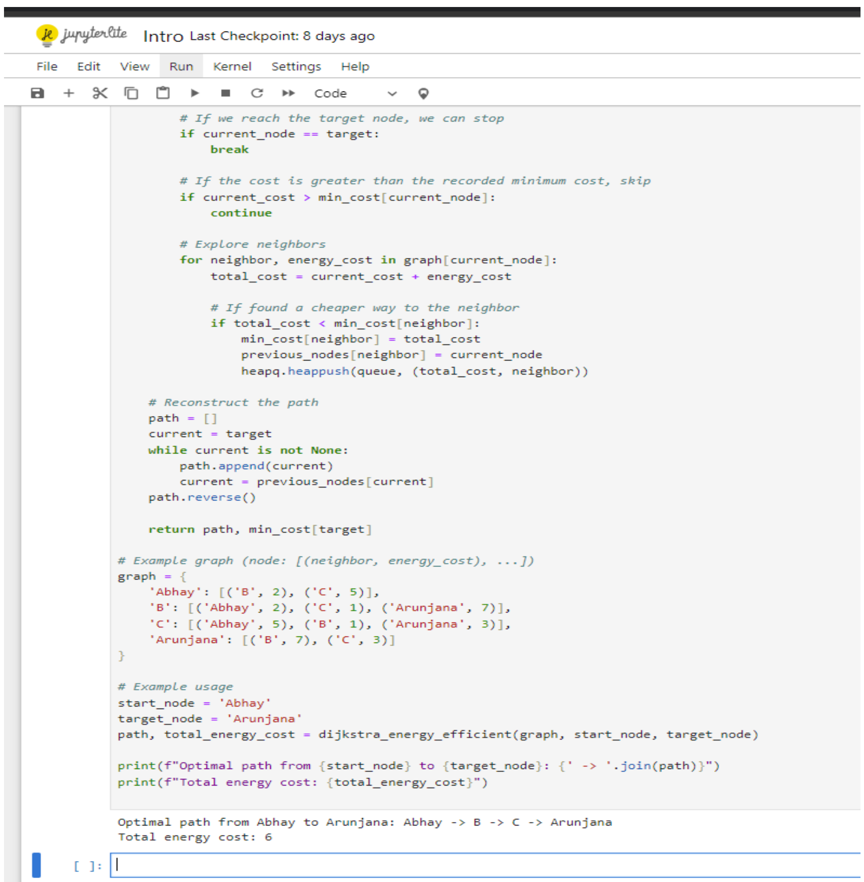
3.2. Energy-Efficient Routing Protocols

3.2.1. Dijkstra Algorithm to Perform Energy-Efficient Routing

Dijkstra's algorithm is a search algorithm that looks for the shortest path in the weighted graph, which is the most familiar among many algorithms. Despite the fact that it was developed for use in the shortest distance search, it presents potential in optimizing energy usage in transport networks. Dijkstra's algorithm runs on the fact of applying the least cost to each node progressively to achieve the nodes. It has a list of nearby nodes labelled by cumulative cost, enabling the system to arrive at the optimal path systematically. Stated below is a Python script that contains an energy-efficiency-based routing algorithm incorporated from Dijkstra's algorithm. This program employs a graph using a dictionary data structure whose nodes have other lists containing tuples of neighbours together with the energy required. The objective of this program is to find the shortest path according to energy consumption between the source node and the destination node.

Explanation:

1. Graph Representation: The graph is represented by a dictionary, and the key is the node's ID, whereas the value is the list of pairs. Each pair consists of a neighbouring node and the energy used to reach that neighbour.
2. A priority queue (heap) is incorporated to find the node with the lowest cost quickly.
   - The min_cost dictionary stores the energy cost to the nodes from the sink node image using the function h(f) with respect to each node.
   - The dictionary previous_nodes is employed to reconstruct the most appropriate path when the destination node is obtained.
   - The previous_nodes dictionary reconstructs the optimal path once the target node is reached.
3. Path Reconstruction**:** After reaching the target, the algorithm reconstructs the path by backtracking from the target node to the start node using the previous node dictionary.
4. Example Usage**:** The example graph demonstrates a small network, and the program finds the optimal path from node 'Abhay' to node 'Arunajna', printing both the path and the total energy cost.



```
jupyterlite  Intro Last Checkpoint: 8 days ago
File  Edit  View  Run  Kernel  Settings  Help
Code

        # If we reach the target node, we can stop
        if current_node == target:
            break

        # If the cost is greater than the recorded minimum cost, skip
        if current_cost > min_cost[current_node]:
            continue

        # Explore neighbors
        for neighbor, energy_cost in graph[current_node]:
            total_cost = current_cost + energy_cost

            # If found a cheaper way to the neighbor
            if total_cost < min_cost[neighbor]:
                min_cost[neighbor] = total_cost
                previous_nodes[neighbor] = current_node
                heapq.heappush(queue, (total_cost, neighbor))

    # Reconstruct the path
    path = []
    current = target
    while current is not None:
        path.append(current)
        current = previous_nodes[current]
    path.reverse()

    return path, min_cost[target]

# Example graph (node: [(neighbor, energy_cost), ...])
graph = {
    'Abhay': [('B', 2), ('C', 5)],
    'B': [('Abhay', 2), ('C', 1), ('Arunjana', 7)],
    'C': [('Abhay', 5), ('B', 1), ('Arunjana', 3)],
    'Arunjana': [('B', 7), ('C', 3)]
}

# Example usage
start_node = 'Abhay'
target_node = 'Arunjana'
path, total_energy_cost = dijkstra_energy_efficient(graph, start_node, target_node)

print(f"Optimal path from {start_node} to {target_node}: {' -> '.join(path)}")
print(f"Total energy cost: {total_energy_cost}")

Optimal path from Abhay to Arunjana: Abhay -> B -> C -> Arunjana
Total energy cost: 6

[ ]:
```

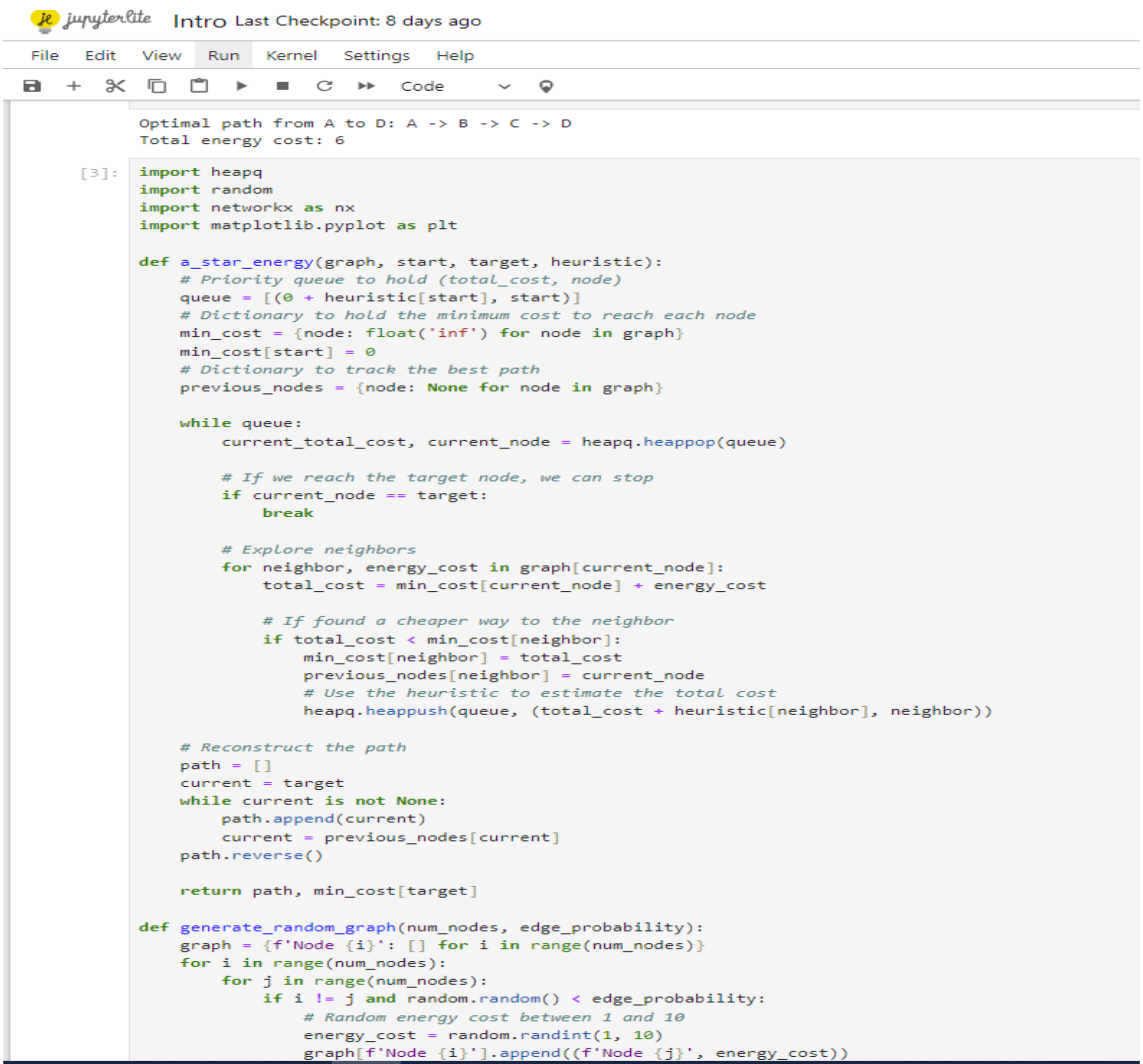
Fig. 1 Dijkstra-based program for energy-efficient routing algorithm

3.2.2. *A* Search with Energy Heuristics*

The A* search algorithm, when augmented with an energy consumption heuristic, can significantly reduce computational complexity while optimizing energy use. The heuristic is often based on speed limits, traffic patterns, and energy recovery mechanisms (e.g., regenerative braking in EVs). Below is a Python program that implements the A* search algorithm with energy heuristics and also generates a random graph. This program uses the Network-X library to create and visualize the graph using Matplotlib. First, ensure you have the required libraries installed. You can install them using pip: pip install networkx matplotlib

Explanation:

1. Graph Generation**:**
   - The generate_random_graph function creates a graph with a specified number of nodes and a probability of edge creation. Each edge has a random energy cost between 1 and 10.
   - The generate_heuristics function assigns random heuristic values to each node, setting the target node's heuristic to zero.
2. A Algorithm*:
   - Similar to the previous implementation, the a_star_energy function performs the A* search algorithm using a priority queue and reconstructs the optimal path.
3. Visualization**:**
   - The program uses NetworkX to create and visualize the generated graph. The edges are labelled with their corresponding energy costs.
4. Example Usage**:**
   - The program sets Node 0 as the start node and the last node as the target then finds and prints the optimal path along with the total energy cost.




```
Optimal path from A to D: A -> B -> C -> D
Total energy cost: 6
```

```python
import heapq
import random
import networkx as nx
import matplotlib.pyplot as plt

def a_star_energy(graph, start, target, heuristic):
    # Priority queue to hold (total_cost, node)
    queue = [(0 + heuristic[start], start)]
    # Dictionary to hold the minimum cost to reach each node
    min_cost = {node: float('inf') for node in graph}
    min_cost[start] = 0
    # Dictionary to track the best path
    previous_nodes = {node: None for node in graph}

    while queue:
        current_total_cost, current_node = heapq.heappop(queue)

        # If we reach the target node, we can stop
        if current_node == target:
            break

        # Explore neighbors
        for neighbor, energy_cost in graph[current_node]:
            total_cost = min_cost[current_node] + energy_cost

            # If found a cheaper way to the neighbor
            if total_cost < min_cost[neighbor]:
                min_cost[neighbor] = total_cost
                previous_nodes[neighbor] = current_node
                # Use the heuristic to estimate the total cost
                heapq.heappush(queue, (total_cost + heuristic[neighbor], neighbor))

    # Reconstruct the path
    path = []
    current = target
    while current is not None:
        path.append(current)
        current = previous_nodes[current]
    path.reverse()

    return path, min_cost[target]

def generate_random_graph(num_nodes, edge_probability):
    graph = {f'Node {i}': [] for i in range(num_nodes)}
    for i in range(num_nodes):
        for j in range(num_nodes):
            if i != j and random.random() < edge_probability:
                # Random energy cost between 1 and 10
                energy_cost = random.randint(1, 10)
                graph[f'Node {i}'].append((f'Node {j}', energy_cost))
```

Fig. 2 Program for A* search algorithm with energy heuristics and generates a random graph

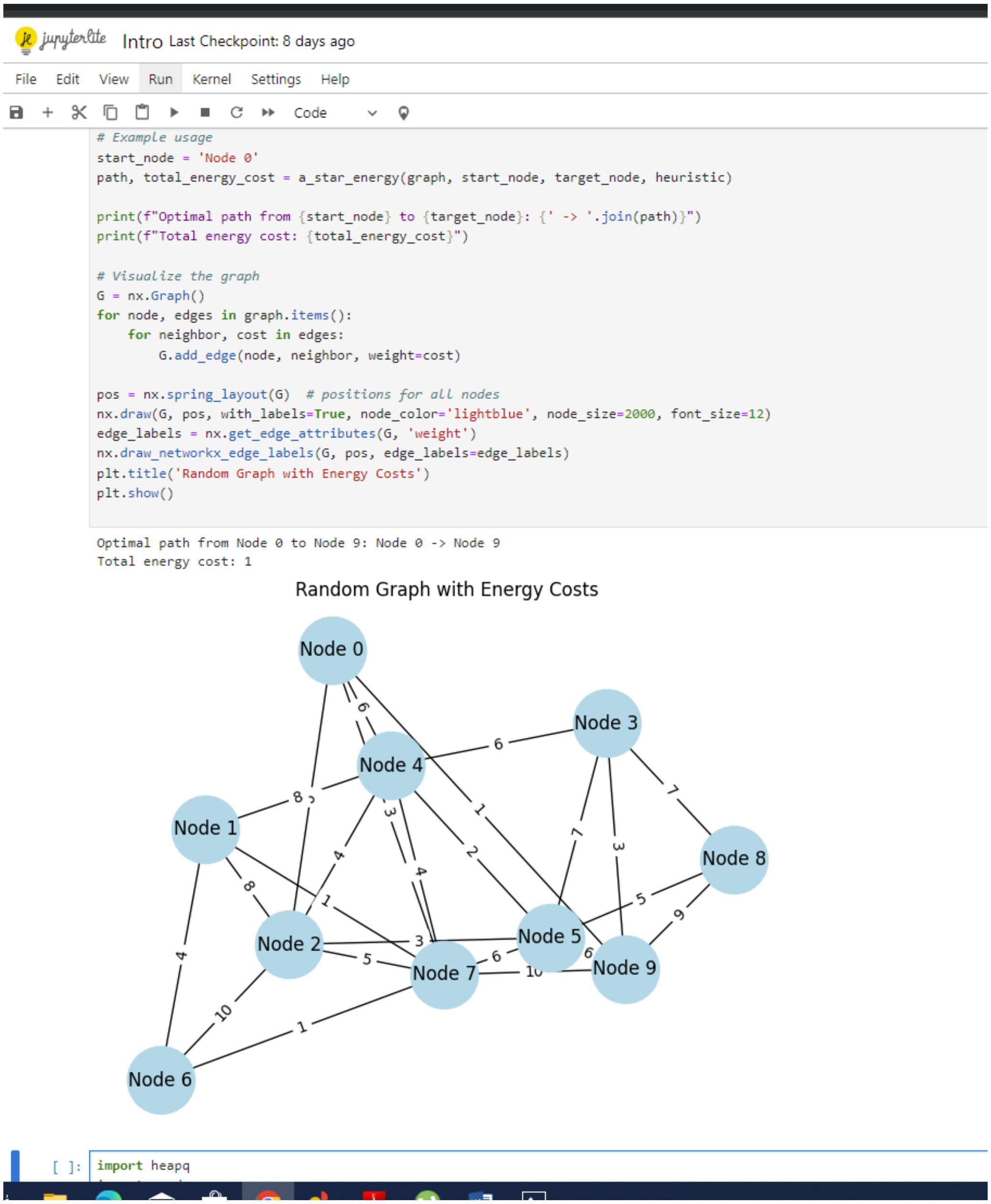


Fig. 3 Output of A* search algorithm with energy heuristics and generates a random graph

3.2.3. Multi-Objective Genetic Algorithms

Multiple Objective Genetic Algorithm (MOGA) has two objectives: minimizing travel time and energy usage. GAs are especially effective when a particular problem has objectives that are mutually exclusive, such as saving energy and causing travel inconveniences.

Below is a Python program that implements a Multi-Objective Genetic Algorithm (MOGA) to solve a simple optimization problem, such as minimizing two objectives: cost and energy consumption. This program also plots a graph randomly to illustrate the optimisation process.

To implement this, we will use Distributed Evolutionary Algorithms in Python (DEAP) for genetic algorithms. First, ensure you have the necessary libraries installed: import of packages became easy. We can stick to our terminal and type the following command to install packages--pip installs deap matplotlib networkx.


```
AttributeError: module 'deap.tools' has no attribute 'initPairwise'
```

```
[5]: import random
import numpy as np
import matplotlib.pyplot as plt
from deap import base, creator, tools

# Problem Constants
NUM_INDIVIDUALS = 100  # Number of individuals in the population
NUM_GENERATIONS = 50    # Number of generations
MUTATION_RATE = 0.2     # Mutation rate
CROSSOVER_RATE = 0.7    # Crossover rate

# Create Fitness and Individual classes
creator.create("FitnessMulti", base.Fitness, weights=(-1.0, 1.0))  # Minimize cost, maximize performance
creator.create("Individual", list, fitness=creator.FitnessMulti)

# Genetic Algorithm Setup
toolbox = base.Toolbox()
toolbox.register("x", random.uniform, 0, 10)  # x in range [0, 10]
toolbox.register("y", random.uniform, 0, 10)  # y in range [0, 10]
toolbox.register("individual", tools.initIterate, creator.Individual, lambda: [toolbox.x(), toolbox.y()])
toolbox.register("population", tools.initRepeat, list, toolbox.individual)

# Define the objective functions
def evaluate(individual):
    x, y = individual
    cost = x ** 2 + y ** 2  # Minimize cost function (simple quadratic)
    performance = -(x - 5) ** 2 - (y - 5) ** 2 + 100  # Maximize performance (inverse quadratic)
    return cost, performance

toolbox.register("evaluate", evaluate)
toolbox.register("mate", tools.cxBlend, alpha=0.5)
toolbox.register("mutate", tools.mutGaussian, mu=0, sigma=1, indpb=0.2)
toolbox.register("select", tools.selNSGA2)

# Main genetic algorithm execution
population = toolbox.population(n=NUM_INDIVIDUALS)

# Run the genetic algorithm
for gen in range(NUM_GENERATIONS):
    offspring = toolbox.select(population, len(population))
    offspring = list(map(toolbox.clone, offspring))

    for child1, child2 in zip(offspring[::2], offspring[1::2]):
        if random.random() < CROSSOVER_RATE:
```

Fig. 4 Code-1 that implements a multi-objective genetic algorithm and generates a random graph

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```python
toolbox.register("select", tools.selNSGA2)

# Main genetic algorithm execution
population = toolbox.population(n=NUM_INDIVIDUALS)

# Run the genetic algorithm
for gen in range(NUM_GENERATIONS):
    offspring = toolbox.select(population, len(population))
    offspring = list(map(toolbox.clone, offspring))

    for child1, child2 in zip(offspring[::2], offspring[1::2]):
        if random.random() < CROSSOVER_RATE:
            toolbox.mate(child1, child2)
            del child1.fitness.values
            del child2.fitness.values

    for mutant in offspring:
        if random.random() < MUTATION_RATE:
            toolbox.mutate(mutant)
            del mutant.fitness.values

    # Evaluate individuals with invalid fitness
    invalid_ind = [ind for ind in offspring if not ind.fitness.valid]
    fitnesses = map(toolbox.evaluate, invalid_ind)
    for fit, ind in zip(fitnesses, invalid_ind):
        ind.fitness.values = fit

    population[:] = offspring

# Gather all the fitnesses in one list
fits = [ind.fitness.values for ind in population]
costs, performances = zip(*fits)

# Plotting the results
plt.figure(figsize=(10, 6))
plt.scatter(costs, performances, c='blue', marker='o')
plt.title('Multi-Objective Optimization Results')
plt.xlabel('Total Cost')
plt.ylabel('Performance')
plt.grid(True)
plt.show()

# Display the best individuals
best_individuals = tools.sortNondominated(population, len(population), first_front_only=True)[0]
print("Best Individuals:")
for ind in best_individuals:
    print(f"Individual: {ind}, Cost: {ind.fitness.values[0]}, Performance: {ind.fitness.values[1]}")
```

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Fig. 5 Code-2 that implements a multi-objective genetic algorithm and generates a random graph

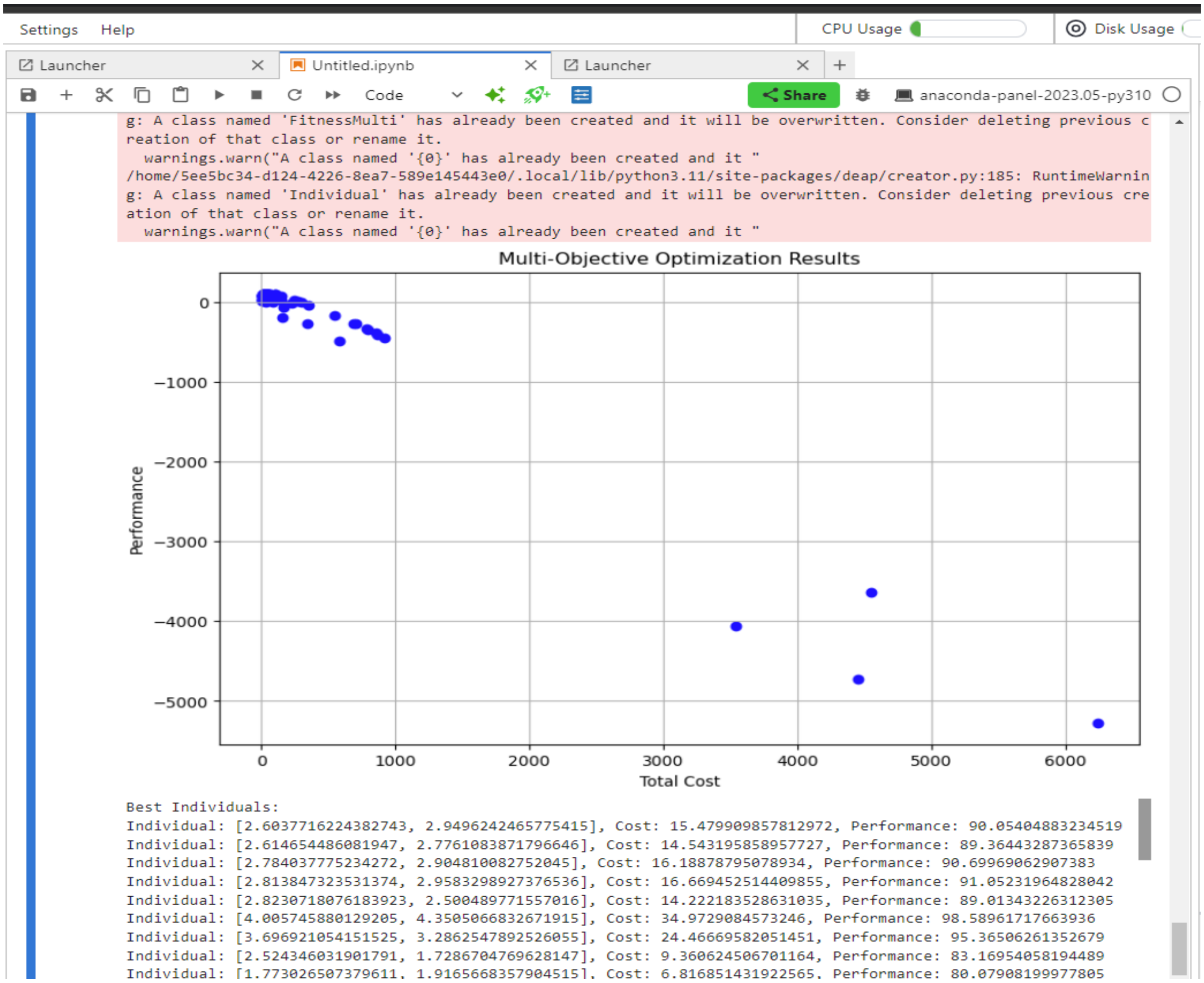


Fig. 6 Output of code-1/2 that generates a random graph

Explanation:

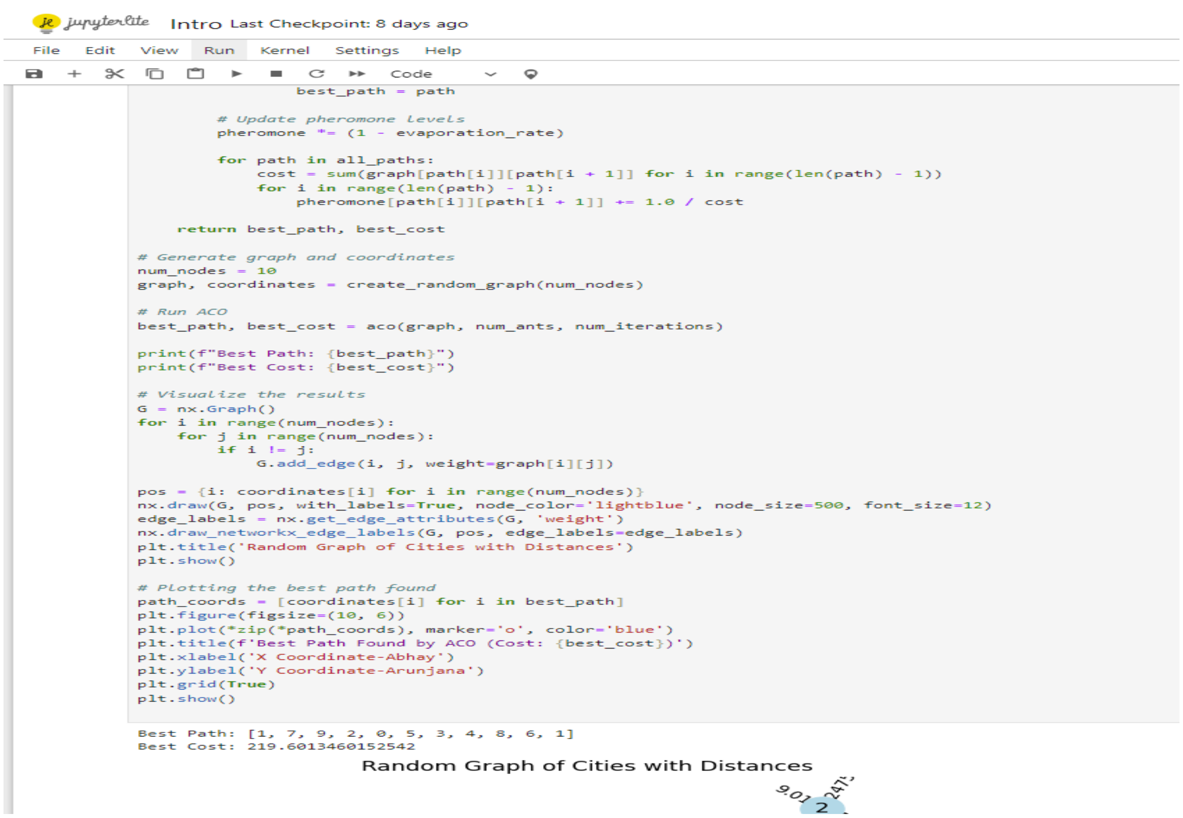
1. Graph Generation**:** The create_random_graph function creates a random directed graph with specified nodes and edges, assigning random costs and energy consumption to each edge.
2. Fitness Evaluation**:** The evaluation function calculates a given individual's total cost and energy consumption (path through the graph).
3. Genetic Algorithm Setup**:**
   - The DEAP library is used to set up the multi-objective genetic algorithm.
   - Individuals are created as lists of node indices. The goal is to minimize the total cost and energy consumption.
4. Algorithm Execution**:** The main genetic algorithm iterates through generations, selecting individuals, performing crossover and mutation, and evaluating fitness.
5. Results Visualization**:**
   - The optimisation results are plotted in a scatter plot showing the trade-off between cost and energy consumption.
   - The generated graph is visualized using NetworkX, displaying the nodes and the costs of the edges.

3.2.4. Ant Colony Optimization (ACO)

ACO is an algorithmic approach inspired by the lifestyle of ants in search of food. Regarding eco-routing, ACO deploys the pheromone trails to determine the least energy-consuming paths in the vehicles. ACO learns changes in traffic conditions and or energy profiles in real-time or in as much as possible real-time. Next is the Python code that simulates the basic ACO algorithm to solve some of the simplest optimization problems like TSP. The program creates a new graph of cities. Then, the ACO algorithm is used to obtain a suboptimal Hamiltonian cycle, passing through each city only once and returning to the start city. We will use the Network-X library to represent and analyze the graph representation. First, ensure you have the necessary libraries installed: Py: pip install matplotlib networkx.

Explanation:

1. Graph Generation**:**
   - The create_random_graph function creates a random set of cities (nodes) with distances (edges) based on their coordinates in a 2D space.
   - The distance between cities is calculated using the Euclidean distance formula.
2. Ant Colony Optimization Algorithm**:**
   - The ACO function implements the main ACO algorithm, which simulates the movement of ants. Each ant builds a path based on pheromone levels and distance.
   - Pheromone evaporation and updating occur after each iteration.
3. Results Visualization**:**
   - The random graph is visualized using NetworkX to show the cities and their distances.
   - The best path found by the ACO algorithm is also plotted, displaying the route taken by the best-performing ant.



```
                best_path = path

        # Update pheromone levels
        pheromone *= (1 - evaporation_rate)

        for path in all_paths:
            cost = sum(graph[path[i]][path[i + 1]] for i in range(len(path) - 1))
            for i in range(len(path) - 1):
                pheromone[path[i]][path[i + 1]] += 1.0 / cost

    return best_path, best_cost

# Generate graph and coordinates
num_nodes = 10
graph, coordinates = create_random_graph(num_nodes)

# Run ACO
best_path, best_cost = aco(graph, num_ants, num_iterations)

print(f"Best Path: {best_path}")
print(f"Best Cost: {best_cost}")

# Visualize the results
G = nx.Graph()
for i in range(num_nodes):
    for j in range(num_nodes):
        if i != j:
            G.add_edge(i, j, weight=graph[i][j])

pos = {i: coordinates[i] for i in range(num_nodes)}
nx.draw(G, pos, with_labels=True, node_color='lightblue', node_size=500, font_size=12)
edge_labels = nx.get_edge_attributes(G, 'weight')
nx.draw_networkx_edge_labels(G, pos, edge_labels=edge_labels)
plt.title('Random Graph of Cities with Distances')
plt.show()

# Plotting the best path found
path_coords = [coordinates[i] for i in best_path]
plt.figure(figsize=(10, 6))
plt.plot(*zip(*path_coords), marker='o', color='blue')
plt.title(f'Best Path Found by ACO (Cost: {best_cost})')
plt.xlabel('X Coordinate-Abhay')
plt.ylabel('Y Coordinate-Arunjana')
plt.grid(True)
plt.show()

Best Path: [1, 7, 9, 2, 0, 5, 3, 4, 8, 6, 1]
Best Cost: 219.6013460152542
```


Fig. 7 code for the Ant Colony Optimization algorithm

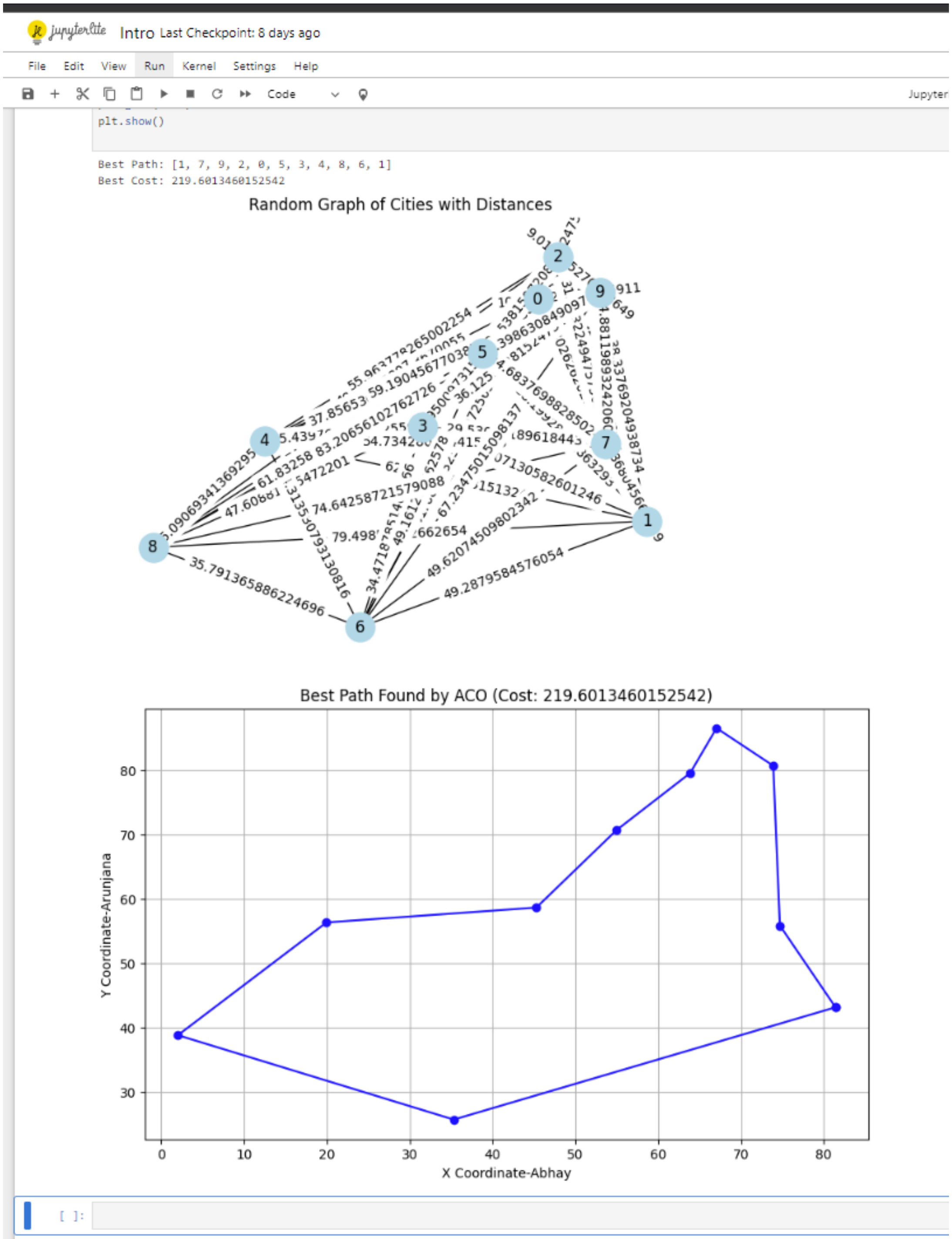


Fig. 8 Output of the Ant Colony Optimization algorithm

4. Environmental and Economic Benefits

Green transportation has many environmental and economic advantages - electric vehicles, hybrid cars, hydrogen fuel cell vehicles, public transportation, and many other sustainable transport [17, 18, 19, 20]. It is little wonder that such benefits cut across aspects such as the quality of air, the reduction in emission of greenhouse gases, the use of scarce resources, energy, employment, and eventual monetary savings. Below is an in-depth exploration of the key environmental and economic advantages:

4.1. Environmental Benefits

4.1.1. Impact, Greenhouse Gas Emissions Cut

Environmentally friendly transportation technologies minimize GHG emissions, which are known to cause global warming and climate change.

- Electric Vehicles (EVs): EVs do not emit direct tailpipe emissions, significantly reducing CO_2, CH_4 and N_2O emissions compared to ICE vehicles. In its life cycle, when charged with renewable energy, electric vehicles have fewer emissions than traditional vehicles.
- Public Transport: Some vehicles grouped in the CAF fleet travel daily to transport many people in buses, subways and trains; therefore, they have reduced emissions per capita compared to the number of cars.
- Hydrogen Fuel Cells: There is no emission produced by cars powered through hydrogen apart from water vapour; thus, they are cleaner than gasoline or diesel cars.

4.1.2. Improved Air Quality

Sustainable modes of transport particularly lead to decreased emission of particulate matter, nitrogen oxides and volatile organic compounds.

- Air Pollution Reduction: Traditional cars release dangerous gases that harm available air quality and cause illnesses, including asthma and bronchitis. Green vehicles are also healthier for the environment as they emit reduced or minimal greenhouse gases, thereby helping to develop healthier urban spaces.
- Fewer Health Impacts: In other words, by enhancing air quality, green transportation is complementary to solving pollution-associated health issues, hence easing public health and related costs.

4.1.3. Conservation of Natural Resources

Green transportation technologies fit within the sustainable resource utilization paradigm, especially with regard to energy and materials.

- Lower Fossil Fuel Consumption: New technology vehicles such as EVs, hybrid vehicles, and those that use other fuel types are less dependent on oils and gases than traditional vehicles. Hydrogen-powered automobiles, when mug with green hydrogen, reduce the consumption of petroleum products even more.
- Sustainable Materials: Green transportation systems can incorporate high recycled content materials in vehicle manufacturing and lightweight materials that help reduce fuel consumption.

Control of noise pollution promotes the sustainable use of resources, particularly in terms of energy and materials.

4.1.4. Reduction in Noise Pollution

Automobiles and other types of transport that are electric or come with similar power sources as their chief mode of operation are relatively quieter than those that rely on internal combustion engines; this makes it easier to reduce noise pollution, especially in urban areas.

- Quieter Streets: Further, EVs and electric buses are much quieter compared to gasoline-engine vehicles, which results in quieter cities and neighbourhoods as well as a higher quality of life for the people who inhabit these cities.

4.1.5. Conservation of Biogeophysical Environment and Species

Emphasis on green transportation reduces emissions and pollution and hence plays an important role in protecting ecosystems from the adverse impact of climate change and industrial products.

- Reduced Habitat Destruction: Transportation using clean energy diminishes the demand for oil drilling, which results in deforestation, oil leaks and general pollution of air, land and water.
- Climate Resilience: Limiting the emission of GH gases has a positive effect on climate change, thereby decreasing the occurrence of natural disasters that have impacts on the ecosystem and biodiversity.

4.2. Economic Benefits

4.2.1. Green Technology Manufacturing

As people require more EVs, batteries, solar, and wind energy-creating devices, they generate manufacturing employment. Electric vehicle production creates new occupations in battery making and assembly, charging station installation, and the integration of renewable energy systems.

4.2.2. Infrastructure Development

Electric vehicles, hybrid cars or fuel cell vehicles leading to charging networks, including micro irradiation, smart public transit systems and construction, logic, and operation can create numerous job opportunities in the engineering and construction domain.

4.2.3. R&D and Innovation

Fiscal incentives for investing in R&D for green transport engender genius innovation, creating new industries and start-ups in tech.

4.2.4. Lower Fuel Costs

Electric and hybrid vehicles, on average, will cost a lot less in fuel costs than vehicles using gasoline or diesel fuel. Electric charging is normally less costly than gasoline refuelling, provided the electricity used for the charging is from renewable energy sources.

4.2.5. Reduced Maintenance

EVs and hybrid vehicles have fewer moving parts than conventional ICEs vehicles. Hence, they have less or low maintenance. One major cost reduction compared to internal combustion engine vehicles is that there are no expenses in routine servicing such as oil changes, repairs to the exhaust system on account of fuel burning, or problems with the fuel system.

4.2.6. Public Transport Savings

Public transport investments mean that the reliance on personal cars will be eliminated.

4.2.7. Electric Vehicles

EVs use more electricity from the grid to power movements than traditional gasoline engines, which lose most energy from heat. This brings in higher efficiency, especially when power is sourced from renewable power, which generates all resources.

4.2.8. Efficient Freight

Converting the freight transportation system to electric or hybrid electric/diesel power can greatly decrease fuel expenditures for long-haul transport and make the logistics function less sensitive to fluctuations in oil prices.

4.2.9. Energy Independence

Energy independence from imported oil and gas facilitates decreases in energy costs generated by international fuel prices and exposure to political conflicts over energy.

4.2.10. Export Opportunities

Those countries that invest in the production of green transportation technology, including EVs or the components of renewable energy, are positioned on the global map for the export of such products, enhancing economic growth and trade balance.

4.2.11. Healthier Population

The incorporation of green transport results in a lower rate of respiratory disorders and heart diseases, hence decreasing health costs.

4.2.12. Public Health Savings

Policies that tend to create healthier people also benefit governments and institutions in the long run because money spent on treating individuals affected by pollution is conserved.

4.2.13. Mitigating Climate Change

When the transportation sector shifts to cleaner technologies, it benefits the economy as a traditional fuel consumer and a risk taker of climate change effects such as natural disasters, high sea levels and extreme climate events that disrupt economic activities and supply chains.

4.2.14. Sustainable Growth

Substantial transportation infrastructure is built to encompass future environmental impacts in a way that will lower expenses incurred when rebuilding or reconstructing transportation systems in the aftermath of climate events.

Essentials of environmental and economic sustainability are embedded in aspects of green transport, which provides a sustainable development agenda. Green transportation thus cuts on greenhouse gases, air pollution, and the use of fossil products while creating employment opportunities and new technology and saving costs for consumers. With more cities, businesses, and taxpayers opting for green transportation, the Earth is protected and healthier, and people get wealthier, resulting in a wonderful future for everyone.

5. Comparative Analysis

5.1. Simulation Setup

To compare the performance of different algorithms, we simulate several real-world transportation scenarios using traffic and energy consumption data. Various vehicle types, including electric, hybrid, and internal combustion engines, are modelled under different road conditions and traffic patterns.

Table 1. The performance of different algorithms

Category	Conventional Transportation Simulation	Simulation of Green Transportation
Simulation Environment	Urban, suburban, or rural environments with existing road networks.	Residential areas such as urban, suburban, or rural with an incorporated direct current vehicle system.
Vehicle Types	Gasoline and diesel-powered Internal Combustion Engine (ICE) vehicles.	Long-distance personal cars, short-distance personal cars, buses & trains, lease cars, taxi & rental cars.
Energy Model	Fuel consumption is based on engine characteristics, road conditions, and driving behaviour.	Consumption ranges from power for battery electric vehicles to efficiency for hybrid and hydrogen vehicles and regenerative models.
Traffic Flow Simulation	Traditional traffic models for ICE vehicles. Focus on fuel consumption during idling and congestion.	After a detailed review of the simulation setup, it is concluded that the employed model correctly represents mixed real-life traffic where both EVs and ICE vehicles

		share the road; it also accounts for charging stops and energy regeneration periods for EVs.
Route Optimization	Routes optimized for fuel efficiency and time.	Routes derived from the battery's limited range, charging station availability, and energy-efficient routes.
Infrastructure Components	Fuel stations, toll booths, traffic signals.	The electric car charging stations, hydrogen refuelling stations, integration of energy grid, and traffic signal with integrated technology.
Vehicle Maintenance Model	Periodic maintenance, such as oil changes and exhaust system checks.	Battery health; degradation effects for EVs; battery charging cycle impacts for EVs; fuel cell for hydrogen vehicles.
Environmental Impact Factors	CO_2, NO_x emissions from fuel combustion.	Zero direct emissions for electric cars; existent emissions model for electrical utility that powers recharging (if not all clean), blended emissions.
Energy Source	Fossil fuels (gasoline, diesel).	The ideal fuel choice for this technology is electricity, which allows for the storage of the source energy.
Network Infrastructure	Pre-established fuel station networks and road conditions.	Simulated charging networks, dynamic energy pricing, and smart grid integration.
Energy Source	Fossil fuels (gasoline, diesel).	Electricity (preferably renewable), hydrogen, and hybrid fuel sources.
Network Infrastructure	Pre-established fuel station networks and road conditions.	Simulated charging networks, dynamic energy pricing, and smart grid integration.

5.2. Metrics for Comparison

The algorithms are evaluated based on the following metrics:

- Energy savings: The reduction in total energy consumption compared to traditional routing algorithms.
- Travel time: The impact of energy-efficient routing on overall travel time.
- Emissions**:** Reduction in CO_2 and other pollutants.
- Scalability**:** The ability of the algorithm to handle large-scale transportation networks.

Table 2. Evaluation based on the metrics

Metric	Conventional Transportation (ICE)	Green Transportation (EVs, Hybrids, Hydrogen)
Fuel/Energy Consumption	Gallons of fuel per mile (GPM).	kWh per mile for EVs; fuel efficiency for hybrids; hydrogen consumption rate.
Total Emissions	CO_2, NO_x, particulate matter (PM) emissions.	Direct emissions from hybrid vehicles; indirect emissions are based on electricity sources for EVs.
Operational Cost	Fuel costs (volatile due to oil prices), maintenance, insurance.	Electricity costs, charging infrastructure costs, lower maintenance costs.
Distance Per Charge/Tank	Miles Per Gallon (MPG) for ICE vehicles.	Range per charge for EVs (in miles or km); range per hydrogen refill for hydrogen vehicles.
Route Efficiency	Time and fuel optimized routes, fuel efficiency losses in traffic congestion.	Battery-efficient routes, charging station availability along routes, energy regeneration.

Infrastructure Costs	Fuel station costs, road maintenance, and traffic infrastructure.	Charging station deployment, hydrogen refuelling infrastructure, grid costs.
Noise Levels	High noise levels from ICE engines, especially in congested urban areas.	Lower noise levels for EVs and hydrogen vehicles, quieter cities.
Environmental Impact	High carbon emissions and environmental degradation from fuel extraction.	Lower emissions (zero emissions for EVs), reduced ecological footprint.
Battery/Fuel Life	Short-term fossil fuel consumption; consistent fuel availability.	Battery degradation over time for EVs; fuel cell life in hydrogen vehicles.
Charging/Refueling Time	Fast refuelling at fuel stations (few minutes).	Charging time for EVs (from fast-charging stations or home charging); hydrogen refuelling is quicker.
Maintenance Frequency	Regular maintenance is required for ICE vehicles (oil, engine, exhaust).	Lower maintenance for EVs (no oil changes); periodic battery checks. Fuel cell upkeep.
Cost of Ownership	Generally, there is a lower initial purchase cost but higher long-term fuel and maintenance costs.	Higher upfront cost for EVs, but long-term savings in fuel and maintenance.

This table provides a comparative simulation setup and metrics for both Conventional and Green Transportation systems, offering insight into the various factors and performance indicators that can be measured in simulations and real-world implementations.

6. Conclusion

It means that energy-efficient routing algorithms can be named the most appropriate solution for decreasing the negative impact of transport systems on the environment. Because of these algorithms, route optimization through real-time traffic, features of the road network, and even specific energy requirements for each vehicle type, genuine reductions in fuel consumption and emissions can be realized on a consistent basis. Energy-efficient routing algorithms ensure vehicles move efficiently and, thereby, reduce the energy consumed in transport.

These algorithms facilitate the possibility of cutting down fuel and emissions by a vast margin in transportation systems, which is why they significantly help in environmental conservation. Through high-definition real-time traffic information and considering various factors, which include the road type and condition, the vehicle type, and distance, the energy-friendly routing computation helps to improve the coordination of logistics and public transport services.

Further, such algorithms can even help organizations and consumers reduce a business's overall expenditure. With the decline of rural populations, increasing congestion in cities, and growing pressures from the increasing demand for transportation, there is an urgent need for smart and efficient green transportation systems. Adapting energy-efficient routing algorithms is not only helpful for achieving the objectives of minimal carbon dioxide emissions but also for fostering new-generation ITS systems.

The meaningful integration of energy-efficient routing algorithms is equally important for establishing a sustainable transportation strategy, improving supply chain management, and the general well-being of the environment. Future advancement in this field will be critical to meeting the emerging needs of mobility and solving the problem of sustainable long-term solutions in transportation.

7. Future Directions

More investigations are required to enhance the energy-efficient routing algorithms that can be implemented on heterogeneous transportation systems. The adaptation of green transport systems with smart city frameworks like smart traffic control and connected cars has the potential to improve the efficiency of the green transport system. Therefore, the development of new energy-efficient routing algorithms will be critical to the improvement of green transportation. Here are several key future directions to consider:

- Enhanced Algorithm Complexity: Future studies should strive to create more complex models considering a broad set of factors, including weather, traffic, and vehicle physical features. This complexity will, in turn, make optimising the route for power easier, leading to better energy conservation.
- Integration of Renewable Energy Sources: Thus, working with the problem of the growing popularity of electric and hybrid vehicles, the routing algorithms should consider the availability of charging points and renewables. This integration can improve the work of the algorithms responsible for routing actions to minimize energy consumption and find possibilities to refuel.
- Collaboration with Autonomous Vehicles: Future routing algorithm paradigms should be developed to consider the existence of autonomous vehicles. Automatic control can include the possibility of interaction between vehicles, improving the choice of a route and economizing energy expenditure with the help of proper driving patterns among car participants.
- Real-Time Data and Predictive Analytics: Incorporating real-time information with other predictive analytics can contribute to the agility of the routing algorithms. More developments in this sphere should concern the application of big data sources from traffic management systems, GPS, and mobile applications for dynamic routing decisions.
- User-Centric Approaches: Subsequent routing algorithms should enable users to choose between their preferred criteria, for instance, low power consumption, no toll route, or shortest time. Such an approach will translate into higher adoption and satisfaction rates as designed for humans.
- Integration with Multi-Modal Transport Systems: In the design of future algorithms, it should be important to consider multi-modal transportation, which incorporates personal and public transport, bicycle, and walking. Such an approach can help with effective interchangeability and the transition to more energy-efficient transport at the level of modal splits.
- Sustainability and Emissions Metrics: To this end, it is important to establish a set of benchmark values to measure the eco-efficiency of routing algorithms. Future work will have to strive towards developing tools that capture not only the energy demand but also the improvement in emission performance and other sustainability works.
- Policy and Regulation Support: The second approach is likely to involve the policy-makers education to ensure that they set the right regulatory measures and offer incentives that will lead to the increased use of efficient routing algorithms. Future research agendas should encourage policy enablers of or for green transportation research, development and implementation.
- Incorporation of Behavioral Insights: Thus, having detailed information on user behaviour and preferences can greatly improve the efficiency of used routing algorithms. Further research should extend to behavioural economic and psychological theories to develop new algorithms that promote positive user behaviour in terms of the sustainability of transportation means.
- Public Awareness and Education: It is crucial to raise awareness of energy-efficient routing technologies and their use to enhance usage. Future measures should include awareness-raising activities that explain the benefits of green mobility solutions to the public and interested parties.

If these future directions are followed, future-oriented energy-efficient routing algorithms will help build the foundation for future generations of vehicles and transportation systems, focusing on sustainable and energy-efficient technologies for sustainable transportation systems that reduce the negative impact on the environment.

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