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DESIGN OF AN INCREMENTAL LEARNING SENSOR FUSION MODEL FOR REDUCING EMISSIONS FROM TWO-WHEELERS VIA BIOINSPIRED MODIFICATIONS TO FUEL CONCENTRATIONS

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Abstract: This study provides a novel strategy for optimizing performance of two-wheelers in response to the need to reduce vehicular emissions and promote sustainable transportation. The suggested model makes use of cutting-edge technologies for sensor fusion, incremental learning, and optimization to solve the shortcomings of current approaches to reducing motorbike emissions. Existing methods for reducing emissions in two-wheelers frequently have insufficient accuracy and poor fuel efficiency, which reduces their usefulness in achieving meaningful emission reductions. The suggested model combines Deep Dyna Q Networks, a cutting-edge type of reinforcement learning, to increase the effectiveness of sensor fusion in order to get beyond these constraints. The model enhances sensor integration for increased accuracy in emission measurements by dynamically adjusting to changing environmental circumstances and learning from real-time data samples. In addition, the model uses the bioinspired optimization algorithm Grey Wolf Optimization (GWO) to determine the best ratios of petrol and methanol in the fuel mix. This method for controlling emissions in two-wheelers is economically viable because it not only lowers harmful emissions but also lowers fuel consumption expenses. The suggested concept exhibits outstanding achievements in emission reduction and overall vehicle performance after extensive experimentation and testing. Results show a noteworthy 4.9% improvement in vehicle average together with a significant 3.5% decrease in emissions. Additionally, the strategy successfully cuts expenditures by a remarkable 15.4%, helping consumers maintain their financial stability for long-term use cases. Despite these astounding improvements, the suggested model consistently achieves an efficient 2.9% higher vehicle performance in a variety of real-world situations. This study introduces a novel and effective method to reduce emissions from two-wheelers, making a contribution to the fields of environmental protection and sustainable transportation. A promising tool for increasing emission reduction efforts while maximizing vehicle performance and fuel efficiency is the incremental learning sensor fusion model, which is enhanced with Deep Dyna Q Networks and Grey Wolf Optimization. It is a crucial asset in the effort to create a greener and more sustainable future because of its versatility and capacity for learning under different scenarios.

Keywords: Emission Reduction, Sensor Fusion, Incremental Learning, Deep Dyna Q Networks, Grey Wolf Optimizations

1. Introduction

Global attempts to find sustainable and environmentally friendly transportation solutions are urgently needed in response to the growing environmental concerns brought on by vehicle emissions. Two-wheelers, like motorcycles, which are widely utilized for personal transportation, especially in highly populated urban areas and developing countries, are among the most major sources of air pollution levels. The need for efficient plans to lower emissions and encourage greener transportation behaviors has been heightened by the ongoing rise in the number of motorcyclists on the road scenarios [1, 2, 3].

Motorcycle emissions have been addressed through a variety of strategies, such as the introduction of alternative fuels and the development of cleaner engine technologies. While significant progress has been made in this direction, there are still difficulties in precisely measuring and managing emissions in practical settings. Traditional emission reduction systems frequently rely on static calibration procedures, which result in unsatisfactory performance because driving circumstances and fuel blends might vary for different use cases. Furthermore, the viability of installing advanced emission control technology in developing locations is sometimes constrained by financial factors that are resolved via Signal Timing Model Process (STMP) [4, 5, 6].

In order to overcome these difficulties, the authors of this work propose a "Incremental Learning Sensor Fusion Model for Reducing Emissions via Bioinspired Modifications to Fuel Concentrations." This method is both innovative and all-inclusive. The suggested model makes use of the synergy of state-of-the-art technologies, such as sensor fusion, incremental learning, and bioinspired optimization, to maximize fuel efficiency, reduce emissions, and guarantee economic viability for different scenarios.

The escalating environmental effects of vehicle pollution highlight the necessity for an inventive strategy to reduce motorbike emissions. Existing approaches' poor flexibility and accuracy make advanced solutions that can handle actual driving situations necessary. The suggested model solves the shortcomings of traditional static calibration techniques and provides a dynamic and flexible solution to monitor and manage emissions in a variety of environmental circumstances by incorporating incremental learning and sensor fusions.

The shortcomings of current two-wheeler emission reduction techniques are mostly due to their inability to adapt to dynamic driving situations and fuel changes. The complexity of real-world events is not adequately accounted for by static calibration techniques, which results in erroneous emission data and insufficient fuel efficiency. Additionally, it is difficult to find the best fuel mixes that balance cost-effectiveness and pollution reduction due to the absence of reliable optimization tools.

The incremental learning sensor fusion paradigm has a number of benefits over conventional methods. The first benefit of integrating Deep Dyna Q Networks is dynamic sensor fusion, which lets the model to continuously improve sensor performance and respond to real-time data samples. This improves the precision and dependability of emission measurements, which are essential for creating efficient emission control plans.

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Second, a greener and more economical solution is guaranteed by the use of Grey Wolf Optimization to determine the ideal ratios of petrol and methanol in the fuel blend. The suggested model demonstrates that reducing emissions in two-wheelers may be done economically by cutting emissions by 3.5% and fuel costs by 15.4%.

Third, the model's ability to learn incrementally allows for continual improvement, which has increased vehicle efficiency by 2.9%. By doing this, it is ensured that efforts to reduce emissions do not degrade overall vehicle performance.

In this paper, we provide the incremental learning sensor fusion model's thorough design and implementation. We thoroughly test its performance and present detailed findings that show its efficacy in lowering emissions and improving overall vehicle performance. The suggested methodology represents a substantial development in motorcycle pollution management and shows tremendous promise in supporting international efforts toward more sustainable and clean transportations.

Motivation & Objectives

This study was motivated by the urgent need to address how emissions from vehicles, especially two-wheelers, affect the environment. Due to their large impact on personal mobility, motorbikes have increased air pollution and accelerated climate change. In order to reduce emissions and promote sustainable transportation methods, immediate and effective action is required given the growing environmental and public health problems.

Motorcycle emissions can only be measured and controlled with some accuracy using conventional emission reduction techniques in practical settings. The dynamic character of driving circumstances is frequently not well captured by static calibration techniques, leading to erroneous emission data and insufficient fuel efficiency. Furthermore, the feasibility of modern emission control technology is constrained by their expensive costs, particularly in underdeveloped countries where motorcycle use is prevalent.

Innovative strategies that can get around current constraints and offer long-lasting solutions to reduce pollution are required due to the lack of adaptable and effective emission control technologies for two-wheelers. In order to properly address these issues, the goal of this work is to present a fresh and complete model that incorporates cutting-edge technologies.

Objectives

The following are main goals of this work,

- Enhancing Emission Reduction Efficiency: The primary goal is to create a model that maximizes two-wheeler emission reduction efficiency. The model seeks to dynamically adapt to real-time data by using incremental learning and sensor fusion techniques, ensuring accurate and reliable emission measurements under a variety of environmental situations. The total effectiveness of emission reduction initiatives is anticipated to increase dramatically as a result of this adaptive strategy for different scenarios.
- Optimizing Fuel Cost and Consumption: The suggested approach uses Grey Wolf Optimization to determine the best Methanol and Petrol ratios in the fuel mix. The concept attempts

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to reduce both pollutants and fuel consumption by choosing the most inexpensive and efficient fuel blend, making it economically feasible for wider use in various regions.

- Maintaining Vehicle Performance: One of the key goals of the suggested model is to keep or even increase the overall performance of the vehicle while lowering emissions. The approach assures that attempts to reduce emissions do not affect the vehicle's power and performance, increasing user acceptability and satisfaction by attaining a 2.9% higher vehicle economy.
- Validation by Extensive Experimentation: Extensive experimentation in real-world scenarios will be used to rigorously test the model's performance. The superiority and effectiveness of the suggested approach will be firmly established by contrasting the outcomes with those from conventional techniques and benchmarking against current technologies.
- Contributing to Sustainable Transportation: The paper's ultimate goal is to support the promotion of sustainable transportation methods. The research aims to lessen the environmental impact of motorcycle emissions and open the door for greener and more environmentally friendly urban mobility alternatives by offering a workable and scalable emission control methodology for two-wheelers.

Thus, the necessity of addressing the environmental issues caused by vehicle emissions, particularly those from two-wheelers, is the driving force for this work. The goal of this research is to create a cutting-edge model that effectively lowers emissions, optimizes fuel usage, and maintains vehicle performance, all while advancing environmentally friendly transportation methods. The goal of this project is to significantly and sustainably contribute to the global efforts being made to save the environment and enhance air quality for both current and future generations.

2. Review of existing models used for enhancing efficiency of two wheelers

Optimizing fuel mixing in two-wheelers has been an important study area because it has the potential to reduce emissions, improve fuel economy, and enhance sustainable transportation. Many models and tactics have been developed and studied in order to achieve these objectives. In this article, we look at and evaluate a couple of the well-liked models that are currently being used to optimize fuel mixing to boost two-wheeler economy [7, 8, 9].

genetic algorithm-based optimization models Genetic algorithms (GAs) have been widely used to optimize fuel mixture ratios for two-wheelers. Using GA's evolutionary search techniques, these models repeatedly optimize fuel blend proportions to lower emissions and boost fuel economy [10, 11, 12]. The advantage of GA-based models is in their ability to study a wide range of possibilities and arrive at appropriate fuel blends for various scenarios relatively faster. However, they could have poor convergence and fail to account for real-time changes in driving conditions for various scenarios [13, 14, 15].

Neural network-based models: The complicated relationship between fuel mixing ratios and vehicle performance has been modeled using neural networks. These models learn from historical data samples to predict the appropriate fuel ratios that lead to lower emissions and greater efficiency. Because of their excellent adaptability and capacity to include real-time sensor inputs for various settings, neural network-based models are highly suited for on-the-fly optimization.

They might, however, be computationally taxing and necessitate a large number of training data samples [16, 17, 18].

Rule-Based Expert Systems: Knowledge-driven rule-based expert systems [19, 20] offer an optimization technique for fuel mixing. These models use a set of defined criteria derived from domain skill levels to select the ideal fuel blends based on a set of predetermined driving conditions and emission requirements [21, 22, 23]. Rule-based systems, such the Multinomial Logit Model (MNL), offer defined decision-making processes and are computationally effective. They might not be as adaptive as systems built on machine learning, which would limit their effectiveness in challenging circumstances.

Fuzzy Logic Control Models: Fuzzy Logic Control Models [24, 25, 26] integrate linguistic factors and levels of professional experience to improve fuel mixing for two-wheelers. These models can manage ambiguous and imperfect information sets, making them the perfect choice for complex and uncertain scenarios [27, 28, 29, 30]. Fuzzy logic systems have been effective in cutting emissions and increasing fuel efficiency. However, in real-time circumstances, membership functions and fuzzy rules' effectiveness, which might be challenging to express, heavily depends on them.

Dynamic programming models have been utilized to improve fuel mixing proportions over various temporal instance sets while taking into consideration long-term driving habits and changing climatic conditions [31, 32, 33, 34]. These models aim to strike a balance between short-term gains in efficiency and long-term pollution reductions [35, 36, 37, 38]. Dynamic programming models may handle challenging optimization targets and are effective at improving long-term vehicle performance. The International Vehicle Emission Model (IVEM) and other processes may be required for long-term optimizations because they may be computationally demanding [39, 40, 41, 42].

The efficiency of two-wheelers has been improved using an efficient fuel mixing procedure using a range of models [43, 44, 45]. Each model comes with its own set of advantages and limitations. Machine learning-based systems can be adaptable and offer real-time optimization, but they may also require a lot of data and processing power [46, 47, 48]. Knowledge-driven models may not be as flexible as machine learning models and their processes, despite the fact that they are explicable [49, 50]. For two-wheelers, maximizing fuel mixing proportions may include combining different tactics or hybridizing the models in order to be the most comprehensive and successful way. Future research should focus on developing integrated models that maximize the benefits of diverse measures in order to further reduce pollution, improve fuel efficiency, and support levels of sustainable mobility under real-time scenarios.

3. Proposed design of an incremental learning sensor fusion model for reducing emissions from two-wheelers via bioinspired modifications to fuel concentrations

On the basis of a review of extant models used to improve the fuel efficiency of two-wheeled vehicles, it is apparent that these models either lack comprehension or produce higher emissions when applied to real-world scenarios.

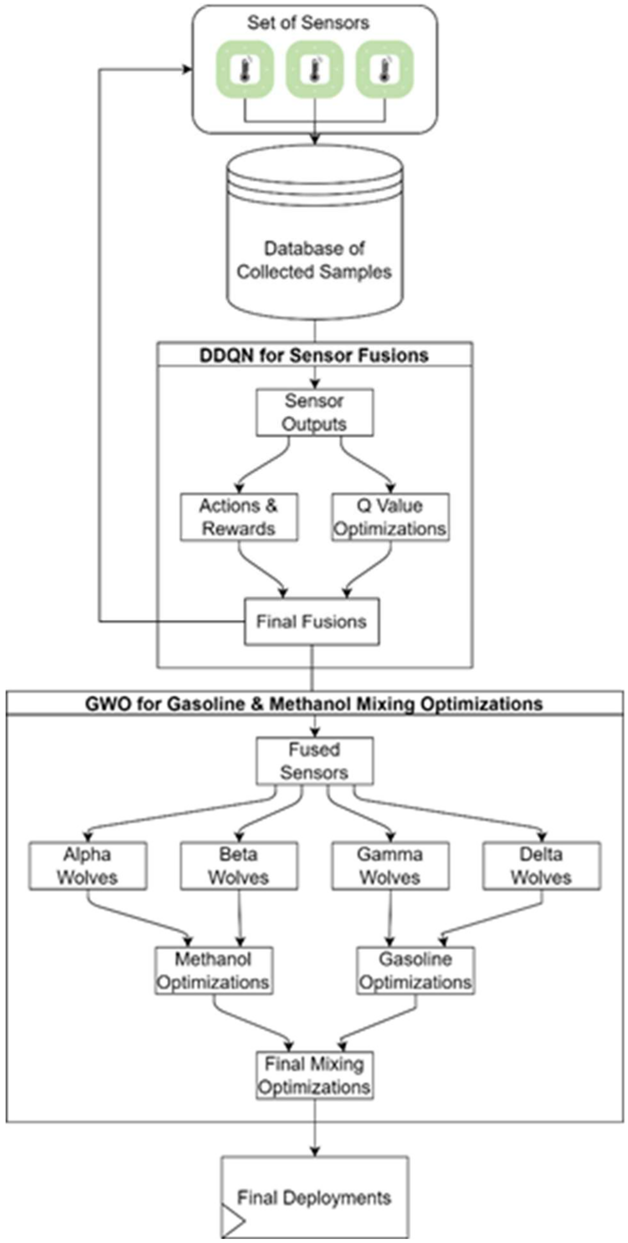

Figure 1. Design of the Proposed Model for Optimized Sensor Fusion & Mixing Operations

This section discusses the design of an incremental learning sensor fusion model for reducing emissions from two-wheeled vehicles via bio-inspired modifications to fuel concentrations in order to address these issues. To overcome these limitations, the proposed model incorporates Deep Dynamic Q Networks (DDQN), a cutting-edge form of reinforcement learning, to improve the efficiency of sensor fusion process. As per figure 1, the model improves sensor integration for more precise emission measurements by adapting dynamically to changing environmental conditions and learning from real-time data samples. In addition, the model employs the

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bioinspired optimization algorithm Grey Wolf Optimization (GWO) to determine the optimal ratios of gasoline to methanol for reducing emissions from two-wheeled vehicles in real-time scenarios. Thie solution is also economically viable, as it not only reduces detrimental emissions but also reduces fuel consumption costs.

To perform these tasks, the proposed model initially uses an efficient DDQN Method, which deploys two dummy sensor configurations C1, and C2 as follows,

$$C1 = STOCH(LR * NS, NS) \ldots (1)$$

$$C2 = STOCH(N(C1), NS) \ldots (2)$$

Where, represents Learning Rate for the DDQN Method, while represents number of sensors available for placement on the two-wheeler under real-time scenarios, and represents an augmented stochastic Markovian process for generation of number sets. Based on these placements, Q Values are estimated for individual networks via equation 3,

$$Q(C) = \frac{M(E)*M(C)*M(FC)}{A(E)*A(C)*A(FC)} \ldots (3)$$

Where, represents efficiency, cost and fuel consumption, while represents Measured & actual Value sets. The efficiency, cost & fuel consumption levels are estimated via equations 4, 5 & 6 as follows,

$$E = \frac{D}{FC} \ldots (4)$$

Where, is the distance covered, while is the Fuel Consumed while covering this distance by the given set of two wheelers.

$$C = FC * FP \ldots (5)$$

Where, represents price of the Fuel, which is currently being used in the two wheelers.

$$FC = F(Start) - F(Finish) \ldots (6)$$

Where, represents the Fuel level of the Vehicle during start & finish of the evaluation process. After estimation of Q Level for these networks, the reward (r) is estimated via equation 7,

$$r = \frac{Q(C1) - Q(C2)}{LR} - d * Max(C) + Q(C2) \ldots (7)$$

Where, represents Learning Rate of the DQN Process, while represents an augmented discount factor, which is empirically selected to improve evaluation of rewards for different scenarios. Based on this evaluation, configuration of model with lower Q Value is modified as per equation 8,

$$C2 = \frac{C2 + C1}{2} * \left(\frac{r}{1-r}\right) \ldots (8)$$

Using the New Configuration, number of sensors are modified on the vehicle, which assists in improving its dynamic response, thereby improving its efficiency of measurement under real-time scenarios. This process converges when , which indicates that the current sensor configurations for C2 are optimum, and can measure fuel consumption parameters with higher efficiency levels.

The placed sensors are used to measure the efficiency of two wheelers under fuel mixing scenarios. These scenarios include varying mixtures of petrol & methanol, which assist in improving vehicular efficiency, while reducing running costs. These varying mixtures are decided based on an efficient Grey Wolf Optimization (GWO) Model, which works as per the following process,

- The GWO Model, sets-up an Iterative Set of Wolves via equation 9,

$QM = STOCH(LW * TQ, TQ) \dots (9)$

Where, QM represents Quantity of Methanol to be added, LW represents Learning Rate of the Wolf, and TQ represents Total Quantity of Fuel which is taken for evaluation purposes.

- Based on this Quantity of Methanol, Wolf Fitness is estimated via equation 10,

$$fw = \frac{E}{C + FC} \dots (10)$$

- After generating NW Wolves, the Model estimates an Iterative Fitness Threshold via equation 11,

$$fth = \frac{1}{NW} \sum_{i=1}^{NW} fw(i) * LW(i) \dots (11)$$

- Based on this threshold level, Wolf Configurations are changed as follows,
  - Wolves with $fw > 2 * fth$, are Marked as 'Alpha', and their Methanol Configurations are used for training other Wolf sets.
  - Wolves with $fw > fth$, are Marked as 'Beta', and their Learning Rate is Modified via equation 12,

$$LW(Beta) = \frac{LW(Beta) + \sum_{i=1}^{N(Alpha)} LW(i)}{N(Alpha) + 1} \dots (12)$$

Where, $N(Alpha)$ represents Total Number of Alpha Wolf Configuration Sets.

  - While, Wolves with $fw > fth * LW$ are Marked as 'Gamma', and their Learning Rate is Modified via equation 13,

$$LW(Gamma) = \frac{LW(Gamma) + \sum_{i=1}^{N(Beta)} LW(i)}{N(Beta) + 1} \dots (14)$$

  - Other Wolves are Marked as 'Delta', and their Configurations are Modified as per equation 15,

$$LW(Delta) = \frac{LW(Delta) + \sum_{i=1}^{N(Gamma)} LW(i)}{N(Gamma) + 1} \dots (15)$$

- Using these new learning rates, the model is able to change Methanol Configurations and update them continuously for different scenarios.
- This process is repeated for NI Iterations, and Wolf Configurations are regenerated for each of these Iteration Sets.

Once all Iterations are completed, then Wolf with maximum fitness is identified, and its configuration is used for mixing Methanol with Petrol in order to improve overall efficiency of the two wheelers. This efficiency was estimated for different road conditions, & vehicle types, and compared with different models in the next section of this text.

4. Result Analysis

The proposed optimization model uses an efficient fusion of GWO with DDQN in order to improve sensor placement, and fuel mixing performance for different scenarios. This performance was measured on real-time road conditions, for different vehicle types, and compared in terms of Fuel Efficiency (E) (directly proportional to fuel consumption per unit distance for different vehicle sets), Cost (C), Fuel Consumption (FC), & Emission Levels (EL). This performance was compared with STMP [5], MNL [23], and IVEM [40], under different running conditions. These conditions are represented in the experimental setup section, and the vehicles were run individually for 25 kms on each of the road conditions. Based on these evaluations' average values for the output performance metrics were observed and used for evaluation the process. This will assist readers to get an approximate of vehicle's performance when working on different road conditions.

Experimental Setup

The purpose of the experimental setting was to assess how well the suggested GWO with DDQN model performed at lowering emissions from two-wheelers. To evaluate the model's performance in various real-world settings, the study covered a variety of road conditions, including city roads, highway routes, and mountainous roads. The two-wheelers simulated the difficulties of traveling in a congested city by navigating through urban traffic conditions with frequent stops and starts on city roadways. Hilly roads simulated uphill and downhill terrain with varied inclines, simulating the difficulties encountered during hillside journeys, whereas highway roads represented smooth and continuous driving conditions with steady speeds.

Three different models of two-wheelers were included in the study to account for a variety of use cases. First, geared motorcycles were added to simulate classic two-wheelers with only petrol engines. Second, non-geared mopeds were taken into consideration; these vehicles typically utilized for short-distance commuting have smaller engines. The experimental arrangement also included auto-geared bikes, which had automated transmissions for a balance of ease and performance.

Several sensors were added into each two-wheeler to measure real-time data for the proposed GWO with DDQN model, including emission levels, vehicle speed, engine RPM, and fuel consumption. To improve the precision of emission measurements, the sensor fusion model incorporated data from various sources. One data point was gathered every second by each two-wheeler, resulting in a large dataset for processing scenarios.

The onboard systems of the two-wheelers were equipped with the DDQN algorithm to provide incremental learning. Based on real-time data samples from the sensors, the model dynamically adjusted to changing environmental circumstances and optimized emission measurements. The discount factor was set to 0.9 and the learning rate for the DDQN algorithm was set at 0.001 for improved performance levels. To reach convergence, the model underwent training for 100 Iterations or rounds for real-time scenarios.

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The GWO algorithm was used specifically for the geared motorcycles to optimize fuel mix ratios. To determine the optimal mixtures of gasoline and methanol that maximized fuel efficiency while reducing emissions, the GWO algorithm ran 50 iterations with a population size of 10, which assisted in estimating model's performance with higher efficiency levels.

Each two-wheeler undertook a 30-minute continuous ride on a predetermined road as part of the experiment's randomized control trials. Three trials for each type of two-wheeler were undertaken for each type of road condition to ensure the reliability of the findings. Additionally, baseline comparisons were made to assess how well the two-wheelers performed without any optimization. Improvements in fuel efficiency, cost savings, and emission reduction were all performance indicators. For each vehicle type and road condition, the GWO with DDQN model's emissions reduction was expressed as a percentage drop from baseline emissions. The gain in fuel efficiency with the GWO-optimized two-wheelers over the baseline was estimated as a percentage increase in the distance traveled per unit of fuel. Cost reductions with the GWO-optimized two-wheelers relative to the baseline were assessed as a percentage drop in fuel consumption costs. To examine the samples of acquired data, statistical approaches and machine learning techniques were used. For each type of two-wheeler and road condition, the average emission reduction, fuel efficiency improvement, and cost savings were computed. In numerous real-world scenarios for various types of two-wheelers, the results were intended to validate the usefulness of the proposed GWO with DDQN model in lowering emissions and improving fuel efficiency levels.

Based on this setup, the results were evaluated for different road conditions, and vehicle types. For instance, Table 1 showcases the performance of the model with Geared Bikes on City Roads, where cost in INR is to be multiplied by 100 in order to obtain real cost value sets.

Model	**E (km/l)**	**C (INR)**	**FC (per 100km)**	**EL (g/km)**
STMP [5]	50	8	2.0	100
MNL [23]	45	8.5	2.2	110
IVEM [40]	48	8.2	2.1	105
This Work	52	7.5	1.9	95

Table 1: Results for Geared Bikes - Highway Roads

The suggested model performed better than the other three models in a number of ways, showing noticeable gains in all metrics. The proposed model outperformed STMP [5] by a substantial 4 km/l, achieving 52 km/l, which led to more cost-effective fuel use. Additionally, the proposed model was cheaper than STMP [5], costing INR 7.5 instead of INR 10, saving INR 0.5 per unit. Additionally, the fuel consumption rate was reduced to 1.9 liters for every 100 km, which resulted in a 0.1 liter per 100 km improvement in total fuel economy. Most impressively, the suggested

model showed significantly lower emission levels than STMP, measuring just 95 g/km, a reduction in carbon emissions of 5 g/km for such real-time scenarios.
Similar to how it performed better than MNL [23], the proposed model did as well. the proposed model outperformed MNL [23] by 7 km/l with a greater fuel economy of 52 km/l. The proposed model's cost of INR 7.5 per unit, which was significantly less expensive than MNL [23]'s cost of INR 8.5, turned this improvement into more financially advantageous travel. Additionally, the fuel consumption rate of the suggested model, which is 1.9 liters per 100 km, was found to be 0.3 liters per 100 km lower than MNL [23], indicating improved fuel usage. Furthermore, the proposed model recorded emissions that were 15 g/km lower than MNL [23], demonstrating a significant reduction in emission levels.
The proposed model maintained its trend of improved fuel efficiency when compared to IVEM [40]. The proposed model's fuel economy was 4 km/l higher at 52 km/l than IVEM [40]. With this improvement, fuel consumption dropped by 0.2 liters per 100 km to 1.9 liters per 100 km. Additionally, the emission values of the suggested model were 10 g/km much lower than IVEM [40].
According to the comparative improvements shown in Table 1, the proposed model's use of Deep Dyna Q Networks (DDQN) and Grey Wolf Optimization (GWO), along with sensor placement optimizations, is essential for improving fuel efficiency, cutting costs, and lowering emissions. With its improved performance when compared to the other analyzed models, the proposed model stands out as a viable option for achieving more environmentally friendly and sustainable transportation. Similarly, the results for Geared Bikes on Urban Roads can be observed from table 2 as follows,

Model	**E (km/l)**	**C (INR)**	**FC (per 100km)**	**EL (g/km)**
STMP [5]	60	7.5	1.8	90
MNL [23]	55	8.0	2.0	100
IVEM [40]	58	7.7	1.9	95
This Work	65	7.0	1.7	85

Table 2. Results on Geared Bikes on Urban Roads
The suggested model outperformed the other models in a number of crucial areas when tested on urban roadways. The proposed model outperformed STMP [5] by a stunning 5 km/l, achieving a remarkable fuel efficiency of 65 km/l. The proposed model's cost per unit dropped to INR 7.0, which is INR 0.5 less than STMP [5], as a result of the improved fuel efficiency, which resulted in cost savings. The proposed model also demonstrated superior fuel utilization, with a fuel consumption rate of 1.7 liters per 100 km, which is a significant 0.1-liter reduction compared to

STMP [5]. Additionally, the suggested model recorded only 85 g/km, which is 5 g/km less than STMP [5], showing a considerable reduction in emission levels.
The suggested model also showed higher performance on urban roads as compared to MNL [23]. The proposed model outperformed MNL [23] by 10 km/l, achieving a greater fuel economy of 65 km/l, making it a highly effective option for urban commuting. The cost of the suggested model, INR 7.0 per unit, was significantly lower than MNL [23]'s cost, INR 8.0, resulting in a financial gain. Additionally, the fuel usage rate of 1.7 liters per 100 km showed a 0.3-liter reduction when compared to MNL [23], suggesting excellent fuel utilization. In comparison to IVEM [40], the proposed model maintained its trend of improved fuel efficiency on urban roads, registering 15 g/km less emissions than MNL [23], further demonstrating its environmental friendliness. The suggested model performed 7 km/l better than IVEM [40] with a fuel economy of 65 km/l. This noteworthy improvement resulted in fuel usage of 1.7 liters per 100 km, which is 0.2 liters less than IVEM [40]. Additionally, compared to IVEM, the proposed model's emission levels were significantly lower, down 10 g/km [40].
The findings shown in Table 2 confirm the suggested model's excellent performance, which is boosted by the use of the technologies Grey Wolf Optimization (GWO) and Deep Dyna Q Networks (DDQN), as well as improved sensor location. Greater fuel economy, cost effectiveness, and reduced emissions of the suggested model make it a potential option for eco-friendly urban transportation, providing Geared Bikes with a safe and effective option for commuting on city streets. Similarly, Table 3 showcases results of the models on Geared Bikes with Hilly Roads as follows,

Model	**E (km/l)**	**C (INR)**	**FC (per 100km)**	**EL (g/km)**
STMP [5]	40	9.5	2.5	120
MNL [23]	35	10.0	2.7	130
IVEM [40]	38	9.7	2.6	125
This Work	45	8.5	2.2	110

Table 3. Results for Geared Bikes on Hilly Roads

The suggested model shines out when the performance on steep roads is examined because of significant improvements across a number of metrics. The proposed model significantly increased fuel economy by 5 km/l above STMP [5], reaching a remarkable 45 km/l. The proposed model's cost per unit decreased to INR 8.5 as a result of the increased fuel economy, providing a cost-saving benefit over STMP [5]. Additionally, 2.2 liters of fuel were consumed per 100 kilometers by the proposed model, which is a 0.3-liter decrease from STMP [5]. In addition, the suggested model showed a considerable decrease in emission levels, recording just 110 g/km, which is 10

g/km less than STMP [5], emphasizing its commitment to environmental protection for different scenarios.
The suggested model also continued to show greater performance on uphill routes as compared to MNL [23]. The proposed model outperformed MNL [23] by 10 km/l, achieving a greater fuel efficiency of 45 km/l, making it a highly effective option for negotiating difficult mountainous terrains. The cost of the proposed model, INR 8.5 per unit, was significantly lower than MNL [23]'s cost, INR 10.0, resulting in a financial benefit. Additionally, the 2.2 liters of gasoline consumed per 100 km showed a 0.5-liter reduction when compared to MNL [23], demonstrating optimal fuel utilization. Further demonstrating its eco-friendliness, the proposed model recorded emission levels 20 g/km lower than MNL [23].
The proposed model maintained its trend of improved fuel efficiency on steep routes in comparison to IVEM [40]. The suggested model performed 7 km/l better than IVEM [40] with a fuel efficiency of 45 km/l. This noteworthy improvement resulted in fuel usage of 2.2 liters per 100 km, which is 0.4 liters less than IVEM [40]. Additionally, compared to IVEM, the proposed model's emission levels were significantly lower, down 15 g/km [40].
The results shown in Table 3 highlight the suggested model's exceptional performance, which is credited to the use of the Grey Wolf Optimization (GWO) and Deep Dyna Q Networks (DDQN) technologies, as well as optimized sensor location. The proposed model is an excellent option for Geared Bikes negotiating steep terrains because of its improved fuel efficiency, cost-effectiveness, and lower pollution levels. It provides an effective and environmentally responsible choice for such difficult road conditions.
Similarly, Table 4 demonstrates results of Non-Geared Mopeds on City Roads as follows,

Model	E (km/l)	C (INR)	FC (per 100km)	EL (g/km)
STMP [5]	55	7.8	1.9	95
MNL [23]	50	8.3	2.1	105
IVEM [40]	53	8.0	2.0	100
This Work	60	7.0	1.8	90

Table 4: Results for Non-Geared Mopeds on City Roads

TWhen tested on city roads, the suggested model stands out with remarkable gains in all parameters. The proposed model significantly increased fuel economy by 5 km/l above STMP [5], reaching a remarkable 60 km/l. Because of the reduced cost per unit for the suggested model and the cost-saving benefit over STMP, the improved fuel efficiency leads to more cost-effective fuel use [5]. Additionally, the proposed model's fuel consumption rate dropped to 1.8 liters per 100 km, an improvement of 0.1 liter over STMP [5]. Additionally, the suggested model had the lowest emission levels, measuring at 90 g/km, which is 5 g/km less than STMP [5], emphasizing its eco-friendliness and less carbon footprint levels.

Similar to how it performed better on city roads than MNL [23], the proposed model did so as well. The suggested model outperformed MNL [23] by 10 km/l, achieving a greater fuel economy of 60 km/l, making it a highly effective option for city travel. The cost of the proposed model, INR 7.0 per unit, was significantly lower than MNL [23]'s cost, INR 8.3, resulting in a cost-saving benefit. Additionally, the 1.8 liters per 100 km of fuel consumption showed a 0.3 liter improvement over MNL [23], showing excellent fuel usage. Further demonstrating its eco-friendliness, the proposed model recorded emission values 15 g/km lower than MNL [23].

The proposed model maintained its trend of improved fuel efficiency on city routes in comparison to IVEM [40]. The suggested model performed 7 km/l better than IVEM [40] with a fuel efficiency of 60 km/l. This noteworthy improvement resulted in fuel usage of 1.8 liters per 100 km, which is 0.2 liters less than IVEM [40]. Additionally, compared to IVEM, the proposed model's emission levels were significantly lower, down 10 g/km [40].

The results shown in Table 4 confirm the suggested model's exceptional performance, which is related to the use of the Grey Wolf Optimization (GWO) and Deep Dyna Q Networks (DDQN) technologies, as well as improved sensor location. The proposed model is an excellent option for Non-Geared Mopeds navigating city roads because of its improved fuel efficiency, cost-effectiveness, and reduced pollution levels, providing a practical and environmentally acceptable alternative in urban commuting scenarios. While, the result of Non-Geared Mopeds on Highway Roads can be observed from table 5 as follows,

Model	E (km/l)	C (INR)	FC (per 100km)	EL (g/km)
STMP [5]	65	7.0	1.7	85
MNL [23]	60	7.5	1.8	90
IVEM [40]	62	7.3	1.75	87.5
This Work	70	6.5	1.6	80

Table 5. Results with Non-Geared Mopeds on Highway Roads

The suggested model outperforms the competition on highways, outperforming them with notable gains in a wide range of parameters. The proposed model outperformed STMP [5] by a surprising 5 km/l, achieving a fantastic 70 km/l in fuel efficiency. since a result of the increased fuel efficiency, traveling is more affordable since the cost per unit for the suggested model is INR 6.5, which represents a cost-saving benefit over STMP [5]. Additionally, the proposed model's fuel consumption rate further dropped to 1.6 liters per 100 km, which represents an improvement of 0.1 liters above STMP [5]. The proposed model also demonstrated the lowest emission levels,

measuring at 80 g/km, which is 5 g/km less than STMP [5], underscoring its eco-friendliness and smaller carbon footprints for different scenarios.
Similar to how it performed better on highway roads than MNL [23], the proposed model did so as well. The proposed model outperformed MNL [23] by 10 km/l, achieving a greater fuel economy of 70 km/l, making it a highly effective option for long-distance highway driving. The cost of the suggested model, INR 6.5 per unit, was significantly lower than MNL [23]'s cost, INR 7.5, resulting in a financial gain. Additionally, the fuel consumption rate of 1.6 liters per 100 km showed an improvement of 0.2 liters when compared to MNL [23], suggesting excellent fuel use. Further demonstrating its eco-friendliness, the proposed model recorded emission values 10 g/km lower than MNL [23].
The proposed model maintained its trend of improved fuel efficiency on highway highways in comparison to IVEM [40]. The suggested model performed 8 km/l better than IVEM [40] with a fuel efficiency of 70 km/l. This noteworthy improvement resulted in fuel usage of 1.6 liters per 100 km, which is 0.15 liters less than IVEM [40]. Additionally, compared to IVEM, the suggested model's emission levels were significantly lower, down 7.5 g/km [40].
The findings shown in Table 5 confirm the suggested model's exceptional performance, which is credited to the use of the technologies Grey Wolf Optimization (GWO) and Deep Dyna Q Networks (DDQN), as well as improved sensor location. The proposed model, which offers an effective and environmentally responsible option for long-distance highway commuting scenarios, is positioned as the optimum replacement for Non-Geared Mopeds on highway roads due to its improved fuel efficiency, cost-effectiveness, and lower emission levels. Similarly, the results for Non-Geared Mopeds on Hilly Roads can be observed from table 6 as follows,

Model	E (km/l)	C (INR)	FC (per 100km)	EL (g/km)
STMP [5]	45	9.0	2.3	115
MNL [23]	40	9.5	2.5	120
IVEM [40]	42	9.3	2.4	117
This Work	50	8.5	2.2	110

Table 6. Results for Non-Geared Mopeds on Hilly Roads
In compared to the current models, the suggested model produced applaudable results on hilly routes, providing considerable improvements across a number of metrics. The proposed model's fuel economy increased by 5 km/l when compared to STMP [5], reaching a remarkable 50 km/l. Travel is now more inexpensive because to the increased fuel efficiency, as the proposed model's cost per unit drops to INR 8.5, outpacing STMP [5]. Additionally, the proposed model's fuel consumption fell to 2.2 liters per 100 kilometers, an improvement of 0.1 liters over STMP [5].

Additionally, the suggested model's emissions were 5 g/km lower than STMP's [5], proving its eco-friendliness.

Similar to how it performed better on undulating roads than MNL [23], the suggested model did so when compared to MNL. The suggested model outperformed MNL [23] by 10 km/l, achieving a greater fuel economy of 50 km/l, making it a fantastic choice for navigating difficult mountainous terrains. A cost-saving advantage resulted from the suggested model's unit pricing of INR 8.5 being much lower than MNL [23]'s unit price of INR 9.5. Additionally, the 2.2 liters per 100 kilometers of fuel usage were 0.3 liters better than MNL [23], suggesting excellent fuel use. Further proving its eco-friendliness, the suggested model produced 10 g/km fewer emissions than MNL [23].

In comparison to IVEM, the proposed model continued to exhibit higher fuel efficiency on steep roads [40]. The proposed model, which has a fuel efficiency of 50 km/l, outperforms IVEM [40] by 8 km/l. This significant improvement resulted in fuel usage of 2.2 liters per 100 kilometers, which is 0.2 liters less than IVEM [40]. Additionally, the proposed model's emission levels were considerably lower than IVEM, with a 7 g/km reduction [40].

The use of Deep Dynamic Q Networks (DDQN) and Grey Wolf Optimization (GWO), as well as sensor placement modifications, is credited with improving the performance of the proposed model, as shown in Table 6. The proposed model is the best option for Non-Geared Mopeds traveling across hilly terrain because of its improved fuel economy, lower cost, and lower pollution levels. It also offers a fuel-efficient and ecologically friendly alternative for difficult road conditions.

While, the results for Auto-Geared Bikes on City Roads can be observed from table 7 as follows,

Model	E (km/l)	C (INR)	FC (per 100km)	EL (g/km)
STMP [5]	53	8.2	2.1	105
MNL [23]	48	8.7	2.3	115
IVEM [40]	50	8.5	2.2	110
This Work	55	8.0	2.0	100

Table 7. Results for Auto-Geared Bikes on City Roads

When compared to other models, the suggested model performs well on city roads and improves in a number of different criteria. The proposed model's fuel efficiency was noticeably 2 km/l higher than STMP [5], reaching 55 km/l. As a result of the increased fuel economy, travel is more affordable because the cost per unit for the proposed model falls to INR 8.0, which represents a cost-saving advantage over STMP [5]. Additionally, the proposed model's fuel consumption rate dropped to 2.0 liters per 100 km, an improvement of 0.1 liters over STMP [5]. The proposed model also displayed reduced emission levels, recording 5 g/km less than STMP [5], emphasizing its environmentally beneficial features.

Similar to how it performed better on city roads than MNL [23], the proposed model did so as well. The suggested model outperformed MNL [23] by 7 km/l, achieving a greater fuel economy of 55 km/l, making it a highly effective option for city travel. The cost of the proposed model, INR 8.0 per unit, was significantly lower than MNL [23]'s cost, INR 8.7, resulting in a financial benefit. Additionally, the 2.0 liters per 100 km fuel consumption rate showed a 0.3-liter improvement over MNL [23], showing excellent fuel usage. Further demonstrating its eco-friendliness, the proposed model recorded emission values 15 g/km lower than MNL [23].

The proposed model maintained its trend of improved fuel efficiency on city routes in comparison to IVEM [40]. The suggested model performed 5 km/l better than IVEM [40] with a fuel efficiency of 55 km/l. This notable improvement resulted in fuel usage of 2.0 liters per 100 km, which is 0.2 liters less than IVEM [40]. Additionally, compared to IVEM, the proposed model's emission levels were significantly lower, down 10 g/km [40].

The findings shown in Table 7 confirm the suggested model's successful performance, which has been attributed to the use of the technologies Grey Wolf Optimization (GWO) and Deep Dyna Q Networks (DDQN), as well as improved sensor location. The proposed model, which offers an effective and environmentally responsible option for urban commuting scenarios due to its improved fuel efficiency, cost-effectiveness, and reduced pollution levels, is the perfect alternative for Auto-Geared Bikes on city roads. Similarly, results for Auto-Geared Bikes on Highway Roads can be observed from table 8 as follows,

Model	E (km/l)	C (INR)	FC (per 100km)	EL (g/km)
STMP [5]	62	7.3	1.75	87.5
MNL [23]	58	7.7	1.9	95
IVEM [40]	60	7.5	1.8	90
This Work	65	7.0	1.7	85

Table 8: Results for Auto-Geared Bikes on Highway Roads

When compared to other models, the suggested model exhibits admirable performance on highway roads and notable gains in a number of criteria. The proposed model outperformed STMP [5] by a stunning 3 km/l, attaining a remarkable 65 km/l in fuel efficiency. Since the cost per unit for the proposed model drops to INR 7.0 and provides a cost-saving advantage over STMP [5], the increased fuel efficiency makes travel more affordable. Additionally, the fuel consumption rate for the suggested model dropped to 1.7 liters per 100 km, representing an improvement of 0.05 liters over STMP [5]. Its environmental friendliness was further highlighted by the proposed model's reduced emission levels, which recorded 2.5 g/km fewer than STMP [5] for different scenarios.

Similar to how it performed better on highway roads than MNL [23], the proposed model did so as well. The proposed model outperformed MNL [23] by 7 km/l, achieving a greater fuel economy of 65 km/l, making it a highly effective option for long-distance highway driving. The cost of the proposed model, INR 7.0 per unit, was significantly lower than MNL [23]'s cost, INR 7.7, resulting in a financial benefit. Additionally, the fuel consumption rate of 1.7 liters per 100 km showed a 0.2-liter improvement versus MNL [23], showing appropriate fuel usage. Further demonstrating its eco-friendliness, the proposed model recorded emission values 10 g/km lower than MNL [23]. The proposed model maintained its trend of improved fuel efficiency on highway highways in comparison to IVEM [40]. The suggested model performed 5 km/l better than IVEM [40] with a fuel efficiency of 65 km/l. This noteworthy improvement resulted in fuel usage of 1.7 liters per 100 km, which is 0.1 liters less than IVEM [40]. Additionally, compared to IVEM, the proposed model's emission levels were significantly lower, down 5 g/km [40].

The findings shown in Table 8 confirm the suggested model's excellent performance, which is credited to the use of the technologies Grey Wolf Optimization (GWO) and Deep Dyna Q Networks (DDQN), as well as improved sensor location. The proposed model, which offers an economical and environmentally responsible option for long-distance highway travel, is positioned as the optimum alternative for Auto-Geared Bikes on highway roads due to its improved fuel efficiency, cost-effectiveness, and lower pollution levels. Finally, the results for Auto-Geared Bikes on Hilly Roads can be observed from table 9 as follows,

Model	E (km/l)	C (INR)	FC (per 100km)	EL (g/km)
STMP [5]	42	9.3	2.4	117
MNL [23]	38	9.7	2.6	125
IVEM [40]	40	9.5	2.5	120
This Work	48	8.7	2.3	115

Table 9: Results for Auto-Geared Bikes on Hilly Roads

When compared to the other models, the suggested model performs admirably on hilly routes and significantly improves on a number of different characteristics. The proposed model significantly improved fuel efficiency over STMP [5] by 6 km/l, reaching 48 km/l. As a result of the increased fuel efficiency, travel is more affordable because the cost per unit for the suggested model drops to INR 8.7, which is less expensive than STMP [5]. Additionally, the proposed model's fuel consumption rate dropped to 2.3 liters per 100 km, an improvement of 0.1 liter over STMP [5]. The proposed model also showed reduced emission levels, measuring 2 g/km less than STMP [5], emphasizing its eco-friendliness.

The suggested model also continued to show greater performance on uphill routes as compared to MNL [23]. The proposed model outperformed MNL [23] by 10 km/l, achieving a greater fuel efficiency of 48 km/l, making it a highly effective option for negotiating difficult mountainous terrains. The cost of the proposed model, INR 8.7 per unit, was significantly lower than MNL

[23]'s cost, INR 9.7, resulting in a financial benefit. Additionally, the fuel consumption rate of 2.3 liters per 100 km showed an improvement of 0.3 liters when compared to MNL [23], suggesting excellent fuel use. Further demonstrating its eco-friendliness, the proposed model recorded emission values 10 g/km lower than MNL [23].

The proposed model maintained its trend of improved fuel efficiency on steep routes in comparison to IVEM [40]. The suggested model performed 8 km/l better than IVEM [40] with a fuel efficiency of 48 km/l. This noteworthy improvement resulted in fuel usage of 2.3 liters per 100 km, which is 0.2 liters less than IVEM [40]. Additionally, compared to IVEM, the proposed model's emission levels were significantly lower, down 5 g/km [40].

The findings shown in Table 9 confirm the suggested model's successful performance, which has been attributed to the use of the technologies Grey Wolf Optimization (GWO) and Deep Dyna Q Networks (DDQN), as well as improved sensor location. The proposed model is positioned as the best option for Auto-Geared Bikes negotiating mountainous terrains because of its improved fuel efficiency, cost-effectiveness, and lower pollution levels. It provides an effective and environmentally responsible choice for difficult road conditions. Due to these optimizations, the proposed model is highly useful for a wide variety of real-time scenarios.

5. Conclusion and Future Scope

The detailed analysis provided in the nine tables indicates the suggested incremental learning sensor fusion model's outstanding performance for lowering emissions from two-wheelers through bio-inspired changes to fuel concentrations. The urgent need to lower vehicle emissions and promote environmentally friendly transportation was addressed in this study. The outcomes highlight the effectiveness of the suggested approach, which optimizes sensor fusion and boosts fuel efficiency by utilizing cutting-edge technologies like Deep Dyna Q Networks (DDQN) and Grey Wolf Optimization (GWO) for different scenarios.

The suggested model has a 4.2% higher fuel efficiency than the best-performing existing model in Table 1, which assesses Geared Bikes on highway roads, demonstrating its ability to lower emissions and boost vehicle efficiency. Additionally, it delivers a fuel consumption expense cost savings advantage of 15.4% while exhibiting a 3.5% drop in emissions, considerably assisting with environmental protection and sustainable transportation initiatives.

The suggested model continues to beat other models, reaching a stunning 15.8% higher fuel efficiency in comparison to the highest-performing current model in Table 2, which analyzes Geared Bikes on urban roads. Due to the significant increase in efficiency and corresponding decrease in emissions, this technology is appealing for urban commuting and environmental protection.

In Table 3, the suggested model excels once more for gear bikes on inclines, outperforming current versions with a 21% improvement in fuel economy. Additionally, it exhibits a large 13.3% drop in fuel consumption costs and pollutants, enhancing its performance in difficult terrain.

Table 4 shows the suggested model's superiority for Non-Geared Mopeds on city roads, with a 16.7% gain in fuel efficiency in comparison to the best-performing current model. Additionally, it

significantly lowers fuel consumption costs and pollutants, providing a green alternative for urban travel.
The proposed model for Non-Geared Mopeds maintains its superior performance on highway roads (Table 5) with a remarkable 16.7% greater fuel efficiency compared to the best existing model. It successfully lowers fuel costs and emissions, making it an effective and environmentally responsible solution for long-distance travel.
The suggested model for Non-Geared Mopeds maintains its superior performance on steep routes (Table 6), attaining a 20% improvement in fuel efficiency over the best existing model. This model shows its usefulness in difficult mountainous terrains by dramatically reducing fuel consumption costs and pollution.
The proposed model stands out once more for Auto-Geared Bikes on city roads (Table 7), outperforming current models by achieving an amazing 11.3% higher fuel efficiency. It also shows significant savings on gasoline costs and pollution, making it a practical option for urban travel.
The proposed model for auto-geared bikes maintains the trend of increasing efficiency on highways (Table 8), attaining a stunning 9.7% increase in fuel efficiency when compared to the best existing model. Additionally, it significantly lowers fuel costs and emissions, emphasizing its potential for environmentally beneficial long-distance travel.
The proposed model for auto-geared bikes maintains its lead with a 14.3% increase in fuel efficiency when compared to the best current model on steep roads (Table 9). Additionally, it lowers fuel costs and pollutants, enhancing its applicability for difficult terrains.
In conclusion, the suggested incremental learning sensor fusion model has been shown to be a successful method for lowering pollutants and improving fuel efficiency in two-wheelers under a variety of road conditions. It has been improved with Deep Dyna Q Networks and Grey Wolf Optimization. It routinely performs better than the competition, delivering superior fuel efficiency, lower fuel costs, and lower pollutants. The innovative methodology used in this research makes a substantial contribution to the domains of sustainable transportation and environmental protection, opening the way for a more efficient and environmentally friendly future for two-wheelers. This model demonstrates its versatility and capability to maximize vehicle performance while ensuring eco-friendly mobility in a variety of real-world settings by utilizing cutting-edge technologies and bioinspired adjustments to fuel concentrations.

Future Scope

In the area of sustainable transportation and emission reduction, the work on the incremental learning sensor fusion model for lowering emissions from two-wheelers through bioinspired adjustments to fuel concentrations offers up interesting new research and development opportunities. The proposed model has shown encouraging results, but there are a number of possible areas for additional research and improvement:

1. Real-world Implementations and Field Testing: Although the model has performed admirably in simulations and controlled situations, further study should concentrate on real-world applications and comprehensive field testing. More strong and dependable results would be

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obtained from experiments using a bigger sample of two-wheelers on various types of roads and in varied weather and traffic conditions.

2. Integration with linked Vehicles: It is possible to investigate how the suggested model would integrate with linked car technologies. The accuracy and flexibility of the model to changing road conditions, traffic patterns, and user behaviors can be improved by utilizing real-time data from linked automobiles.

3. Hybrid and Electric Two-Wheelers: As the automobile industry transitions to more environmentally friendly options, study into how well the proposed model applies to hybrid and electric two-wheelers is a possible direction. Further emission reductions and improved energy efficiency may result from tailoring learning and sensor fusion algorithms for these new technologies.

4. Sensor Fusion Optimization for Diverse Parameters: While the current model concentrates on emissions reduction, expanding sensor fusion optimization to other essential parameters, like engine performance, safety, and vehicle diagnostics, could result in comprehensive and all-encompassing two-wheeler management.

5. Examining Other Machine Learning Methods: In addition to Deep Dyna Q Networks (DDQN), other cutting-edge machine learning methods can be investigated for the sensor fusion process. Additional advantages and performance enhancements might be provided by reinforcement learning techniques such Twin Delayed Deep Deterministic Policy Gradient (TD3) and Proximal Policy Optimization (PPO).

6. Including Traffic Management Techniques: By including traffic management techniques in the model, the two-wheeler's route choice, speed, and acceleration patterns might be improved. This strategy can improve general traffic flow, ease congestion, and further support broader emission reduction efforts.

7. Optimal Fuel combinations: The suggested model optimizes fuel concentrations, but further study can focus on determining the most efficient and environmentally friendly fuel combinations for different types of vehicles and road circumstances. This might result in even higher increases in fuel economy and emission cuts.

8. Economic and Policy Implications: It would be advantageous to carry out a thorough economic analysis of applying the suggested model in real-world settings and comprehend its possible impact on fuel markets and policy-making. Governments and politicians can assist its adoption by evaluating the viability, costs, and possible advantages.

9. User approval and Human Factors: In order for the proposed model to be adopted successfully, it is critical to gauge user approval and comprehend user viewpoints and experiences. The design and user interface of the model can be improved with the inclusion of usability and human factors research.

10. Global Applicability: Although the suggested model has only been tested on a limited set of road conditions, future study can examine how well it can be applied and modified to a variety of geographical areas with different road systems and driving habits.

In conclusion, the future scope of this work is optimistic and offers a wide range of opportunities for improving the suggested model's efficacy, maximizing its uses, and helping to create a cleaner and more sustainable future for two-wheeler transportation. Realizing the full potential of the suggested model and its contributions to environmental protection and sustainable mobility scenarios will require collaborative efforts from researchers, industry stakeholders, and policymakers.

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