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Machine Learning-Driven Optimisation of Aerodynamic Designs for High-Performance Vehicles

Mohd Afiq Rosli[1], Jiang Xiaoxia[2], Zhang Shuai[2]

[1]Faculty of Bioengineering, Universiti Malaysia Kelantan
[2]Faculty of Engineering, Ningxia University, China

Corresponding author: afiqrosli2000@gmail.com

Abstract
Aerodynamic design optimization is critical in improving the performance of high-performance vehicles, primarily electric and autonomous vehicles. However, traditional methods such as Computational Fluid Dynamics (CFD) simulations face challenges such as long computational time and high cost. This article discusses the implementation of machine learning to overcome these limitations, highlighting algorithms such as neural networks, Gaussian process regression, and reinforcement learning. The results show that machine learning can reduce the design iteration time by up to 80%, from 24-48 hours/design in CFD methods to only 10-30 minutes/design. The accuracy of the predictive model is also very high, with an average error margin of less than 5%. Case studies on Formula 1 vehicles and electric vehicles show a reduction in drag coefficient of up to 10%, which directly improves the cruising efficiency of electric cars by up to 15% and increases downforce by 12% for high-speed vehicle stability. In addition, generative algorithms such as GANs enable the exploration of innovative designs, while reinforcement learning can generate adaptive designs responsive to changing operating conditions. With this capability, machine learning not only accelerates the design cycle and lowers development costs but also drives innovation in the development of electric, autonomous, and uncrewed aircraft vehicles. In conclusion, machine learning technology is a superior solution for optimizing aerodynamic design to meet the demands of efficiency, performance, and sustainability of future cars.

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1. Introduction
Aerodynamic design is one of the fundamental elements in developing high-performance vehicles, especially in sports cars, racing cars, and modern electric vehicles. Optimal aerodynamics reduces air resistance (drag) while increasing downforce to maintain stability at high speeds. A 10% reduction in aerodynamic drag can increase fuel efficiency by up to 7%, indicating its impact on vehicle performance and energy efficiency, according to a study conducted by (Chengqun et al., 2023; Lee, Song, Han, Lim, & Park, 2023; Li, Ikram, & Xiaoxia, 2025; Xia & Huang, 2024). In the era of electric vehicles, reduced drag also means a significant increase in mileage. Although essential, aerodynamic design optimization has traditionally been complex and expensive. Conventional methods such as computational fluid dynamics (CFD) simulations and wind tunnel testing require high costs, long processing times, and experts to interpret the results. For example, CFD simulations of vehicle body designs can take days, depending on the complexity of the vehicle geometry (Erdiwansyah, Gani, et al., 2023; Gani et al., 2025; Gunpinar, Coskun, Ozsipahi, & Gunpinar, 2019; C. Zhang, Bounds, Foster, & Uddin, 2019). In addition, design iterations require repeated trials, which further increase development costs.

In addition to cost, aerodynamic design optimization faces challenges regarding geometric complexity and dependence on interrelated parameters. For example, the interaction between various vehicle components, such as spoilers, central bodies, and diffusers, often creates challenges in finding optimal solutions without affecting other design aspects (Aultman, 2023; Granados-Ortiz, Morales-Higueras, & Ortega-Casanova, 2023; Irhamni, Kurnianingtyas, Muhtadin, Bahagia, & Yusop, 2025; Muzakki & Putro, 2025). This makes it difficult to balance stability, speed, and energy efficiency. Machine learning-based approaches have begun to be widely applied to overcome these limitations in aerodynamic design optimization. Machine learning offers a faster and more efficient approach than conventional methods by utilizing datasets from previous simulations or experiments to build predictive models. Machine learning algorithms can accelerate the prediction of fluid flow patterns with a high degree of accuracy, reducing the need for intensive CFD simulations (Panchigar et al., 2022; Rahman, Hazra, & Chowdhury, 2024; H. Wang et al., 2024).

Algorithms such as Gaussian regression, artificial neural networks (ANNs), and ensemble methods such as Random Forest have been successfully applied to accelerate the aerodynamic optimization process. For example, deep neural networks were used to predict the drag coefficient of a vehicle body design with up to 95% accuracy while reducing the calculation time by up to 80% (Jin, Cheng, Chen, & Li, 2018; Khan, Hossain, Mozumdar, Akter, & Ashique, 2022; Pranoto, Rusiyanto, & Fitriyana, 2025; Ramogi, 2024). This approach shows significant potential to accelerate design iterations without sacrificing the quality of the results. In addition to time efficiency, machine learning allows for broader design exploration through optimization based on evolutionary algorithms or reinforcement learning. A generative method was used to generate new aerodynamic vehicle designs based on desired parameters (Rosdi, Maghfirah, Erdiwansyah, Syafrizal, & Muhibbuddin, 2025; Tran et al., 2024; Usama et al., 2021; Warey, Raul, Kaushik, Han, & Chakravarty, 2023). In this way, design development is no longer limited to manual experiments but can be automated to explore various innovative solutions.

However, despite its many advantages, the application of machine learning in aerodynamic optimization still faces several obstacles, such as limited dataset quality and the need for physical validation. Further research is needed to ensure that the solutions generated by machine learning models can be practically applied to accurate vehicle designs. Integration efforts between traditional simulation and machine learning-based approaches have also been the focus of many recent studies. This article discusses how machine learning can address challenges in the aerodynamic design optimization of high-performance vehicles. By combining knowledge from previous studies and experimental results, this article provides insight into the opportunities and limitations of this technology while also providing directions for future research.

2. Machine Learning-Based Optimization Methodology

Aerodynamic Modeling

Optimization of a high-performance vehicle's aerodynamic design begins with identifying the main parameters that contribute to aerodynamic performance. These key parameters include the drag coefficient (Cd), the lift coefficient (Cl), and downforce. The drag coefficient measures the air resistance generated by the vehicle geometry, with lower values indicating higher aerodynamic efficiency. On the other hand, the lift coefficient indicates the lift force acting on the vehicle, which must be controlled to prevent the vehicle from losing stability at high speeds. Downforce is the downward force required to increase the traction of the wheels on the road, which is crucial in sports and racing vehicles. The relationship between these parameters is complex and interdependent, requiring a systematic approach to the optimization process. To obtain accurate data, experimental and simulation studies are used to analyze the interaction between the geometric design of the vehicle and the airflow. Computational Fluid Dynamics (CFD) is a standard tool to simulate car airflow patterns. CFD allows a detailed analysis of the pressure distribution, vorticity, and airflow velocity that affect aerodynamic performance. The CFD simulation results are the basis for building a dataset representing the relationship between vehicle design geometry and aerodynamic parameters. For example, simulations of variations in the shape of a spoiler, diffuser, or main body produce a large dataset that includes the effect of each design parameter on the values of Cd, Cl, and downforce.

Once the dataset is acquired, the next step is to integrate machine learning methods to build a predictive model. The model is trained using a dataset of CFD simulation results to learn the non-linear relationship between design parameters and aerodynamic performance. Algorithms such as neural networks, Gaussian process regression, or support vector machines are often used in this context because they capture complex patterns. The model is then used to predict the aerodynamic parameter values of a new design, allowing for faster design exploration without the need for CFD simulations for each iteration. The final step in this methodology is an iteration-based validation and optimization process. The trained machine learning model is used to identify the optimal design based on specific criteria, such as drag minimization or downforce maximization. The resulting design is then validated through additional CFD simulations or physical testing to ensure the accuracy of the model's predictions. This process allows for a more efficient design iteration cycle, reducing the time and cost of developing a high-performance vehicle. The combination of CFD simulations and machine learning creates a hybrid approach that optimizes aerodynamic performance with higher efficiency than traditional methods.

Machine Learning Integration

The machine learning-based optimization process for vehicle aerodynamic design begins with collecting comprehensive datasets from simulation and experimental results. These datasets include geometric data of vehicle design, such as spoiler dimensions, diffuser shapes, body contours, and aerodynamic parameters such as drag coefficient (Cd), lift coefficient (Cl), and downforce. Combining Computational Fluid Dynamics (CFD) simulations with data from wind tunnel testing can produce a rich and representative dataset (Arenzana, López-Lopera, Mouton, Bartoli, & Lefebvre, 2021; bin Ismail & Nguyen, 2023; Khalisha, Caisarina, & Fakhrana, 2025). A large and high-quality dataset is essential for effectively training a machine learning model because the algorithm's performance is highly dependent on the completeness and accuracy of the data. Machine learning algorithms such as neural networks, random forests, and Gaussian process regression have been widely used to process and predict the complex relationship between design geometry and aerodynamic performance. Gaussian process regression can provide accurate predictions for aerodynamic parameters with a small dataset, as it uses a probabilistic-based approach that accommodates uncertainty in the data (Leco, 2020; Teymouri, 2023). Meanwhile, artificial neural networks (ANN) were used to capture complex non-linear relationships in vehicle design, enabling highly accurate predictions for a wide range of design geometries (Kong, Abdullah, Schramm, Omar, & Haris, 2019).

Supervised learning approaches play a key role in this method. In aerodynamic optimization, supervised learning models are trained with input-output pairs, where the inputs are design parameters (such as spoiler pitch angle or diffuser length), and the outputs are aerodynamic performance (such as Cd, Cl, and downforce). The model learns the relationship patterns between inputs and outputs from the training dataset. Once trained, the model can be used to predict new designs' performance without running CFD simulations for each iteration. For example, ANN was used to predict the Cd value of a new vehicle design with an accuracy of up to 95% (Alzyout & Alsmirat, 2020; Gani et al., 2025). After training and validating the model, it explored optimal designs by combining algorithm-based optimization methods. For example, Bayesian optimization-based approaches have been used to find the best design by minimizing drag or maximizing downforce. In another study, Random Forest was used as a predictive model and integrated with an evolutionary algorithm to generate significantly more efficient vehicle designs (Koc, Ekmekcioğlu, & Gurgun, 2021). This approach saves substantial time and costs compared to pure simulation-based iterative methods while still producing optimal and real-world applicable design solutions.

3. Implementation and Case Studies

As a case study, aerodynamic design optimization in vehicles is often the main research focus due to the high demand for aerodynamic efficiency and stability. The geometry of the front wing and diffuser significantly affects the drag coefficient (Cd) and downforce, directly impacting the vehicle's speed and traction on the track (Ahlfeld, Ciampoli, Pietropaoli, Pepper, & Montomoli, 2019). Using Computational Fluid Dynamics (CFD) simulations, the researchers generated a dataset that included various design variations on the front wing and diffuser. This dataset was then used to train a neural network model that predicts Cd and downforce with high accuracy. This model allows the team to quickly evaluate new designs without running full simulations for each iteration, thus saving significant development time. In its implementation, the Gaussian process regression model was integrated with evolutionary algorithm-based optimization to maximize the aerodynamic performance of a sports car (Erdiwansyah, Mahidin, et al., 2023; Peixoto, 2021). The study focused on variations in the design of the main body and rear spoiler. As a result, this approach produced a design that reduced drag by 8% and increased downforce by 12% compared to the initial design. Validation through CFD simulations and physical testing in a wind tunnel shows that the machine learning model predictions are in good agreement with the experimental results, confirming the reliability of this approach. This case study demonstrates the efficiency of the optimization process and opens opportunities for faster and more affordable design innovations in other high-performance vehicles.

In the aerodynamic design optimization process, parameters such as spoiler dimensions, airflow around the body, and vehicle body contour are the focus. Variations in spoiler dimensions significantly impact downforce and drag coefficient, as demonstrated in research by (Valencia & Lepin, 2024). On the other hand, the importance of vehicle body contour in directing airflow to be more laminated, reducing drag without sacrificing stability (James, 2020). A dataset covering these design variations was generated through CFD simulations and wind tunnel experiments, which were then used to train a machine-learning model. This approach allows for a broader exploration of design parameters by considering the effects of interactions between aerodynamic components.

Machine learning has shown much higher efficiency than traditional simulations in evaluating aerodynamic performance. The Gaussian process regression model can predict aerodynamic parameters with much faster computation time than CFD simulations, achieving a prediction accuracy rate of more than 90%, as found by (Kumar, Patil, Kovacevic, & Ponnusami, 2024; Morita et al., 2022). Meanwhile, neural networks were used to evaluate the design of spoilers and vehicle bodies, reducing the analysis time from several hours in CFD simulations to seconds (Hsiao, Lin, Lo, & Ko, 2016). Although CFD simulations provide very detailed results, this method requires significant computational resources, while machine learning models allow for faster design development, especially in the early iteration phase.

A critical step in implementing machine learning is validating model predictions with simulation results or physical experiments. Validating a neural network model against wind tunnel test results on a spoiler design yielded an average error of less than 5%, proving the model's reliability (Stephan, Heyen, Stumpf, Ruhland, & Breitsamter, 2024). A similar validation was conducted for a sports car body design, where machine learning predictions highly correlated with CFD simulation results and physical experiments (Roznowicz, Stabile, Demo, Fransos, & Rozza, 2024). However, model accuracy is highly dependent on the quality and representativeness of the training dataset (Tang, Zhan, & Yang, 2024). Therefore, a hybrid approach that combines traditional simulation with machine learning is often used to ensure higher accuracy in aerodynamic design validation.

Implementing machine learning-based optimization results show significant improvements in the aerodynamic design performance of high-performance vehicles compared to traditional methods. Optimizing spoiler and diffuser designs using the Gaussian process regression model reduced the drag coefficient (Cd) by 10% and increased downforce by 15% compared to the initial design (Peixoto, 2021). The study also revealed that the machine learning approach reduced the design iteration time from several weeks (with conventional CFD simulation methods) to only a few days. This success is due to the model's ability to accurately predict aerodynamic parameters, allowing for broader design exploration without requiring physical simulations for each design variation. In a similar study, neural networks integrated with evolutionary algorithms were used to optimize the primary body geometry of a sports vehicle (Rostamzadeh-Renani, Baghoolizadeh, Rostamzadeh-Renani, Toghraie, & Ahmadi, 2022). The optimization results showed an increase in aerodynamic efficiency with an 8% reduction in drag and vehicle stability at high speeds through a 12% increase in downforce. Validation of the optimization results through CFD simulations and wind tunnel testing showed a high correlation between model predictions and physical results, confirming the accuracy of the machine learning method in this context. Compared to the study, which relies solely on CFD simulations for design iterations, the machine learning-based approach demonstrates greater efficiency in terms of time and resources while achieving more optimal aerodynamic performance (Le Clainche et al., 2023; Panchigar et al., 2022).

4. Result & Discussion

The results of the implementation of aerodynamic design optimization show that machine learning-based methods are significantly more efficient than traditional methods such as Computational Fluid Dynamics (CFD) simulations. Machine learning allows for predicting aerodynamic parameters with much faster computational time without sacrificing accuracy. For example, design iteration time can be reduced by up to 80% using the Gaussian process regression model compared to CFD simulations (Morita et al., 2022). In addition, the prediction accuracy of the machine learning model shows a small margin of error, averaging less than 5%, as shown in the study by (Soares & Gray, 2019). This efficiency makes the machine learning approach a superior solution, especially in the early design iteration stage, which requires rapid evaluation of many design variations. The comparative data of time efficiency and accuracy between traditional and machine learning methods are presented in **Table 1**.

Table 1. Comparison results of time efficiency and accuracy between traditional and machine learning methods

Method	Average Iteration Time	Margin Error	Advantages
CFD Simulation (Traditional)	24-48 hours/design	<2%	High accuracy, detailed analysis
Machine Learning	10-30 minutes/design	<5%	Faster time, save resources

Machine learning provides significant advantages in the aerodynamic design iteration process, especially in terms of time efficiency, flexibility of design exploration, and reduction of development costs. One of the main advantages is the ability of machine learning to quickly predict design performance based on a trained model without the need for physical simulation or CFD for each iteration. For example, a neural network-based approach allows the exploration of up to 500 designs simultaneously while completing only 10 iterations using traditional methods (L. Wang & Liu, 2021). In addition, integrating optimization algorithms such as Bayesian optimization or evolutionary algorithms with machine learning allows for automatic search of optimal designs, expanding the design space that can be evaluated. This reduces the reliance on time-consuming and costly manual iterations. Comparative data on the advantages of machine learning in the design iteration process compared to traditional methods are presented in **Table 2**. Machine learning-based approaches enable the development of more efficient, affordable and competitive designs, especially in high-performance vehicles that require continuous optimization.

Table 2. The results of the comparison of machine learning benefits in the iteration process

Aspects	Traditional Methods	Machine Learning	Advantages of Machine Learning
Iteration Time	24-48 hours/design	10-30 minutes/design	Save up to 80% of your time
Number of Iterations	10-20 iterations in 1 week	100-500 iterations in 1 week	Exploration of wider designs
Development Cost	High (CFD/wind tunnel costs)	Low (less computational costs)	Cost savings of up to 50%
Prediction Accuracy	<2% margin error	<5% margin error	Prediction performance is close to the CFD method

Although machine learning offers significant efficiency in aerodynamic design optimization, some limitations must be considered. One of the main obstacles is the quality and representativeness of the dataset. Datasets that do not cover a wide variety of designs can cause the model to overfit, reducing its predictive ability for new designs that have not been analyzed (Cawley & Talbot, 2010). In addition, machine learning prediction results still require validation using CFD simulations or physical testing to ensure accuracy in real-world conditions. Machine learning models sometimes have difficulty handling very complex design geometries, as they require much larger training datasets (Regenwetter, Nobari, &

Ahmed, 2022). Therefore, further development is needed in integrating hybrid methods that combine the advantages of CFD simulations and machine learning and the exploration of more adaptive algorithms, such as physics-informed neural networks, to improve the reliability of predictions. Data related to limitations and areas of development in machine learning-based optimization are presented in **Table 3**.

Table 3. Limitations and areas of development in machine learning-based optimization

Aspects	Current Limitations	Development Areas
Dataset Quality	Limited datasets can lead to overfitting	Collecting more representative and richer datasets
Design Validation	Still need CFD validation or physical testing	Development of a hybrid ML-CFD algorithm
Complex Geometry	Difficulty in handling very complex design geometries	More adaptive algorithms, such as physics-informed ML
Model Generality	Model is challenging to adapt to new design scenarios	Training with a more expansive multi-source dataset
Initial Computational Cost	Model training requires intensive computation	Use of cloud computing or lightweight algorithms

5. Advantages and Impacts of Technology

Machine learning has great potential to drive innovation in future vehicle design by providing unprecedented efficiency and flexibility. In autonomous and electric vehicles, machine learning's ability to rapidly optimize aerodynamic design is particularly relevant to improving energy efficiency and cruising range. Neural network-based algorithms can predict aerodynamic performance and generate designs that directly adapt to minimal energy requirements, which is critical for electric vehicles (Urooj & Nasir, 2024). Furthermore, generative algorithms such as generative adversarial networks (GANs) have begun to generate innovative geometries that are aerodynamically efficient, enabling design explorations that would be impossible with traditional approaches. As a result, machine learning technologies accelerate the development process and enable better integration with emerging technologies, such as digital twin-based simulations or intelligent vehicles that can adapt to environmental conditions. Reinforcement learning-based approaches can be used to develop vehicle designs that dynamically adapt to speed, road conditions, and the environment to maximize aerodynamic efficiency (Alenezi, Erdiwansyah, Mamat, Norkhizan, & Najafi, 2020; Du et al., 2022). This opens a huge opportunity to create more energy-efficient vehicles responsive to user needs and operating conditions. With continued advancements, machine learning has the potential to become the backbone of future vehicle design innovation, combining speed, accuracy and creativity to meet the demands of an increasingly competitive industry. **Table 4** summarizes the potential of machine learning to drive future vehicle design innovation and its technological impact.

Table 4. The potential of machine learning and innovation in future vehicle design.

Aspects	The Potential of Machine Learning	Impact of Technology
Design Process Efficiency	Rapidly predict aerodynamic parameters accurately (Zhang et al., 2021).	Accelerate design iterations by up to 80%, reducing development costs.
Design Geometry Innovation	Generative algorithms like GANs to generate innovative new designs.	Opening previously impossible design exploration spaces
Adaptation to Electric Vehicles.	Design optimization for energy efficiency in electric vehicles (Zhang et al., 2021).	Increasing the cruising range of electric vehicles by reducing drag by up to 10%
Integration with Advanced Technologies.	Reinforcement learning adaptive design to	Vehicles that are responsive to changes in speed and road conditions

	environmental conditions (Li et al., 2022).	
Digital Twin Capabilities	Use of real-time data for continuous design simulation and optimization.	Dynamic vehicle performance improvement throughout its life cycle
Energy Efficiency Improvement.	Design optimization to minimize air resistance and improve stability.	More energy-efficient and environmentally friendly vehicles

Machine learning technology has great relevance for electric vehicles, autonomous vehicles, and other future transportation platforms, as it can address the unique design challenges of these types of vehicles. In the context of electric vehicles, reducing aerodynamic drag is a top priority to improve energy efficiency and cruising range. A 10% reduction in drag coefficient through machine learning-based design optimization can increase the cruising range of electric vehicles by up to 15%, as demonstrated by (Y. Zhang et al., 2021). In addition, machine learning allows the exploration of lighter and more efficient vehicle body designs, which are essential to offset the considerable weight of the battery. Algorithms based on neural networks and Gaussian process regression have proven to be very effective in predicting the aerodynamic design performance of electric vehicles with high accuracy. In autonomous vehicles, the relevance of machine learning extends to aerodynamic optimization tailored to complex operational dynamics. Autonomous vehicles often operate at varying speeds, environmental conditions, and traffic patterns, requiring adaptive designs. Using reinforcement learning algorithms allows the development of designs that can dynamically adapt to operational conditions, such as high speeds on highways or efficiency at low speeds in urban areas, as demonstrated by (Gregurić, Kušić, & Ivanjko, 2022). In addition, this technology is also relevant for other vehicles, such as drones and heavy-duty vehicles, where reducing air resistance can significantly improve operational efficiency. With its ability to accelerate design iterations, reduce costs, and generate adaptive solutions, machine learning is a key technology driving efficiency, performance, and innovation in the future vehicle industry. **Table 5** summaries the relevance and impact of machine learning technologies on electric, autonomous, and other vehicles.

Table 5. The relevance and impact of machine learning technology on electric, autonomous and other vehicles.

Vehicles	The Relevance of Machine Learning Technology.	The Impact of Technology
Electric Vehicle.	Design optimization to reduce drag and improve battery efficiency.	The cruising range increased by 15%, resulting in energy savings.
Autonomous Vehicles.	Adaptive design for various operating conditions (reinforcement learning).	Aerodynamic efficiency is responsive to speed and environmental conditions
Uncrewed Aerial Vehicles (Drones).	Shape optimization for stability and energy efficiency.	Increased flight time and battery life.
Heavy Vehicles.	Drag reduction to reduce fuel consumption.	Fuel savings of up to 10%, increased transport efficiency

6. Conclusion

Machine learning-based aerodynamic design optimization has significantly improved the time, cost, and performance efficiency of high-performance vehicle designs. Compared to traditional methods such as CFD simulation, machine learning approaches can reduce design iteration time by up to 80, where analysis time drops from 24-48 hours/design to only 10-30 minutes/design. In addition, predictive models such as Gaussian process regression and neural networks show an average error margin of less than 5% in predicting aerodynamic parameters, approaching the accuracy of traditional simulations at a much lower computational cost. In the context of future vehicles, this technology has a real impact on electric and autonomous vehicles. Studies have shown that a 10% reduction in drag coefficient can increase the cruising range of electric cars by up to 15%. At the same time, machine learning-based design optimization allows the exploration of up to 500 design variations in the same time as 10 design iterations using traditional methods. In addition, the relevance of machine learning for autonomous vehicles is seen in the ability of reinforcement learning algorithms to generate adaptive designs that can adjust to varying operating conditions, such as speed and road environment, which improves overall efficiency. Another advantage is the potential for broader design innovation. Approaches such as generative adversarial networks (GANs) have enabled the development of more efficient design geometries, opening previously impossible design exploration opportunities. With these benefits, machine learning-based optimization supports the development of more efficient, energy-efficient and responsive vehicles for future needs. It shortens the design cycle at a more affordable cost. This technology is essential for developing electric cars, autonomous vehicles and other transportation platforms.

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