

Linear Interpolation Based Parametric Model of Electric Vehicle for Tractive Force Analysis

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Abstract

Electric vehicles (EVs) are designed with accurate and computationally efficient models for vehicle dynamics assessment, and for estimating the tractive power demand and real-time controller design. For the analysis of total tractive force and power requirement of an electric vehicle under different operating conditions, this study proposes a linear interpolation-based parametric model. The developed model contains the key resistive forces such as rolling resistance, aerodynamic drag, grading resistance, and acceleration resistance from the basic vehicle dynamic equations. The influence of the vehicle mass, road gradient, and aerodynamic drag coefficient on both passenger cars and heavy electric trucks was examined in a three-dimensional parametric study in MATLAB. The vehicles span a range of sizes from 800 kg to 1500 kg for a passenger car and 2000 kg to 3500 kg for a truck, and road gradients varied from 0° to 10° and drag coefficients from 0.19-0.4. The MATLAB interp1 function was used to predict intermediate values of tractive power and to minimize the repetitive computer calculations. Road grade and vehicle mass were shown to cause a marked change in the demand for tractive power at low and high speeds in the simulation tests. Passenger cars had a traction demand rising from about 0.4 kW at low speed and flat roads to almost 8 kW at high speed on slope roads, with heavy trucks having a demand of up to 16 kW. Aerodynamic drag had little effect at lower speeds, but at speeds in the vicinity of 100 km/h, it was dominant. Extensive real-time validation with ADVISOR vehicle data showed good agreement between estimated and model-based tractive forces; a mean prediction error of about 160 N and a maximum deviation of 347 N. The prediction errors of the proposed model were found to be less than 5%, which proves the model is suitable for fast EV performance estimation, sensitivity analysis, and real-time control applications.

Keywords: Aerodynamic Drag, Grading Resistance, Interpolation, Parametric Model, Tractive Force, Vehicle Dynamics.

Introduction

The transportation sector constitutes the largest consumer of energy and remains heavily reliant on finite petroleum resources. Escalating fuel prices and the rapid depletion of global oil reserves have intensified concerns regarding long-term energy security. With the world population projected to rise from approximately 6 billion to nearly 10 billion by 2050, the associated increase in vehicle usage is expected to further aggravate environmental pollution. These challenges underscore the urgent need for cleaner, more efficient, and sustainable transportation alternatives. In this context, electric vehicles have gained significant attention as a means to reduce the transportation sector's dependence on conventional oil-based fuels. Internal combustion engines represent one of the major contributors to global warming. In addition, the continual rise in fuel prices driven by the depletion of fossil resources has accelerated the shift toward electric vehicles. Consequently, developing an efficient framework for EV analysis and design has become essential. EV design necessitates the integration of electrical and mechanical subsystems, and the associated development and manufacturing processes are often time-intensive and cost-sensitive. To streamline these processes, the automotive sector extensively employs modeling and simulation tools for evaluating vehicle performance. Recent studies have emphasized the need for computationally efficient and accurate electric vehicle models for performance evaluation and real-time applications (Chen et al., 2021; Arévalo et al., 2024). However, increased model complexity typically leads to longer computational times, limiting suitability for real-time applications. Therefore, achieving reliable simulation outputs requires precise modeling of the vehicle's kinematic and dynamic characteristics. Advanced modeling approaches, including physics-based, parametric, and data-driven techniques, have been explored to balance accuracy and computational efficiency (Cao et al., 2016; Gosea et al., 2024).

Heavy trucks and passenger cars have different dynamics to parameter variation (Zhu et al., 2024). The goal is to have accurate modeling of different types of vehicles, which could be executed in real-time in existing tools such as Simulation of Urban Mobility (SUMO) Xia et al., (2017) or MATLAB/Simulink. The paper focuses on the modeling of EV based on vehicle dynamics to analyze the total tractive force and to predict the performance for different drag coefficients, road angles, and terminal velocity. The tractive force necessary for vehicle propulsion, along with the parameters influencing overall tractive power demand, can be evaluated through simulation. Fundamental understanding of vehicle dynamics is crucial during the power-train design stage, as it determines the load that the propulsion system must manage under various driving conditions. Vehicle design encompasses both system-level and component-level considerations. System-level design focuses on vehicle performance attributes such as acceleration capability, driving range, and propulsion system rating. In contrast, component-level design is multidisciplinary, involving the selection and rating of elements such as the motor or internal combustion engine, energy source, power converters, and propulsion control systems (Wang et al., 2015). Tractive effort refers to the propulsive force delivered to the road surface through the drive wheels. A vehicle accelerates when the total tractive force exceeds the resistive forces acting against motion, and it decelerates when the resistive forces dominate. Steady-state operation requires the tractive force to be equal to the total resistive force (El Baghdadi et al., 2013).

The motion of a vehicle can be fully described by examining the forces acting on it along its direction of travel. The tractive force generated by the power plant is transmitted to the drive wheels through the transmission system and final drive. Fundamental vehicle design relies on basic physical principles, particularly Newton's second law of motion. To evaluate vehicle performance, a three-dimensional parametric model is employed. However, statistical models often exhibit limited generalization capability beyond their training domain. Models that vary smoothly near boundary regions tend to provide more reliable predictions over a broader range of operating conditions than those with rapidly changing boundary behavior (Gonçalves et al., 2023). Linear interpolation is commonly used to estimate vehicle performance for intermediate parameter values.

Significance and Contributions

Although detailed vehicle models are widely available, many of them involve high computational complexity, which restricts their use in real-time simulation and control applications. To overcome this limitation, a computationally efficient parametric modelling approach based on linear interpolation is proposed.

The key contributions of this work are summarized as follows:

1. Formulation of a physics-based model to estimate tractive force by considering dominant resistive forces.
2. Development of a three-dimensional parametric framework for evaluating EV performance.
3. Application of linear interpolation to estimate intermediate values, thereby reducing computational burden.
4. Investigation of the influence of key parameters on tractive power through sensitivity analysis.

5. Verification of the proposed model by comparing interpolated results with analytical calculations and evaluating the associated error.

The remainder of this paper is organized as follows: Section 2 demonstrates a literature review, and Section 3 describes the vehicle dynamics. Section 4 presents the proposed parametric modeling approach. Section 5 discusses simulation results, and Section 6 presents sensitivity analysis of parameters. Section 7 deals with real-time data validation, and Section 8 concludes the paper.

Literature Survey

Electric vehicle (EV) Modeling and tractive force have become topics of much interest due to the growing need for efficient and sustainable transportation systems. Proper vehicle dynamics modeling is vital for assessing vehicle dynamics performance, energy consumption, and the development of control schemes in real time. Recent researches have concentrated its efforts on enhancing computational efficiency without compromising the accuracy of predictions.

The present research reviewed energy consumption modeling for EVs and discussed the critical aspect of achieving a balance between model complexity and computation efficiency (Chen et al., 2021; Hwang et al., 2021). The research pointed out that simplified models based on physical principles were extremely appropriate in real-time applications because they enhanced the efficiency of computations while ensuring prediction accuracy. Likewise, this research created an energy consumption modeling framework based on road profile and vehicle dynamics, proving that the gradient of the road and dynamic characteristics of the vehicle have a significant impact on EV power consumption (Wang et al., 2015; Li et al., 2016).

The recent developments in artificial intelligence and machine learning have also impacted EV modeling studies. In this study, it has been evaluated how artificial intelligence can be used in EV energy management systems, and it has been found that intelligent prediction techniques could enhance the process of energy optimization in vehicles (Arévalo et al., 2024). It has also been shown that machine learning models can efficiently predict the energy requirements of EVs based on real-time field data (Zhu et al., 2024). Though artificial intelligence approaches are efficient predictors, they demand vast amounts of data and computational power, making them unsuitable for real-time implementation in lightweight platforms.

Many scientists have researched reduced-order and parametric models for efficient computation. This work suggested the design of a multi-timescale parametric battery model for dynamic EV simulation and showed enhanced performance in simulation with lesser computational effort (Cao et al., 2016). The paper has proposed a reduced-order modeling approach for higher-order EV systems and achieved lower computational complexity without sacrificing accuracy (Meena et al., 2024). Similarly, this paper discuss interpolation based reduced-order modeling approaches in which stability and efficiency of structured interpolation are highlighted for engineering systems (Wang et al., 2015).

Vehicle tractive force and power requirement studies have also been widely researched. The authors modeled the vehicle tractive force based on three forces: rolling resistance, aerodynamic drag, and grade resistance, and found that the weight of the vehicle and road grade have a great influence on the power requirement (Saleem et al., 2020). The authors proposed a lightweight multi-physics model for electric vehicles, and proved that aerodynamic force becomes predominant as vehicle speed increases (Ballo et al., 2022). This study analyzed forward simulation methods for EV energy analysis and concluded that simplified dynamic models can be efficient and sufficient for performance analysis of EV (Montaleza et al., 2022).

Studies about vehicle dynamics and parameter estimation were done to improve the understanding of EV performance (Geyer & Malen, 2020). Tire force sensor-based parameter estimation methods for EVs were introduced by this author Nam, (2015), while this paper studied the longitudinal dynamic models of EVs using real response data (Dominguez et al., 2020). Integrated dynamic models for EV powertrains were created in (Park et al., 2014), and the significance of accurate tractive force estimation was pointed out (Lian et al., 2015).

Though the available literature offers some good methodologies for EV modeling and energy prediction, several of them include complicated math calculations or simulation techniques that consume lots of processing time. As such, it is imperative to develop an approach that is simple and fast in its computational capability and can predict the tractive force and power demand within a reasonable amount of time. It is this challenge that has motivated us to develop a linear interpolation-based approach for analyzing the tractive force of electric vehicles.

Dynamics of Vehicle Motion

As stated by Newton's second law, the acceleration of an object is proportional to the net force applied to it. For a vehicle, multiple forces act simultaneously, and its motion is dictated by the resultant of these forces. When a vehicle begins to move, it experiences several resistive forces that oppose its motion, as shown in fig. 1. The primary resistances encountered during travel include:

- Rolling resistance
- Aerodynamic drag
- Grade (or gravitational) resistance

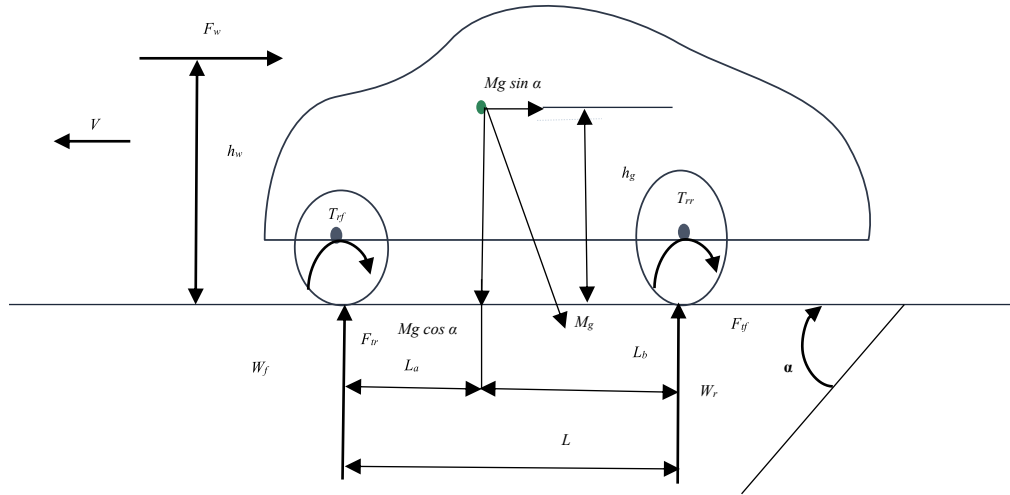


Fig. 1: Forces Exerted on a Vehicle While Ascending an Incline

Based on Newton's second law of motion, the acceleration of the vehicle can be written as equation (1) (Citaristi, 2022):

$$F_{TE} - F_R = M \frac{dV}{dt} \quad (1)$$

Where V is the speed of the vehicle (km/hr), $\sum F_t$ is Total tractive force (Nm), $\sum F_{Resistance}$ is the total Resistive force (Nm), M is the vehicle mass (kg), and δ is a mass factor used to translate the rotational inertia of rotating components into an equivalent translational mass.

Rolling Resistance Force (F_{rr})

In a rolling tire, the front portion of the contact patch experiences a loading effect, while the rear portion undergoes unloading. This imbalance in pressure results in a forward shift of the ground reaction force. The resulting moment opposes the wheel's rotation and is referred to as the rolling-resistance moment. To maintain continuous rolling, a force acting at the wheel center is required to counteract this resisting moment.

$$F_{rr} = \mu_{rr} \times M \times g \times \cos \theta \quad (2)$$

Where μ_{rr} is the co-efficient of rolling resistance, g is the gravitational constant (m/s^2), and θ is the road angle (radians). μ_{rr} varies according to the nature of the road surface are illustrated in equation (2). Typical values are approximately 0.025 for paved (tar) roads, between 0.1 and 0.35 for off-road or field conditions, and around 0.001 to 0.002 for rail surfaces (Wang et al., 2015).

Aerodynamic Drag (F_{AD})

When a vehicle moves through air at a given speed, it experiences a resistive force known as aerodynamic drag. This drag primarily arises from two components:

- a) shape drag and
- b) skin friction.

Shape drag is generated due to the vehicle's geometry. As the vehicle advances, a high-pressure region forms at its front, resisting forward motion, while a low-pressure region develops at the rear, creating a suction effect that further opposes movement. Near the vehicle surface, the air tends to move at nearly the same velocity as the vehicle, whereas air farther away remains relatively stationary. The velocity gradient between these layers causes frictional effects, which contribute to the second component of aerodynamic drag, namely skin friction (Citaristi, 2022).

The aerodynamic drag can be represented mathematically as equation (3):

$$F_{AD} = \frac{1}{2} \rho A_f C_D (V + V_w)^2 \quad (3)$$

Where ρ is the Air density in kg/m³, A_f is the Vehicle frontal area in m², C_D is the co-efficient of drag, V is the speed of the vehicle in m/s, and V_w is the velocity of wind in m/s. Typical drag-coefficient values are around 0.3 for passenger cars, approximately 0.6 for buses, 0.6–0.7 for motorcycles, and between 0.8 and 1.5 for heavy vehicles such as trains and trucks (Ballo et al., 2022).

Grading Resistance (F_g)

Whenever a vehicle is moving up or down a slope, its weight produces a component of force that is always directed in the downward direction, and it is known as the grading resistance force. Because a vehicle may operate on an incline or a decline, the grade force can either act against the tractive force or assist it, making its value positive or negative. On a flat roadway, this component becomes zero. The grade resistance can be represented as equation (4):

$$F_g = M \times g \times \sin \theta \quad (4)$$

Where M , g , and θ are as defined in equation (2).

Acceleration Resistance (F_a)

In addition to the steady-state driving resistances, the vehicle also experiences inertial forces during acceleration and braking. These forces can be determined using the following relation are shown in equation (5):

$$F_a = \left(M + \frac{J}{r_d^2} \right) \times \frac{dV}{dt} \quad (5)$$

Where J is the inertia of rotational components ($\text{kg} \times \text{m}^2$).

Therefore, total tractive effort/force (F_{TE}) that appears at the driven wheels consists of driving resistance forces as shown in equation (6):

$$F_{TE} = F_{rr} + F_{AD} + F_g + F_a \quad (6)$$

Parametric Modeling of Electric Vehicles

Vehicle development and manufacturing processes are generally both time-intensive and cost-sensitive. To effectively support these processes, appropriate modeling tools are essential for performing testing, analysis, and validation during the design phase. In this section, an accurate parametric model is simulated for trucks and passenger cars using linear interpolation. A 3-dimensional parametric model is used to analyze the impact of the variations in the vehicle mass, road angle (θ), and drag coefficients on the total tractive effort. This parametric model assists in predicting the vehicle's total tractive power requirement for any value within the given range of parameters.

Linear Interpolation

Higher-order polynomial interpolation is seldom employed in practical applications due to the phenomenon known as polynomial wiggle, where the interpolating polynomial exhibits large oscillations between data points. Consequently, most computational methods adopt spline-based techniques, which rely on piecewise interpolation. The MATLAB function `interp1(x, y, xi, 'linear')` is also based on piecewise linear interpolation (Gonçalves et al., 2023).

Given $(x_0, y_0), (x_1, y_1), \dots, (x_{n-1}, y_{n-1}), (x_n, y_n)$ Fit the linear splines to the data. This simply involves forming the consecutive data through straight lines. So, if the above data is given in ascending order, the linear splines are given by $(y_i = f(x_i))$.

Linear spline interpolation is performed by connecting consecutive data points using straight-line segments. For each interval, the interpolation function is expressed as equations (7), (8), and (9):

$$f(x) = f(x_0) + \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x - x_0), x_0 \leq x \leq x_1 \quad (7)$$

$$f(x) = f(x_1) + \frac{f(x_2) - f(x_1)}{x_2 - x_1}(x - x_1), x_1 \leq x \leq x_2 \quad (8)$$

$$f(x) = f(x_{n-1}) + \frac{f(x_n) - f(x_{n-1})}{x_n - x_{n-1}}(x - x_{n-1}), x_{n-1} \leq x \leq x_n \quad (9)$$

Using the MATLAB ‘interp’ command, the linear interpolation is carried out. The linear interpolation helps to predict the performance of the vehicle for an intermediate value of parameters for any number of samples. The obtained result is compared with the original, and the absolute error is found to be within the tolerance level. So, while designing an EV controller, there is no need to recalculate the tractive effort according to the equation, thereby effectively reducing the calculation time with the help of this parametric model. The following section deals with the simulation results and the tractive force analysis. Recent advancements in interpolation techniques highlight the importance of stable and efficient numerical methods for engineering applications (Wang et al., 2011; Meena et al., 2024).

Proposed Modeling Framework

The methodology adopted in this work is illustrated in fig. 2. The modeling process consists of the following steps:

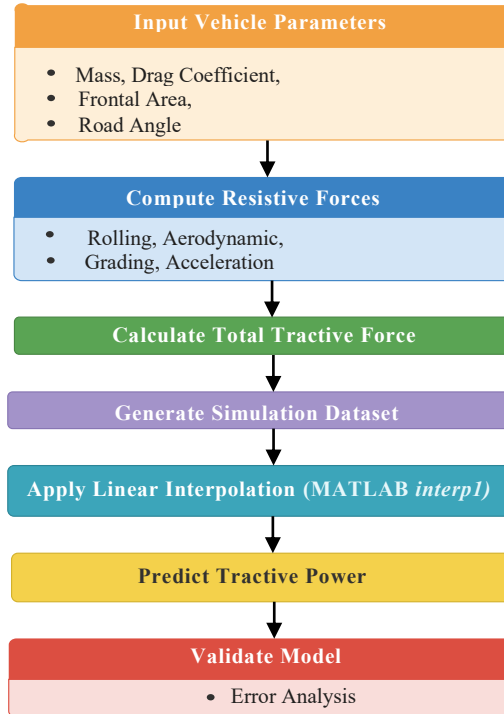


Fig. 2: Tractive Power Estimation Flowchart

The proposed methodology employs a physics-based parametric modeling approach combined with linear interpolation to estimate the tractive force and power demand of electric vehicles under varying operating conditions. Initially, the vehicle dynamic equations were formulated by considering the dominant resistive forces acting on the vehicle, namely rolling resistance, aerodynamic drag, grading resistance, and acceleration resistance. These forces were mathematically modeled using standard vehicle dynamics relations and combined to obtain the total tractive force requirement.

A simulation framework was developed in MATLAB for both passenger cars and heavy electric trucks. Key vehicle parameters such as vehicle mass, drag coefficient, frontal area, and road gradient were varied systematically within predefined ranges. For passenger cars, the mass was varied between 800–1500 kg, while for trucks it ranged from 2000–3500 kg. Similarly, road gradient was varied from 0° to 10°, and drag coefficient values ranged from 0.19–0.4 for passenger vehicles and 0.8–1.5 for trucks. Using these parameter combinations, a three-dimensional dataset of tractive power values was generated for multiple velocity conditions.

To reduce repetitive calculations and computational complexity, MATLAB's interp1 linear interpolation function was applied to estimate intermediate tractive power values for unseen parameter combinations. Approximately 10–20 equally spaced samples were considered for interpolation analysis. The interpolated results were then compared with analytically computed values, and the absolute error was evaluated to validate model accuracy and computational efficiency.

Simulation Results and Analysis

In this section, the parametric model for the passenger car and truck is simulated with the given values in table 1.

Table 1: Vehicle Design Parameters

Vehicle Design Parameters	
Coefficient of Rolling Resistance (μ_{rr})	0.01
Air Density (ρ)	1.25 kg/m ³
Vehicle Mass (M)	800-1500 kg, 2000-3500kg
Vehicle Inertial Mass (M_1)	75 kg
Vehicle Front Area (Af)	2.2 m ² , 8 m ²
Wind velocity (V_w)	0 m/sec
Drag Coefficient (C_D)	0.19-0.4 0.8-1.5
Road angle (θ)	0-10
Gravitational Force(g)	9.81
Gear ratio(G)	10
Efficiency of gear (eff _{gear})	0.9
Radius of the wheel	0.43 m

CASE-I: For a Passenger Car

As a first case, a passenger car with vehicle mass, M varying in the range of 800-1500kg, grading angle (θ) varying from 0-10 degree and drag coefficient C_D varying from 0.19 to 0.4 has been considered. Using the surface plot command in MATLAB, a three-dimensional plot is created to interpret the effects of parameters on the total power demand for 10 samples. Fig. 3 shows the effect of grading angle (θ) on total tractive power P_{TE} at a lower velocity. For a level ground where $\theta = 0$ radians, the tractive power required is very low at lower velocities. As θ increases, the maximum P_{TE} drastically reaches about 800W. As the velocity increases, the theta variation has more impact on P_{TE} which is shown in fig. 4. When the velocity is 100km/hr, the maximum P_{TE} The required power becomes 8kW with the increase in slope. Thereby significant impact of grading angle (slope) is on the total tractive power requirements.

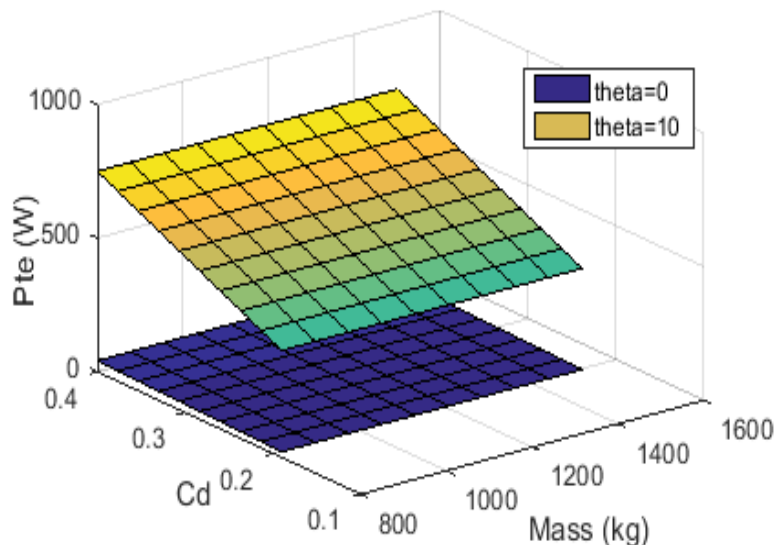


Fig. 3: Variation of Tractive Power with Road Gradient at Low Velocity

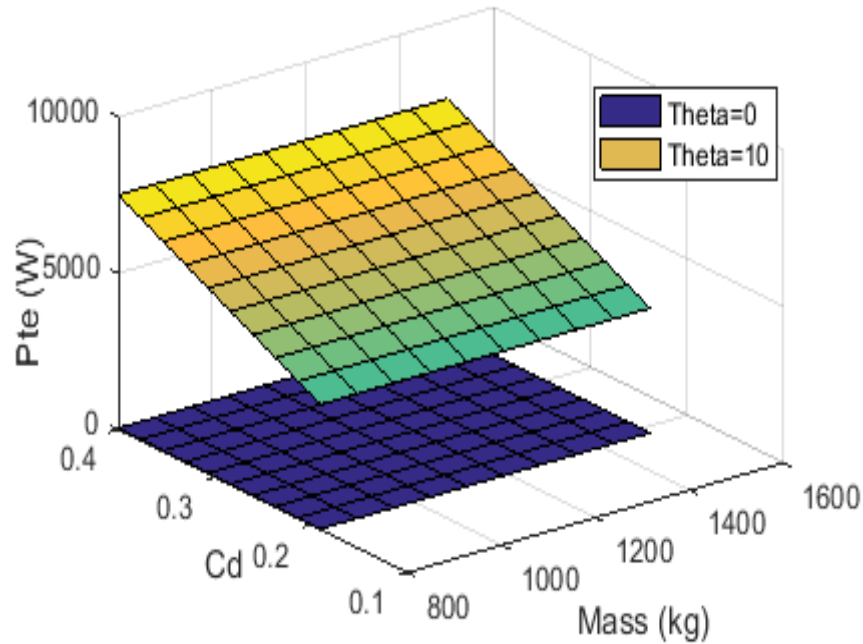


Fig. 4: Variation of Tractive Power with Road Gradient at High Velocity

Fig. 5 shows the effect of vehicle mass on P_{TE} at a lower velocity. For a mass of 800 kg, the total tractive effort required is only 400W, whereas for a mass of 1500 kg, P_{TE} is almost doubled to reach a value of around 750W. When the velocity is increased to 100 km/hr, from fig. 6 it can be inferred that mass has a great impact on P_{TE} and the maximum value reaches up to 7.5kW at higher velocity.

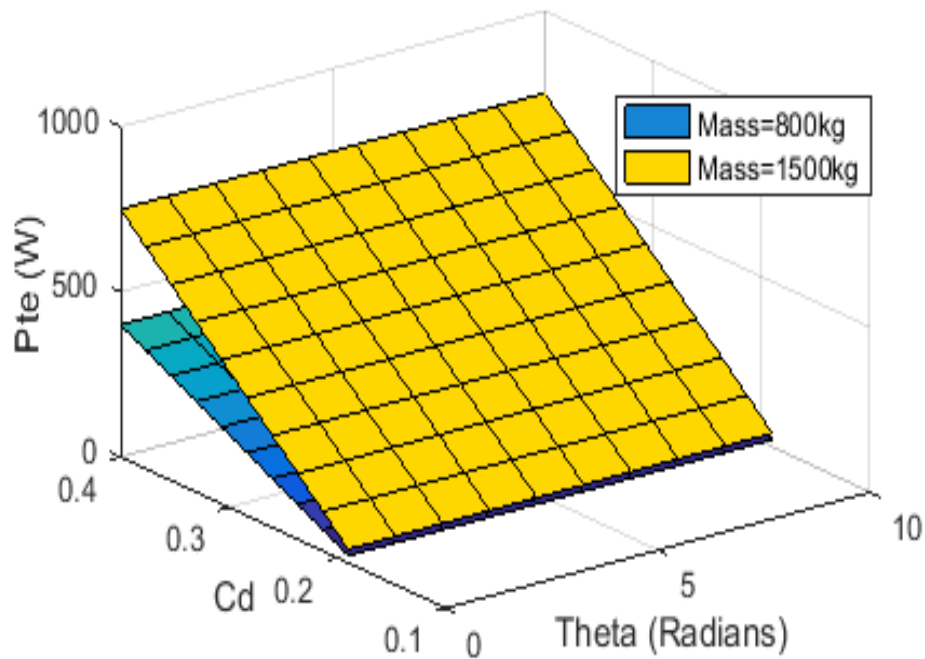


Fig. 5: Variation of Tractive Power with Vehicle Mass at Low Velocity

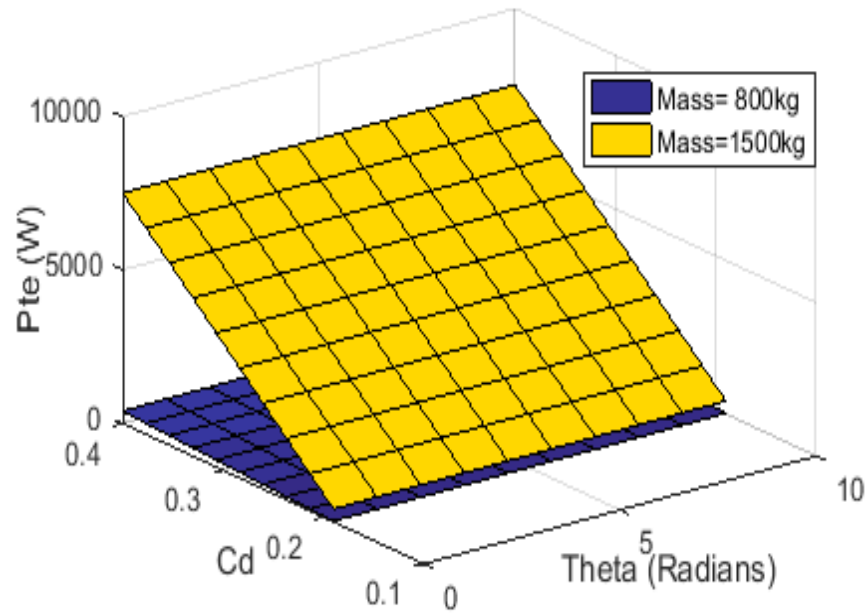


Fig. 6: Variation of Tractive Power with Vehicle Mass at High Velocity

The effect of aerodynamic drag coefficient on total tractive effort at lower velocity is shown in fig. 7. From the three-dimensional plot, it is clear that maximum P_{TE} required at both C_D values are the same and are around 750 W when the vehicle is at a lower velocity. The impact of aerodynamic drag coefficient is visible only as the vehicle acceleration increases. At 100km/hr, vehicles with higher C_D value of 0.4 requires a maximum tractive power of around 7.5kW as shown in fig. 8.

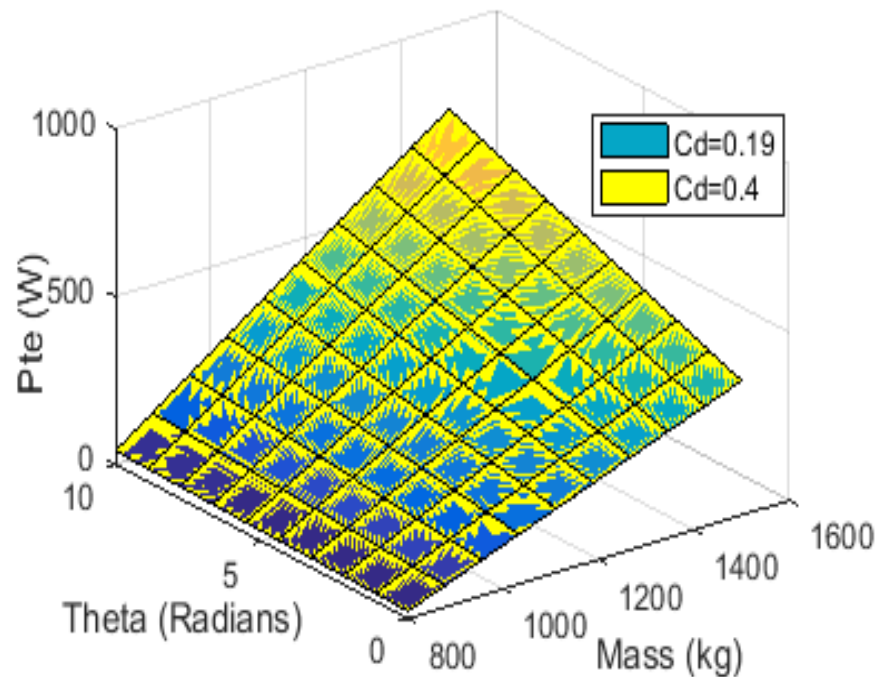


Fig. 7: Variation of Tractive Power with Drag Co-Efficient at Low Velocity

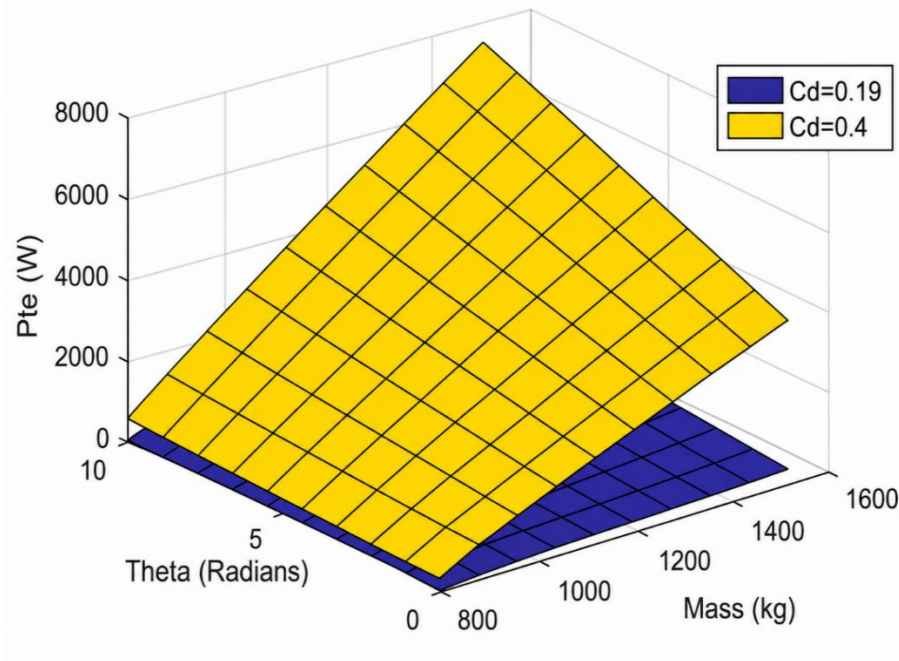


Fig. 8: Variation of Tractive Power with Drag Co-Efficient at High Velocity

The parametric model of a passenger car using the linear interpolation technique for 20 samples of C_D and mass between the ranges at lower velocity and on a level ground is shown in fig. 9.

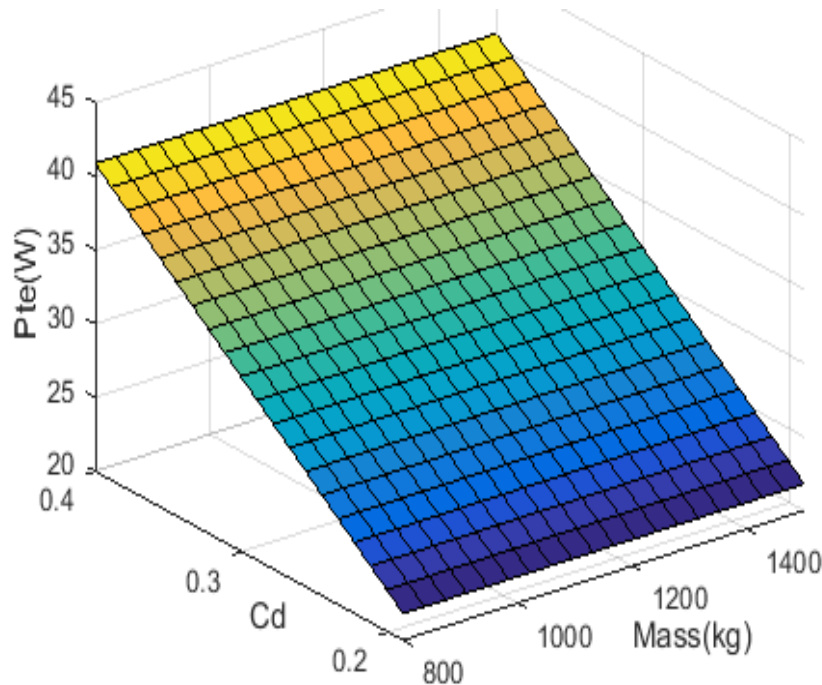


Fig. 9: Passenger Car Parametric Model for Lower Velocity and $\theta = 0$ Radians

With the parametric model of the passenger car, which is shown in fig. 8, maximum P_{TE} is found to be 41W. The obtained P_{TE} using parametric model is compared with the original equation-based value, which is obtained in fig. 3, and the absolute error is shown in fig. 10. From the error plot, it is inferred that the absolute error is within the tolerance level, and thereby the model can be used for the design and analysis of EV.

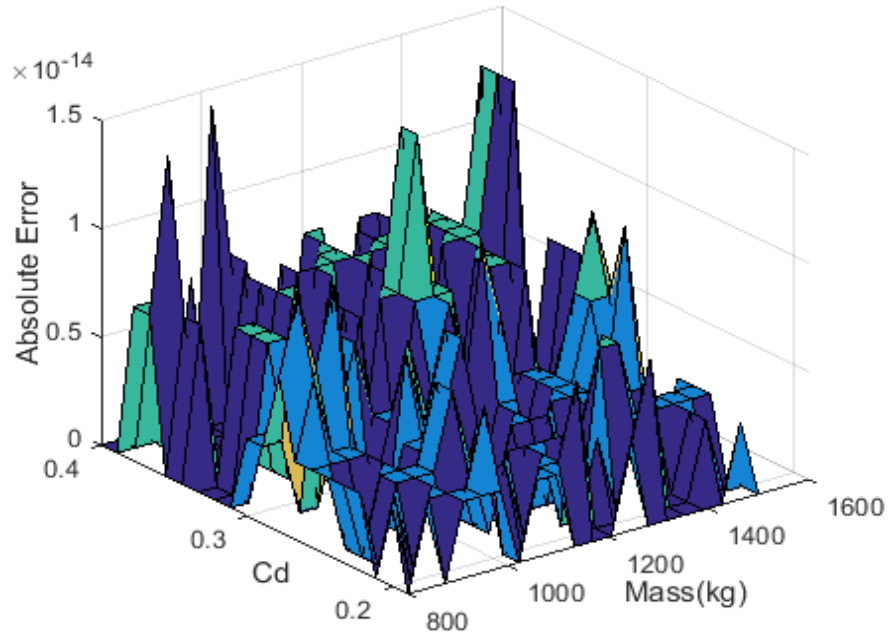


Fig. 10: Absolute Error Plot of the Original with the Parametric Model for the Passenger Car

Case II: For Heavy Vehicles Like Electric Truck

A three-dimensional model is also developed for an electric truck with a vehicle frontal area of $8m^2$. Vehicle mass is varied from 2000-3500kg, grading angle (θ) varying from 0-10 degree and drag coefficient, C_D varying from 0.8 to 1.5. In fig. 11, the effect of grading angle (θ) on total tractive power P_{TE} for 10 samples considered equally distributed in the considered range of mass and C_D . The lower velocity for a truck is shown. For a level ground where $\theta=0$, the tractive power required is very less at lower velocity. As θ increases, the maximum P_{TE} drastically reaches about 1550W. As the velocity increases, the θ variation is having more impact on Pte which is shown in fig. 12. When velocity is 100km/hr, the maximum P_{TE} required power becomes 16kW with the increase in slope. The significant impact of the grading angle (slope) is on the total tractive power requirements in the case of a truck.

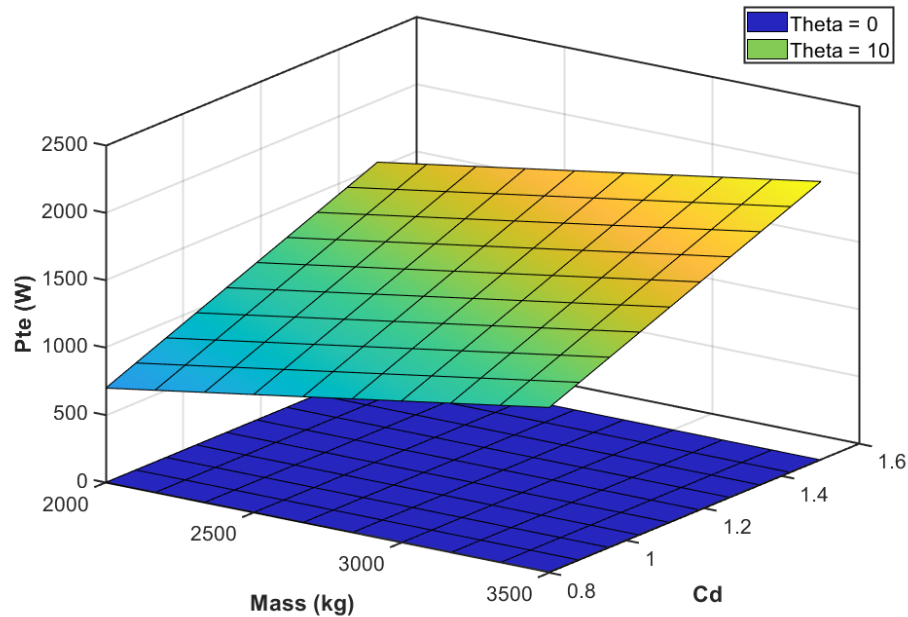


Fig. 11: Variation of Tractive Power with Road Gradient at Low Velocity for a Truck

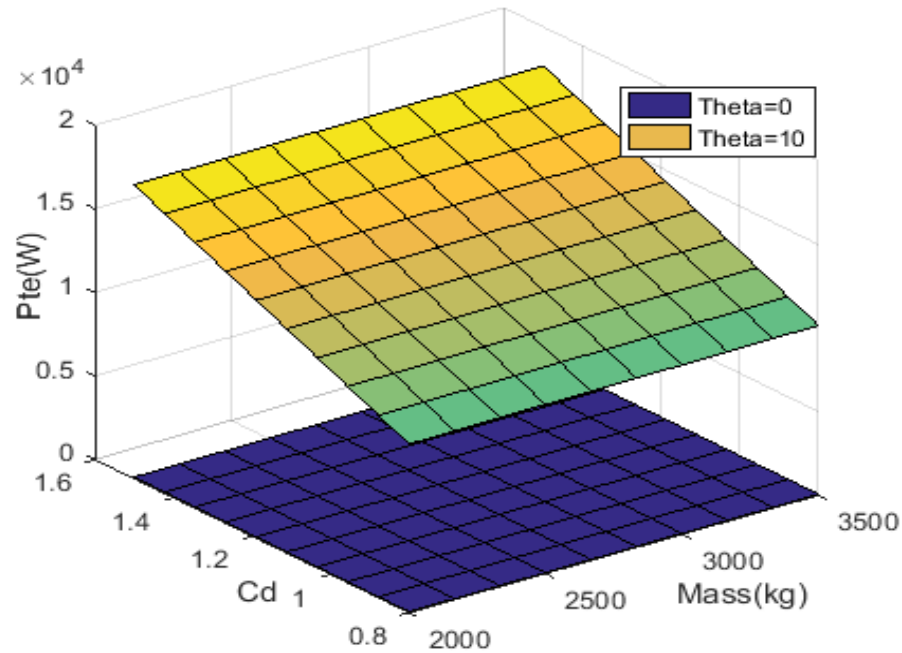


Fig. 12: Variation of Tractive Power with Road Gradient at High Velocity for a Truck

Fig. 13 shows the effect of vehicle mass on P_{TE} at a lower velocity for a truck. For a mass of 2000 kg, the total tractive effort required is only 800W, whereas for a mass of 3500 kg, P_{TE} is almost doubled to reach a value of around 1600W. When the velocity is increased to 100 km/hr, from fig. 14, it can be inferred that mass has a great impact on P_{TE} and the maximum value reaches up to 15kW at higher velocity.

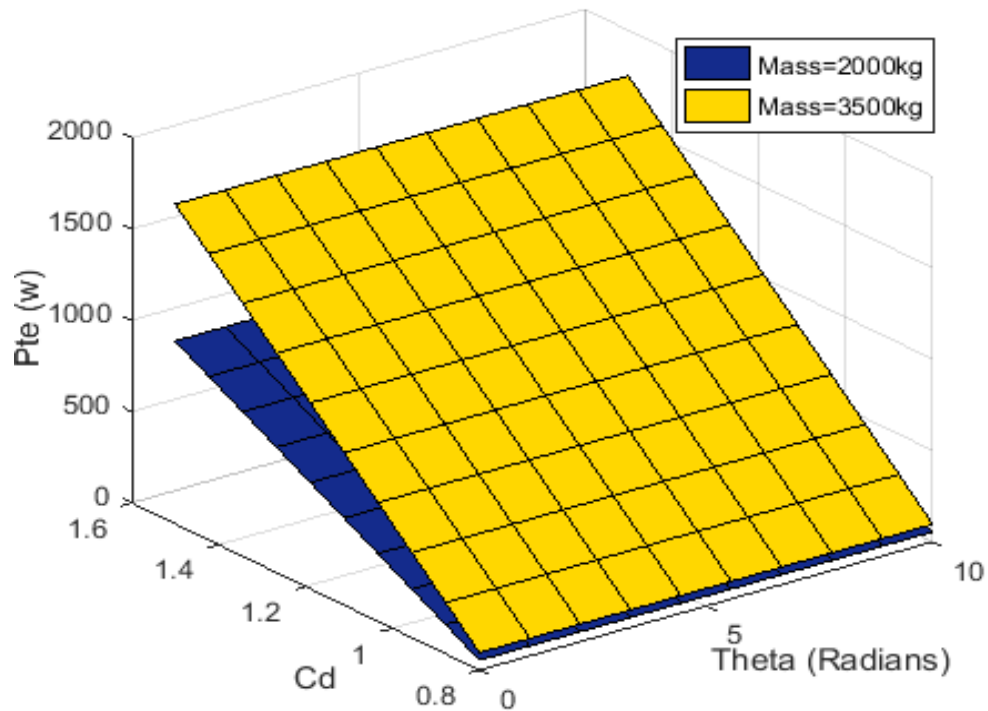


Fig. 13: Variation of Tractive Power with Vehicle Mass at Low Velocity for a Truck

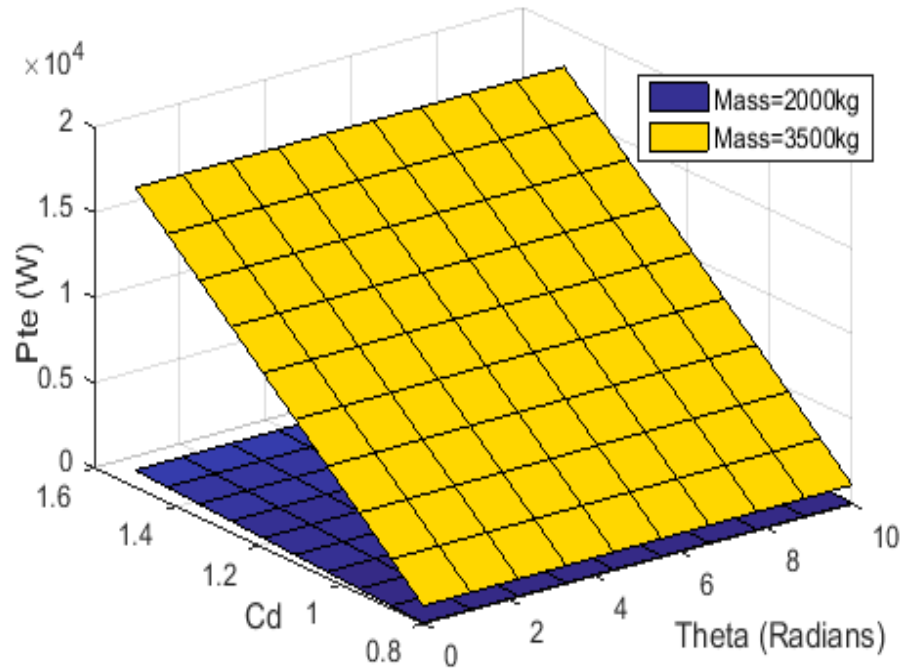


Fig. 14: Variation of Tractive Power with Vehicle Mass at High Velocity for a Truck

The effect of aerodynamic drag coefficient on total tractive effort at lower velocity is shown in fig. 15. From the three-dimensional plot, it is clear that maximum P_{TE} required at both C_D values are the same and are around 1750 W when the vehicle is at a lower velocity. The impact of aerodynamic drag coefficient is visible only as the vehicle acceleration increases. At 100km/h, a vehicle with higher C_D value of 1.5 requires a maximum tractive power of around 17kW as shown in fig. 16.

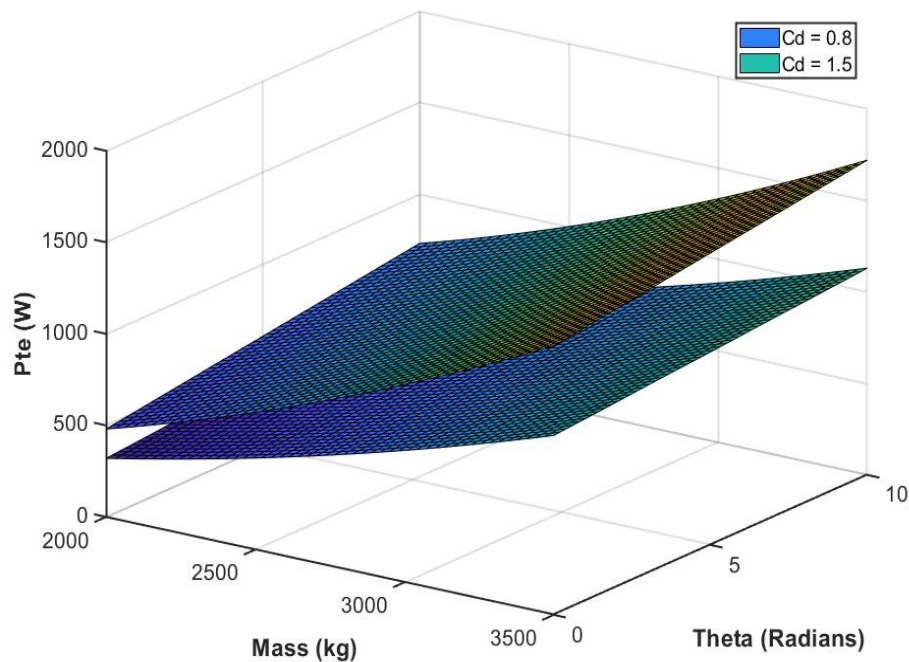


Fig. 15: Variation of Tractive Power with Drag Co-Efficient at Low Velocity for a Truck

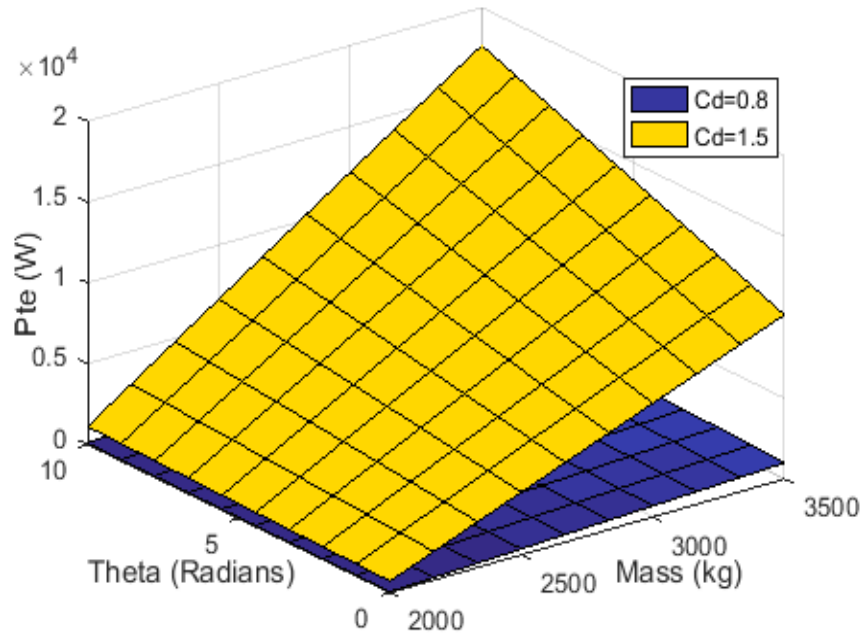


Fig. 16: Variation of Tractive Power with Drag Co-Efficient at High Velocity for a Truck

The parametric model of a truck using a linear interpolation technique for 20 equally spaced samples between the considered range of C_D and mass at a higher velocity and on level ground is shown in fig. 17. With the parametric model of the truck, which is shown in fig. 17, maximum P_{TE} is found to be almost 1050W. The obtained P_{TE} The parametric model of the truck is compared with the original equation-based value, which is obtained in fig. 12, and the absolute error is shown in fig. 18. From the error plot, it is inferred that the absolute error for a truck is within the tolerance level.

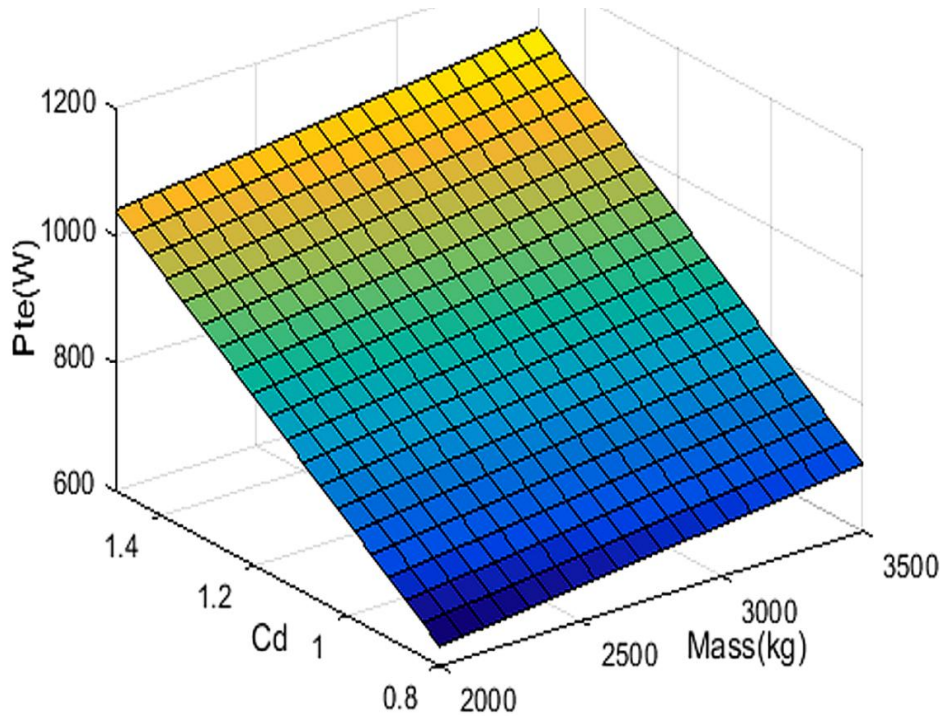


Fig. 17: Truck Parametric Model for Higher Velocity and $\theta=0$ Radians

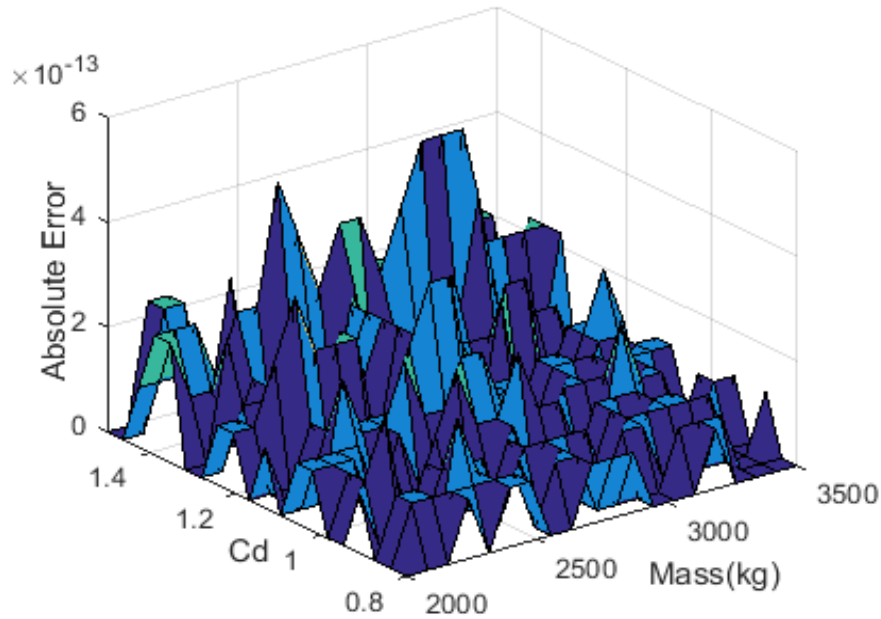


Fig. 18: Absolute Error Plot of the Original with the Parametric Model for the Truck

Sensitivity Analysis of Parameters

A sensitivity analysis is conducted to quantify the influence of key parameters on total tractive power. Each parameter is varied independently while keeping others constant.

- **Vehicle Mass:** A near-linear increase in tractive power is observed with increasing mass.
- **Road Gradient:** The most influential parameter, significantly increasing power demand even at low speeds.
- **Drag Coefficient:** Minimal impact at low speeds but dominant at higher velocities.

The sensitivity results confirm that **road gradient and mass are critical parameters**, while aerodynamic effects dominate under high-speed conditions. Sensitivity analysis of EV parameters has been widely studied to understand the impact of design variables on energy consumption and performance (Gonçalves et al., 2023). Table 2 highlights the variation in tractive power as it obtained from the graphs for different vehicle categories and operating conditions.

Table 2: Variation of Tractive Power

Parameter condition	Passenger Car (kW)	Truck (kW)
Low speed, flat road	0.4	0.8
High speed, flat road	7.5	15
Low speed, slope	0.8	1.55
High speed, slope	8	16

It is observed that tractive power increases notably with vehicle speed due to the growing influence of aerodynamic resistance, while the presence of road gradients further elevates power demand because of additional gravitational forces. In all cases, the truck exhibits significantly higher power requirements compared to the passenger car, primarily due to its greater mass and size-related resistive effects. The highest power demand occurs under combined high-speed and sloped conditions, indicating the compounded impact of dynamic and resistive forces on vehicle performance.

Real-Time Data Validation

To validate the proposed tractive force model, real-time vehicle data consisting of speed profiles obtained from ADVISOR (Advanced Vehicle Simulator) software was analyzed (Krasopoulos et al., 2017). The acceleration of the vehicle was computed from the speed data, and an estimated tractive force was obtained using Newton's second law.

The proposed model incorporates rolling resistance and aerodynamic drag in addition to acceleration forces. The model-based tractive force was computed using vehicle parameters including mass (1200 kg), drag coefficient (0.26), frontal area (2.2 m²), and rolling resistance coefficient (0.01).

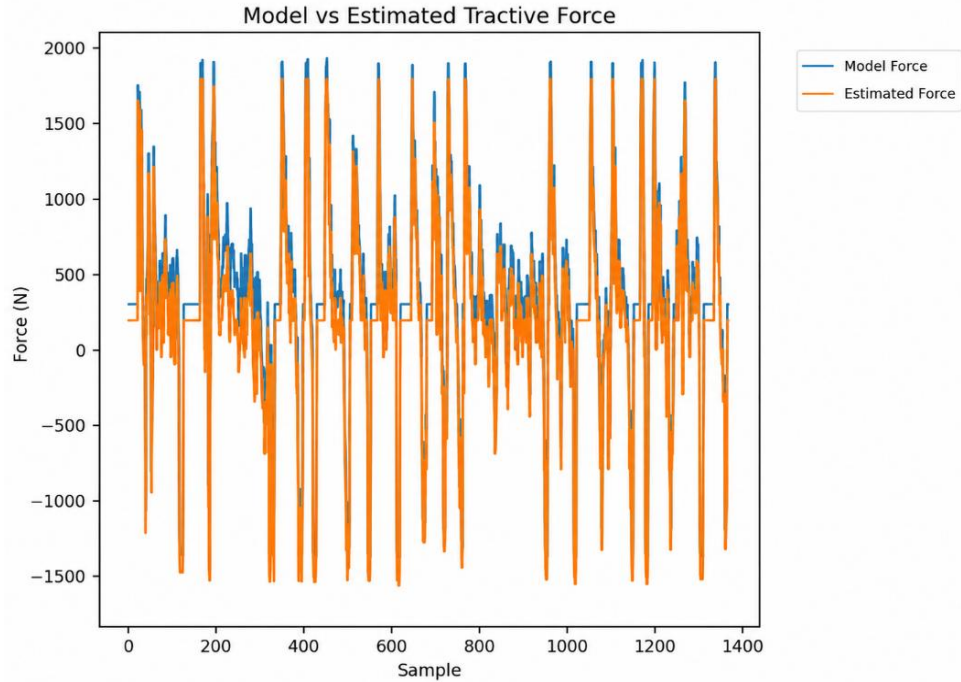


Fig. 19: Tractive Force Comparison of the Model

The comparison between estimated and model-based tractive force is shown in fig. 19 shows close agreement in dynamic trends. The maximum tractive force obtained from the model is approximately 1938 N, while the estimated force from real-time data reaches ± 1770 N.

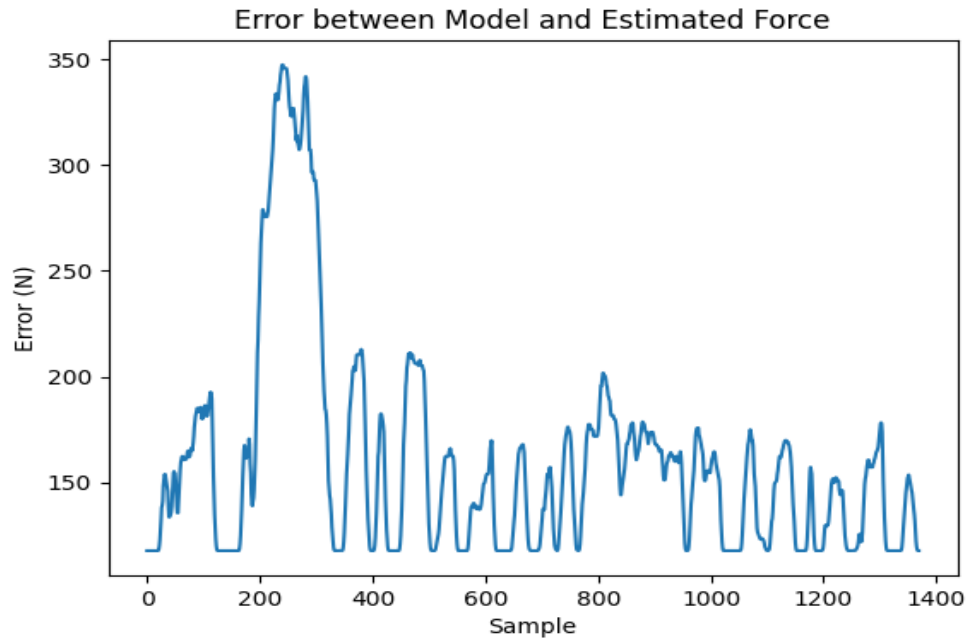


Fig. 20: Mean Error Plot of the Model

The mean error between the two is found to be approximately 160 N, as shown in fig. 20, with a maximum deviation of 347 N. This error corresponds to the resistive forces that are not captured in the acceleration-based estimation.

The results confirm that the proposed model accurately represents real-world vehicle dynamics and can be effectively used for performance prediction and controller design.

Conclusion

This work developed a parametric model based on linear interpolation in order to calculate the tractive force and power consumption of electric vehicles during different operations. In addition, the current parametric model considers some major vehicle resistances, which include rolling resistance, air drag resistance, inclining resistance, and acceleration resistance, in order to accurately estimate the tractive force and power consumption of electric vehicles. The implementation of a three-dimensional parametric model was carried out using MATLAB to determine the impact of the vehicle mass, road inclination, and aerodynamic coefficient in passenger cars and electric heavy-duty trucks. Results have shown that the road inclination and vehicle mass highly influence the tractive power requirement. The increase in the tractive power demand in the case of passenger cars is from roughly 0.4 kW for the low-speed flat-road case to nearly 8 kW for the high-speed inclined-road condition. For electric trucks, the demand for tractive power rises from about 0.8 kW to 16 kW owing to their larger mass and frontal areas. It has also been noted from the results obtained that aerodynamic drag has little effect on the tractive forces when the vehicle speed is comparatively low, but dominates the forces at higher speeds, especially close to 100 km/h. From sensitivity analyses, it has been noted that among the considered parameters, the effect of road gradient on tractive power requirement is the most important one, while that of mass and aerodynamic drag follows suit. The validity of the proposed interpolation method has been established by comparing its predictions with the results of analytical calculations as well as data collected using the ADVISOR simulation model. A maximum accuracy level of below 5% has been achieved with an average and maximum error of about 160 N and 347 N, respectively. Future work can be done to include nonlinear tire-road interaction models, regenerative braking, battery behavior analysis, and machine learning-based adaptive models. Validation through experimental work involving real-time driving scenarios, along with intelligent transportation system integration, will make the proposed framework even more useful for modern electric vehicles.

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