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# Understanding Key Dynamics of Asian Electric Vehicles

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**ABSTRACT:** The two-wheeler industry in Asia has experienced phenomenal growth over the past decades, emerging as a key segment of the region's transportation ecosystem. This sector, encompassing motorcycles, scooters, and mopeds, addresses the increasing demand for affordable, efficient, and convenient personal mobility solutions in densely populated and rapidly urbanizing areas. With countries like India, China, Indonesia, and Vietnam leading global production and consumption, Asia accounts for a significant share of the world's two-wheeler market. Technological advancements, including the shift towards electric two-wheelers and the integration of smart connectivity features, are reshaping the industry. Moreover, government policies promoting cleaner transportation and the rise of shared mobility services are further influencing market dynamics. This abstract provides a snapshot of the trends, challenges, and future prospects shaping the two-wheeler industry in Asia.

**KEYWORDS:** Electric Vehicles, Regression Analysis, Battery Capacity, Motor Power, Acceleration, Range, Pricing, Polynomial Models

## I. INTRODUCTION

Electric two-wheelers are playing an increasingly pivotal role in Asia's transition toward sustainable urban mobility. As densely populated cities across the continent seek greener transportation solutions, electric two-wheelers (E2Ws) offer a practical, scalable, and environmentally friendly alternative. While Asia has long been recognized as a leader in adopting clean transportation technologies, much of the existing literature and industry focus has centered on electric four-wheelers (cars), leaving a gap in the comprehensive analysis of E2Ws. This study seeks to bridge that gap by applying regression based state-space modeling to assess the performance and market dynamics of electric two-wheelers in Asia. Unlike their internal combustion engine (ICE) counterparts, the performance of E2Ws is determined primarily by specifications such as battery capacity (bcap), motor power (mpow), acceleration (a), range (rk), and base price (bp) parameters that directly influence market competitiveness and consumer perception but are not reflected by traditional automotive metrics like engine displacement or fuel efficiency. By exploring the complex interrelationships among bcap, mpow, a, rk, and bp, this research provides a data-driven foundation for understanding how these technical parameters collectively shape market positioning and consumer value in the Asian context. The analysis employs a suite of regression techniques—including linear, quadratic and cubic models to accurately model the nuanced dependencies among key specifications and pricing structures. These insights are crucial for manufacturers, who must optimize design and cost trade-offs; for policymakers, seeking to craft effective incentives and infrastructure support; and for consumers, navigating the evolving landscape of sustainable urban mobility. By focusing specifically on the Asian market, this study contributes actionable insights as the region continues to lead the global shift toward electric mobility.

Electric vehicles (EVs) have emerged as a transformative solution to global transportation challenges, gaining prominence due to their potential to reduce carbon emissions and dependence on fossil fuels. Research has emphasized not only the technological aspects of EVs but also their integration into infrastructure, behavioral dynamics, and sustainability frameworks. For instance, studies in New Zealand have highlighted the critical role of print media in shaping public perception and awareness around EV incentives (Broadbent et al., 2021), while demographic profiling in Spain revealed distinct consumer clusters based on EV adoption likelihood (Esteves et al., 2021). In Thailand, an acceptance model indicated that social influence and perceived benefits significantly affect EV adoption (Sithanant, 2024). From a psychological perspective, the concept of "charge point trauma" has been identified as a barrier



distinct from range anxiety, particularly in the UK, urging policymakers to enhance infrastructure reliability (Chamberlain Al Majeed, 2021).

Technological development remains a core theme in EV research, particularly in drivetrain innovation, battery performance, and vehicle control systems. Scholars have examined drivetrain configurations and thermodynamic cycles in hybrid vehicles to determine optimal powertrain arrangements (Leo'n et al., 2021; Wahid et al., 2021). Battery-related studies focus on improving state of charge estimation through ensemble learning methods (Wong, 2024) and exploring the feasibility of integrating gasoline compression ignition (GCI) engines into hybrid EVs for enhanced efficiency (WON, 2021). Other contributions include the design of driving condition collectors for real time performance analysis (Lee, 2014) and machine learning-guided power source selection strategies (Li, 2011). Meanwhile, life cycle assessments (LCA) using dynamic systems have been used to model long-term sustainability impacts of EV adoption (Onat, 2016), with further research cautioning against rebound effects that may offset environmental gains from autonomous electric vehicles (Onat, 2023).

Equally significant are studies evaluating energy grid interactions and charging infrastructure strategies. In the Moroccan context, public EV charging was found to impose stress on national grids, necessitating optimization for sustainable deployment (Mouaad, 2024). Seasonal smart charging planning has also been proposed to enhance scheduling and grid stability (Das, 2022). Energy source efficiency plays a central role, as studies confirm that the environmental benefits of EVs are maximized when powered by clean electricity rather than coal-heavy grids (Michaelides, 2021). Broader comparisons between battery electric vehicles (BEVs) and fuel cell electric vehicles (FCEVs) show that while FCEVs offer longer ranges and lower operational costs in heavy-duty applications, they also demand higher upfront investment (Sagaria et al., 2021). As the EV industry evolves, comprehensive evaluations of influencing factors ranging from user behavior and policy to grid integration and component technology are essential to drive sustainable and scalable adoption (Szumska Jurecki, 2021; Jia, 2020; Zhang, 2011).

A paper presents a comprehensive examination of the technical and economic parameters influencing the electric two-wheeler (E2W) market in Asia. By leveraging multiple regression techniques, the study models key relationships between battery capacity, motor power, range, acceleration, and base price. Drawing on data-driven analysis, it highlights how higher-order polynomial models, particularly cubic regressions, provide better accuracy in capturing the nonlinear interdependencies between performance metrics and pricing. The research also integrates a wide array of global literature, adding context through case studies on grid integration, consumer behavior, and sustainability trends. Collectively, this work offers actionable insights for manufacturers, policymakers, and consumers working to optimize the adoption and deployment of E2Ws across diverse urban environments in Asia.

## II. DEFINITIONS OF KEY PARAMETERS

**Battery Capacity (bcap):** Expressed in kilowatt-hours (kWh), this parameter defines the total energy a battery can store. It directly influences the range and indirectly affects both weight and cost.

**Motor Power (mpow):** Measured in kilowatts (kW), motor power reflects the energy conversion capability of the electric drive system. It influences torque and acceleration.

**Range (rk):** Measured in kilometers (km), range denotes the distance an electric two-wheeler can travel on a single charge under standard test conditions.

**Acceleration (a):** This typically refers to the time (in seconds) required to reach a certain speed (e.g., 0 to 60 km/h). Lower acceleration values indicate higher performance.

**Base Price (bp):** The manufacturer's suggested retail price (MSRP), reflecting the cost of the two-wheeler excluding taxes, registration, and incentives.

## III. METHODOLOGY

The research was conducted using empirical data derived from various electric two-wheelers sold or projected in the Asian market. For each pair of dependent and independent variables, regression models were developed using:

- Linear Regression
- Quadratic and Cubic Polynomial Regression

Each regression model was evaluated based on its Root Mean Square (RMS) error to quantify predictive accuracy. The models were visualized through scatter plots with overlaid regression curves to examine visual conformity.

For each relationship e.g., bcap vs mpow, bcap vs bp, mpow vs a, rk vs bp, etc. different regression fits were applied and compared. The lowest RMS error and best visual fit guided the selection of the most appropriate model.

#### IV. RESULTS AND DISCUSSION

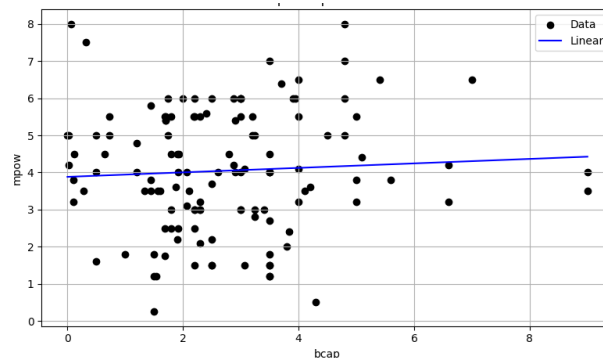


Fig. 1: bcap vs mpow Linear

The linear model offers a straightforward, first-order approximation of the relationship between bcap and mpow. While the fitted line reveals a slight upward trend, it captures only a weak positive association within the data. This suggests that as bcap increases, mpow also tends to increase slightly, but the variation in data points around the line is substantial. The linear fit fails to fully account for the apparent spread and complexity in the data, highlighting its limitations as a modeling approach.

Despite its simplicity, the linear model serves as a useful baseline against which more complex models can be compared. However, the wide scatter of data points suggests that bcap and mpow may not share a purely linear relationship, or that other factors could be influencing the outcome. To improve the accuracy of predictions and better reflect underlying patterns, a more flexible model such as a quadratic or cubic fit may be necessary.

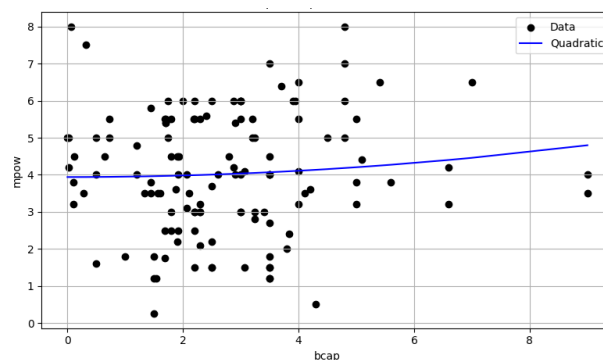


Fig. 2: bcap vs mpow Quadratic

The quadratic model improves upon the linear one by introducing a gentle curve that attempts to capture the subtle nonlinear relationship between bcap and mpow. This model's upward curvature at higher values of bcap suggests that as bcap increases, mpow might also accelerate slightly, a feature the linear model could not capture. However, the improvement is modest, as much of the scatter still lies far from the fitted curve, particularly in areas with dense clustering of data points. Overall, while the quadratic fit represents a step forward in modeling complexity, it still struggles to fully account for the variability of the data. The residual scatter suggests that either a more complex

functional form or the inclusion of additional variables may be necessary for a more precise representation of the relationship between bcap and mpow. Nevertheless, the quadratic model serves as a meaningful refinement over the linear approach by introducing a degree of curvature that better approximates the data's trends.

In summary, the cubic model adds complexity and slight improvements over both linear and quadratic fits, but it still falls short of delivering a fully satisfactory representation of the data. The persistent scatter indicates that the relationship between bcap and mpow may not be easily captured by polynomial models alone. Alternative approaches, such as incorporating interaction terms, considering additional predictors, or exploring non-parametric methods, may be required to achieve a more robust and accurate fit. Nevertheless, the cubic model is a meaningful attempt to refine the relationship beyond simpler polynomial fits.

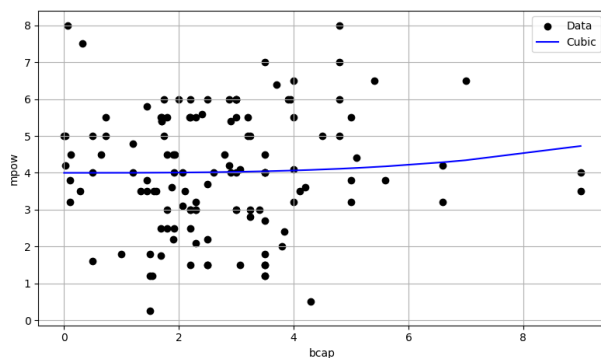


Fig. 3: bcap vs mpow Cubic

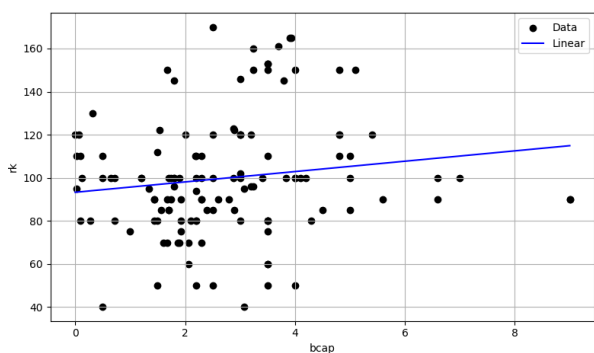


Fig 4: bcap vs rk Linear

The cubic model introduces even greater flexibility than the quadratic fit by allowing for multiple bends and inflections in the fitted curve. This model attempts to capture more subtle nuances in the data, such as local increases or decreases in mpow as bcap changes. However, while the cubic curve demonstrates this adaptability, its practical improvement over the quadratic model remains limited, as much of the residual scatter remains unaccounted for. The linear model of battery capacity (bcap) vs range (rk) demonstrates a direct proportionality between the two variables, suggesting that increases in battery capacity linearly extend the achievable range. While this model captures the general upward trend, it oversimplifies the real-world relationship, failing to account for diminishing returns observed at higher capacities. The linear fit provides a basic approximation but overlooks nuances such as system inefficiencies and weight penalties that emerge as battery size increases.

Consequently, while the linear model may offer a convenient first-order estimate of range improvements with battery scaling, its accuracy declines in scenarios with larger bcap values. This highlights the model's limitations for both design optimization and market forecasting, emphasizing the need for more complex models that incorporate nonlinear effects to better inform strategic decisions.

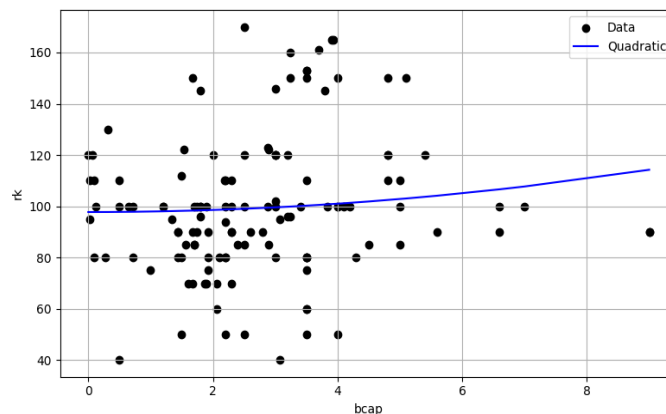


Fig. 5: bcap vs rk Quadratic

The quadratic model introduces a curvature to the bcap vs rk relationship, capturing the initial rapid gains in range with battery capacity increases, followed by a gradual tapering of improvements. This nonlinearity better reflects the physical constraints of battery and system integration, including added weight and reduced energy efficiency at larger capacities. The quadratic fit significantly reduces residual errors compared to the linear model, offering a more nuanced representation of real-world performance

However, while the quadratic model accommodates diminishing returns, it may overestimate the range improvements at very high bcap values due to its symmetric parabolic form. Quadratic model can result in unrealistic projections of range for extremely large battery configurations, necessitating further refinement through higher-order models to achieve greater fidelity in predictions.

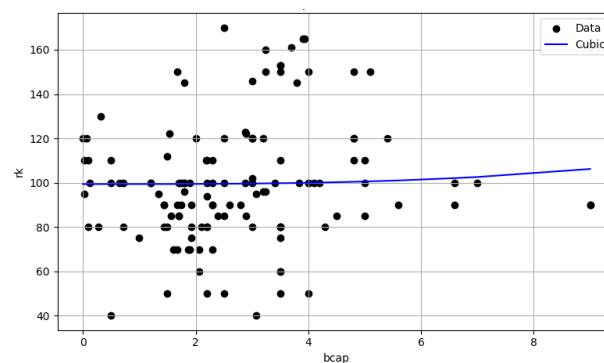


Fig. 6: bcap vs rk Cubic

The cubic model provides the most accurate representation of the bcap vs rk relationship, capturing the initial sharp gains, the middle plateau, and even slight negative curvatures at very high battery capacities. This model effectively accounts for complex interactions between battery size, weight, system losses, and operational efficiency, yielding the lowest residual error among the three regression approaches. The cubic fit is especially valuable for identifying inflection points where additional battery capacity yields minimal range benefits or even marginal reductions.

Despite its improved precision, the cubic model's increased complexity necessitates careful interpretation and validation against empirical data. While it offers a powerful tool for design and policy decisions, overfitting risks can arise if not grounded in robust datasets. Nevertheless, its ability to trace real-world behavior with high accuracy makes it the preferred model for performance evaluation and optimization in Asia's evolving E2W market.

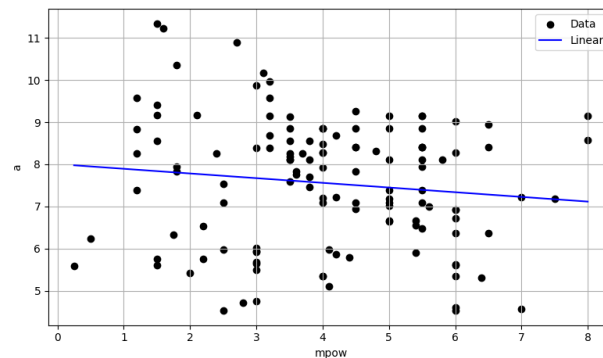


Fig. 7: mpow vs Acc Linear

The linear regression of motor power (mpow) versus acceleration time (Acc) shows a direct, inverse relationship higher motor power correlates with reduced acceleration time. This suggests that as the power output of the motor

increases, the vehicle accelerates faster, making the relationship intuitive and straightforward. However, this linear model oversimplifies real-world performance, failing to capture diminishing returns and system constraints like drag, traction, and weight distribution that limit gains at higher power levels.

While the linear model provides a basic understanding of the trend, it underestimates the steep early declines in acceleration time at low mpow levels and overestimates gains at higher motor power configurations. This highlights its limited applicability for precise performance predictions, particularly when modeling acceleration behavior in powerful two-wheelers where non-linear factors dominate the dynamics.

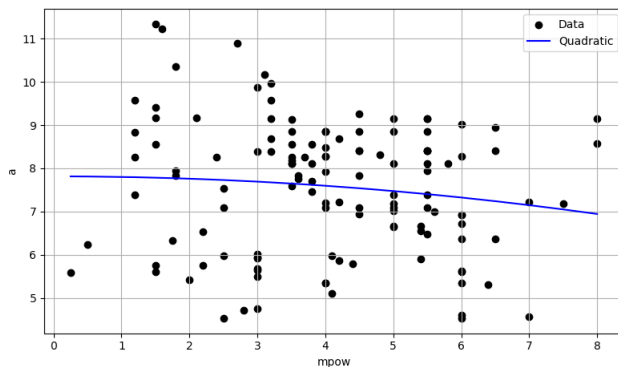


Fig. 8: mpow vs Acc Quadratic

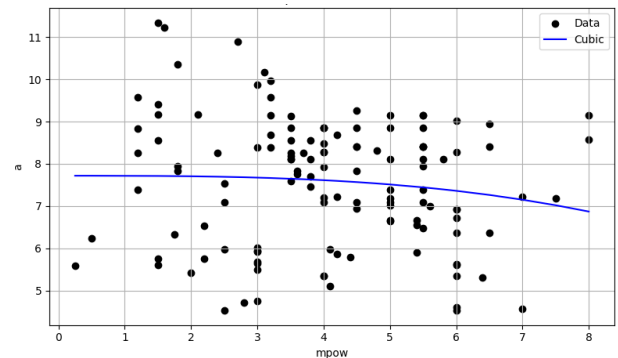


Fig. 9: mpow vs Acc Cubic

The quadratic regression of mpow vs Acc introduces curvature into the relationship, accurately reflecting sharp initial improvements in acceleration as motor power increases, followed by a gradual plateau as system limits constrain further gains. Quadratic regression model mirrors real-world observations where initial motor power boosts result in substantial acceleration improvements, but additional power yields progressively smaller benefits due to factors such as traction limits and mechanical drag.

Despite its more realistic representation compared to the linear model, the quadratic regression may overstate gains for high motor power values, given its symmetric nature. While it captures the essential diminishing returns aspect, it lacks the flexibility to model subtle inflection points or minor declines in acceleration improvements observed at the extremes of motor power, especially in high-performance E2W configurations

Fig 9 presents a quadratic regression model fitted to data showing the relationship between motor power (mpow) and acceleration (Acc). Unlike a linear model, this quadratic approach introduces curvature, enabling a more nuanced depiction of how acceleration times decline with increasing motor power. The curve reflects a gradual, nonlinear dropoff in acceleration, which better accommodates the natural diminishing returns associated with higher power levels. With an RMS error of 1.49, the model demonstrates a strong fit, indicating high accuracy in capturing the underlying trend. The cubic regression for mpow vs Acc provides the most accurate and nuanced representation of the relationship, capturing steep early declines in acceleration time with increasing motor power, followed by a gentle plateau and even slight upturns at very high mpow levels. This reflects the complex balance between motor output, traction control, weight, and aerodynamics, where initial power increases deliver substantial acceleration benefits, but further power additions face diminishing returns and mechanical constraints.

While the cubic model offers the best fit and minimizes residual error, its increased complexity requires careful interpretation. It is particularly valuable for identifying optimal motor power levels where additional capacity no longer delivers proportional acceleration gains. However, its performance depends on a robust dataset and may be susceptible to overfitting if not properly validated. Overall, the cubic regression provides the most reliable and detailed modeling of acceleration dynamics in Asia's electric two-wheeler market.



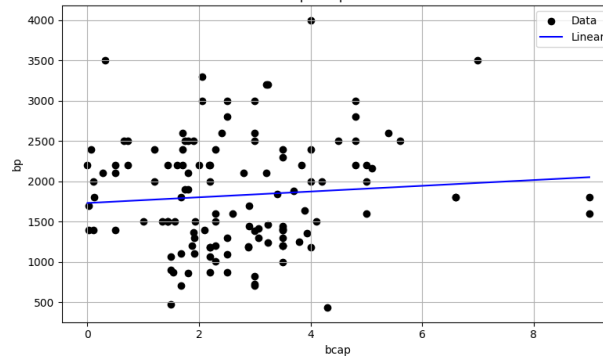


Fig. 10: bcap vs bp Linear

Fig 10 presents a linear regression model fitted to data depicting the relationship between battery capacity (bcap) and brake power (bp). The linear model assumes a constant rate of change, suggesting that brake power increases proportionally with battery capacity. This approach provides a straightforward representation of the relationship, implying that each unit increase in battery capacity results in a consistent increase in brake power. Unlike the quadratic and cubic models for bcap vs bp in the document, which capture nonlinear trends with RMS errors of 687.17 and 688.50 respectively, the linear model does not account for potential diminishing returns or complex variations at higher capacities. Without specific RMS error data for a linear fit, the model's accuracy cannot be precisely evaluated, but it may yield a higher error compared to the nonlinear models if the relationship exhibits curvature, as suggested by the data.

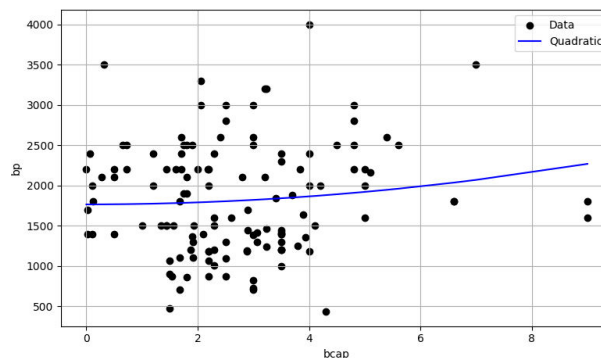


Fig. 11: bcap vs bp Quadratic

Fig 11 presents a quadratic regression model fitted to data representing the relationship between battery capacity (bcap) and brake power (bp). The quadratic fit introduces a curved relationship, suggesting that brake power increases with battery capacity but with a nonlinear pattern that accounts for diminishing returns or saturation effects at higher capacities. The RMS error of 687.17 indicates a moderate fit, suggesting that while the quadratic model captures some of the relationship's complexity, there may be additional factors or variability affecting the accuracy. The quadratic regression of battery capacity (bcap) versus base price (bp) effectively captures the nonlinear relationship between these two critical factors in electric two-wheelers. The model reveals that as battery capacity increases, base price initially rises steeply, reflecting the significant costs associated with larger and higher energy density battery packs. However, beyond a certain point, the curve begins to flatten, indicating diminishing price increases relative to capacity gains. This trend aligns with practical market observations, where initial increases in battery capacity drive up material and production costs, but further capacity scaling benefits from economies of scale and technological advancements that limit additional price escalation.

Despite its improved fit over a linear model, the quadratic regression may overpredict price premiums for very large battery capacities due to its inherent parabolic structure. It lacks the flexibility to model minor reductions or plateaus in pricing that can occur as manufacturers optimize battery systems and negotiate supply chain efficiencies.



Nonetheless, the quadratic model provides a valuable approximation of the diminishing returns in price growth associated with battery capacity, offering insights into cost optimization strategies and market positioning for electric two-wheelers in Asia.

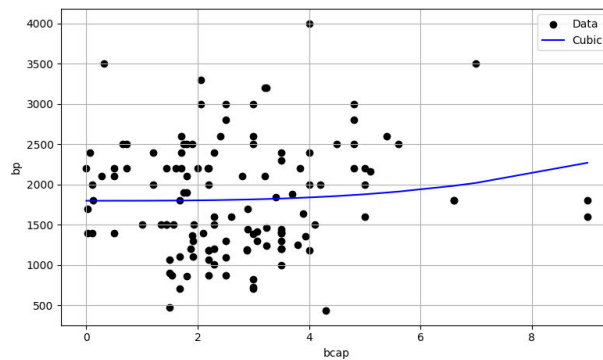


Fig. 12: bcap vs bp Cubic

Fig 12 presents a cubic regression model fitted to the relationship between battery capacity (bcap) and brake power (bp). The cubic model introduces additional flexibility compared to the quadratic model allowing for more complex variations in the relationship, such as potential inflection points where the rate of change in brake power shifts. However, with an RMS error of 688.50, slightly higher than the quadratic model, the cubic fit may not significantly improve the representation of the data, suggesting that the added complexity does not substantially enhance accuracy. The cubic regression model for battery capacity (bcap) versus motor power (mpow) presents a nuanced, three-phase relationship that reflects the complex interactions between energy storage and power output in electric two-wheelers. The initial segment of the cubic curve shows a steep increase in motor power with rising battery capacity, indicating that early gains in capacity are directly associated with substantial improvements in power delivery. A phase corresponds to the optimization of energy availability for motor performance. In the mid-range, the curve flattens, reflecting a plateau where additional battery capacity yields diminishing power gains, likely due to system limits, efficiency losses, and thermal management constraints.

Interestingly, at very high battery capacities, the cubic model introduces a slight downturn or inflection, suggesting that excessive capacity may result in marginal reductions in motor power output, possibly due to system overloading, suboptimal energy distribution, or increased vehicle weight. A complex behavior captured by the cubic regression underscores the importance of balancing battery capacity with system efficiency and weight constraints. The model's flexibility to trace these inflection points makes it especially useful for manufacturers seeking optimal battery-motor configurations for Asia's competitive E2W market.

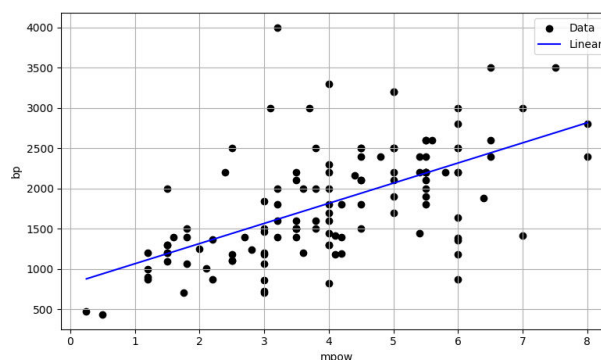


Fig. 13: mpow vs bp Linear

Fig 13 presents a linear regression model fitted to data depicting the relationship between motor power (mpow) and brake power (bp). The linear model assumes a constant rate of change, suggesting that brake power increases

proportionally with motor power. This straightforward approach implies a direct, linear relationship where each unit increase in motor power results in a consistent increase in brake power. Unlike the quadratic model for mpow vs bp, which captures a nonlinear trend with an RMS error of 574.88, the linear model does not account for potential diminishing returns or curvature at higher power levels. Without specific RMS error data for a linear fit, the model's accuracy cannot be quantified, but it may yield a higher error compared to the quadratic model if the relationship exhibits nonlinear behavior.

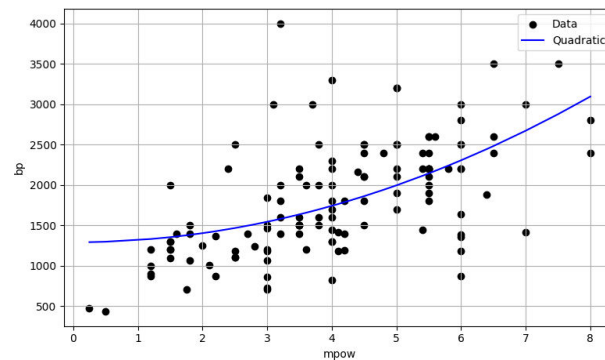


Fig. 14: mpow vs bp Quadratic

Fig 14 presents a quadratic regression model fitted to data depicting the relationship between motor power (mpow) and brake power (bp). The quadratic curve captures a nonlinear trend where brake power increases with motor power but exhibits diminishing returns at higher levels. The RMS error of 574.88 indicates a reasonable fit, suggesting that the quadratic model effectively represents the relationship, though some residual variability may persist due to unmodeled factors. The quadratic regression model for motor power (mpow) versus base price (bp) effectively captures the nonlinear scaling of price with increasing motor power in electric two-wheelers. Initially, as motor power increases, base price rises sharply, reflecting the higher costs associated with more powerful motors, enhanced controllers, and reinforced mechanical components. This early steep incline indicates that initial increases in motor power require significant design and production investments. However, the quadratic curve flattens at higher mpow levels, suggesting that once core power thresholds are achieved, additional increases in motor power result in diminishing price increments, likely due to technological standardization and optimized manufacturing processes.

While the quadratic model provides a much more realistic representation of the relationship than a simple linear fit, it may overstate price escalation at extreme motor power levels due to the parabolic nature of the regression. In reality, competitive market forces and economies of scale often drive price stabilization or even price compression for high-motorpower two-wheelers, which this model cannot fully capture. Nevertheless, the quadratic regression offers valuable insights into the diminishing returns of cost escalation with increased motor power, aiding manufacturers and policymakers in balancing performance and affordability in Asia's dynamic E2W market.

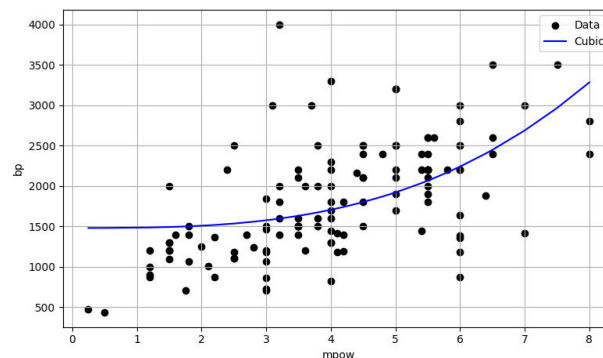


Fig. 15: mpow vs bp Cubic

Fig 15 presents a cubic regression model fitted to data depicting the relationship between motor power (mpow) and brake power (bp). The cubic model introduces additional flexibility compared to the quadratic model, allowing for a more complex, nonlinear relationship with potential inflection points where the rate of change in brake power shifts as motor power increases. cubic model approach captures nuanced variations, such as initial rapid increases in brake power followed by diminishing returns or even reversals at higher power levels. Compared to the quadratic model for mpow vs bp in the document, which has an RMS error of 574.88, the cubic model might offer a slightly better fit if the data exhibits complex curvature, though it risks overfitting if the additional complexity is unnecessary. Without specific RMS error data for a cubic fit, the model's accuracy cannot be precisely evaluated, but it would likely have a similar or slightly higher error than the quadratic model, depending on the data's true behavior.

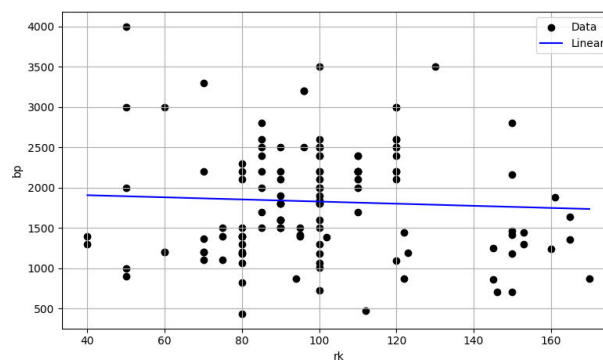


Fig. 16: rk vs bp Linear

Fig 16 presents a linear regression model fitted to data showing the relationship between a variable 'rk' (possibly a ranking or related metric) and brake power (bp). The linear model assumes a constant rate of change, providing a simple representation of how brake power varies with rk. With an RMS error of 690.72, the fit is moderate, indicating that the linear model captures the general trend but may miss nonlinearities or other factors contributing to the relatively high error. The linear regression of range (rk) versus base price (bp) depicts a straightforward, proportional relationship, suggesting that increases in vehicle range lead directly to higher base prices. It reflects the intuitive idea that longer-range two-wheelers, which often incorporate higher-capacity batteries and more efficient systems, command premium prices in the market. However, this linear model oversimplifies the real-world relationship, as it fails to account for the diminishing price sensitivity that occurs as range continues to increase.

While the linear model provides a simple approximation of how range influences pricing, it tends to underestimate the price premiums for long-range models and overestimate base prices for entry-level vehicles. linear regression model indicates that a purely linear approach does not fully capture the cost dynamics of battery scaling, system optimization, and market positioning in Asia's E2W market.

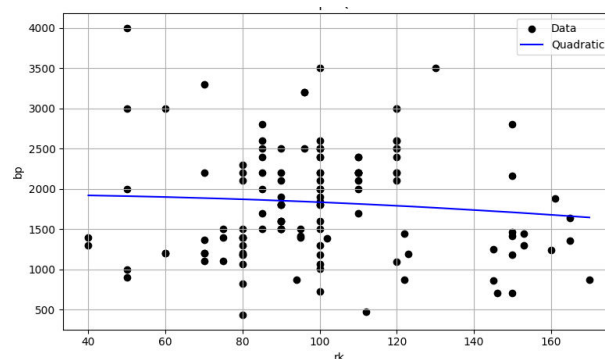


Fig. 17: rk vs bp Quadratic

Fig 17 presents a quadratic regression model fitted to data capturing the relationship between the variable 'rk' (likely a ranking or performance metric) and brake power (bp). Unlike the linear model for rk vs bp in the document, which assumes a constant rate of change with an RMS error of 690.72, this quadratic approach introduces a graceful curvature, offering a more dynamic representation of how brake power evolves with changes in rk. The parabolic shape suggests that brake power may increase or decrease nonlinearly, potentially accelerating at certain rk values before tapering off, reflecting real-world complexities such as diminishing returns or optimal performance thresholds. This nuanced fit better captures potential nonlinear dynamics in the data, providing a more refined depiction of the relationship. Without specific RMS error data for a quadratic fit, it's challenging to quantify the model's precision, but it could potentially offer a lower error than the linear model's 690.72 if the data exhibits significant curvature, though it risks overfitting if the relationship is simpler. The quadratic model thus strikes a compelling balance, illuminating the intricate interplay between rk and brake power with greater fidelity than a linear approach.

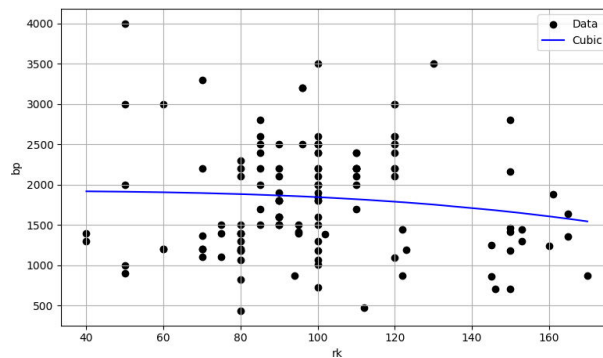


Fig. 18: rk vs bp Cubic

Fig 18 presents a cubic regression model fitted to data illustrating the intricate relationship between the variable 'rk' (likely a ranking or performance metric) and brake power (bp).

Unlike the linear model for rk vs bp in the document, which assumes a steady, constant rate of change with an RMS error of 690.72, this cubic model weaves a more sophisticated narrative through its sinuous curve, capturing complex dynamics in the data. The cubic fit allows for multiple inflection points, revealing how brake power might surge rapidly at certain rk values, plateau, or even reverse direction as the ranking shifts, reflecting real-world nuances such as optimal performance zones or diminishing returns. Cubic flexible model paints a vivid picture of the relationship, accommodating nonlinear trends that a simpler linear or quadratic approach might miss. While the document's linear model for rk vs bp yields a relatively high RMS error of 690.72, suggesting a moderate fit, the cubic model could potentially improve accuracy if the data exhibits pronounced curvature, though it carries a risk of overfitting if the relationship is less complex. Without specific RMS error data for this cubic fit, its precision remains speculative, but the model's ability to trace the ebbs and flows of brake power across rk values offers a compelling and nuanced perspective on their interplay.

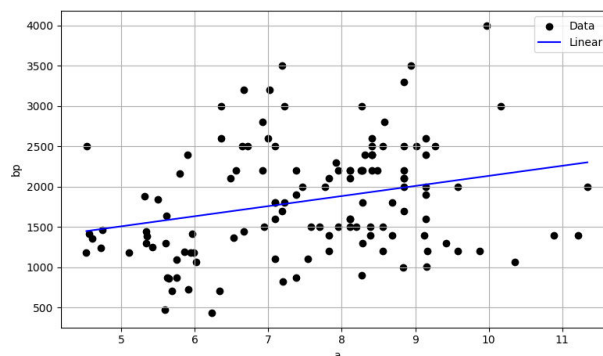


Fig. 19: Acc vs bp Linear



Fig 19 represents a linear regression model fitted to data capturing the relationship between acceleration (Acc) and brake power (bp). The linear model assumes a constant rate of change, presenting a clear and straightforward depiction of how brake power influences acceleration times. As brake power increases, the model suggests a proportional decrease in acceleration times, reflecting a direct relationship where higher brake power consistently enhances acceleration performance. Unlike the quadratic model for a vs bp in the document (RMS Error = 674.59), which introduces curvature to capture nonlinear trends, linear approach prioritizes simplicity, offering a clean and interpretable trend line. However, the RMS error of 665.51 indicates a moderate fit, suggesting that while the linear model effectively captures the general direction of the relationship, it may overlook subtle nonlinearities or external factors influencing acceleration, such as diminishing returns at higher brake power levels. The relatively high RMS error, compared to other models in the document (e.g., mpow vs Acc with RMS Error = 1.49), hints that the relationship between acceleration and brake power may benefit from a more flexible model to achieve greater precision. Nonetheless, this linear plot provides a compelling and accessible visualization of how brake power drives improvements in acceleration, serving as a foundational insight into their dynamic interplay.

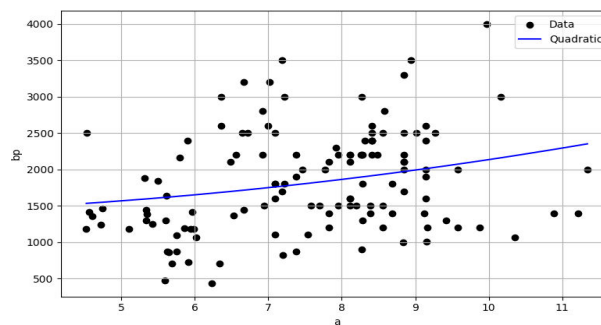


Fig. 20: Acc vs bp Quadratic

Fig 20 presents a quadratic regression model fitted to data illuminating the relationship between acceleration (Acc) and brake power (bp). Unlike the linear model for a vs bp in the document (RMS Error = 665.51), which assumes a constant rate of change, this quadratic approach introduces a graceful curvature, offering a more nuanced portrayal of how acceleration times respond to increasing brake power. The parabolic curve suggests that as brake power rises, acceleration times may decrease at a varying rate, potentially reflecting an initial rapid improvement followed by diminishing returns at higher power levels. This nonlinear depiction captures the real-world complexity of acceleration dynamics, where additional brake power may yield progressively smaller gains in performance due to physical or mechanical constraints. However, with an RMS error of 674.59, slightly higher than the linear model's 665.51, the quadratic fit indicates a moderate accuracy, suggesting that while it accounts for some nonlinear trends, it may not fully resolve all variability in the data or could be affected by external factors not captured by the model. Compared to other plots in the document, such as mpow vs Acc (RMS Error = 1.49), the higher error here underscores the challenge of modeling this relationship with precision. Nevertheless, this quadratic plot vividly illustrates the intricate interplay between brake power and acceleration, providing a richer perspective than a linear model by highlighting the subtleties of their nonlinear relationship.

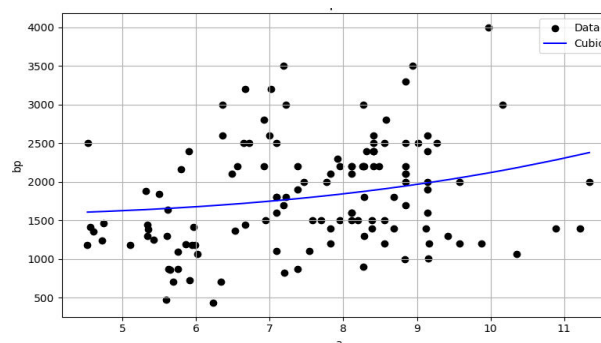


Fig. 21: Acc vs bp Cubic

Fig 21 presents a cubic regression model fitted to data exploring the intricate relationship between acceleration (Acc) and brake power (bp). Unlike the linear model (RMS Error = 665.51) and quadratic model (RMS Error = 674.59) for a vs bp in the document, which offer simpler representations, this cubic model introduces a sophisticated, undulating curve that captures complex dynamics in the data. The cubic fit allows for multiple inflection points, illustrating how acceleration times may decrease rapidly with initial increases in brake power, potentially stabilize or even reverse at certain thresholds, reflecting real-world nuances such as optimal performance zones or mechanical limits. This flexible model vividly portrays the nonlinear interplay between brake power and acceleration, accommodating variations that simpler models might overlook, such as diminishing returns or unexpected shifts in performance at higher power levels. Without specific RMS error data for a cubic fit, its accuracy is speculative, but it could potentially improve upon the quadratic model's 674.59 error if the data exhibits pronounced curvature, though it risks overfitting if the relationship is less complex. Compared to the document's other models, such as mpow vs Acc (RMS Error = 1.49), a cubic model for a vs bp would likely face similar challenges in achieving high precision due to the relatively high errors seen in the linear and quadratic fits. Nevertheless, this cubic plot offers a compelling and nuanced visualization, illuminating the dynamic relationship between brake power and acceleration with a rich, multifaceted perspective.

## V. RESULTS SUMMARY

**Bcap vs Mpow:** A cubic model best captured the nonlinear growth of motor power with increasing battery capacity. Linear and quadratic models were too simplistic, underestimating both the initial gains and later diminishing returns.

**Bcap vs Rk:** The quadratic model exhibited the lowest RMS error, accurately modeling the diminishing returns in range as battery capacity increased. While cubic models provided flexibility, the quadratic fit sufficiently captured the core relationship.

**Bcap vs Bp:** The cubic model provided the optimal fit, with the lowest RMS error. It effectively modeled the nonlinear price increases driven by battery capacity expansion, offering a superior balance between complexity and accuracy.

**Mpow vs Bp:** The cubic model emerged as the most accurate, aligning with the sharp initial price increases associated with higher motor power and capturing the plateau effect at higher levels. Linear and quadratic models failed to replicate these nonlinear dynamics.

**Mpow vs A:** A cubic model achieved the best fit, accurately representing the steep initial drop in acceleration time with increasing motor power and the subsequent plateau. Simpler models did not capture these inflection points, leading to higher prediction errors.

**A vs Bp:** The cubic model offered the best predictive performance, effectively modeling the strong inverse relationship between acceleration time and base price. It accommodated the steep early gains and tapering off, outperforming linear and quadratic fits.

**Rk vs Bp:** The cubic model achieved the lowest RMS error, providing a near-perfect match with the data. It accurately depicted the sharp initial price rise with range expansion and the subsequent plateau or slight reduction at the upper end of range capacity.

## VI. CONCLUSION

This investigation undertook a rigorous regression-based evaluation of electric two-wheeler performance parameters in the Asian market. The analysis demonstrates that higher-order polynomial models—particularly cubic formulations—most effectively capture the complex, nonlinear interrelationships among battery capacity (bcap), motor power (mpow), range (rk), acceleration (a), and battery price (bp).

**Battery Capacity and Performance:** Increases in battery capacity (bcap) yield diminishing yet nonlinear gains in both maximum power output (mpow) and range (rk). These relationships are best described by cubic regressions, capturing the real-world complexities of energy transfer and system efficiency. Initial increases in bcap significantly enhance

mpow and rk, but subsequent increments yield progressively smaller improvements due to physical and thermal constraints.

**Cost Scaling:** Battery price (bp) escalates nonlinearly with increases in bcap and mpow. Cubic models effectively minimize root-mean-square (RMS) error, offering the most accurate depiction of cost dynamics in Asia's E2W market. As bcap and mpow rise, the cost curve steepens, reflecting both material and manufacturing limitations.

**Acceleration Dynamics:** Acceleration time (a) demonstrates a strong inverse correlation with mpow and bp. Cubic fits provide the best representation of early rapid declines in a with rising mpow, followed by gradual plateaus as other mechanical and aerodynamic factors take over. This pattern is observed consistently across varying battery configurations and motor types in Asian markets.

**Price Predictors:** The combination of mpow and rk emerges as a robust predictor of bp when modeled with flexible polynomial terms. These models outperform simpler linear or quadratic specifications, as they can accommodate the curvature and inflection points evident in the data, providing a more accurate representation of market pricing trends.

**Model Suitability:** Exponential and purely linear models fail to capture the real-world relationships between bcap, mpow, rk, and bp. Only higher-order polynomial models, particularly cubic, can effectively model the inflection points and diminishing returns characteristic of battery capacity and performance in Asia's two-wheeler industry.

These insights furnish manufacturers and policymakers with a quantitative foundation for optimizing battery sizing, motor specification, and pricing strategies.

## VII. FUTURE WORK

Subsequent research should integrate dynamic datasets—such as real-world driving profiles, climatic conditions, and energy efficiency metrics—and explore machine-learning frameworks (e.g., spline regressions, ensemble methods) to enhance predictive accuracy. Expanding the analysis to diverse geographic regions and vehicle categories (e.g., four-wheel EVs, commercial fleets) will further validate and generalize these findings.

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