Modern Applied Science; Vol. 14, No. 3; 2020
ISSN 1913-1844 E-ISSN 1913-1852
Published by Canadian Center of Science and Education

Electric Vehicle Sales Catastrophe Averted (?)

Timothy Sands[1]

[1]Department of Mechanical Engineering (CVN), Columbia University, New York, USA

Correspondence: Timothy Sands, Department of Mechanical Engineering (CVN), Columbia University, New York, NY 10027, USA.

Received: December 16, 2019 Accepted: February 7, 2020 Online Published: February 19, 2020

doi:10.5539/mas.v14n3p1 URL: https://doi.org/10.5539/mas.v14n3p1

Abstract

The literature indicates catastrophic potential for electric vehicles around the year 2019. Amidst the predicted time, this research revisits the prequel analysis with state-of-the-art deterministic artificial intelligence methodologies to posit the potential for catastrophe in the upcoming year. The methodology has proven effective with motion mechanics, electrodynamics, and even financial analysis of sales date in the prequels, since the model commences with simple regression for mathematical model formulation asserting the certainty equivalence principle, followed by derivative modeling and eventually catastrophe analysis of the derivative models. The prequel analysis paradigms are retained in this sequel utilizing both monthly and cumulative sales data in simple least squares algorithms for predictive curve fitting to establish context and help correctly model the mathematical degree of the data. Extrapolation by forward time-propagation established predictions for models of various mathematical degrees (again merely for context). Next, catastrophe analysis (of the derivative form) revealed stable and unstable equilibrium points and then parametric variation was induced to evaluate the resulting behavior of the derivative models, highlighting the importance of the coefficient of the second order term (the acceleration or change of rate of sales as a forcing function). While the forcing function typically embodies both gasoline prices and vehicle charging proliferation, the relative stability of gas prices together with factors such as vehicle-to-grid elevate charging-station proliferation as the primary forcing function of slow-dynamics in catastrophe analysis. This brief manuscript revisits the prequel research to test the validity of those conclusions and with the benefit of the passage of time, reveal how well the mathematical modeling predicted real behavior. The main finding is the predicted potential catastrophe is less likely to occur and recommendations are made to insure catastrophe is averted.

Keywords: electric vehicles, catastrophe theory, equilibrium point, jump theory, deterministic artificial intelligence, sustainable transportation, demand response, gas prices, charging stations

1. Introduction

1.1 Introduce the Problem

Recent literature (Sands, 2017) revealed the distinct possibility of an unexpected catastrophic crash in sales of electric vehicles in 2019.

1.1.1 Why is This Problem Important?

How does the study relate to previous work in the area? Subsequent to that prequel research, the rapid rise of non-stochastic artificial intelligence methodologies (Baker, 2018), (Sands, InTech, 2019), (Lobo, 2018) stemming from combinations of physics-based controls (Sands, Lorenz, 2009), (Sands, 2012), (Sands, 2015) and mathematical system identification from data (Sands, *Comp*., 2017), (Sands, *J.Space Exp.*, 2017), (Sands, Kenny, 2017), (Sands, *Phys J.*, 2017), (Sands, *J.Space Exp.*, 2017), (Sands, Armani, 2018) together with adaptive systems methods (Nakatani, 2014), (Nakatani, 2016), (Sands, *Aero*, 2019), (Cooper, 2017), (Smeresky, 2018), (Sands, *Algor.*, 2019), (Sands, Bollino, 2018) has been adopted and incorporated into new educational schemes driven by military operational imperatives (Kuklinski, et al., 2019), (Sands, Mihalik, 2016), (Bittick, et al., 2019), (Sands, "satellite", 2009), (Sands, *Intl. J. Electro.,* 2018) with accompanying educational imperatives (Mihalik, et al., 2017), (Camacho, et al., 2017). How does this manuscript differ from, and build on, the earlier report? These methods have been successfully applied to quite disparate disciplines piecemeal as the techniques have been developed, bestowing the ability for data-informed decision-making, e.g. should a military plan to invest heavily in electric vehicles with a realistic anticipation of a robust commercial industrial base.

1.1.2 What are the Primary and Secondary Hypotheses and Objectives of the Study, and What, if any, are the Links to Theory?

In this manuscript, state-of-the-art deterministic artificial intelligent methodologies (Smeresky, et al., 2020) are applied to first utilize optimal system-identification (simple regression) to provide deterministic models. By invoking the certainty-equivalence principle, those deterministic models are parameterized to establish decision-making and process control motivations by establishing the deterministic self-awareness statement. The math models are differentiated to yield differential models that are used in catastrophe analysis to predict a potential shock event in vehicle sales. Shock events inherent in some classes of differential equations embody rapid, unexpected dramatic changes in data, and they are also referred to as “jump discontinuities”.

1.1.3 How do the Hypotheses and Research Design Relate to One Another?

Utilizing such methods previously used on (non-electric) military systems increase the likelihood of adoption, since the methods are well known and trusted.

1.1.4 What are the Theoretical and Practical Implications of the Study?

The main aim of this work is to ascertain whether the potential catastrophe has been averted, and use this information to make recommendations for the future. Catastrophe is driven by a slow-moving dynamic driven by a forcing function, predominantly gasoline prices and also electric-vehicle charging proliferation which is amplified by vehicle to grid (V2G) technology. (Vehicle to grid, 2018)

2. Materials and Methods

Materials and methods normally comprised of three sections: definitions, data, and methods to include details on the new additional data since the 2015 data used in the prequel (Sands, 2017). Here the definitions (Gohlke, 2018) and data (Light Duty, 2018), (Monthly Plug-in, 2018), (Plug-in, 2018), Cobb, 2018) are placed in the appendix at the end of the manuscript; while a brief contextual introduction to the methods (taken from deterministic artificial intelligence) utilized to produce the results in section 3 are included immediately in section 2.2 with background materials on electric vehicles in section 2.1

2.1 Materials (Literature Review)

An interesting manuscript “The effect of perceived risk on the purchase intention of electric vehicles: an extension to the technology acceptance model” (Thilina, 2019) seeks to analyze significant market penetration for the sale of electric vehicles accompanied by the analysis (Mo, 2018) of life-cycle cost of ownership including congestion and environmental impacts (Tu, 2019), (Rajeev, et al., 2019), (Hao, 2017), (Philipsen, et al., 2019), (Lopez-Arboleda, et al., 2019), (Almeida, et al., 2019). Considerable emphasis have been placed on improvements in vehicle charging (Wolbertus, et al., 2019) amongst many other underlying technological areas (Zhao, et al., 2019) seeking to improve the value proposition to potential buyers (Jager, et al., 2019), (Zhang, L., et al., 2019), (Li, et al., 2019), (Minnerup, et al., 2019), (Muller, 2019) and also make recommendations in both technology (Zha, et al., 2019), (Li, et al., 2019), (Zha, et al., 2019), (Li, et al., 2019), (Jiyan, et al., 2019), (Pier, et al., 2019), (Agaton, et al., 2019), (Fujita, T., et al., 2019), (Watanabe, et al., 2019), (Kusaka, et al., 2019), (Zhang, W., et al., 2019), (Fujita, H., et al., 2019), (Mayer, et al., 2019), (Ricciardi, et al., 2019), (Chen, et al., 2019), (Yu, Z., et al., 2019), (Senda, et al., 2019), (Marquez-Fernandez, et al., 2019), (Wu, D., et al., 2019), (Wang, H., et al., 2019), (Obayashi, et al., 2019), (Gong, et al., 2019), (Vermeulen, et al., 2019), (Jia, J., et al., 2019), (Li, Q., et al., 2019) and policy incentives (Zhang, X., et al., 2019), (Ortar, et al., 2019), (Li, W., et al, 2019) culminating in charging strategies to influence the obvious trade-off between gasoline prices and charging availability (Zhao, Y., et al, 2019), (Wolbertus, et al., 2019), (Zethmayr, et al., 2019), (Bansal, et al., 2019), (Yuan, et al., 2019). This manuscript presumes all of these contending aspects are self-evident in vehicle sales data as a reflection of buyers’ perceptions. Therefore sales data remain the focus for analysis here as we seek to predict the future electric vehicle market (Lee, et al., 2011), (Electric Vehicle, 2019), (EV Sales, 2019), (Researchers, 2019), (Electric Vehicles Markets, 2019), (Electric Vehicle (EV) Transmission, 2019), (Electric Vehicle Market Size, 2019), (Electric Vehicle Market, 2019), (Global Electric, 2019), (Global EV, 2019), (Electric Vehicle Market by, 2019), (Electric Vehicle Market Forecast Report, 2019), (Electric Vehicle Market by Type, 2019), (Driving into 2025, 2019), (Electric Vehicle Market Outlook, 2019), (Electric Vehicle Sales Forecast and the Charging, 2019), (For Widespread Adoption, 2019), (Global Electric Vehicle Market (BEV, PHEV), 2019) .

2.2 Methods

Using the new data articulated and explained in sections 2.1-2.3 along with, analysis methods taken from deterministic artificial intelligence are applied to the exact dataset used for the prequel, where the data has merely been appended with the new data bestowing results in the following section of this manuscript comparable to the prequel. Definition of equations for the system that are optimal commence the effort such that sales data is reflected by the modeling. A brief divergence is taken (simple time-extrapolation) to establish the paradigm of the dynamics and grant a remedial expectation of the results. Next, the impact of slow-moving dynamics on the fast-moving (dominant) dynamic is investigated using differential forms of the optimal system equations. Such dual dynamic (slow and fast-moving) is the hallmark of Catastrophe theory, where often confounding nonlinear affects are seen. Decisions are often made using systems assumed to be linear, while otherwise unstable linear system models (those not settling at zero steady-state) can be slowly changing such that they can rapidly become stable (i.e. catastrophically settle at zero monthly sales). Equilibrium points are revealed by equating the differential forms (the principle re-parameterization) of the system equations to zero. Stability or instability is determined at each equilibrium. Slow modification of the differential equations illuminates "jump discontinuities" associated with potential catastrophe. Sales undesirably go to zero at a stable equilibrium point with a jump discontinuity.

The modification of system equations is driven by a forcing function predominantly comprised of gasoline prices and charging station proliferation, while gas prices are presumably not the dominant factor due to relative stability; and thus, EV charging station adoption amplified by V2G enhancements predominantly establish the forcing function.

3. Results

The following results follow the general process-flow of deterministic artificial intelligence: 1) perform optimal system identification, and then 2) reparametrize the optimal system dynamics to bestow predictive decision making. In this research, an intermediate step is inserted to establish the paradigm of the system dynamics and provide some measure of anticipation of expected results.

3.1 System Identification: Optimally Fitting Data to Assumed Models

Figure 1a shows the least squares analysis based on monthly and total sales of vehicles. The significant fact that actual cumulative sales data does not require a third-order (or higher) mathematical model to optimally fit the data, implying the existance of catastrophe of cumulative sales data (precititous, unexpected plummeting) is unlikely. The variance proportion of the dependent variable predictable by the independent variable is the coefficient of determination R in equation (1), while the correlation coefficient *r*, indicates the strength between variables and relationships, and may be calculated enroute to the coefficient of determination in equation (2). The basic equation of least squares is purposefully ommitted to preclude the accidental implication that system identificaion must be done with least squares, while other algorithms (e.g. extended least squares, posterior residuals, exponential forgetting, etc.) would also suffice (Sands, *Computation* 2017), (Sands, *J.Space Exp.* 2017).

$$R=r^2, \tag{1}$$

$$r=\frac{1}{n-1}\sum\left(\frac{x-\bar{x}}{S_x}\right)\left(\frac{y-\bar{y}}{S_y}\right), \tag{2}$$

$$y=219.7x, \tag{3}$$

$$y=0.4348x^2+189.34x, \tag{4}$$

$$y=0.0658x^3-7.5938x^2+409.7x, \tag{5}$$

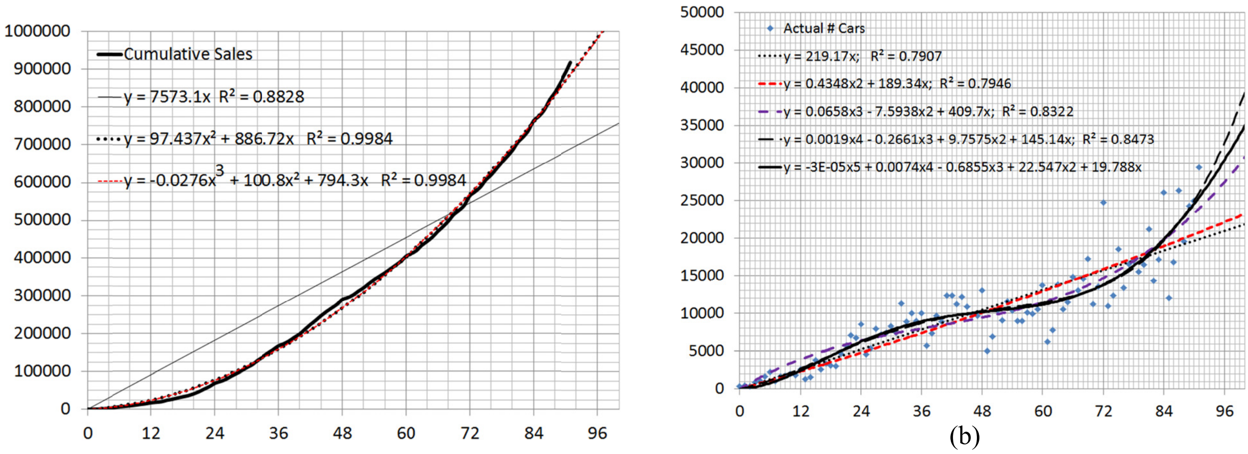
$$y=0.0019x^4-0.2661x^3+9.7575x^2+145.14x, \tag{6}$$

$$y=-3\times10^{-5}x^5+0.0074x^4-0.6855x^3+22.547x^2+19.788x, \tag{7}$$

Notice the proportion is not increased by increasing the order of the mathematical model, and thus a third-order system (and accompanying risk of catastrophe) is unnecessary. These facts fit intuition, since the cumulative total has built over years, and it is difficult to fathom a non-theoretical occurrence that would cause the cumulative total to go to zero (implying rapid depletion of the cumulative total via removal of hundreds of thousands of cars from the streets). This initial analysis is provided as an intermediate check of theory. Next, we commence the catastrophe analysis by switching to analysis of monthly sales data derivatives (as opposed to cumulative sales data) where equations (3)-(7) are the optimal system models established in the generic procedure of deterministic artificial intelligence, whose subsequent step is to parameterize to establish decision-making and process control motivations. The re-parameterization utilizes differential forms, but first we take a short informative digression to use extrapolation via forward time progression to bestow an initial instinct and establish an expected-result from the subsequent catastrophe analysis using differential forms.

It is also noteworthy to compare the prequel research results which concluded a potential catastrophe in 2019.

Figure 2 in reference (Sands, 2017) displayed a downward trend after the 40th month. This downward trend indicated the fast, dominant dynamics indeed is acted upon by a slow dynamic, and this slow dynamic was shown to potentially generate a catastrophic crash in vehicles sales in 2019. Figure 1 in this sequel reveals the previously-predicted downward trend was successfully reversed in very recent years without large steady-state reduction in gas prices implying electric vehicle charging station proliferation amplified by V2G seems to be one forcing function that has averted the previously-predicted potential catastrophe, and subsequent paragraphs investigate whether this trend reversal is sufficient to avoid any potential catastrophe.



(a) (b)

Figure 1. Abscissa displays months since December 2010, while the ordinant displays number of vehicles sold. (a) Least squares curves fitting *cumulative* sales data. (b) Least squares curves (lines) fitting *monthly* sales data (points).

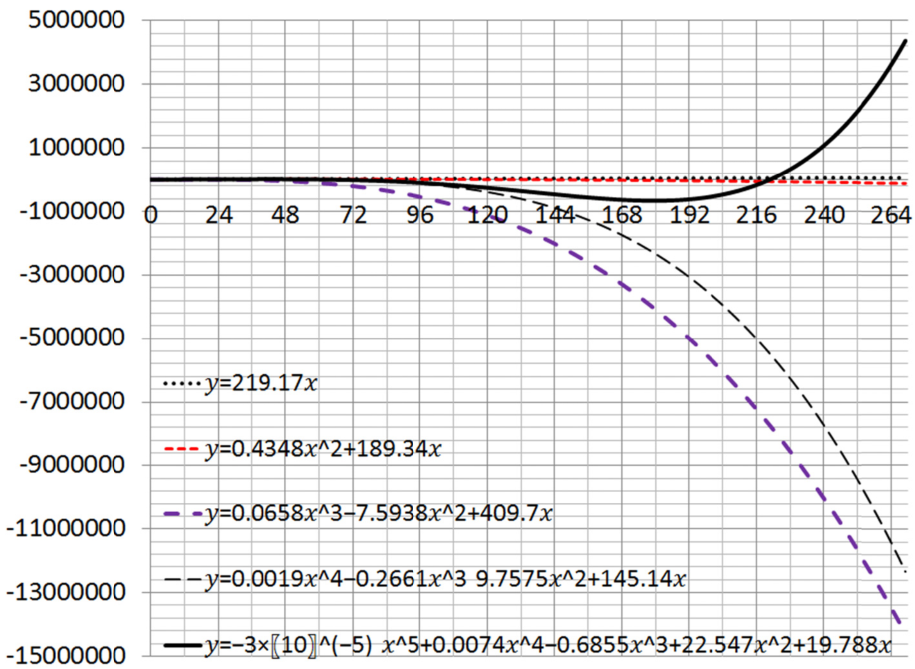


Figure 2. Inherent dynamics (optimal math models) extrapolated to future time. Abscissa displays months since December 2010, while the ordinant displays *monthly* number of vehicles sold.

3.2 ASIDE: Extrapolation by Forward Time Propagation

Often, nominal future sales are guessed by propagating forward the optimal system equations' curves (Figure 2). Since higher order models can account for higher order affects, accuracy increases with order (i.e., data is better fit by the curves) Order is usually increased until the correct model is achieved, after which increasing order no longer yields significant accuracy improvement. Cumulative sales data indicated that high-order forms did not more-accurately represent the sale data. Investigating monthly sales data five models are investigated, where low-order models indicate a near-static, slight decline in monthly sales, while the third and fourth ordered forms indicate potential catastrophe, and the fifth order model indicated an initial (lengthy) catastrophe followed by a rebound eighteen years later.

3.3 Sales Rates from Differentiation of Assumed Models

Each point in Figure 1b is sales for a given month, and each line represent sequentially higher-ordered models. All the curves generally oscillate in an increasingly upward direction. It is easy to (perhaps mistakenly) conclude increasing sales (without a catastrophic jump) should be expected, but we learned in the prequel research (Sands, 2017) that upward trend was would continue if permitting to continue based on the system's own internal dynamics defined by the optimal system equations. Figure 2 reveals that catastrophic sales decline remains a distinct possibility, as was revealed in the prequel (Sands, 2017), despite equations 8-12 (corresponding to equations (3)-(7) respectively) differing from the results in the prequel. The differences in equations indicate something has changed since the prequel, so next we perform catastrophe analysis using equilibrium points of the differential forms (equations 8-12) whose results are displayed in figure 3.

$$\frac{dy}{dx} = 219, \tag{8}$$

$$\frac{dy}{dx} = 0.9296x + 189.34, \tag{9}$$

$$\frac{dy}{dx} = 0.1974x^2 - 15.1876x + 409.7, \tag{10}$$

$$\frac{dy}{dx} = 0.0076x^3 - 0.7983x^2 + 19.515x + 145.14, \tag{11}$$

$$\frac{dy}{dx} = 15 \times 10^{-5}x^4 + 0.0296x^3 - 2.0565x^2 + 45.094x + 19.788, \tag{12}$$

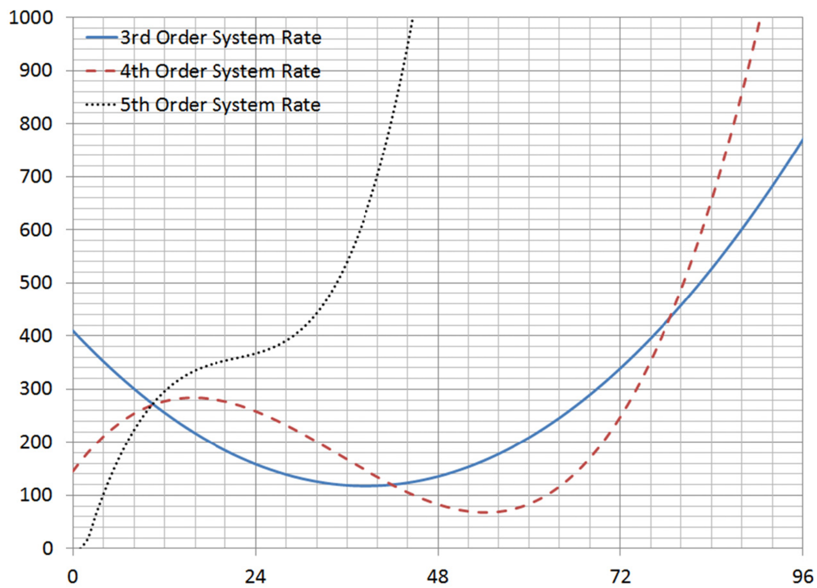


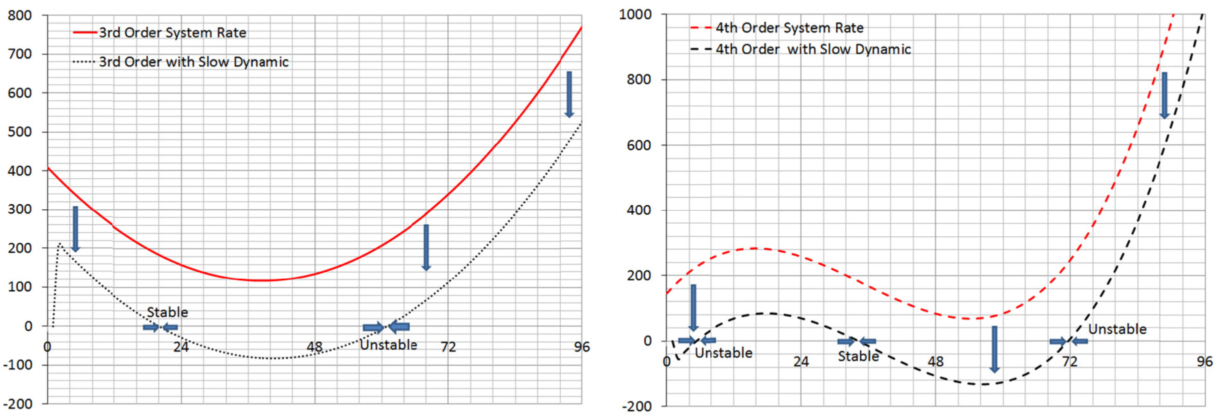
Figure 3. Sales rate dynamics

3.4 Fast and Slow Dynamics of Catastrophe Theory Starts with Finding Equilibrium Points

Continuing with our analysis, we investigate whether these system equations are susceptible to "jumps" associated with catastrophe theory. Differentiating the optimal system equations would reveal equilibrium points in the system equation where the rate equations cross zero (Figure 4a and 4b). A stable equilibrium point indicates potential, since the system's inherent dynamic would seek to stay at the stable equilibrium poing (zero monthly sales…a catastrophe).

3.5 Slow Moving Dynamics in Systems: Impulse Iteration

Since the fifth order form indicates eventual catastrophe recovery, we focus the examination on the third and fourth degree forms (see figure 4). Both forms indicate potential catastrophy in the past associated with stable equilibrium points, while unstable equilibrium points equilibrium points exist in the immediate past, indicating the upward trends unanimously indicated in figure 1b are positively reinforced by catastrophe analysis. This indicates the risk of catestrophic decline has past, and it is now reasonable to predict a sustained increase in electric vehicle sales, adding to the robust potential of the industrial base.



(a) **(b)**

Figure 4. Use dy/dx = 0 to locate equilibrium points.

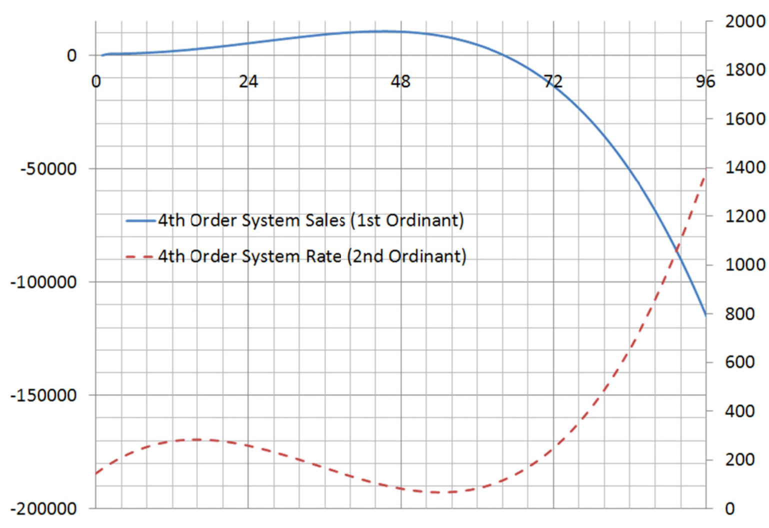


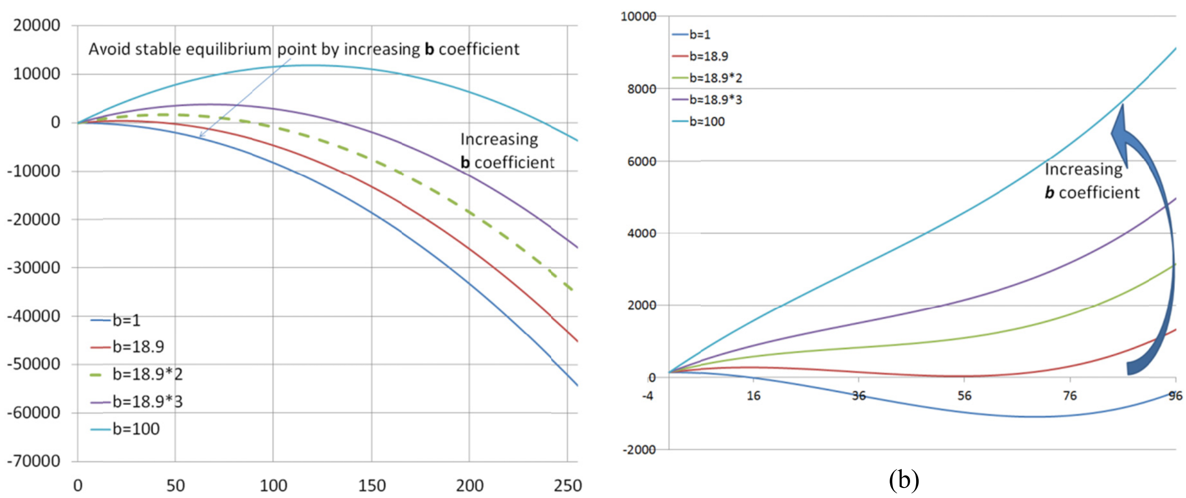
Figure 5. Sales and rate equations extrapolated in time.

This result is different than the prequel analysis (Sands, 2017), so explanatory investigation is warranted to be sure we can believe the most recent sales data has indeed changed the underlying optimal system dynamics. Figure 5 compares the 4th order system model, emphasizing the behavior leading up to the year 2018. The figure reveals that 2018 culminated a dramatic change in the system dynamics that began in 2015 (the last data available for the prequel research). Thus, the prequel research was amidst a system-recovery indicated by modeled declining sales, yet sharply improving sales rates.

Equation 6, whose differential form is equation 11 illustrate the importance of the coefficient "*b*" as articulated in the prequel representing the forcing function of relative gas prices (whose importance is minimized by relatively stable gas prices) and charging station proliferation (whose importance is amplified by V2G). The prequel iterated control variables *a*, *b*, and *c*, and control variable *b* was found to have the most significant impact. Furthermore, iteration of coefficients in the prequel revealed modification between stable and unstable is best achieved by modifying the *b* coefficient on the squared-term as displayed in figure 6a (reminder: this figure displays the prequel results, which lacked data after 2015). Physically, the *b*-coefficient represents a forcing function due to its second-order form. Such forcing functions include changes in gasoline prices, changes in availability of charging stations, and overall attractiveness of electrical vehicles to buyers (performance, comfort, appearance, etc.).

Figure 6b depicts the least squares optimal system equation (*b*=18.9 from the prequel) compared to higher and lower values of *b*, where we see that 18.9 remains a key inflection value. Notice in figure 11b that values of *b* higher than 18.9 preclude a future catastrophe. Meanwhile it remains apparent that reducing *b* degrades sales and could be associated with higher gas prices or other negative forcing functions. Lowering gas prices (or other positive forcing functions) could be associated with increasing b which improves sales performance.

A key point is the gross nature of the curves in figure 6 a and b. Notice the prequel (figure 6a) revealed all of the system definitions resulting in stable equilibrium points, and increasing the b coefficient (the forcing function) merely delayed the potential catastrophe. Meanwhile using the updated sales data, the curves revealed in this study displayed in figure 6b indicate all curve eventually turn upward (good). Thus, new innovative forcing functions are not necessary, rather continuation of the forcing functions used in the recent past (policy in particular) should be continued to maintain the momentum.



(a) (b)

Figure 6. Increasing b coefficient to increase sales. (a) results of original data in ref (Sands, 2017), (b) updated results using latest sales data

4. Discussion

The results of this sequel research indicates that positive measures exemplified by charging station proliferation amplified by V2G leading up to the year 2015 have resulted in a modification of the governing inherent dynamics of electric vehicle sales. The predicted catastrophe in 2019 seems to have been averted. Subsequent to very recent years, it seems that electric vehicle monthly sales have passed an unstable equilibrium point, indicating the system is very unlikely to crash or rapidly reduce to zero. These results therefore predict (contrary to the prequel) the industrial base will be supported by robust electric vehicle sales, and future adopters (e.g. military units that currently strictly rely on petroleum fueled small and medium vehicles) can legitimately contemplate using electric vehicles to support their operational imperatives. Previous policy actions should be celebrated and continued to maintain the momentum behind electric vehicle adoption by such potential new users. Adoption by military units should be pursued, since such would establish a (non-fickle) client base, as such units tend to react relatively slowly to negative forcing functions.

4.1 Future Research

Periodic re-evaluation with updates sales data should be considered, especially in instances when driving functions change, especially gasoline prices).

Acknowledgments

Authorship has been limited to those who have contributed substantially to the work. This research received no external funding. No sources of funding apply to the study. Grants were not received in support of our research work. No funds were received for covering the costs to publish in open access, instead this was an invited manuscript to the special issue. Timothy Sands is not a tenured faculty member of Columbia University; rather he is the Associate Dean of the Naval Postgraduate School's Graduate School of Engineering and Applied Sciences. In order to avoid legal jeopardy, Timothy Sands publishes government-funded research under his association with the Naval Postgraduate School, while publishing non-government funded research under his continuing associations with Stanford and Columbia Universities. The author declares no conflicts of interest.

References

Agaton, C.B., Guno, C.S., Villanueva, R.O. & Villanueva, R.O. (2019). Diesel or Electric Jeepney? A Case Study of Transport Investment in the Philippines Using the Real Options Approach. *World Electr. Veh. J., 10*, 51 https://doi.org/10.3390/wevj10030051

Almeida, A, Sousa, N. & Coutinho-Rodrigues, J. (2019). Quest for Sustainability: Life-Cycle Emissions Assessment of Electric Vehicles Considering Newer Li-Ion Batteries. *Sustainability, 11*, 2366. https://doi.org/10.3390/su11082366

Baker, K, Cooper, M, Heidlauf, P. & Sands, T. (2018). Autonomous trajectory generation for deterministic artificial intelligence. *Elect. and Electron. Eng, 8*(3), 59.

Bansal, P. (2015). Charging of Electric Vehicles: Technology and Policy Implications. *J. Sci. Pol. Gov, 6*(1).

Bittick, L. & Sands, T. (2019). Political Rhetoric or Policy Shift: A Contextual Analysis of the Pivot to Asia. *Journal of Social Science, 15*, 92-125. https://doi.org/10.3844/jssp.2019.92.125

Camacho, H, Mihalik, R. & Sands, T. (2017). Education in nuclear deterrence and assurance. *J. Def. Manag, 7*(2), 166-166. https://doi.org/10.4172/2167-0374.1000166.

Chen, T, Chen, L, Xu, X, Cai, Y, Jiang, H. & Sun, X. (2019). Sideslip Angle Fusion Estimation Method of an Autonomous Electric Vehicle Based on Robust Cubature Kalman Filter with Redundant Measurement Information. *World Electr. Veh. J, 10*, 34 https://doi.org/10.3390/wevj10020034

Cobb, Jeff, (2018). *December 2018 Dashboard. HybridCars*, January 4, 2018. http://www.hybridcars.com/december-2017-dashboard/ (accessed 23 August 2018).

Cooper, M, Heidlauf, P. & Sands, T. (2017). Controlling Chaos—Forced van der Pol Equation. *Mathematics, 5*(4) 70. https://doi.org/10.3390/math5040070.

Driving into 2025: The Future of Electric VehiclesAvailable online: https://www.jpmorgan.com/global/research/electric-vehicles (accessed 30 August 2019).

Electric Vehicle Outlook (2019). Available online: https://about.bnef.com/electric-vehicle-outlook/ (accessed 30 August 2019).

Electric Vehicles Market (EVs) Insights (2019). *Industry Demand Growth, Sales, Trends, Top Players Analysis – BYD*, Bayerische Motoren Werke, Daimler, Dongfeng Electric Vehicle, Forecast 2025. Available online: https://socioherald.com/electric-vehicles-market-evs-insights-2019-industry-demand-growth-sales-trends-top-players-analysis-forecast-2025/159302/ (accessed 30 August 2019).

Electric Vehicle (EV) (2019). *Transmission Market to Reach $15.38 Bn, Globally, by 2026 at 25.8% CAGR: Allied Market Research.* Available online: https://finance.yahoo.com/news/electric-vehicle-ev-transmission-market-125000426.html (accessed 30 August 2019).

Electric Vehicle Market Size, Analytical Overview, Growth Factors, (2019). *Demand and Trends Forecast to 2026.* Available online:

https://scoopjunction.com/electric-vehicle-market-size-analytical-overview-growth-factors-demand-and-trends-forecast-to-2026/143577/ (accessed 30 August 2019).

Electric Vehicle *Market - Global Forecast to 2030: Market Volume is Expected to Reach 26,951,318 Units. Available* online: https://www.prnewswire.com/news-releases/electric-vehicle-market---global-forecast-to-2030-market-volume-is-expected-to-reach-26-951-318-units-300882634.html/ (accessed 30 August 2019).

Electric Vehicle *Market by Type (Battery Electric Vehicle, Hybrid Electric Vehicle, and Plug-in Hybrid Electric Vehicle), and Vehicle Type* (Passenger Car, Commercial Vehicle, and Two-Wheeler) - Global Opportunity Analysis and Industry Forecast, 2018-2025. Available online: https://www.alliedmarketresearch.com/electric-vehicle-market (accessed 30 August 2019).

Electric Vehicle *Market by Vehicle (Passenger Cars & Commercial Vehicles), Vehicle Class (Mid-priced & Luxury), Propulsion (BEV, PHEV & FCEV), EV Sales (OEMs/Models) Charging Station (Normal & Super) & Region - Global Forecast to 2030*. Available online: https://www.marketsandmarkets.com/Market-Reports/electric-vehicle-market-209371461.html (accessed 30 August 2019).

Electric Vehicle *Market Forecast Report, 2023 - Top Key Players Analyzed: Tesla*, Volkswagen, Mitsubishi, Renault, Nissan, & BMW. Available online: https://www.bloomberg.com/press-releases/2019-05-14/electric-vehicle-market-forecast-report-2023-top-key-players-analyzed-tesla-volkswagen-mitsubishi-renault-nissan-bmw (accessed 30 August 2019).

Electric Vehicle Market Outlook - Segmentation by Electric Vehicle (EV) *Battery Analysis, Charging Station Infrastructure Trends - Growth, Trends, and Forecast* (2019 - 2024). Available online: https://www.mordorintelligence.com/industry-reports/electric-vehicle-market-outlook (accessed 30 August 2019).

Electric Vehicle *Sales Forecast and the Charging Infrastructure Required Through 2030.* Available online: https://www.edisonfoundation.net/iei/publications/Documents/IEI_EEI%20EV%20Forecast%20Report_Nov2018.pdf (accessed 30 August 2019).

EV Sales Forecasts. Available online: https://evadoption.com/ev-sales/ev-sales-forecasts/ (accessed 30 August 2019).

For Widespread Adoption of Electric Vehicles, (2019). *Many Roadblocks Ahead*. Available online: https://morningconsult.com/2019/05/22/for-widespread-adoption-of-electric-vehicles-many-roadblocks-ahead/ (accessed 30 August 2019).

Fujita, H, Itoh, A. & Urano, T. (2019). Newly Developed Motor Cooling Method Using Refrigerant. *World Electr. Veh. J, 10*, 38. https://doi.org/10.3390/wevj10020038

Fujita, T, Kishi, H, Uno, H. & Kaneko, Y. (2019). A Real-Car Experiment of a Dynamic Wireless Power Transfer System Based on Parallel-Series Resonant Topology. *World Electr. Veh. J, 10*, 49. https://doi.org/10.3390/wevj10030049

Global Electric Vehicle (EV) Market Forecasts to 2030 - Market Volume Projected to Grow from 3,269,671 Units in 2019 to 26,951,318 Units by 2030. Available online: https://www.globenewswire.com/news-release/2019/08/06/1897431/0/en/Global-Electric-Vehicle-EV-Market-Forecasts-to-2030-Market-Volume-Projected-to-Grow-from-3-269-671-Units-in-2019-to-26-951-318-Units-by-2030.html (accessed 30 August 2019).

Global Electric Vehicle Market (BEV, PHEV) 2019 Sales, Key Manufacturers, Size, Share, Demands and Forecasts to 2025. Available online: https://finance.yahoo.com/news/global-electric-vehicle-market-bev-120000078.html (accessed 30 August 2019).

Global EV Outlook (2019). Scaling up the transition to electric mobility. Available online: https://www.iea.org/publications/reports/globalevoutlook2019/ (accessed 30 August 2019).

Gohlke, D & Zhou, Y, (2018). *Impacts of Electrification of Light-Duty Vehicles in the United States*, 2010 – 2017, Argonne National Laboratory, Lemont, IL USA, Technical Report ANL/ESD-18/1, 2018. https://doi.org/10.2172/1418278

Gong, X, Qian, L, Ge, W. & Wang, L. (2019). Research on the Anti-Disturbance Control Method of Brake-by-Wire Unit for Electric Vehicles. *World Electr. Veh. J, 10*, 44. https://doi.org/10.3390/wevj10020044

Hao, H, Mu, Z, Jiang, S, Liu, Z. & Zhao, F. (2017). GHG Emissions from the Production of Lithium-Ion Batteries for Electric Vehicles in China. *Sustainability, 9*, 504. https://doi.org/10.3390/su9040504

Jäger, G, Hofer, C. & Füllsack, M. (2019). The Benefits of Randomly Delayed Charging of Electric Vehicles. *Sustainability, 11*, 3722. https://doi.org/10.3390/su11133722

Jia, J, Liu, C. & Wan, T. (2019). Planning of the Charging Station for Electric Vehicles Utilizing Cellular Signaling Data. *Sustainability, 11*, 643. https://doi.org/10.3390/su11030643

Jiyan Qi, Jingshun Fu. & Jiaqi Jin. (2019). Parameter matching and sensitivity analysis for the powertrain system of micro-electric vehicle. *Int. J. Elec. Hyb. Veh, 11*(1), 23-35 https://doi.org/10.1504/IJEHV.2019.098720

Kuklinski, C, Mitchell, J. & Sands, T. (2020). Bipolar strategic stability in a multipolar world. *Journal of Politics and Law, 13*(1).

Kusaka, K, Inoue, K & Itoh. 7 J.-I. (2019). Comparative Verification of Radiation Noise Reduction Effect Using Spread Spectrum for Inductive Power Transfer System. *World Electr. Veh. J, 10*, 40. https://doi.org/10.3390/wevj10020040

Lee, H. & Lovellette, G, (2011). *Will Electric Cars Transform the U.S. Market?* Faculty Research Working Paper Series, RWP11-032, Harvard Kennedy School of Government, August 2011. https://doi.org/10.2139/ssrn.1927351

Li, L, He, W. Yingcong Wang & Xu Li, (2019). Modelling of the wide frequency equivalent circuit of the three-phase AC motor based on vector fitting method. *Int. J. Elec. Hyb. Veh, 11*(1), 12-22. https://doi.org/10.1504/IJEHV.2019.098722

Li, Q, Xiao, Y, Zhao, S, Zhu, X, Wang, Z, Liu, Z, Wang, L, Yan, X & Wang, Y. (2019). Performance Status Evaluation of an Electric Vehicle Charging Infrastructure Based on the Fuzzy Comprehensive Evaluation Method. *World Electr. Veh. J, 10*, 35. https://doi.org/10.3390/wevj10020035

Li, W, Long, R, Chen, H, Chen, F, Zheng, X & Yang, M. (2019). Effect of Policy Incentives on the Uptake of Electric Vehicles in China. *Sustainability, 11*, 3323. https://doi.org/10.3390/su11123323

Light Duty Electric Drive Vehicles Monthly Sales Updates. Available online: https://www.anl.gov/es/light-duty-electric-drive-vehicles-monthly-sales-updates (accessed on 23 Aug 2018).

Lobo, K, Lang, J, Starks, A & Sands, T. (2018). Analysis of deterministic artificial intelligence for inertia modifications and orbital disturbances. *Int. J. Cont. Sci. Eng, 8*(3), 53.

Lopez-Arboleda, E, Sarmiento, A.T & Cardenas, L.M. (2019). Systematic Review of Integrated Sustainable Transportation Models for Electric Passenger Vehicle Diffusion. *Sustainability, 11*, 2513. https://doi.org/10.3390/su11092513

Márquez-Fernández, F.J, Schuch, S, Lindgren, L & Alaküla, M. (2019). Electric Safety Challenges with a Conductive Electric Road System—Chassis Potential Modeling and Measurement. *World Electr. Veh. J, 10*, 30. https://doi.org/10.3390/wevj10020030

Mayer, B, Schier, M & Friedrich, H.E. (2019). Stand-Alone Battery Thermal Management for Fast Charging of Electric Two Wheelers—Integrated Busbar Cooling. *World Electr. Veh. J, 10*, 37. https://doi.org/10.3390/wevj10020037

Mihalik, R & Sands, T. (2016). Outcomes of the 2010 and 2015 nonproliferation treaty review conferences. *World J. Soc. Sci. Hum, 2*(2), 46-51. https://doi.org/10.12691/wjssh-2-2-4.

Mihalik, R. Camacho, H. & Sands, T. (2018). Theoretical Context of the Nuclear Posture Review. *J. Soc. Sci, 14*(1), 124-128, https://doi.org/10.3844/jssp.2018.124.128.

Mihalik, R. Camacho, H. & Sands, T. (2017). Continuum of learning: Combining education, training and experiences. *Education, 8*, 9-13. https://doi.org/10.5923/j.edu.20180801.03

Minnerup, K, Herrmann, T, Steinstraeter, M & Lienkamp, M. (2019). Case Study of Holistic Energy Management Using Genetic Algorithms in a Sliding Window Approach. *World Electr. Veh. J, 10*, 46. https://doi.org/10.3390/wevj10020046

Mo, J.Y & Jeon, W. (2018). The Impact of Electric Vehicle Demand and Battery Recycling on Price Dynamics of Lithium-Ion Battery Cathode Materials: A Vector Error Correction Model (VECM) Analysis. *Sustainability, 10*, 2870. https://doi.org/10.3390/su10082870

Monthly Plug-In Sales Scorecard, available online: https://insideevs.com/monthly-plug-in-sales-scorecard/ (accessed 23 August 2018).

Müller, J.M. (2019). Comparing Technology Acceptance for Autonomous Vehicles, Battery Electric Vehicles, and Car Sharing—A Study across Europe, China, and North America. *Sustainability, 11*, 4333. https://doi.org/10.3390/su11164333

Nakatani, S. (2014). *Simulation of spacecraft damage tolerance and adaptive controls, Proceedings of the IEEE Aerospace Conference*, Big Sky, Montana, USA, 1-16. February, 2014. https://doi.org/10.1109/AERO.2014.6836260.

Nakatani, S. (2016). Autonomous damage recovery in space. *Intl. J. Auto. Contr. Intell. Sys, 2*(2), 22.

Nakatani, S. & Sands, T. (2018). Battle-damage tolerant automatic controls. *Electr. Electron. Eng, 8*(1), 23.

Obayashi, S, Shijo, T, Suzuki, M, Moritsuka, F, Ogawa, K, Ogura, K, Kanekiyo, Y, Ishida, M, Takanaka, T, Tada, N, Takeuchi, F, Take, S, Yamauchi, Y, Yang, W.-H & Kamiya, Y. (2019). 85 kHz Band 44 kW Wireless Rapid Charging System for Field Test and Public Road Operation of Electric Bus. *World Electr. Veh. J, 10*, 26. https://doi.org/10.3390/wevj10020026

Ortar, N & Ryghaug, M. (2018). Should All Cars Be Electric by 2025? The Electric Car Debate in Europe. *Sustainability, 11*, 1868. https://doi.org/10.3390/su11071868

Pier Giuseppe Anselma & Giovanni Belingardi. (2019). Comparing battery electric vehicle powertrains through rapid component sizing. *Int. J. Elec. Hyb. Veh, 11*(1), 36-58. https://doi.org/10.1504/IJEHV.2019.10020149

Philipsen, R, Brell, T, Biermann, H & Ziefle, M. (2019). Under Pressure—Users' Perception of Range Stress in the Context of Charging and Traditional Refueling. *World Electr. Veh. J, 10*, 50. https://doi.org/10.3390/wevj10030050

Plug-In Electric Vehicle Sales Report Card, available online: https://insideevs.com/december-2015-plug-electric-vehicle-sales-report-card/(accessed 23 August 2018).

Rajeev Goswami & Gireesh Chandra Tripathi. (2019). Economic, environmental and congestion impact on the life-cycle cost of ownership: a case study in the Delhi transit bus system. *Int. J. Elec. Hyb. Veh, 11*(1), 72.https://doi.org/10.1504/IJEHV.2019.10020150

Ricciardi, V, Ivanov, V, Dhaens, M, Vandersmissen, B, Geraerts, M, Savitski, D & Augsburg, K. (2019). Ride Blending Control for Electric Vehicles. *World Electr. Veh. J, 10*, 36. https://doi.org/10.3390/wevj10020036

Researchers have no idea when electric cars are going to take over. Available online: https://qz.com/1620614/electric-car-forecasts-are-all-over-the-map/ (accessed 30 August 2019).

Sands, T. (2019). *Deterministic Artificial Intelligence*, Publisher: InTechOpen Publishers, London, U.K, ISBN: 978-1-78984-112-1

Sands, T. (2017). The Catastrophe of Electric Vehicle Sales. *Mathematics, 5*(3), 46.https://doi.org/10.3390/math5030046

Sands, T, Lorenz, R. (2009). *Physics-Based Automated Control of Spacecraft. Proceedings of the AIAA Space* 2009 Conference and Exposition, Pasadena, CA, USA, 14–17 September 2009.https://doi.org/10.2514/6.2009-6625

Sands, T. (2012). *Physics-based control methods.* In Adv. Space. Sys. Orb. Det, Edited by Rushi Ghadawala, InTech Open, London, 2012, pp. 29- 54. https://doi.org/10.5772/2408.

Sands, T. (2015). Improved Magnetic Levitation via Online Disturbance Decoupling, *Phy. J, 1*(3), 272.

Sands, T. (2017). Nonlinear-adaptive mathematical system identification. *Computation*, *5*(4), 47. https://doi.org/10.3390/computation5040047.

Sands, T. (2017). Space systems identification algorithms. *J. Space Exp, 6*(3), 138, ISSN: 2319-9822.

Sands, T, Kenny, T. (2017). Experimental piezoelectric system identification. *J. Mech. Eng. Autom, 7*(6), 179. https://doi.org/10.5923/j.jmea.20170706.01.

Sands, T. (2017). Phase lag elimination at all frequencies for full state estimation of spacecraft attitude. *Phys. J, 3*(1), 1.

Sands, T. (2018). Experimental Sensor Characterization , *J. Space Exp, 7*(1), 140.

Sands, T & Armani, C. (2018). Analysis, correlation, and estimation for control of material properties. *J. Mech. Eng. Autom, 8*, 7–31. https://doi.org/10.5923/j.jmea.20180801.02.

Sands, T. (2019). Optimization provenance of whiplash compensation for flexible space robotics. *Aerospace, 6*(9), 93**.**

Sands, T. (2019). Predictive control design paradigm for optimality and robustness. *Algorithms*, under review (invited submission).

Sands, T, Bollino, K. Kaminer, I & Healey, A. (2018). Autonomous Minimum Safe Distance Maintenance from Submersed Obstacles in Ocean Currents*. J. Mar. Sci. Eng, 6*(3), 98. https://doi.org/10.3390/jmse6030098

Sands, T. (2016). Strategies for combating Islamic state. *Soc. Sci, 5*(3), 39. https://doi.org/10.3390/socsci5030039.

Sands, T. (2009). *Satellite electronic attack of enemy air defenses.* In Proceedings of the IEEE Southeast Conference, Atlanta, GA USA 5-8 March 2009. https://doi.org/10.1109/SECON.2009.5174119.

Sands, T. (2018). Space mission analysis and design for electromagnetic suppression of radar. *Intl. J. Electromag. and Apps, 8*(1) 1-25. https://doi.org/10.5923/j.ijea.20180801.01.

Senda, K, Uesaka, M, Yoshizaki, S & Oda, Y. (2019). Electrical Steels and Their Evaluation for Automobile Motors. *World Electr. Veh. J, 10*, 31.https://doi.org/10.3390/wevj10020031

Smeresky, B, Rizzo, A & Sands, T. (2018). Kinematics in the Information Age. *Mathematics, 6*(9), 148, https://doi.org/10.3390/math6090148

Smeresky, B, Rizzo, A & Sands, T. (2020). Optimal learning and self-awareness. *Algorithms, 13*(1), 23.https://doi.org/10.3390/a13010023

Thilina, Dk (2019). Gunawardane, N. The effect of perceived risk on the purchase intention of electric vehicles: an extension to the technology acceptance model *Int. J. Elec. Hyb. Veh, 11*(1), 73 – 84. https://doi.org/10.1504/IJEHV.2019.10020148

Tu, J.-C & Yang, C. (2019). Key Factors Influencing Consumers' Purchase of Electric Vehicles. *Sustainability*, *11*, 3863. https://doi.org/10.3390/su11143863

Vehicle-to-grid project reveals challenges of the early days, available online at https://chargedevs.com/features/vehicle-to-grid-project-reveals-challenges-of-the-early-days/ (accessed 10 September 2018).

Vermeulen, I, Helmus, J.R, Lees, M & van den Hoed, R. (2019). Simulation of Future Electric Vehicle Charging Behavior—Effects of Transition from PHEV to FEV. *World Electr. Veh. J, 10*, 42. https://doi.org/10.3390/wevj10020042

Wang, H & Wu, H. (2019). Implementation of an Energy Management Strategy with Drivability Constraints for a Dual-Motor Electric Vehicle. *World Electr. Veh. J, 10*, 28. https://doi.org/10.3390/wevj10020028

Watanabe, T & Hakuta, Y. (2019). Evaluation of the Magnetic Field Leakage from Two Wireless Power Transfer Systems for EV/PHV Driven Simultaneously. *World Electr. Veh. J, 10*, 41. https://doi.org/10.3390/wevj10020041

Wolbertus, R & Van den Hoed, R. (2019). Electric Vehicle Fast Charging Needs in Cities and along Corridors. *World Electr. Veh. J, 10*, 45. https://doi.org/10.3390/wevj10020045

Wolbertus, R & Bas Gerzon, B, (2018). Improving Electric Vehicle Charging Station Efficiency through Pricing. *J. Adv. Trans, article ID 4831951,* 11. https://doi.org/10.1155/2018/4831951

Wu, D, Ren, J, Davies, H, Shang, J & Haas, O. (2019). Intelligent Hydrogen Fuel Cell Range Extender for Battery Electric Vehicles. *World Electr. Veh. J, 10*, 29. https://doi.org/10.3390/wevj10020029

Yu, Z, Cheng, D & Huang, X. (2019). Low-Frequency Road Noise of Electric Vehicles Based on Measured Road Surface Morphology. *World Electr. Veh. J, 10*, 33. https://doi.org/10.3390/wevj10020033

Yuan, W, Huang, J & Zhang, Y.J.A (2017). Competitive Charging Station Pricing for Plug-In Electric Vehicles. *IEEE Trans. Smart Grid, 8*(2), 627.

Zethmayr, J & Kolata, D. (2019). Charge for Less: An Analysis of Hourly Electricity Pricing for Electric Vehicles. *World Electr. Veh. J, 10*, 6. https://doi.org/10.3390/wevj10010006

Zha, Y, Song, J, Zhang, Q. Guoqing Liu & Ronghui Guo (2019). Optimisation of control strategy of a range-extended electric bus. *Int. J. Elec. Hyb. Veh, 11*(1), 1-11. https://doi.org/10.1504/IJEHV.2019.098705

Zhang, W, Yang, J, Zhang, W & Ma, F. (2019). Research on Regenerative Braking of Pure Electric Mining Dump Truck. *World Electr. Veh. J, 10*, 39. https://doi.org/10.3390/wevj10020039

Zhang, L, Zhao, Z, Chai, J & Kan, Z. (2019). Risk Identification and Analysis for PPP Projects of Electric Vehicle Charging Infrastructure Based on 2-Tuple and the DEMATEL Model. *World Electr. Veh. J, 10*, 4. https://doi.org/10.3390/wevj10010004

Zhang, X, Xie, J, Rao, R & Liang, Y. (2014). Policy Incentives for the Adoption of Electric Vehicles across Countries. *Sustainability, 6*, 8056-8078. https://doi.org/10.3390/su6118056

Zhao, Y, Huang, H, Chen, X, Zhang, B, Zhang, Y, Jin, Y, Zhang, Q, Cheng, L & Chen, Y. (2019). Charging Load Allocation Strategy of EV Charging Station Considering Charging Mode. *World Electr. Veh. J, 10*, 47.https://doi.org/10.3390/wevj10020047

Appendix A

Definitions and Data

Definitions, verbiage, and data are taken directly from (Gohlke, 2019) and (Light Duty, 2019), where verbiage is modified for clarity and easier reading. The background material and methods reside on a "living-website" that routinely updates its content leading to the unavailability of this material following website updates. For example, seeking the 2015 data in the prequel article (Sands, 2017), readers who go to the referenced citations can no longer access the raw data to duplicate the prequel results. Therefore, in this sequel enough material taken directly from the cited sources (with credit to them) has been added in the appendix, so the readers of this new sequel can duplicate the research.

A.1. Definitions Taken Directly from (Gohlke, 2019) and (Light Duty, 2019)

Currently available electric-drive vehicles in the U.S market include hybrid electric vehicles, plug-in hybrid electric vehicles, battery electric vehicles and fuel cell electric vehicles. Plug-in vehicles include both plug-in hybrid electric vehicles and battery electric vehicles. Hybrid electric vehicles debuted in the U.S. market in December 1999 with a mere seventeen sales of the first-generation Honda Insight, while the first plug-in hybrid electric vehicles (Chevrolet Volt) and battery electric vehicles (Nissan Leaf) more recently debuted in December 2010. Electric drive vehicles are offered in several car and sport-utility vehicle models, and a few pickup and van models.

A.2. Data Taken Directly from (Gohlke, 2019) and (Light Duty, 2019)

Historical sales of hybrid electric vehicles, plug-in hybrid electric vehicles, and autonomous and electric vehicles are compiled by Argonne's Center for Transportation Research and reported to the U.S. Department of Energy's Vehicle Technologies Office each month. These sales are shown in Figures 1-5. Figure 1 shows monthly new battery electric vehicles and plug-in hybrid electric vehicles sales by model. Figure 2 shows cumulative U.S. plug-in vehicle sales. Figure 3 shows yearly new hybrid electric vehicles sales by model. Figure 4 shows electric drive vehicles sales share of total light-duty vehicle sales since 1999. Figure 5 show hybrid electric vehicles and plug-in vehicle sales change with gasoline price.

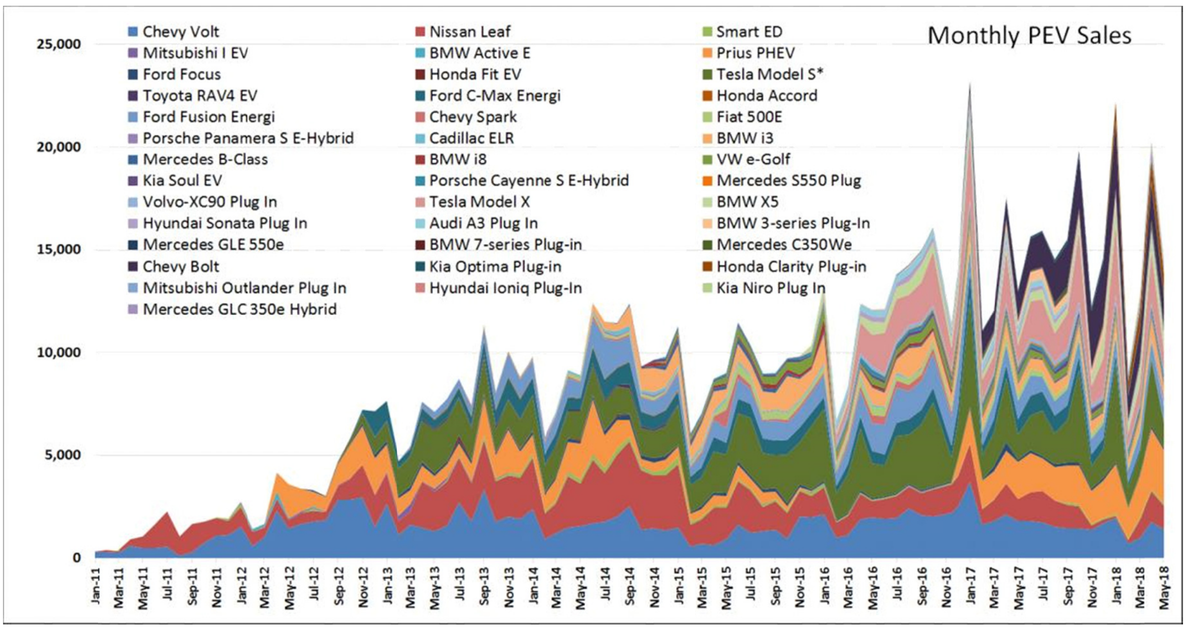


Figure 1. Monthly new plug-in vehicle sales.

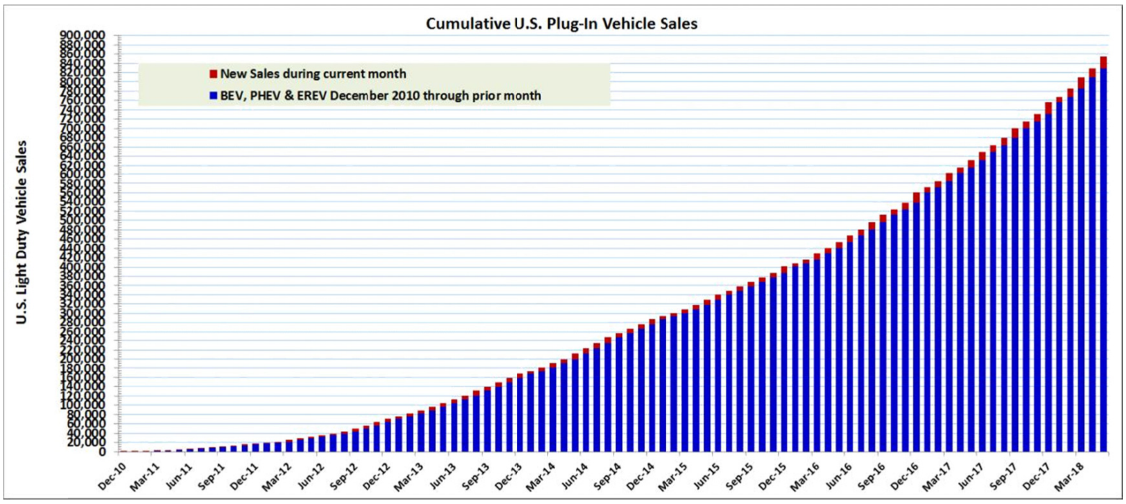


Figure 2. Commercial U.S. plug-in vehicle sales

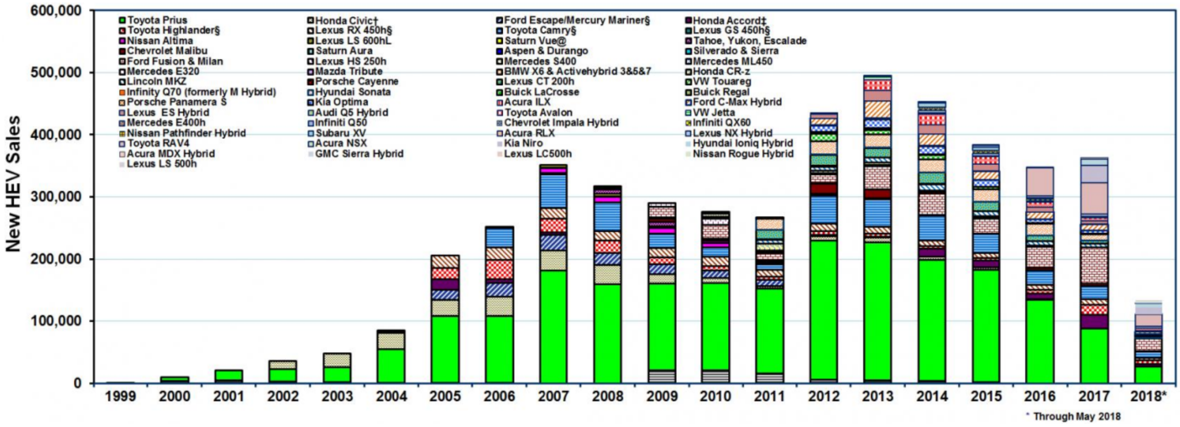


Figure 3. Yearly new hybrid electric vehicles sales by-model.

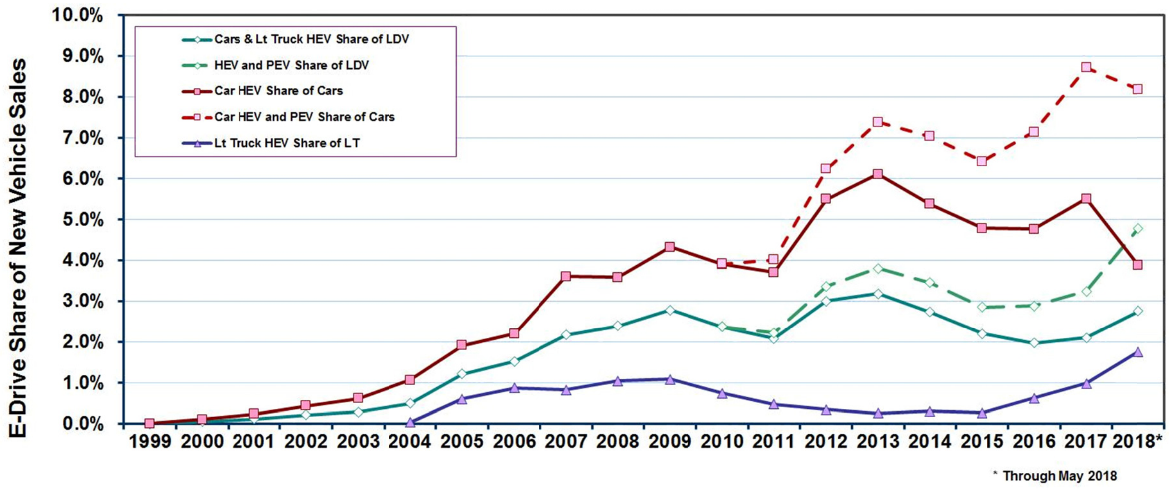


Figure 4. Electric-drive vehicle share of new vehicle sales

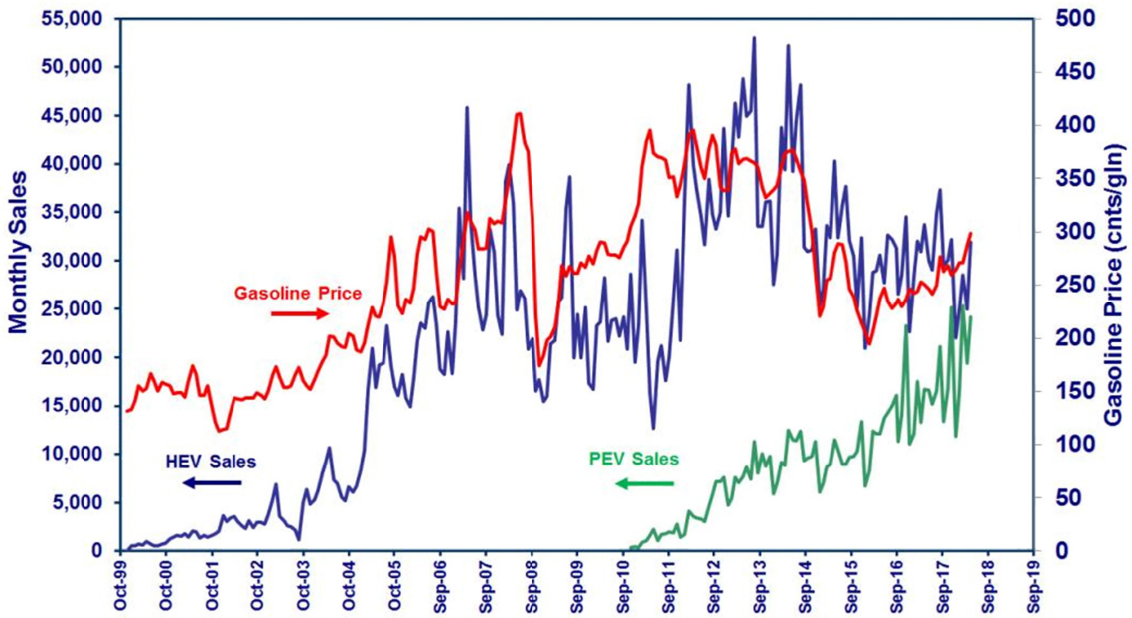


Figure 5. Monthly new electric-drive vehicle sales

A.2.1. Latest Monthly Sales Data taken directly from (Gohlke, 2019) and (Light Duty, 2019)

Sales data are compiled from several sources at different points in time. Initially, the data were compiled from J.D. Power and associates' sales reports, and Electric Drive Transportation Association and hybrid electric vehicle manufacturers' information. Later, the data were supplied to the Argonne National Laboratory by Green Car Congress. Currently, the data are collected from Hybrid Market Dashboard. Civic hybrid sales are as reported by Honda in 2003 and 2004. Data from 2005 and later represent sales as reported by Electric Drive Transportation Association, Hybrid Dashboard, and Green Car Congress. The Escape, Highlander, RX 400h, Camry, and GS 450h hybrid sales represent registration information from Electric Drive Transportation Association through 2006. The 2007 Escape and GS450h sales data are from Green Car Congress. Accord hybrid sales data are from Electric Drive Transportation Association and Green Car Congress. The 2007 Vue hybrid sales data are from Electric Drive Transportation Association (January to May only), and later sales data are from Hybrid Dashboard and Green Car Congress. These numbers are by calendar year, not by model year as reported by the U.S. EPA in its "Light Duty Automotive Technology, Carbon Dioxide Emissions and Fuel Economy Trends Report." The hybrid electric vehicles percent shares reported by U.S. Environmental Protection Agency are for vehicles weighing <=8,500 lbs. while shares reported here are for vehicles weighing <=10,000 lbs. The Alternative Fuels and Advanced Vehicles Data Center at the Department of Energy website also provides annual hybrid electric vehicles sales data.

A.2.2. Plug-in vehicle sales (see Table 1)

Table 1. Plug-in vehicles sales[1]

Vehicle	*June 2018*	*Comparison to June 2017*
Total hybrid-electric vehicles	31,123	+3.5%
Cars	22,692	
Light trucks	8,431%	
Total plug-in vehicles	29,514	+94.1%
Battery-electric vehicles	20,235	
Plug-in hybrid-electric vehicles	9,279	

[1] Data taken from [0-0].

A.2.3. Hybrid electric vehicle sales taken directly from (Gohlke, 2019) and (Light Duty, 2019)

During May 2018, 31,918 hybrid electric vehicles (23,041 cars and 8,877 light trucks) were sold in the United States, down 5.4% over the sales in May 2017. Toyota accounted for 53.0% share of total hybrid electric vehicles sales in this month. Prius (Prius C, Prius V and Prius Liftback in total) accounted for 18.0% (5,748 vehicles) of total hybrid electric vehicle sales, down 29.2% from May 2017. The May 2018 hybrid electric vehicle sales share of light-duty vehicle (<= 10,000 lbs. GVW) sales was 2.01%, while May 2018 hybrid electric vehicle cars captured 4.59% share of total car sales.

A.2.4. Hydrogen fuel cell electric vehicle sales

There were 102 Toyota Mirai, 30 Honda Clarity and 19 Hyundai Tucson sold in the United States in May 2018. Data and verbiage is taken directly from (Gohlke, 2019) and (Light Duty, 2019), where verbiage is modified for clarity and easier reading including definition of some terms left undefined in the cited reference

A.3.4. Light duty Vehicle Sales

Total 1,590,729 light duty vehicles (502,240 cars and 1,088,489 light trucks) were sold in the United States during May 2018, up 4.7% from the sales in May 2017. Light trucks continued to outsell cars in this month, 68.4% to 31.6%. Data and verbiage is taken directly from (Gohlke, 2019) and (Light Duty, 2019), where verbiage is modified for clarity and easier reading including definition of some terms left undefined in the cited reference