Nonlinear dynamics of electric vehicle sales in China: a fractal analysis*

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Abstract

Electric vehicles (EVs) are rapidly growing in the global automobile market, especially in China, which accounted for 45% of EV sales in 2020. However, forecasting the sales of EVs is challenging due to the complex and nonlinear nature of the market dynamics. In this paper, we apply three methods of nonlinear analysis to investigate the properties of the monthly sales volumes of the leading EV manufacturers in China from January 2016 to June 2022. The methods are: the Hurst normalized range method, phase analysis, and recurrence plots. We use the R software environment to perform the calculations and visualize the results. We find that the sales dynamics exhibit fractal features, trend stability, long-term memory, cyclicity, quasi-cycles, and determinism. These findings can inform the selection of relevant forecasting methods and their parameters for the EV market in China.

Keywords

electric vehicles, China, nonlinear dynamics, fractal analysis, phase analysis, recurrence plots, Hurst exponent

1. Introduction

Transportation is one of the major consumers of energy and a significant source of greenhouse gas emissions. To reduce the dependence on fossil fuels and mitigate the environmental impact, many developed countries have been promoting the adoption of electric vehicles (EVs) as a cleaner and more efficient alternative. EVs are vehicles that use electric motors powered by batteries or fuel cells, instead of internal combustion engines. EVs have been gaining popularity in the global automobile market, especially in China, which is the largest and fastest-growing EV market in the world.

The main drivers for the increasing demand for EVs can be classified into three categories. The first category is legislative factors, such as subsidies, discounts, free parking, free charging, and other incentives offered by governments to encourage EV purchases. The second category is environmental factors, such as the awareness of the negative effects of carbon dioxide emissions and the social responsibility of consumers to choose eco-friendly vehicles. The third category

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is energy security factors, such as the volatility of oil and gasoline prices and the vulnerability of supply chains. In contrast, electricity generation is more diversified and less dependent on external factors.

The competition in the EV market has stimulated the development of new technologies, enterprises, business models, and markets. The global EV market is still in its formative stage, with a large amount of investments in EV production and infrastructure. The decisions made during this period will shape the future architecture of the global market, from educational and production standards, urban infrastructure design, to new business models and market regulation conditions.

The EV market is an important and dynamic object of study, as it has significant implications for the global economy and the individual countries. According to Bloomberg rating agency estimates, EV sales will account for two-thirds of the global automobile market by 2040 [2]. Therefore, it is essential to understand the nature and dynamics of the EV market.

The global EV market is evolving, so it is necessary to determine the models for its evolution. Based on the statistical analysis of the EV market, it can be observed that China is the dominant player in EV sales and market penetration. In particular, in 2013, China achieved phenomenal growth in vehicle sales in the segment of battery electric vehicles (BEV) and plug-in hybrid vehicles (PHEV). For six consecutive years from 2012 to 2017, the annual growth rate of the market volume was at least 45 per cent [3]. And in 2020, according to the International Energy Agency [4], the Chinese market accounted for almost 45 per cent of global sales. Thus, the study of the development dynamics of the EV market in China is necessary as a basis for further research in the markets of other countries.

2. Related works

Zhang et al. [5] presents Singular Spectral Analysis (SSA) as a one-dimensional time series model and Vector Autoregressive Model (VAR) as a multivariate model that displays the sales volume of automobiles with electric and hybrid engines in China. Empirical calculation results show that SSA satisfactorily indicates the market trend. The VAR model, which contains exogenous parameters related to the market, according to the authors, can significantly improve the accuracy of the results when used to build forecasts.

The price of charging the automobile is important for owners during its operation. Zhang et al. [6] proposes a pricing model for public-private partnership projects of automobile charging infrastructure in China, which is based on the use of the system dynamics (SD) method. In paper [7], based on predictive data on the number of automobiles, a simulation of the spread of electric vehicles is presented using the example of France and Germany.

Articles [8, 9] are devoted to predicting the dynamics of the distribution of electric vehicles within the European Union. For this, logistic models are used, in particular, the logistic and Bass diffusion model [8], which is used in [9] to predict the number of cars used in Beijing.

An overview of the methods that are used to predict the penetration of electric vehicles into the passenger vehicle market is presented in [10]. Two groups of models are distinguished: econometric models with disaggregated data (such as discrete choice) and simulation models based on agents. Some methods have been found to have a stronger methodological basis, while others require complex datasets or can be more flexibly combined with other methods. Despite the absence of a dominant method, Jochem et al. [10] justify the advantage of hybrid approaches and managed data that take into account micro and macro aspects, which allows obtaining more accurate results.

In [11], using a logistic growth model, a long-term forecast of stocks of electric vehicles in 26 countries on five continents is provided. The findings show that in 2032, 30 per cent of the global vehicle fleet will be electric vehicles. However, the results obtained by the authors also demonstrate significant differences between countries, which may be due to differences in government support.

Electric vehicle sales are influenced by many factors (especially in China) and there are not many sales forecasting models available. In particular, Wan et al. [12] used decomposition and integration procedures based on the TEI@I methodology. So, in the forecasting model, principal component regression analysis (PCR) was used to work with a linear relationship. Then a BP neural network and a support vector machine (SVM) were used to work with non-linear dependence. In the last step, all models were integrated together. The Granger causality test and the degree of gray correlation are used to quantify the factors that affect EV sales through consumer network data analysis. On the example of two automobile models, it was found that the PCR-BP models and the PCR-SVM models have better predictive performance than one model. According to the authors, this approach is more suitable for making decisions about forecasting markets for similar products.

Dingab and Li [13] proposes to use the modified gray model as a promising tool for predicting sales of electric vehicles.

The use of different approaches to forecasting the sales of electric vehicles indicates that the quality of the results is not satisfactory. A common feature of almost all almost all forecasting methods that are presented in the review is that they provide for the subordination of volume dynamics to a linear paradigm. However, today it is a recognized fact that the dynamics of most markets does not obey the law of normal distribution, and therefore their modeling by traditional methods leads to significantly unsatisfactory results. The linear paradigm has been replaced by a nonlinear paradigm [14, 15], which is based on the recognition of the fractal nature of the market and is actively developed for analysis and modeling [16, 17, 18, 19]. This statement is based on such features of time series (TS) of indicators characterizing financial markets: the lack of independence of levels, the presence of long-term memory, and others [20, 21, 22, 23]. The use of statistical methods for their research and further forecasting (as the ultimate goal of the analysis) turns out to be inadequate. Therefore, there is a need to use new, different from statistical, methods of analysis.

The purpose of this research is to diagnose the nature and properties of the dynamics of sales of electric vehicles in the Chinese market using non-linear analysis tools for further use in choosing a relevant forecasting method.

3. Materials

The object of analysis of this research is the sales volumes of cars, which are contained in the reports of the China Association of Automobile Manufacturers [24] and published by the online publication "Chinese Cars" [25].

An analysis of the structure of the electric vehicle market in China revealed that in the period from January 2016 to June 2022, 37.5 per cent of the electric vehicle market belongs to five automakers, namely: BYD, Mercedes-Benz, Roewe, Geely, Chery. Most of these companies are representatives of the Chinese automotive industry, which is due, in particular, to state support for manufacturers of this type of transport [26]. Let's characterize these companies in more detail.

BYD is the only automobile manufacturer that has mastered batteries, electric motors, and vehicle control technologies. BYD was founded in 1995 as a pioneer in the battery technology industry. Its stated goal is to change the world by creating a complete zero-emission ecosystem that runs on clean energy and reduces dependence on oil. BYD's innovative products are leaders in many sectors, including battery electric vehicles, buses, medium and heavy duty trucks and forklifts. In 2003, the company entered the automotive business, and in 2005, the first BYD brand automobile went on sale [27]. The company holds 16 per cent of the electric vehicle market in China.

Mercedes-Benz is a world-famous automaker that in recent years has been investing more resources in its advanced research and design capabilities in China as the new center of gravity for the auto industry [28]. The company holds 9 per cent of the electric vehicle market in China.

Roewe is owned by the Shanghai Automotive Industry Corporation (SAIC) and is one of the few Chinese luxury brands that actually manufacture modernized copies of older Rover models [29]. The company holds 6 per cent of the electric vehicle market in China.

Geely Auto Group is a leading automobile manufacturer that was founded in 1997 as a subsidiary of Zhejiang Geely Holding Group. For the past five years, the company has maintained its position as the best-selling Chinese brand [30]. The company holds 4 per cent of the electric vehicle market in China.

Chery was founded in 1997 under the patronage of state-owned companies and holdings, as well as smaller investors. In 2006, Ukraine was one of the first countries to introduce the assembly of automobiles of this brand outside China. In 2012, in pursuit of a globalization strategy, Chery and Jaguar Land Rover Motors jointly invested in the establishment of Chery Jaguar Land Rover Motors Co., Ltd., which is China's first Sino-British automobile joint venture [31]. The company holds 3 per cent of the electric vehicle market in China.

Thus, we will analyze the nature of the dynamics of the behavior of agents of the electric car market in China on the basis of time series (TS) of monthly sales volumes of automobile companies (manufacturers) BYD, Chery, Geely, Mercedes-Benz and Roewe. These automakers were selected based on the fact that they are among the top 9 most popular electric mobile brands in terms of sales for the period from January 2016 to June 2022 [25] and have sufficient data for analysis for this period. When analyzing the dynamics, we will identify the sales volumes of electric vehicles with the volume of demand for them.

4. Methodology

To identify the nonlinear (chaotic) behavior of economic data, various methods of time series analysis are used [32]. In particular, tests for deterministic chaos have been developed for this purpose, which allow one to study the main features of chaotic phenomena: nonlinearity, a fractal attractor, and sensitivity to initial conditions.

In this research, to diagnose the nature and properties of the dynamics of sales of electric vehicles in the Chinese market, we will use three tools for analyzing nonlinear dynamics, namely: traditional R/S-analysis – the Hurst normalized range method, phase analysis and recurrence analysis.

For the purpose of a general assessment of the fractal properties of time series, we use the Hurst normalized range algorithm for analysis [14]. It is known that if the system gives the Hurst statistics for a sufficiently long period, then this indicates the result of interrelated events. As is known, a measure of the mutual connection of events is the correlation coefficient. The influence of the present on the future can be represented by the following correlation:

$$C = 2^{2H-1} - 1, \tag{1}$$

where C – measure of correlation,

H – Hurst exponent.

The range of the Hurst exponent (H) is the interval [0; 1]. The indicator value allows classifying all time series into three groups:

1) $H = 0{,}5$;
2) $0 \leq H < 0{,}5$;
3) $0{,}5 < H \leq 1$.

The value $H = 0{,}5$ indicates a random time series: the events are random and not correlated ($C = 0$ according to (1)). The present does not affect the future.

If $H \in (0{,}5; 1]$, then the considered time series is persistent or trend-resistant and is characterized by the effect of long-term memory. Events are the more correlated, the closer the value is to 1 (correspondingly, C also approaches 1 or 100 per cent correlation according to (1)).

The value $H \in [0; 0{,}5)$ corresponds to antipersistent or ergodic time series. In a loose definition, antipersistence means reverting to the mean or, in other terminology, reversing (alternating positive and negative increments) more often than in a random process. Thus, the Hurst exponent (H) is decisive in diagnosing the nature of the development of a system or process.

To check the validity of the results on the presence of long-term memory based on the value of the Hurst exponent (H), we will use a test for random mixing of the levels of the time series.

Phase analysis is one of the effective methods for obtaining information about the nature of the dynamics of the system under consideration [16]. To the time series ($X = (x(t), t = \overline{1,n})$) that characterizes the dynamics of demand in the market of electric vehicles, we will apply such a presentation method, which can be used to return from the observed state of the system to its previous state. This "return" is implemented by the method of time delays and is produced by constructing a phase trajectory (phase portrait) of dimension ρ:

$$\Phi_\rho(X) = \left\{(x(t), x(t+1), ..., x(t+\rho-1)), t = \overline{1,n}\right\}, \tag{2}$$

which is a set of points called "ρ-history". For any time series, the list of all its M-histories determines the corresponding set of points in the pseudo-phase (or lag) space. In this case, when using the terms "phase portrait" or "phase trajectory" it means that the neighboring points of the set (2) are connected by segments of a straight or curved line for clarity.

Thus, the graphic representation of the system on the phase plane (or in the phase space), along the coordinate axes of which the values of the variables of the system (TS levels) are plotted, is called the phase portrait of the system. The behavior of phase points in time, which is described by the phase trajectory and the set of such phase trajectories for any initial conditions form a phase portrait. A phase portrait is a mathematical method for representing the behavior of a system and a geometric representation of individual movements, and also displays the state of equilibrium, periodic and chaotic movement of a phase point, the logic of the system's behavior and its dependence on external and internal influences.

Objective information about the nature of the behavior of a dynamic process can be obtained by observing the time series X, based on the Takens theorem [33]: if the system generating the time series is m-dimensional and inequality $\rho \geq 2m + 1$ is satisfied, then in the general case, phase trajectories reflect the dynamics of the system under study. There is a dipheomorphism between the phase trajectories and the true data generated by the system. This result allows one to draw conclusions about the behavior of the system based on observational data, and, moreover, to obtain information to predict this behavior.

Analysis of the phase portrait makes it possible to determine the type and characteristic features of the dynamics of a particular system. To deepen such an analysis, Eckmann et al. [34] proposed in 1987 a new diagnostic tool, the recurrence plot.

The recurrence plot is a projection of the ρ-dimensional pseudo-phase space onto the surface. Let point x_i-correspond to the point of the phase trajectory (2), which describes a dynamical system in m-dimensional space at times $t = i$, for $i = 1, \ldots, n$. Then the recurrence plot is an array of points, where non-zero elements with coordinates (i, j) correspond to the case when the distance between x_i and x_j is less then γ:

$$\begin{aligned} RP_{i,j} &= \theta\left(\gamma - \|x_i - x_j\|\right), \\ x_i,\ x_j &\in R^m,\ i, j = 1, \ldots, n, \end{aligned} \tag{3}$$

where γ – size of the point x_i,

$\|x_i - x_j\|$ – distance between points,

$\theta(\cdot)$ – Heaviside function.

For the practical reconstruction of the attractor for a given time series, it is necessary to determine the values of the parameters: ρ – the embedding dimension of the time series, d – the time lag of the time series [35].

To determine the time lag of the time series, the function (S) – the adjusted mutual information function (AMI) was used for the time series under research, which takes into account non-linear correlations [36]:

$$S = -\sum_{ij} p_{ij}(\Phi_\rho(X)) \cdot \ln \frac{p_{ij}(\Phi_\rho(X))}{p_i p_j}, \tag{4}$$

where $p_{ij}(\Phi_\rho(X))$ – joint probability that an observation falls into the i-th interval and the observation time d later falls into the j-th;

p_i – the probability to find a time series value in the i-th interval;

p_j – the probability to find a time series value in the j-th interval.

To calculate the optimal time lag of the time series (d), we will use the tseriesChaos library of the R environment.

To determine the embedding dimension of the time series, the false nearest neighbor method given in [37] was used. This method is based on the assumption that at the next iterations the neighboring points of the phase trajectory remain sufficiently close. But if the nearest points move away from one another, then they are called false nearest neighbors. The task of the method is to choose such a dimension of the time series (ρ), in which the proportion of points that have false neighbors is minimized.

Based on the calculated parameters of the embedding dimension and time lag, recurrence diagrams of time series are built. The analysis of the statistical characteristics of the recurrence diagram makes it possible to determine the measures of complexity of the structure of the recurrence diagrams [38]:

- percent recurrence (%REC),
- percent determinism (%DET),
- average (ADL) and maximum (MDL) diagonal lines lengths of the recurrence diagram.

The construction and determination of the statistical characteristics of recurrence diagrams will be implemented in the R environment using the tseriesChaos and nonlinearTseries libraries.

Based on the analysis of the statistical characteristics of the recurrence diagram, it is possible to determine the presence of homogeneous processes with independent random values; processes with slowly changing parameters; periodic and oscillating processes that correspond to nonlinear systems. Thus, the analysis of the recurrence surface makes it possible to evaluate the characteristics of a non-linear object on relatively short time series, which makes it possible to make prompt decisions regarding the control of the object.

5. Results

The analysis of the behavior of Chinese electric automobiles market agents was carried out on the basis of monthly sales data from January 2016 to June 2022 of five automobile companies (BYD, Chery, Geely, Mercedes-Benz, Roewe) (figure 1).

Time series of sales of electric vehicles in the Chinese market denoted by $X_k = (x(t),\ t = \overline{1,n}),\ k = \overline{1,5}$ where n is the length of the time series, k is the index assigned to the corresponding manufacturer (in order of priority): BYD, Chery, Geely, Mercedes-Benz, Roewe.

Table 1 shows the results of the Hurst exponent calculations (H) for these time series and the value of the Hurst exponent (H_{mixing}) obtained after applying the mixing test.

According to table 1, we can conclude that all time series of sales volumes (demand for electric automobiles) of all manufacturers have signs of persistence, that is, they have a long-term memory. This is evidenced by the following:

a) the value of the Hurst exponents for all time series are in the interval $H \in [0,817;\ 0,873]$, which corresponds to the area of black noise;
b) the results of the mixing test ($H_{mixing} \in [0,546; 0,597]$) confirm the significance of the time series structure: its violations lead to the complete destruction of the trace of long-term memory.

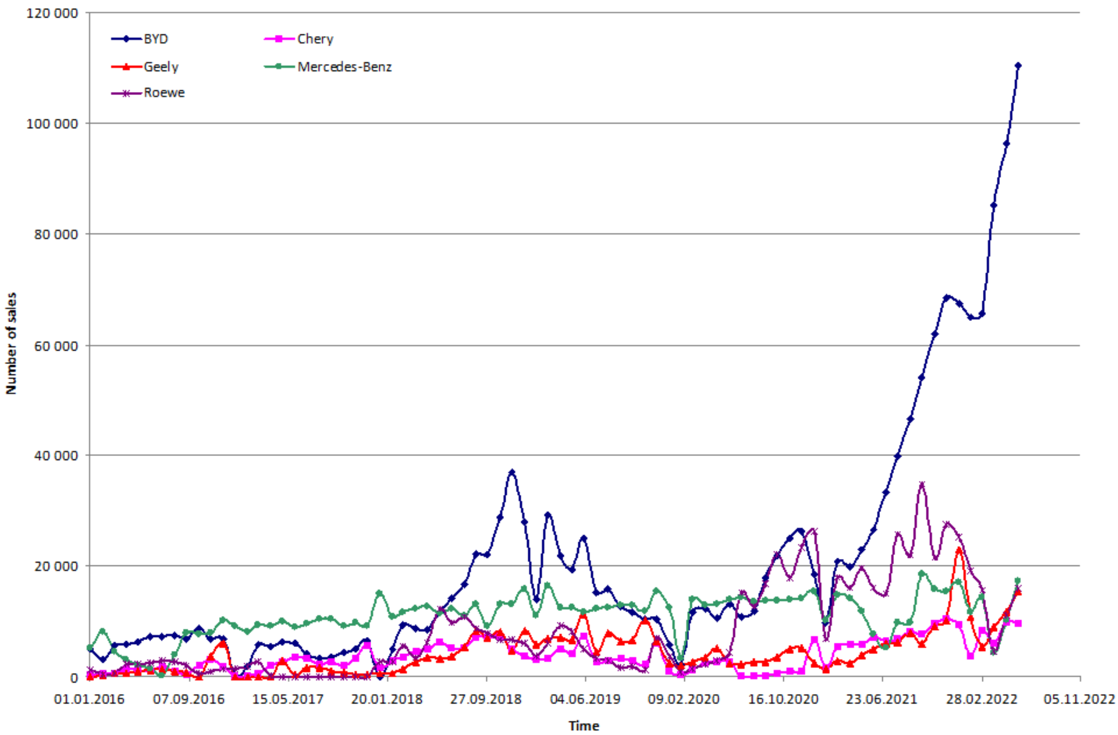

Figure 1: Number of sales of electric vehicles in the Chinese market from January 2016 to June 2022.

Table 1
The value of the Hurst exponent for the series of dynamics of sales volumes of electric automobiles of manufacturing companies for the period from January 2016 to June 2022.

Manufacturer (TS)	H	H_{mixing}
BYD (X_1)	0,84655	0,56659
Chery (X_2)	0,82696	0,58156
Geely (X_3)	0,81668	0,57214
Mercedes-Benz (X_4)	0,86762	0,54563
Roewe (X_5)	0,87330	0,59666

The presence of significant Hurst statistics for the time series of sales of electric vehicles is explained by the following reasoning.

The change in the volume of demand for electric vehicles is based on an increase in the overall demand for vehicles, the perception of buyers of a certain expediency to follow the trend in energy security (increased charging stations), legislative incentives and social responsibility (concern for the environment). The demand for electric vehicles is partly determined by fundamental information such as the state of the energy market, public discussion of environmental issues, current economic circumstances, expectations, and so on. This information is often useful in making decisions when purchasing a type of vehicle. Of great importance in this belongs to the marketing activities of manufacturing companies, the volume and quality of their offers on the market. Another important component of demand volumes is the extent to which buyers are able to pay for a new and usually more expensive product (an electric car). This "sensory component" is also analyzed, and as a result, a certain range of demand volume is formed around the existing one. This combination of information and thoughts results in displacement of volumes. If buyers see that the trend is in line with their positive expectations for a particular electric vehicle, they start buying like others. Yesterday's activity has an impact on today – the market remains mindful of yesterday's trend. The bias will change when demand reaches the upper limit of some actual value. At this point, the offset will change. The interesting thing is that the "range" of demand does not remain constant, but changes. New information regarding a particular electric vehicle (innovations and shortcomings) or the market as a whole can change this range and cause a sharp increase in sales volumes of the manufacturer (in particular, the introduction of breakthrough innovations) or a negative turn in the market situation, or for an individual seller (in particular, in case of deficiencies, and so on).

Let's proceed to the consideration of the results of the phase analysis of time series X_k, $k = \overline{1,5}$ of sales of electric vehicles in the Chinese market. Figure 2 shows phase portraits in a two-dimensional pseudo-phase (lag) space $\Phi_2(X_k) = \{(x(t),\ x(t+1))\}$, $k = \overline{1,5}$.

A more detailed analysis of phase portraits makes it possible to identify the following individual features.

In the dynamics of sales of the automobile company BYD (figure 2a)), at the beginning of the observation period for the first 5 years (from January 2016 to February 2021), almost stable quasi-cycles of length 7 were observed, which indicates the presence of long-term memory in them (confirmed by the value $H \approx 0{,}85$). However, since February 2021, the dynamics has changed dramatically in the direction of increasing sales volumes and almost no cyclicity when moving along the bisector of the coordinate angle. This indicates an increase in the memory depth of the time series.

The dynamics of sales of automobile companies Chery and Gelly (figure 2b), c)) are characterized by shorter quasi-cycles (length 4 or 5), and there is an increase in the amplitude of these quasi-cycles in the final interval of the time series (from February 2021 to June 2022), but no significant movement along the bisector of the coordinate angle is observed. The dynamics is characterized by less trend resistance, which is confirmed by the values $H \approx 0{,}83$) and $H \approx 0{,}82$) for the respective manufacturers.

The dynamics of sales of automobile companies Mercedes-Benz and Roewe (figure 2d), e)) is characterized by the presence of the longest quasi-cycles (length 9), their slow movement along the bisector of the coordinate angle (increase in volumes) and an increase in amplitude. This is evidence that the dynamics of sales volumes of these manufacturers is characterized by the greatest trend resistance (confirmed by the value of the Hurst exponent $H \approx 0{,}87$) for both companies).

Thus, the analysis of phase portraits $\Phi_2(X_k)$ in a two-dimensional pseudo-phase (lag) space makes it possible to identify the characteristic features of the dynamics of sales volumes of each agent in the Chinese electric car market.

At the first stage, using the tseriesChaos library of the R environment, the values of the embedding dimension (ρ) and the time lag (d) of the considered time series were calculated (table 2).

At the second stage, using the tseriesChaos and nonlinearTseries libraries in the R environ-

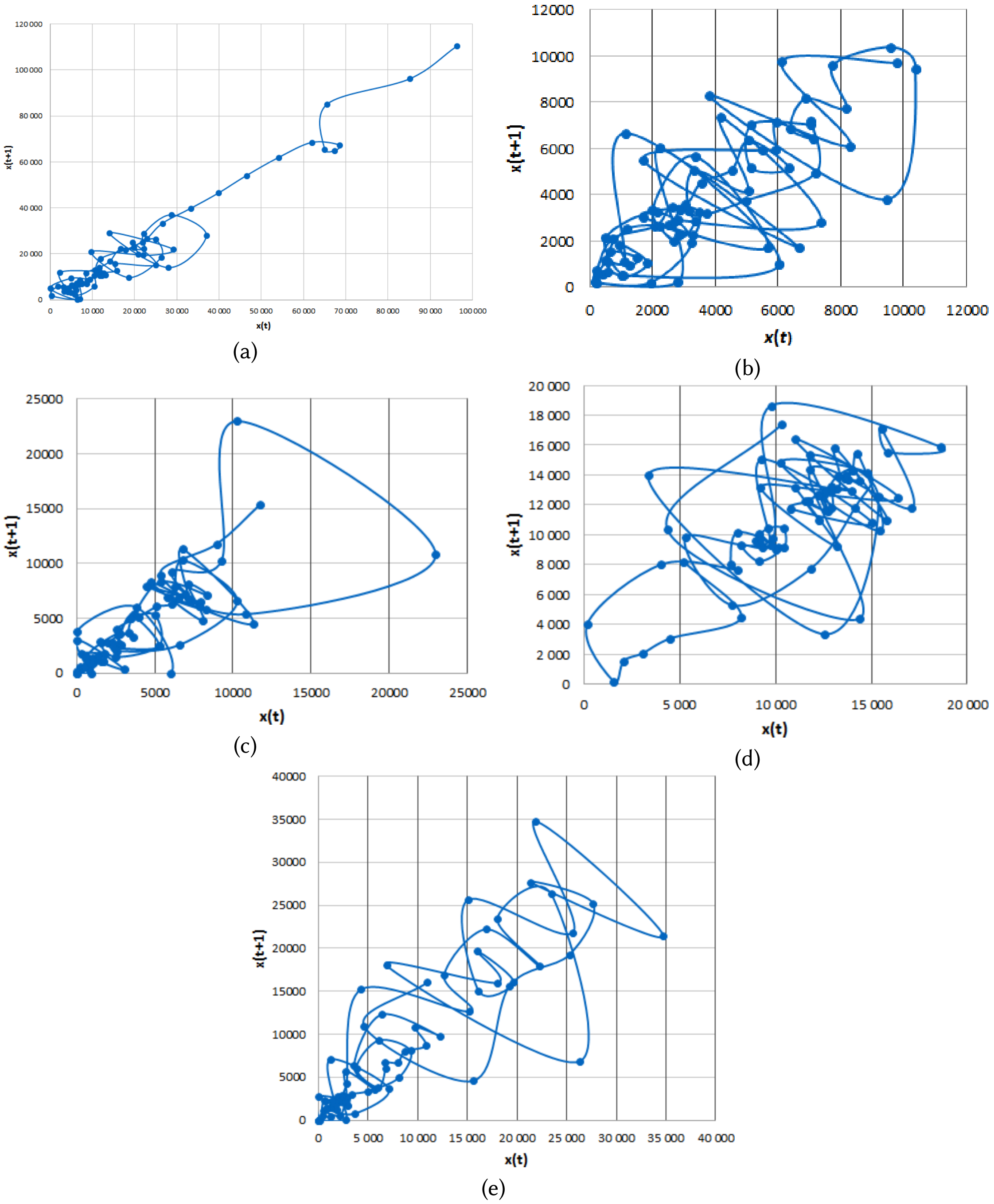

Figure 2: Phase portraits in a two-dimensional pseudo-phase space $\Phi_2(X_k) = \{(x(t),\ x(t+1))\}$, $k = \overline{1,5}$ for time series X_k, $k = \overline{1,5}$ from January 2016 to June 2022: a) BYD, b) Chery, c) Gelly, d) Mercedes-Benz, e) Roewe.

Table 2
The value of the embedding dimension (ρ) and time lag (d) for the series of dynamics of sales volumes of electric automobiles of manufacturing companies for the period from January 2016 to June 2022.

Manufacturer (TS)	The embedding dimension (ρ)	The time lag (d)
BYD (X_1)	5	9
Chery (X_2)	4	3
Geely (X_3)	4	3
Mercedes-Benz (X_4)	4	1
Roewe (X_5)	6	2

Table 3
Statistical characteristics of recurrence plots of electric automobiles sales in China from January 2016 to June 2022.

Manufacturer (TS)	%REC	%DET	ADL	MDL
BYD (X_1)	2,381	100	0	42
Chery (X_2)	1,429	100	0	70
Geely (X_3)	1,429	100	0	70
Mercedes-Benz (X_4)	1,333	100	0	75
Roewe (X_5)	1,471	100	0	68

ment, recurrence plots were constructed (figure 3a)-f)) and their statistical characteristics were determined (table 3).

The topology of the recurrence plots for electric automobiles sales in China shows abrupt changes in the dynamics of the system that generates the time series and causes white areas or bands to appear. On the recurrence plots, there is a gradual change in the parameters of the behavior of the agents of the automobile market, and there is also a drift of the attractor (white lower and upper corners of the diagram, crosses). The absence of short diagonal stripes on the recurrence plots indicates the absence of a stochastic process and the non-return of the trajectory to the same region of the phase space in different time periods.

The determinism of the behavior of companies in the automobile market is confirmed by the calculated statistical characteristics of recurrence plots, which are shown in table 3.

The value of the %REC indicator for all time series falls within the interval from 1% to 5%, which indicates the regular behavior of the time series.

The measure of determinism (%DET) of the recurrence plot characterizes the level of system predictability. Diagonal structures show the time during which a segment of the trajectory comes very close to another segment of the trajectory. For all five recurrence plots, the level of predictability is 100%. Note that this measure does not determine the real determinism of the process.

The average diagonal lines lengths (ADL) characterizes the average time during which two sections of the trajectory pass close to each other, and can be considered as the average predictability time of the system. An interesting fact is that, according to the calculation results, the smallest average predictability time of time series is 0.

The maximum diagonal lines lengths (MDL) characterizes the length of the trend. The shortest trend is in the BYD time series (42 points), and the longest is in Mercedes-Benz (75

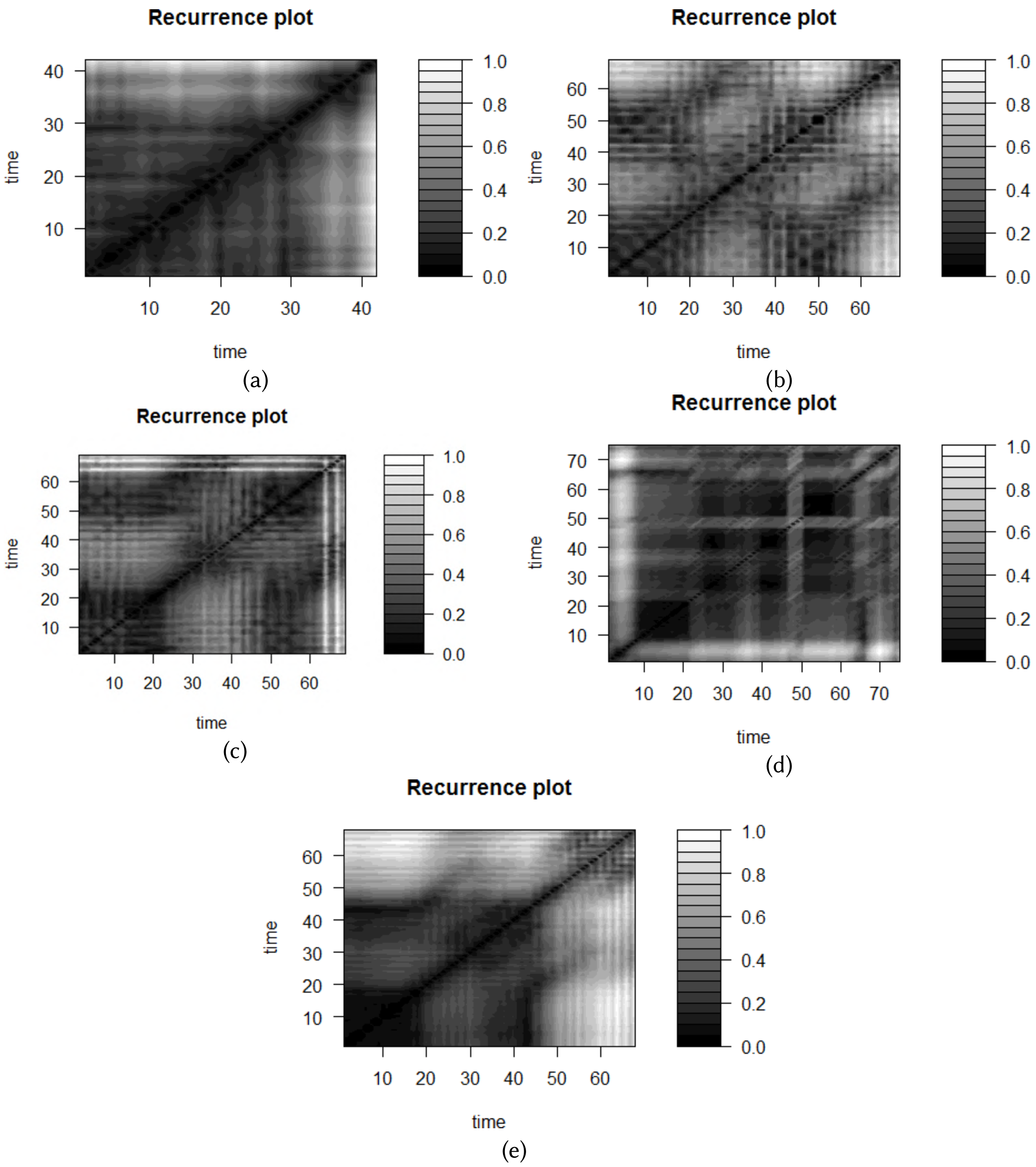

Figure 3: Recurrence plots of electric automobiles sales in China from January 2016 to June 2022: a) BYD, b) Chery, c) Gelly, d) Mercedes-Benz, e) Roewe.

points).

6. Conclusion

This paper presents a nonlinear analysis of the sales dynamics of electric automobiles in the Chinese market, which is the largest and fastest-growing EV market in the world.

The data used for the analysis are the monthly sales volumes of five EV manufacturers in China: BYD, Chery, Geely, Mercedes-Benz and Roewe, from January 2016 to June 2022.

The paper employs three methods of nonlinear dynamics: the traditional R/S-analysis, the phase analysis, and the recurrence plots.

The R/S-analysis reveals the trend stability and the long-term memory of the sales time series, indicating their nonlinear (fractal) nature. This implies that the classical forecasting methods are not suitable and may lead to poor results. The forecasting methods and their parameters should consider the long-term memory and its features.

The fractal analysis based on the R/S-analysis, however, only provides qualitative insights into the properties of the EV market and the trend stability of each time series. The quantitative characteristics obtained by this method are averaged over the entire series. Therefore, to obtain more differentiated characteristics of the memory, it is promising to apply fractal analysis methods based on the sequential R/S analysis algorithm [16].

The phase analysis in a two-dimensional phase space allows to identify the cyclicity and the attractors (quasi-cycles) of the sales dynamics for each EV manufacturer. The results provide a basis for further research on the features of the dynamics by decomposing the phase portrait into quasicycles, determining their characteristics, and analyzing the dynamics of their sizes and centers.

The recurrence plots in ρ-dimensional phase space and their topological analysis confirm the attractor drift for all EV manufacturers. A gradual change in the behavior parameters of each manufacturer is also detected.

The quantitative analysis of recurrence plots based on the complexity measures of their structure (such as %REC and %DET) confirms the fractal (deterministic) nature of the sales dynamics of EVs in China. It should be noted that the data used for this study are short time series, which may affect the possibilities, features, and results of applying these methods. However, their application – separately or in combination – enables to gain new knowledge about the characteristics of the dynamics in a new and rapidly developing market with global implications – the EV market.

The results of this study can be used to select relevant forecasting methods and their parameters for the EV market in China.

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