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Forecasting vehicle's spare parts price and demand

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Abstract

Purpose – These days vehicles' spare parts (SPs) are a very big market, and there is a very high demand for these parts. Forecasting vehicles' SPs price and demand are difficult because of the lack of data and the pricing of the SPs is not following the normal value chain methods like normal products.

Design/methodology/approach – A proposed model using multiple linear regression was developed as a guide to forecasting demand and price for vehicles' SPs. A case study of selected hybrid vehicle is held to validate the results of the research. This research is an original study depending on quantitative and qualitative methods; some factors are generated from realistic data or are calculated using numerical equations and the analytic hierarchy process (AHP) method; online questionnaire and expert interview survey.

Findings – The price and demand for SPs have a linear relationship with some independent variables is the hypothesis that is tested. Even though the proposed models are generally recommended for predicting demand and price, in this research the linear relationship models are not significant enough to calculate the expected price and demand.

Originality/value – This research should concern both academics and practitioners since it provides new intuitions on the distinctions between scientific and industrial world regarding SPs for vehicles as it is the first study that investigates price and demand of vehicles' SPs.

Keywords Vehicle spare parts, Hybrid vehicles, Forecast demand, Forecast price

Paper type Research paper

Introduction

In the last decades, hybrid electric vehicles (HEVs) become wildly spread all over the world, thus, the demand for hybrid vehicles has increased because of many reasons such as fuel efficiency, reducing unhealthy emissions and government rebates. European Union, United Kingdom and the United States of America governments promote hybrid vehicles and electronic vehicles by setting regulations to control the emissions of new vehicles (Bennett *et al.*, 2016). Jordan was not an exception for supporting hybrid vehicles spread as a way of promoting a healthier environment, a magnificent increase in numbers of hybrid vehicles. On the other hand, spare parts (SPs) are important to vehicle/hybrid vehicle industry since a vehicle consists of about hundreds of components (Chatras *et al.*, 2015); consequently, SPs should be available in the market with the appropriate quality and quantity. Companies are improving after-sales services in order to increase the product life cycle and maintenance revenues, especially in the automotive industry (Lorentz *et al.*, 2011). Van der auweraer *et al.* (2019) explains that the lack of SPs may affect the productivity of a product in terms of delay and high costs.

Predicting consumer demand accurately is one of the key roles of the companies in order to meet consumer satisfaction and trust, thus, SPs are very important in the after-sale services, preventive maintenance and corrective maintenance as well. In addition, Syntetos *et al.* (2009) claim that managing SPs is very important, challenging and complicated. Van der auweraer *et al.* (2019) categorize SPs according to demand patterns into intermittent demand, erratic

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and lumpy, while aftermarket parts are the parts manufactured by the original manufacturer and other companies, with different level of quality (Achetoui *et al.*, 2019).

Noticeably, a crucial question has been raised whether the selection for these particular types of vehicles by customers was taking into consideration SPs prices, when they need preventive or corrective maintenance for the vehicle since SPs availability in the local market and the price range play a critical role in the demand pattern of vehicles' types in market. Normally, traditional products are priced depending on their cost. SPs, particularly the used ones are not following this basic pricing strategy, it has a more complicated procedure; used vehicle SPs are taking from a salvage car, where the cost is the salvage car price, and these costs are divided between the components of the salvage car.

Forecasting is the process of predicting future events based on past and present data, accurate forecasting improves decision-making and planning, which gives the people in control the ability to change the present parameters to have better results in the future of any business (Hadavandi *et al.*, 2010). Price forecasting is crucial to aftermarket sales. In forecasting demand for vehicle's SPs, the demand is intermittent that is why it is difficult to predict (Hasni *et al.*, 2019).

This research presents a thorough analytical study of SPs' prices and demand forecasting for hybrid vehicles in Jordan and its association to a group of factors. The structure of the research hypotheses is focused on the relationship between the independent variables and the SPs price and demand. This research is suggesting testable hypotheses: There will be no significant relationship between SPs' price and demand as dependent variables with these independent set of variables $H_0$1: Number of Vehicles (NoVs), $H_0$2: Vehicles Generation (VG), $H_0$3: Total Maintenance Cost (TMC), $H_0$4: Origin Country (OC), $H_0$5: Failure Rate (FR), $H_0$6: Originality (OR), $H_0$7: New or Used (NoU), $H_0$8: Selling Location (SL), $H_0$9: Repair Service location (RL), $H_0$10: Repair or Replacement Cost (RC), $H_0$11: Criticality (CR), $H_0$12: Online Price (OP), $H_0$13: Car Type (CT), $H_0$14: Spare Part Type (SP) and $H_0$15: Car Price (CP).

Literature review

SPs are defined according to Au-Yong *et al.* (2016), as all the parts that work for a certain duration of time in a specific system they need replacement. Roda *et al.* (2014) illustrate that a well-developed management plan for SPs will improve the performance of any company; the key point is the availability of SPs. Goossens and Basten (2015), Au-Yong *et al.* (2016) and Hassan *et al.* (2012) refer to the importance of SPs availability for maintenance procedures; the performance and cost control of a manufactured product/system increase when it is repairable, that being said SPs availability will have a direct impact on maintenance procedures through repair or replacement (Pérès and Grenouilleau, 2003), for best maintenance procedure. Goossens and Basten (2015) also introduce three main criteria related to SPs; commonality presence, SPs amount and SPs availability, while Au-Yong *et al.* (2016) find that maintenance quality depend on SPs price, quantity, quality and parts' life cycle. Hassan *et al.* (2012) illustrate that maintenance is greatly affected by SPs availability, especially the critical SPs, similarly Hellingrath and Cordes (2014) refer to SPs demand and maintenance which originate from part breakdown and failure, resulting in cost. El Hayek *et al.* (2005) mention that the amount of SPs affects the life cycle maintenance cost of a complex end product. Syntetos *et al.* (2009) claim that SPs' management is an important challenging and complicated process, that is why categorizing SPs is crucial in order to increase attention to the most essential SPs, Van der Auweraer *et al.* (2019) classify the SPs' characteristics: the first characteristic was demand patterns; intermittent demand, erratic and lumpy which makes it hard to present demand by the normal distribution, the second one is that SPs are different from end products which have independent demand, while SPs depend on the failure of parts or preventive maintenance procedures. The last one is that the production of SPs stays longer than the production of the end product itself. Whereas, Callegaro (2010) classifies SPs according to cost and criticality (CR). While CR has different meanings according to the field is used in; critical parts from a maintenance point of view is different than logistics or financial point of view. On the other hand, Roda *et al.* (2014) suggest different criteria based on SPs' classification to obtain better maintenance management, by using the traditional ABC classification, the fuzzy-rule-based multi-criteria classification model and analytic hierarchy process (AHP) classification.

Vehicle buyers always seek and demand a higher service quality from the manufacturer and dealers to serve better products and services through implementing better qualitative management, Fraser *et al.* (2013) classify the vehicle industry into four main categories; component suppliers, car manufacturers, dealership network and buyers. Many authors illustrate the importance of SPs to the vehicle industry; in present days, a vehicle consists of about hundreds of components as explained by Chatras *et al.* (2015), some of these parts need to be replaced or maintained, consequently, SPs should be available in the market with the appropriate quality and quantity. Henkelmann (2018) states that the SPs sector has developed into a steadily rising and more complex market for the automotive companies, since it is included in the aftersales services, its profit is nearly ten times that of the car sales. Similarly, Aboltins and Rivza (2014) explained how SPs become a critical issue for studying due to its significant role in after sales market profit for manufacturer companies and dealers, and the accelerating technology related to SPs by linking it with online sales and online car services.

Automotive aftermarket is defined by Achetoui *et al.* (2019) as the process of manufacturing, distribution, maintenance, repair of SPs to elongate the vehicle life for end customers, the automotive market is fluctuating according to the technological advancement of automotive, the SPs markets and the competition between agencies, this would also affect supply chain planning. Furthermore, Lorentz *et al.* (2011) explain that aftermarket service for SPs increased enormously in the last ten years with 150 $ billion around the world and a rising average of 5–9% yearly. After market services produce 25% of an organization's total profit, this leads to a rise in the demand for SPs. In vehicle industry, the product has a long-life cycle, this makes after-sales service a very crucial business opportunity. Automotive aftermarket is divided in two main head streams: car manufacturer and independent distribution channel. These two streams contain the original equipment manufacturer (OEM), dealers, authorised repair, customers, etc. Achetoui *et al.* (2019) divide equipment manufacturers into first OEMs, second manufacturer of equivalent SPs; those have the same features as the original SPs, third other manufacturers including small and medium size companies which manufacture non-brand, less price and low quality SPs. Achetoui *et al.* (2019) also explain the relation between car manufacturers and OEMs depending on an agreement that the car manufacturers sell SPs until the agreement is finished, afterwards OEMs can manufacture and sell SPs to car manufacturers and other distributers. The post-product life cycle for SPs is organized by Inderfurth and Mukherjee (2008) through three choices; producing a large amount of SPs with the final stage of end-product manufacturing, additional production for SPs during the service period and finally using SPs of used products. A clear example of such procedures that is suggested by Inderfurth and Mukherjee (2008) is manufacturing the OEMs for vehicles; a vehicle may be used for 12–15 years, therefore, in many countries, there are several agreements with OEMs to afford SPs during the post-product life cycle. Mandják *et al.* (2018) highlight the economic, political and social impacts on the aftermarket sales of vehicle SPs, using the Tunisian Jasmine Revolution as a case study, Tunis had a steady market with rising business fields before the revolution, it was noticed afterwards that repair shops started to use lower price SPs counterfeit or smuggled product due the rising financial problems, they study the relationship between manufacturers and sellers in the form of retail shops and repair shop owners and repair technicians.

In a more developed country as Japan, according to Yu and Chen (2010), there are strict governmental regulations that demand vehicles inspections as a vehicle getting old which can be very expensive and tough, consequently Japanese customers usually buy a new vehicle every four years on average, they present Japanese Toyota company as a case study, the company have a considerable section for dealing with customer management, in order to keep customer information in a data base to keep in touch with them which increases customer satisfaction and loyalty to the company, however, vehicle customers and companies in other countries especially the developing countries do not follow the same procedure, as they are more often replacing vehicle parts with SPs. After the end of warranty duration, Corrêa *et al.* (2007) find that the customers have options to maintain their vehicles either by branded vehicle dealers which provide vehicle maintenance during warranty or by independent garages, a comparison was held between the two options and the results were analysed. The maintenance services were relatively weak by the branded dealers while independent garages are much better in the same category.

Forecasting plays an essential role in all human life experiences, its aim is to make predictions and possibilities in order to suggest accurate decisions afterwards (Armstrong and Green, 2018). Further, Roland *et al.* (2016) point out the significance of forecasting as one of the key elements of an organization's competitiveness, as it directly affects the future of an organization, in order to make accurate price forecasting in the future, an organization should have deep understanding and analysis of past and present data. Proper decisions can be made only when accurate, reliable and scientific forecasting method is used (Armstrong and Green, 2018). Boylan and Syntetos (2010) propose three stages for improving forecasting methods for SPs; pre-processing is the condition that classifies SPs into fast moving or slow moving and intermittent or lumpy, processing; choosing the correct software application for forecasting method, finally summarized in using judgemental methods. While Sharma *et al.* (2017) find that when applying accurate forecasting, the result is reduction of SPs' stocks and saving money. Case, were obtained by Rieg (2010), investigates the sale plans per month and the present data for three car models in six different countries and over 15 years, in order to scale forecasting accuracy.

The importance of price forecasting for SPs will be explained; Talari *et al.* (2017) illustrate the importance of price forecasting, having definite price forecasting allow users and dealers to make clear decisions about economic risks. Further, Wattanarat *et al.* (2010) claim that price is affected by a variety of factors, this complicates price forecasting. Thus, maintenance quality depends on SPs' price, quantity, quality and parts' life cycle (Au-Yong *et al.*, 2016); therefore, forecasting SPs' price will greatly affect maintenance quality and efficiency. It is important to collect and analyse historical pricing data in order to gain information to enhance decision-making for the next pricing cycle. Besbes *et al.* (2020) develop a pricing method for the aircraft rotatable SPs. They used many independent variables such as repair time, cost and price–demand relationship. Several papers apply price forecasting techniques on used SPs to different case studies such as Lessmann and Voß (2017), Syntetos *et al.* (2009) and Wu *et al.* (2009). Noticeably, Lessmann and Voß (2017) examine different forecasting price methods of used vehicle in a statistical comparative study in order to determine the most accurate methods. Danes and Lindsey-Mullikin (2012) predict the price for new product and re-priced old product, taking automobiles and computers as a case study. Similarly, Wu *et al.* (2009) develop a method to forecast used car price, by applying adaptive neuro-fuzzy inference system (ANFIS) with back-propagation (BP) network. The main factors affecting car price in this method was the mark of the car, year of manufacture and engine style/type. Krykawski and Fihun (2012) first highlight the innovation impact on automotive growth; combining SPs in modules that can fit many vehicle types, this will reduce SPs' cost to the customer, also standardization may decrease the SPs' cost and minimizing the number of SPs. Second, develop a decision-making hierarchy for optimizing logistic costs, and the needs for SPs in the maintenance sector is explained, analysing data by classifying costs according to production, storage and sales stage. According to this paper, hypothetically, SPs' price may decrease in the future.

Moon (2018) defines demand as the need to purchase a product from the market by consumers. Zhu *et al.* (2017) remark that in SPs' management demand forecasting plays a key role. SPs' demand becomes crucial when product fails or needs replacement (Syntetos *et al.*, 2009). Huiskonen (2001) clarifies the four main features of operational control for SPs; CR, specificity, demand pattern and the value for the part, to enhance creating a logistic system for SPs. The main issue that makes forecasting SPs demand a complex process is that SPs' demand is intermittent, moreover, SPs' demand is affected by many factors such as maintenance policy, the failure rate (FR) of a product, etc. Through the literature review of Van der auweraer *et al.* (2019), many authors propose forecasting SPs' demand techniques relying on only historical data, they classify the information about SPs' demand into three categories; SPs' nature, maintenance guidelines and environmental factors. They also illustrate that one of the key factors of SPs' demand is its dependency on the product life cycle. Wang (2012) mentions that the demand of SPs is caused by preventive maintenance or corrective maintenance; On the other hand, maintenance is also connected to the SPs' availability, this resulted in more costs for waiting SPs' delivery, these extra costs and failures can be reduced if there is an accurate forecast plan for maintenance.

There is a noticeable variation in SPs' units; due to the different cost, service requirement and demand patterns, that is why SPs' classification is hugely useful for forecasting and management control (Armenzoni *et al.*, 2015). Mostly, SPs have wide variation in cost, service, need and demand nature, thus classification is essentially needed (Syntetos *et al.*, 2009), Ghobbar and Friend (2002) categorize SPs demand into four main groups; intermittent, erratic, slow moving and lumpy demand, an essential factor that effect forecasting directly the FR of the product. Moon *et al.* (2012) divide the non-normal demand into intermittent demand which occurs infrequently, the slow moving demand that have low volume rates, and the erratic demand that is volume varies highly; Wang (2012) investigates forecasting intermittent demand by Croston method; according to Xu *et al.* (2012), demand is fluctuating due to the change in customer decision and preference, advertising actions, competition between companies and supply chain arrangement.

Turrini and Meissner (2019) classify forecasting SPs into parametric and non-parametric, non- parametric method depends on bootstrapping process, while parametric forecasting depends on predicting the parameters from data that follows lead time distribution through estimation method, such as the exponential smoothing. This research classifies the inter arrival time within the SPs intermittent demand into discrete variable using Bernoulli model and continuous variable using poison model. Dekker *et al.* (2013) mention from other literatures that SPs' management is highly complicated due to many reasons; high cost of the part, the demand is erratic and intermittent, that is why forecasting SPs demand is very important, also introduce the characteristics of SPs' demand that is intermittent, erratic and slow moving. Additionally, they note that the product life cycle on SPs which can be a causal factor effecting the SPs' demand. While Wang *et al.* (2018) goal is to evaluate the precision of forecasting methodologies for SPs' demand, the process was started with briefing eight forecasting models for SPs' demand by applying the grey comprehensive correlation degree to classify the models.

The wide variation in the automotive industry regarding vehicle types validate studying customer demand according to product variety, a case study was introduced by Jonsson *et al.* (2011) for three models of one vehicle manufacturer in order to study product variety demand through realistic customer orders. Armenzoni *et al.* (2015) hold an analytical study in order to examine SPs' management differences between research and practice, and also study SPs' classifications and demand forecasting through a comparison of ten case studies. Atsalakis and Valavanis (2009) explain how stock market forecasting can be successful by getting the best results from the least amount of input data, and the method that was applied in this research is neuro-fuzzy techniques to forecast stock market behaviour. Hofmann and Rutschmann (2018) also explore the same two main methods used in forecasting; qualitative and quantitative, through illustrating the definition of each one when it is applied and the challenges facing forecasting; insufficient amount of data, the lack of skills, high cost, immature method or time limitations. Van der auweraer *et al.* (2019) outline forecasting methods for SPs' demand into four main categories: the Croston's method, bootstrapping method, neural network and judgemental forecasting. Hua and Zhang (2006) develop a hybrid forecasting method for 30 types of SPs for a petrochemical company in China in order to evaluate the precision of time series method to forecast demand. Whereas Li and Kuo (2008) develop an advance forecasting SPs demand method; the fuzzy neural network (FNN), the parts are automobiles spares which are held in a main warehouse. Yu and Chen (2010) suggests a new forecasting demand method in automotive SPs; the artificial neural network, the objective of this study is to develop services and decrease the operational cost thus improving supply chain management. Finally, Wattanarat *et al.* (2010) is the only found study to combine demand with price forecasting in one study; it focuses on increasing the precision of forecasting demand and price by comparing a real option method which is related to financial studies based on geometric Brownian motion and investments with the autoregressive integrated moving average (ARIMA) method using the MATLAB to big data analysis, this research uses realistic data of die casting company and copper price. One of the interesting examples of the advancement in the future of new technologies regarding vehicle' SPs is combining SPs in modules that can fit many vehicle types, this will reduce SPs' cost to the customer, while on the other hand, standardization may decrease the SPs' amount and cost thus its price.

Research methodology

The intent of this research is to forecast demand and price for hybrid vehicles SPs in Jordan, based on the assumed related factors with the most convenient forecasting method and technique, also to investigate the relationship between demand and price. A quantitative approach was carried out proposing multiple linear regression (MLR) model for demand and price forecasting (Braglia *et al.*, 2004). A case study was held using real-world data of selected HEV types in Jordan to validate the results of the research. Methodology is concentrated on calculating demand and price of HEV's SPs, assuming that there is a significant relationship between HEV's SPs demand and price as dependent variables, with a number of independent variables, by using MLR model to forecast demand and price, the analysis of the results was run by SPSS software. This research holds a thorough analytical study of SPs' prices and demand forecasting for HEVs and its association to a group of independent variables, these variables were divided into two categories: the first is related to the vehicle's type, which are CT, CP, NoV, VG or year of used, TMC for 10 years, and OC, where the second is related to the spare parts which are SP, FR, OR, NoU, SL, RL, RC, Global OP.

The study population of this research is all the hybrid vehicle types in Jordan, and all its SPs. The sample frame has been created using the available data from hybrid vehicle branch companies and the drivers and vehicles licence department. A sample of 4 hybrid vehicle types was taken out of around 65 types in Jordan, number of cars for most of these 65 are very low, that why only 4 types are selected, the total number of these 4 types represents more than 66.3% of 191,005 which are the total number of hybrid vehicles in Jordan in February 2020. The given sample of SPs was obtained from five main systems in the vehicle as the most critical parts of each system based on expert interview and hybrid vehicles SPs retail stores; engine sys., transmission sys., chassis sys., electrical sys., servicing. The total sample of the SPs is 37 parts. The data were collected from the database of formal institutions, interview survey and online questionnaire survey. The Drivers and Vehicles Licence department database is the source of the numbers of registered hybrid vehicles in Jordan. The data regarding prices of the chosen SPs were taken from the Jordan Free Zone Corporation, local retail stores and repair shops, experts' technicians of service centres and the official vehicle companies' branches. Hybrid vehicle different generations' data were also taken from the official vehicle companies branches. TMC data were taken from your mechanic website, which is an industry leader in vehicles repair maintenance and inspection a study was conducted about the lowest vehicle maintenance cost which is based on total vehicle maintenance costs over ten years (Martin, 2016). Some data like the OPs were collected from some authorized websites. Another important source of the required data is a form of interview schedule that is categorised under the interviewer-administered questionnaire, and in order to calculate CR, also, a survey method in a form of online questionnaire illustrated by Saunders *et al.* (2016), in order to calculate the FR for HEV's SPs, FR for each SPs was estimated based on survey. CR was estimated according to a proposed AHP classification method based on expert interview survey method.

A questionnaire survey was conducted in January 2020 in Jordan, targeting calculating FRs in HEVs' SPs; the survey strategy was focused on designing suitable questions in order to catch qualitative and quantitative information. The survey was restricted to users who own hybrid vehicles. The responses were obtained through a Google online survey tool. The number of the responses that was used in FR calculations for HEV's SPs was 521 responses. The survey was classified into four parts based on the HEV's main systems and each part contains the associated SPs; the first one is the electric system which contains hybrid battery, battery 12 V, mirrors, switch, window regulator machine, wiper/water reservoir, coolant temperature sensor, anti-lock braking system abs, air compressor and air bag, bulb. The second system is the engine system that contains motor, injections, cylinder head, engine oil pump, water pump, radiator, catalytic converter, exhaust, engine mounts, fuel pump and throttle. While the third one is the transmission system which contains shock absorber, axle, control arm, stabilizer bar link, steering linkage, tie rod, sway bar, wheel hub, ball joint, and the last one is the chassis system including doors, front bumper, rear bumper, fenders and mud guard. Then the data were classified according to HEVs' types: Hyundai Sonata, Toyota Camry, Toyota Prius and Ford Fusion. Then, each generation was classified separately with all the related filtered SPs which have responses from the survey. Based on Equation (1), the FR per each SPs was calculated where X is number of HEV's in a specific generation have the same SPs replacement, Y is total number of HEV's in a specific generation and Z is total period in years for a specific generation that users owned a vehicle.

$$\text{FAILURE RATE} = \frac{X}{Y*Z} \tag{1}$$

Note that the consumable's (oil, oil filter, spark plug, cabin air filter, engine air filter) were not a part of the survey because they follow schedule maintenance and their replacement period are mentioned in the owner maintenance manual for each company, the FR for consumables was calculated depending on the average driven distance since owning the HEV in kilometres; this data were taken from the survey, according to Equation (2), where D is total distance in Km for a specific generation that users owned a vehicle, W is the schedule maintenance replacement period for each part in miles and L is total number of HEVs in a specific generation.

$$\text{Failure Rate for Consumables} = \frac{D}{WL} \tag{2}$$

Note that FR was used along with numbers of hybrid vehicles in Jordan to calculate the estimated demand, as FR time the numbers of vehicles in Jordan.

CR is one of the most important factors affecting SPs' price and demand forecasting for HEVs, thus CR analysis of the HEV's SPs was performed. In order to calculate CR, the qualitative AHP classification model was proposed (Li and Kuo, 2008). AHP classification is a qualitative method used to classify SPs according to a subjective weight, many authors advised the use of AHP method (Roda *et al.*, 2014). The AHP method was developed more than two decades ago and it is still highly used in decision-making technique. It is a very strong, flexible and multi-criteria tool that considers qualitative and quantitative issues, it helps in organising critical issues into a family tree like arrangement, using comparisons and rankings to simplify solutions and results (Braglia *et al.*, 2004). These are the main steps in applying the AHP classification method: (1) Define a hierarchy of objectives on levels from the top through intermediate levels to the lowest level. (2) Weight the criteria, according to their importance by using simple pairwise comparisons and rankings to determine weights. The qualitative judgements by the analyst are translated into a score of nine-point scales (i.e. Equally one-fourth 1, Moderately one-fourth 3, Strongly one-fourth 5, Very strongly one-fourth 7, Extremely one-fourth 9). The intensity of importance for each SPs was given according to experts' interview survey. (3) Develop the judgement matrix to calculate a priority vector to weigh the matrix elements this is called eigenvector. The criteria weight was calculated by constructing a pairwise comparison matrix of the relevant contribution or impact of each element or each governing criterion in the next higher level, then calculating the summation of each SPs, afterwards dividing each cell by the sum, and finally: Calculating the criteria weight. (4) Assess the goodness of judgements by calculating the inconsistency ratio (IR) (Saaty and Vargas, 2012). Starting with calculating the consistency index (CI) of an $n \times n$ matrix (of judgements) defined by the ratio: CI = $(\lambda_{max}-n)/((n-1))$ where λ_{max} is the maximum eigen value of the matrix. IR is defined as the ratio: CI/RI and RI is the corresponding average random value of CI for an $n \times n$ matrix. The judgements are acceptable if IR ≤ 0.1 (Braglia *et al.*, 2004).

MLR with stepwise method is used when the data are clustered meaning that variables are not independent; there is a level of collinearity between variables, errors range vary in different clusters and the effects of descriptive variables differ highly within the same environment. MLR maximizes the use of data, in order to make the most accurate estimation from the different given slopes from the chosen variables. Thus, the use of this model based on the collected data within this research is more convenient than the traditional regression model to increase forecasting results accuracy (Gelman and Hill, 2006).

There are many methods in MLR, this research applied the stepwise regression method which is a mix of forward selection and backward elimination. The procedure of using stepwise method depends on adding and removing independent variables for each step as much as needed, note that after each step when adding a new variable all the variables are evaluated in terms of its significant, thus when finding a non-significant variable it will be removed from the model automatically. In other words, the procedure ends in each step for selecting the variables, when p-value of all variables within the proposed model is less than the specified alpha will enter this variable, on the other hand, the p-value greater than the specified alpha will remove this variable from the constructed model (Gelman and Hill, 2006). The general equation for MLR model can be described in Equation (4). Where Y is the dependent variable β_0:constant, $j = 0, \cdots, k$, k the number of independent variables, X_j are the regressor variables β_j are the parameters or regression coefficients) and ϵ is the error.

$$Y = \beta_0 + \beta_1\, x_1 + \beta_2\, x_2 + \cdots + \beta_K x_k + \epsilon \tag{3}$$

Analysis, results and discussion

This study will assess the proposed forecasting MLR model, an assessment of MLR model assumptions and independent variables are held to investigate the outcoming results. The MLR model uses SPs' price and demand as the dependent variable, while the selected independent variables will be inserted when building the SPs' price and demand models, noted that the FR and NoV was removed when calculating the expected demand because they were included in demand calculations. The used data are saved into an excel file with 7,657 observations. The collected data are divided into two groups, the first group is selected randomly and represents 10% of the total data which is collected and used to validate the model. The second group is used for building the model. As a preceding step for the MLR some assumptions shall be checked (Fox, 2015). First assumption is to check if the independent variables are measured on a continuous scale, this assumption is achieved because SPs' price and its demand are measured by continuous scales. On the second side, the independent variables are either continuous or categorical variables that correspond to the second assumption. Third assumption is to check and eliminate all the significant outliers, high leverage points or highly influential points. Outliers, leverage and influential points are assigned and eliminated based on the Mahalanobis distance and Cook's distance. The maximum value of Mahalanobis distance is calculated based on the table of chi square value where the degree of freedom is the number of the independent variable, chi square in this case is 24.996, then any Mahalanobis distance above 24.996 is eliminated from the data. Cook's distance should be less than 1, then any distance greater than 1 is eliminated from the data. 6,671 observation is remaining out of 6,920 (Field, 2013). Fourth assumption is to check the residual of the data. Durbin–Watson statistic is used to test the data. The value of Durbin–Watson is 2.011 as shown in Table 1, where the target value should be between 1 and 3 (Field, 2013).

Fifth assumption is to check the linear relation between the dependent variables and the independent variables. The ZRESID is plotted against ZPRED to check it. Figure 1 shows that assumption is achieved because the dots are random arrayed (Field, 2013). Next assumption is the multicollinearity test. The VIF values is calculated for all the independent variables to check the assumption of no multicollinearity, the VIF values, which are listed in Table 2, are less than 3 excluded some values these extreme values are related to the vehicle generation and the vehicle price, these two variables are eliminated from the regression (Field, 2013). Final assumption is to check the normality of the residuals (Fox, 2015).The kurtosis and skewness test are used to test the normality, kurtosis and skewness are −0.143 and 32.784 for the price model with standard error equal to 0.03 and 0.06 respectively, and for the demand model are 21.923 and 619 with standard error equal to 0.03 and 0.06, which means the residual is not following the normal distribution.

After running the regression analysis through the Statistical Product and Service Solutions (SPSS) software, the outputs from this software is as follows for the SPs' price. The models' summaries that provides the value of R and R^2 for the regression models. According to price model summary, it is concluded that multiple correlation coefficient (R) which is equal to 0.89. When R equal to 0.89, it is a good indication for a strong relationship with the predictors and the dependent variable model summary and overall fit statistics. Adjusted R^2 is found equal to 0.791 with the coefficient of determination R^2 equal to 0.791. This means that the linear regression explains 79.1% of the variance in the data. While column R^2 indicates the proportion of variation in the dependent variable, in this model $R^2 = 0.791$ gives a good relationship meaning that this is an efficient model to forecast the outcome. Notice 20.9% (100–79.1%) of the variation is caused by factors other than the predictors included in this model. Finally, if there is a high discrepancy between the values of R-squared and adjusted R-square then that indicates a poor fit of the model, in this model the two values are very close to each other. The predictors of this model by using the pairwise regression are OP, NoU, OC,

Table 1. Summaries of SPSS output price and demand models

Models' summaries

Dependent variable	Model	R	R square	Adjusted R square	Std. error of the estimate	Durbin–Watson
Price	9	0.889	0.791	0.791	367.634	2.011
Demand	6	0.168	0.028	0.027	52.50929	2.011

The coefficients for models

Model	Variables	Unstandardized coefficients B	Unstandardized coefficients Std. error	T	Sig	95.0% Confidence interval for B Lower bound	95.0% Confidence interval for B Upper bound	Collinearity statistics Tolerance	Collinearity statistics VIF
Price model	(Constant)	−48.234	32.407	−1.488	0.137	−111.762	15.294		
	OP	1.126	0.009	126.621	0.000	1.108	1.143	0.675	1.482
	NoU	186.840	11.254	16.602	0.000	164.779	208.902	0.691	1.446
	OC	−109.995	8.062	−13.643	0.000	−125.799	−94.190	0.841	1.189
	TMC	0.016	0.003	5.157	0.000	0.010	0.022	0.856	1.168
	RC	−1.470	0.206	−7.125	0.000	−1.874	−1.065	0.695	1.439
	SP	3.122	0.568	5.496	0.000	2.009	4.236	0.631	1.586
	OR	48.832	15.960	3.060	0.002	17.545	80.118	0.807	1.240
	CR	−400.083	112.199	−3.566	0.000	−620.029	−180.138	0.981	1.019
	RL	41.752	13.287	3.142	0.002	15.704	67.799	0.706	1.417
Demand model	(Constant)	−8.965	4.329	−2.071	0.038	−17.451	−0.479		
	OC	7.500	1.145	6.549	0.000	5.255	9.745	0.851	1.176
	TMC	0.003	0.000	6.240	0.000	0.002	0.004	0.858	1.165
	SP	−0.318	0.066	−4.846	0.000	−0.446	−0.189	0.965	1.036
	OR	−8.426	2.180	−3.865	0.000	−12.700	−4.153	0.882	1.134
	CR	−51.267	15.979	−3.208	0.001	−82.590	−19.944	0.987	1.013
	SL	1.989	0.802	2.479	0.013	0.416	3.562	0.925	1.081

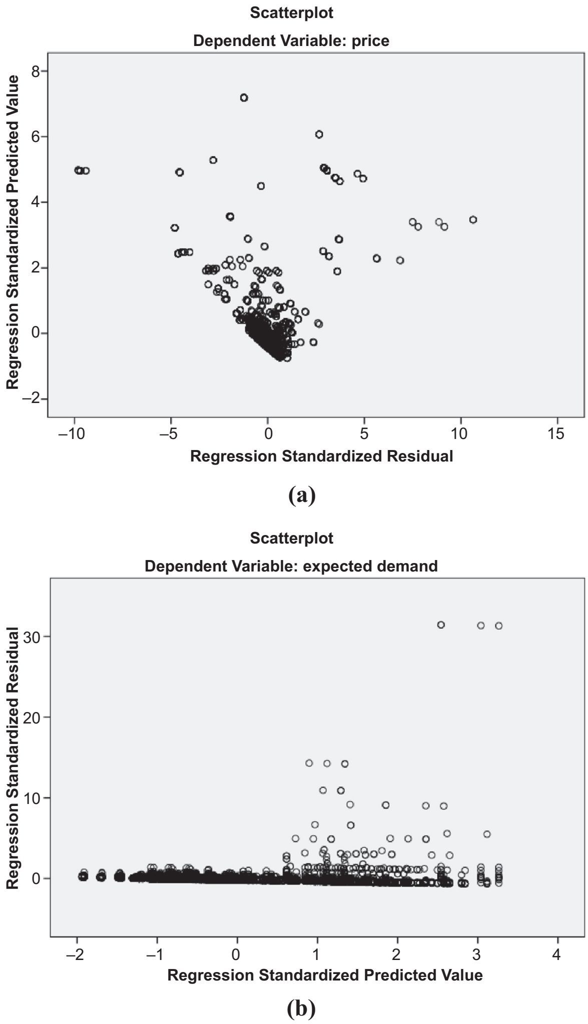

Figure 1.
The scatter plot of ZRESID against ZPRED for price (a) and for demand (b)

car TMC, RC, SP, OR, CR and the RL. The model ($F_{9,\ 6661} = 2{,}800$, $p = 0.000$). The F value shows that the independent variables statistically significantly predict the dependent variable.

According to demand model summary, the multiple correlation coefficient (R) is equal to 0.168. When R is equal to 0.168, it is a good indication for a weak relationship between predictors and the dependent variable model summary and overall fit statistics. Adjusted R^2 is found almost equal to 0.027 with the coefficient of determination R^2 equal to = 0.028. This means that the linear regression explains 2.8% of the variance in the data. While column R^2 indicates the proportion of variation in the dependent variable, in model $R^2 = 0.028$ gives a weak relationship, and 97.2% (100–2.8%) of the variation is caused by factors other than the predictors included in this model. The predictors of this model by using the pairwise regression are OC, car TMC average, SP, OR, CR, and SL. The model ($F_{6,\ 6668} = 32.078$,

Table 2.
Collinearity statistics (VIF)

Independent variables	CT	OC	VG	SP	CP	OR	NoU	SL	RL	RC	TMC	CR	OP	NoV
CT	–	1.715	2.077	2.985	1.861	2.984	2.964	2.974	2.984	2.985	1.986	2.985	2.985	2.975
OC	1.293	–	2.131	2.251	2.060	2.250	2.249	2.249	2.251	2.245	1.437	2.251	2.251	2.223
VG	7.397	10.06	–	10.63	1.106	10.63	10.63	10.63	10.63	10.63	10.27	10.63	10.63	10.36
SP	1.592	1.592	1.592	–	1.592	1.592	1.546	1.586	1.584	1.451	1.592	1.586	1.303	1.592
CP	7.145	10.48	1.192	11.46	–	11.45	11.46	11.46	11.46	11.46	10.51	11.46	11.46	11.23
OR	1.530	1.530	1.530	1.530	1.530	–	1.141	1.240	1.512	1.530	1.528	1.519	1.521	1.531
NoU	2.180	2.194	2.196	2.133	2.196	1.637	–	1.454	2.129	2.189	2.196	2.196	2.130	2.196
SL	2.251	2.258	2.260	2.252	2.260	1.831	1.496	–	2.051	2.260	2.260	2.259	2.259	2.260
RL	1.564	1.565	1.565	1.557	1.565	1.546	1.517	1.421	–	1.458	1.565	1.565	1.560	1.565
RC	1.439	1.435	1.439	1.311	1.439	1.439	1.434	1.439	1.341	–	1.439	1.434	1.378	1.439
TMC	1.303	1.251	1.892	1.959	1.797	1.955	1.959	1.959	1.959	1.959	–	1.959	1.958	1.927
CR	1.020	1.020	1.020	1.016	1.020	1.012	1.020	1.020	1.020	1.017	1.020	–	1.019	1.020
OP	1.483	1.483	1.483	1.214	1.483	1.474	1.439	1.483	1.479	1.420	1.483	1.481	–	1.483
NoV	1.117	1.107	1.093	1.121	1.099	1.121	1.121	1.121	1.121	1.121	1.103	1.121	1.121	–

p = 0.000). The F value shows that the independent variables statistically significantly predict the dependent variable.

SPSS is also generating the coefficient that represents the parameters of the model. In this price model, all the independent variables excluding the OC and CR have positive B values, this means that they have significant positive relationships with price, while the OC and CR have a significant negative relationship. In this demand model, OC, TMC and SL have positive B values, this means that they have significant positive relationships with demand. SP, OR and CR have a significant negative relationship. All the independent variables are significantly contributing to the demand model except the RL.

According to the data analysis done by SPSS, a statistical linear model is produced in order to predict the values of the price and demand based on the independent variables, the price and demand models are formulated as shown in Equations (4) and (5). These equations are tested by the remaining data which are kept for the validation. The mean square errors were 195,084 and 1,396 respectively, and the mean absolute values were 179 and 14.2, respectively, these results support the conclusion, that this is not strong model to calculate the expected price and demand.

$$\begin{aligned} \text{SP price} = {} & -48.234 + 1.126\ \text{OP} + 186.84\ \text{NoU} - 109\ \text{OC} + 0.016\ \text{TMC} - 1.470\ \text{RC} \\ & + 3.122\ \text{SP} + 48.832\ \text{OR} - 400.083\ \text{CR} + 41.752\ \text{RL} \end{aligned} \tag{4}$$

$$\begin{aligned} \text{SP demand} = {} & -8.965 + 7.5\ \text{OC} + 0.03\ \text{TMC} - 0.318\ \text{SP} - 8.426\ \text{OR} - 51.267\ \text{CR} \\ & + 1.989\ \text{RL} \end{aligned} \tag{5}$$

Last step testing the hypothesis according to the proposed model as the following: $H_0 2$ and $H_0 15$ are not tested because NoV and VP data shows multicollinearity problem. $H_0 3$, $H_0 4$, $H_0 6$ and $H_0 11$ are rejected because the $p < 0.05$. $H_0 5$, $H_0 1$, $H_0 13$ and $H_0 14$ are not rejected. $H_0 7$, $H_0 9$, $H_0 10$ and $H_0 12$ are not rejected for the demand and rejected for the price. $H_0 8$ is rejected for the demand and not rejected for the price.

Conclusion

HEVs all over the world occupied the vehicles' market, there is a noticeable positive change in customers' perspective towards it. Jordan has witnessed an obvious increase in hybrid vehicles' market, this increases the need of maintenance, which is directly affected by the availability of SPs. SPs availability and price ranges in the local market play an essential role in the demand pattern of different types of hybrid vehicles in the Jordanian market. It was also concluded from literature that many variables are heavily affecting the forecast of demand and price; internal and external factors are introduced such as social, economic and political factors. The main assumption was made that regression method is a good match to the collected data. Forecasting hybrid vehicles' SPs price and demand was not previously mentioned as it is an exclusive contribution of this research. It was obtained through a real case study by suggesting a number of factors affecting the demand and price. The results uncovered that in many circumstances, the model was not strong enough to calculate the expected future price and demand. The results also revealed that most independent variables effecting SPs price as well as demand; SPs' price has significant relation with OC, total maintenance cost, FR, OR, NoU, SL, RL, RC and CR. Note that manufacturer defect was not tested because of the lack of data. While expected demand has significant relation with OC, FR, OR, TMC, NoU, SL, RC and CR. Furthermore, results in this research provided the effectiveness level of using the multiple regression model within the given data; a limited number of parameters were selected along with investigating only four hybrid vehicles models, along with a definite number of SPs inside each vehicle, therefore extending this research to provide additional values outside the given data scope, and even further investigation for the suggested existing parameters would extremely support the proposed methodology, and make the results more reliable.

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