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RESEARCH PAPER

Decision Support for the Automotive Industry

Forecasting Residual Values Using Artificial Neural Networks

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Abstract In the automotive industry, it is very common for new vehicles to be leased rather than sold. This implies forecasting an accurate residual value for the vehicles, which is a major factor for determining monthly leasing rates. Either a systematic overestimation or underestimation of future residual values can incur large potential losses in resale value or, respectively, competitive disadvantages. For the purpose of facilitating residual value related management decisions, an operative decision support system is introduced with emphasis on its forecasting capabilities. In the paper, the use of artificial neural networks for this application is demonstrated in a case study based on more than 250,000 data sets of leasing contracts from a major German car manufacturer, completed between 2011 and 2017. The importance of determining price factors and the effect of different time horizons on forecasting accuracy are investigated and practical implications are discussed. In addition, the authors neither found a significant explanatory nor predictive power of external economic factors, which underlines the importance of collecting and taking advantage of vehicle-specific data or, in more general terms, the exclusive data of corporations, which is often only available internally.

Keywords Decision support systems · Business intelligence · Artificial neural networks · Residual value forecasts · Car leasing

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1 Introduction and Motivation

The leasing market is an important business segment for car manufacturers. Automotive assets, which include passenger cars and commercial vehicles, accounted for a volume of 65% (178.2 billion Euros) of total new leasing contracts granted in 2014, which makes it the largest individual asset segment of the European leasing market (Leaseurope 2014). Almost a third of all new cars sold by German premium brands in 2015 was financed by leasing (DAT Group 2016). Hence, this business model provides tremendous market opportunities, particularly for car manufacturers and leasing companies. Nevertheless, there are also risks which are difficult to quantify. The focus of our research is the so-called residual value risk (Prado and Ananth 2012). While the customer pays a contractually fixed leasing rate over the entire period of use, the residual value of the vehicle is uncertain until the end of the leasing period. In order to compensate the loss in value of the vehicles with adequate leasing payments, forecasts of residual values must be as exact as possible. Hence, accurate forecasts of future residual values constitute a critical success factor for competitiveness in the leasing market. Either a systematic overestimation or underestimation of future residual values would have negative consequences. If an overestimate is determined, the leasing payments may be lower, but not sufficient to compensate the loss in value of the vehicle. If predicted residual values are systematically too low, higher leasing rates must be set. This means that either avoidable competitive disadvantages occur or leasing rates must be substantially subsidized by car manufacturers. Car manufacturers nowadays often already have a sufficiently good data history of completed transactions in the leasing sector. They also record resale prices in the used car market for the corresponding vehicles. This potential, however, is often not sufficiently utilized to improve predictions of residual values.

In our pilot study (Gleue et al. 2017) we investigated the general suitability of an artificial neural network (ANN) approach for residual value forecasts and achieved superior, more accurate results compared to those obtained from pure linear models. We also introduced a first operational decision support system (DSS), which was developed and successfully implemented in cooperation with a large German car manufacturer. The system is now in operative use and continuously and automatically collects, cleanses and processes vehicle sales and additional necessary data. The present extended study focuses on the forecasting capabilities of the system. We use an extended data set covering the years 2011–2017 and additional explanatory variables. The availability of data over six complete years now permits a first realistic case study based on the three most important application areas of the DSS: firstly, dealers who have to buy and sell returned vehicles after the leasing period on the used car market need support to assess current market values. Secondly, the risk management department of the car manufacturer or leasing company requires valid estimations about future market values to assess the current risk of their leasing portfolio or to calculate possible depreciations. Thirdly, a forecast of the expected resale price is the most important factor when determining the necessary leasing rates in negotiations.

The residual value forecast is a typical regression problem in which certain characteristics such as the age and mileage of a particular vehicle determine its residual value. This study is based on more than 250,000 records of completed leasing transactions and resale values. In order to obtain an accurate forecast it is essential to gain a better understanding of the leasing market characteristics and especially the factors which determine the actual resale price. Insights into data characteristics specific to the problem domain as well as a comprehensible description of underlying rules and mechanisms are especially important for the assessment and interpretability of business analytics applications (Ionescu et al. 2016). Besides the factors which apply on an individual vehicle level, we are thus also interested in trends and seasonal patterns (a critical factor for ANN forecasts) in the market (Nelson et al. 1999) and the influence of external economic factors such as the oil price. Based on the latter, we also discuss practical implications when forecasting over longer time horizons. For this purpose, the development of vehicle values depending on the vehicle type age and time factor is of particular interest. The vehicle type age measures the time between the market launch of a new vehicle type and the resale date of a specific vehicle belonging to this type. The continuously increasing vehicle type age means that the expected residual value of two identical vehicles of exactly the same age and with the same mileage is not necessarily constant over time.

Facing these typical challenges in the leasing business, our contribution can be summarized as follows: A collaborative case study with a large German car manufacturer is conducted to illustrate three major application areas of residual value forecasts and how ANNs with the necessary data preprocessing can be properly applied to support and improve decision making. We therefore provide exclusive insights into the explanatory and predictive power of internal and external pricing factors for the used car market and investigate, in particular, how the influence of time affects forecast accuracy in uncertain leasing markets.

The remainder of this paper is structured as follows. The next Sect. 2 provides an overview of the existing literature in the field of residual value forecasts. The structure of the DSS and the available input data are presented and explained in Sect. 3. Section 4 specifies an exploratory analysis about price trends and seasons and investigates external factors on the used car market. In Sect. 5 the forecasting methodology and the data preparation is introduced. The results of the case study are presented in Sect. 6. Section 7 provides a discussion and addresses limitations, implications for practical use and further research opportunities. Section 8 concludes with a short summary.

2 Related Work

This section presents the existing literature in the field of residual value forecasts. Due to the exclusivity of the data, only few studies on this subject exist, each of which have different data at their disposal. This fact, however, also highlights the enormous research potential. One of these studies is provided by Lessmann et al. (2010). On the basis of 124,386 transaction data of the same vehicle type (upper class) of a major car manufacturer, the authors develop a decision support system by means of a support vector regression (SVR). This method extends the classical linear regression such as to permit a non-linear transformation of the independent variable. Each vehicle is described by 176 attributes. The large number of attributes results from the use of dummy variables that represent features such as different optional equipment. Transaction-specific characteristics such as typical features of the customer constitute a crucial point in this method. The authors demonstrate the benefits of using this information in a forecasting model. As such, they recommend the expansion of residual value forecasts within the company to achieve improved predictive power on the basis of exclusive datasets which are not available to external service providers or residual value institutes. Based on this, we are particularly interested in the influence of the available internal and possible external factors which determine future resale prices (see Sect. 4).

Wu et al. (2009) forecast used car prices on the Taiwanese market. Their input parameters comprise the cars' brand name, the year of manufacture, the engine type and an equipment index. A new combination of ANNs and ANFIS (adaptive neuro-fuzzy inference system) models are proposed to improve forecasting accuracy. An earlier study carried out by Lian et al. (2003) describes the problem of the residual value forecast from a time series perspective. Evolutionary artificial neural networks (EANNs) are used in this study to model the residual value of vehicles (all 24-month-old) over time (from 1993 to 1997). The authors find cyclical fluctuations, according to which the residual value is at a high level at the beginning of the year and falls to a lower level towards the end of the year (see Sect. 4.1 of our paper for a similar seasonality analysis). Other studies often use mostly macroeconomic indicators in addition to internally available data sources in order to explain the residual value distribution. Prado (2009) implements the price of diesel fuel and the industrial production index as explanatory variables in addition to vehicle-specific variables such as age and mileage. At the present time, it is evident that no scientific standard methods are reported in the respective literature. Fan et al. (2008) provide a comparison between data mining model approaches such as AutoRegressive Trees (ART), ANNs and linear regression. Their investigations focus on heavy construction machines. According to their analyses, the CART model provides the best results compared to the ANN and the linear regression model.

Besides the purely data-driven forecast techniques, other theoretical model approaches exist to explain price developments and the implications for risk management. This aspect is not a focal point of our work. For a deeper insight, we refer to Rode et al. (2002), Storchmann (2004), and Smith and Jin (2007).

3 System Structure and Input Data

In the following sections, the data and methodology presented in this paper are put in the larger context of a DSS for residual value- and leasing-related issues. In Sect. 3.1, an overview of the complete system structure (see Fig. 1) is presented, followed by a more in-depth description of the input data used for this study in Sect. 3.2.

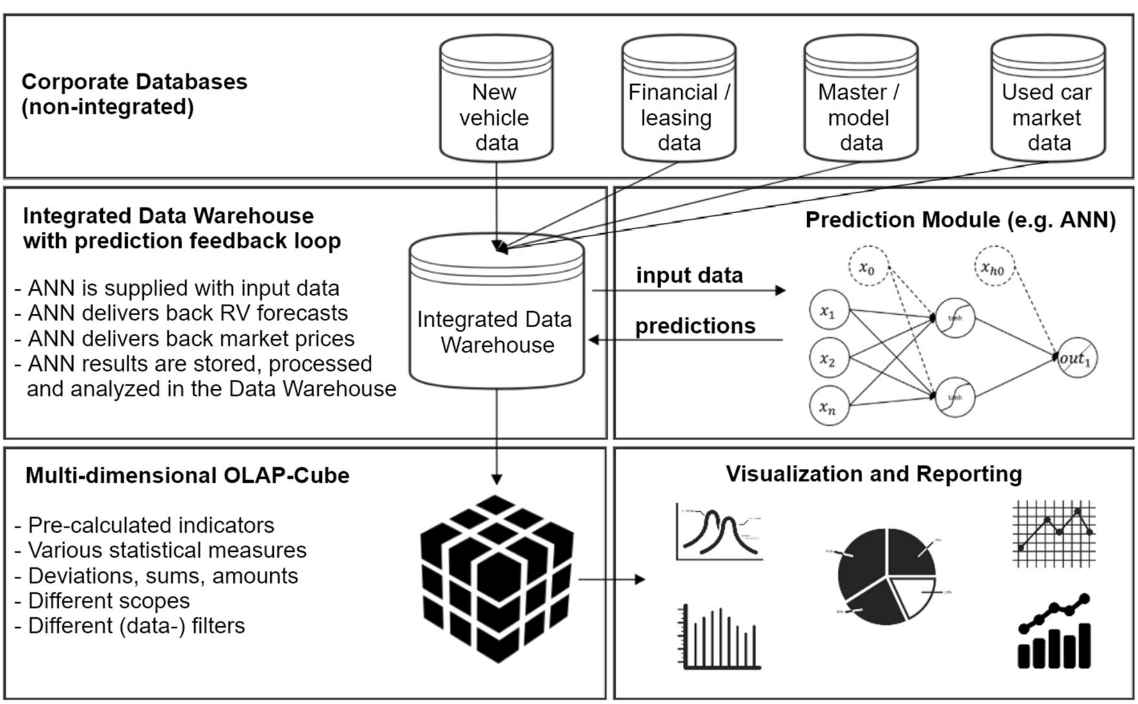

Fig. 1 Decision support system for RV forecasts

3.1 Structure of a DSS for Residual Value Forecasts

In this section, the larger context of the DSS is explained (see Fig. 1). The forecasting models need to be trained with historical data. Thus, the first step of the development was to collect and integrate data from different sources within the corporation. The most important of all sources is the used car market database, which stores all used car data collected from the dealerships. It contains every single transacted resale in Germany since 2011, including the vehicle identification number (VIN) as a unique identifier for the vehicle, its mileage, the age of the vehicle, additional vehicle-related information (e.g., vehicle type, engine, fuel type etc.), resale date and the desired output of the forecasting model, the net resale price. As all data from this source is entered manually in the dealerships and then transferred via a common interface for all dealer management systems in the market, it has to be joined and validated with data from other, internal sources to serve as training data set for the forecasting model.

One of those sources is the new vehicle database, which collects data from the factory invoicing system directly after production. Besides the corresponding VIN numbers, it contains the original list price of the vehicles, divided into base price, color surcharge and the extra charge for optional equipment, the complete list of optional equipment packages and also an indicator if the vehicle was produced for a promotional offer (with a discount on the original list price).

The information delivered by these systems is decoded using additional data from a Master Data Management system which contains general information about vehicle types, promotional campaigns (such as list price discounts on special edition vehicle types), engine power and capacity, gearbox type (manual, automatic, double clutch), number of gears and the vehicle type age (number of months since the market launch). Ultimately, there is a connection to the leasing database which provides the initial forecasts and market prices assumed by the captive leasing company. For every single resold vehicle, all of the aforementioned information is gathered, cleansed and stored automatically in a central, integrated data warehouse. This data warehouse, in turn, has a direct connection to the prediction module. The (trained) forecasting model is being fed with input data directly from the data warehouse, predicts market values (actuals) and expected residual values for all vehicles in the database and delivers them back to the data warehouse, where they are stored for further processing and analyses. The next and penultimate layer of the DSS is a multi-dimensional cube for Online Analytical Processing (OLAP). It serves as the basis for visualizations and reports for different purposes, e.g., benchmarking of the forecasting models, market analyses and, most importantly, leasing- and pricing-related decision support. It provides numerous pre-calculated indicators, deviations, sums, amounts, arithmetic means and other statistical measures as well as pre-configured scopes and data filters, e.g., to differentiate between the list price of special edition and standard vehicles or young used cars and cars representing the traditional leasing segment with a leasing term of at least 12 months.

Hence, the OLAP cube can be seen as an extensive toolbox for management reports and visualizations. Used correctly, it can be utilized to find answers for many different used-car- or leasing-related questions, such as individual dealership sales performance rankings, analyses of the used car market price levels after external shocks, monitoring of the car manufacturers' own residual value setting or influences of particular parts of optional equipment on the resale price. These reports need to be configured once on the OLAP level and can then be standardized and visualized with additional software.

The modules previously described, from data collection and integration to reporting and visualization, all play an important role in the operational DSS outlined in this section. Nevertheless, all the results and reports in our particular area of application rely on accurate predictions of actual market and residual values. Subsequently, the prediction module and its mode of operation represent the core of our DSS and thus, the main focus of the research presented in this paper. The next Sect. 3.2 provides a description of the input data used for the forecasting model.

3.2 Input Data

Vehicles are included in the database as soon as they have been successfully resold on the used car market after the end of the leasing period. By this means, the residual values realized on the market are included in the database. We distinguish between individual vehicle-specific and vehicle type-specific variables. The vehicle-specific variables refer to the leasing contract agreements, which include the mileage, the leasing term (age of the vehicle) and extra charges for special paintwork and optional equipment. The vehicle type-specific variables describe the general characteristics of the vehicle and are the same within each vehicle type group. 928 different vehicle types are represented in the data. For further analyses, categorical variables like “fuel type” are encoded as binary variables for each occurring category. Table 1 shows the available features.

These variables are directly related to the vehicles under investigation. For an exploratory analysis, we use a simple linear regression approach to explain (in-sample) the residual values based on the factors from Table 1. The age of the vehicle and the mileage have the strongest negative

Table 1 Input data variables

Variable	Encoded as	Description
Accident free	Binary	Accident free (yes/no)
Color	Continuous	Extra charge for special paintwork (in % of list price)
Customer	Binary	Customer type (e.g., end customer or reseller)
Distribution center	Binary	Location of the dealership (sales region/state)
Equipment	Continuous	Extra charge for optional equipment (in % of list price)
Financing type	Binary	How the vehicle was financed (leased, financed, purchased)
Initial list price	Continuous	Original, "historical" list price of the vehicle
Mileage	Continuous	Vehicle mileage in km
Vehicle age	Continuous	Vehicle age (registration date to resale date in days)
Engine capacity	Continuous	Engine capacity in cubic centimeters
Engine power	Continuous	Engine power in horsepower
Four wheel	Binary	Four-wheel drive indicator (yes/no)
Fuel type	Binary	Gasoline, diesel, CNG, LPG
Gear number	Binary	Number of gears
Gear type	Binary	Transmission type: automatic, double-clutch, manual
Vehicle type age	Continuous	Age of the vehicle type since market launch in months
Vehicle specifics	Binary	Other specifications of the vehicle type appearance
Residual value	Continuous	Residual value in percent $\frac{resale\ price}{list\ price}$

impact on the residual value. For a forecasting application, the vehicle type age is also a crucial factor. Here we face the problem that the age of a specific vehicle type constantly increases over time. Compared to the age of a specific vehicle where we have a wide range of training examples, the age of the vehicle type is not available beyond the present point in time. The results of this regression analysis indicate that in-sample, the effect of the vehicle type age is significantly negative. Using this factor in a forecasting application therefore requires extrapolation. Another interesting finding is that the extra charge for optional equipment has a negative effect on the residual value, which shows that the more optional equipment a vehicle is fitted with, the more value it loses over time in percentage terms.

4 Explanation of Prices

4.1 Trend and Season

In this section, we use the model errors of the previously mentioned naïve regression analysis to investigate the phenomenon of seasonality and trend in the used car market, which provides valuable insights to perform a subsequent unbiased forecast. Using the regression approach, effects of the aforementioned independent variables are eliminated. Now, the following approach is applied: firstly, model errors are sorted with respect to time. Secondly, the model errors for each month during the observation period are averaged. This results in a monthly time series of averaged model errors. Figure 2 shows the resulting time series.

The results show a clear downward trend during the 6 years of observation, which flattens in the last 2 years from 2015 to 2017. After controlling for all contract-specific variables, the results indicate a price decline based on general market conditions (the regression already controls for the constantly increasing vehicle type age). Since we are also interested in seasonal patterns, a decomposition of this time series is performed by the Seasonal and Trend decomposition using Loess (STL) method (Cleveland et al. 1990). A seasonal period of 12 (for each month) is assumed. Figure 3 shows the time series decomposition to determine seasonal and trend effects. The ordinate shows

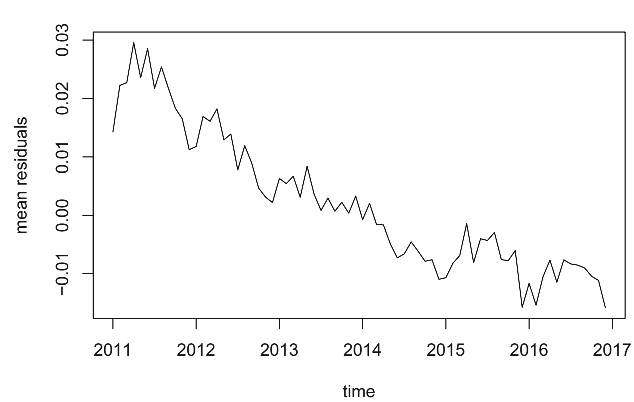

Fig. 2 The influence of the time factor on the residual value

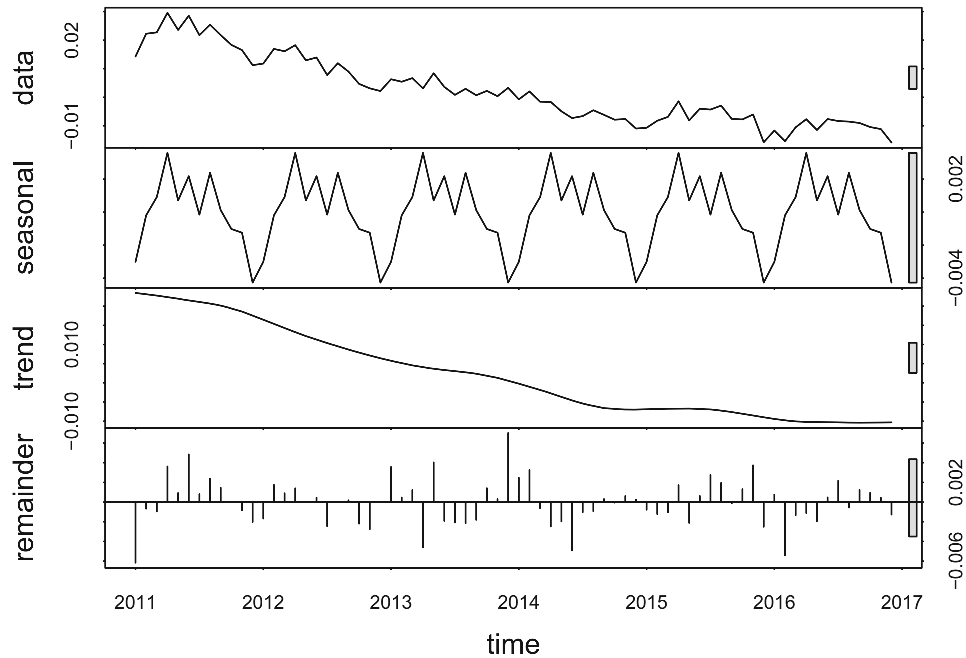

Fig. 3 Time series decomposition: seasonal and trend effects

the mean residuals in total (data) and their three different components. It can be observed that the residuals are subject to a trend and a season. The detrended seasonal component shows that towards the end of the year, lower residual values are achieved than during the rest of the year. Accordingly, the residual values tend to be higher during spring, even though these effects are rather small (in the range of 0.8% points of the list price during a year).

These observations illustrate the time dependence of prices in the used car market. When performing further analyses, monthly dummy variables may be used to control for the seasonal component. Although this trend may be simulated by adopting a steadily increasing time factor in the regression models, the fact that a flattening of the trend is observed during the last 2 years means that the effect is rather unclear and can produce misleading results in a forecasting application (Sect. 6).

4.2 External Factors

In order to understand residual values on the used car market, external influences such as the oil price or the number of new vehicle registrations in a particular month might also be important explanatory factors. Studies by Prado (2009), for example, use such factors in their forecasting models. The general applicability of using external factors in a forecasting application depends on the model objective. Incorporating factors which, e.g., represent the current macroeconomic situation is reasonable only if the aim is to estimate the current market value of a given used car. For a residual value risk management application on the other hand, an actual forecast of this price must be produced at the time when the leasing conditions are specified, i.e., at the beginning of the leasing contract. In order to prevent a look-ahead bias, only the factors which are known at this point in time can be incorporated into the forecasting model. This means that only current values of external factors may be incorporated, or the factors themselves must be predicted in advance, which may cause other biases. Nevertheless, investigating external influences on current residual values is important to understand the general characteristics of the used car market and to assess the applicability for the above-mentioned application of estimating current market values.

In this study we use the ten most represented vehicle types in our data set (sample size of 49,297 vehicles) to estimate linear mixed effects models. Vehicles within a vehicle type class are completely identical with respect to factors such as horsepower, fuel type, number of gears etc. In this way we are able to effectively control for all vehicle characteristics in the regression. We also control for the characteristics of individual vehicles specific to the leasing contract such as vehicle age and mileage and additionally incorporate monthly dummy variables and a time factor. For each external factor under investigation we have random intercepts for vehicle type and by-vehicle type random slopes. p values represent the results of the likelihood ratio test. These results are shown in Table 2.

Table 2 Influence of external (macroeconomic) input factors

Factor	t value	χ^2	p value
DAX close	1.41	1.9043	0.1676
Oil close	− 1.39	1.8376	0.1752
Ifo business climate index	− 0.87	0.7638	0.3821
Ifo current business situation	0.88	0.7822	0.3765
Ifo business outlook	0.89	0.7929	0.3732
GfK economic outlook	0.08	0.0058	0.9390
GfK income expectations	− 0.08	0.0056	0.9401
GfK buying propensity	− 0.21	0.0459	0.8304
GfK consumer climate	− 1.18	1.3827	0.2396
Unemployment rate	0.5	0.2511	0.6163
Diesel price	− 0.19	0.0368	0.8479
Gasoline price	0.64	0.4113	0.5213
Consumer price index	0.73	0.5249	0.4688
ECB interest rate	0.14	0.0190	0.8903
GDP	0.01	0.0002	0.9891
GDP growth	− 0.43	0.1832	0.6687
Vehicle registrations in month of resale	1.1	1.1780	0.2778
Average vehicle registrations (1 year ago)	1.44	2.0017	0.1571
Average vehicle registrations (2 years ago)	1.17	1.3676	0.2422
Average vehicle registrations (3 years ago)	0.74	0.5523	0.4574
Average vehicle registrations (4 years ago)	− 0.15	0.0226	0.8806
Average vehicle registrations (5 years ago)	0.35	0.1206	0.7284

The tabulated results show that actually none of the investigated effects have significant explanatory power for the realized residual price (i.e., none of the p values are below 0.1). It is important to mention that our sample covers a time period without any major economic disruptions. For this reason, it should not be concluded from the results that residual values are completely independent of external influences such as market shocks or economic crises. During normal market conditions, which are assumed for a general forecast, a systematic influence of these factors is not detectable.

Although linear models are easy to interpret and therefore suitable for inference, they have certain limitations in forecasting applications. Although ANNs on the other hand are hardly interpretable, they are able to learn complex interrelationships within the data, which makes them a suitable choice when predictive capability is the focus of attention.

5 Forecasting Methodology and Data

5.1 Artificial Neural Networks

ANNs (Bishop 1995; von Mettenheim and Breitner 2010) are particularly suitable for the use with non-linear relationships. Their applications range from forecasts in the finance (Sermpinis et al. 2014; Zimmermann et al. 2001), and risk management area (von Spreckelsen et al. 2014) to decision support systems (Eilers et al. 2014; Gleue et al. 2017; Kuo et al. 2001). They are robust to very noisy, unstructured, or missing data (Schocken and Ariav 1994), have powerful pattern recognition capabilities (Zhang et al. 1998) and are therefore well suited to the present real-life problem. Nevertheless, ANNs are only one possible supervised machine learning approach suitable for our area of application. There are several other learners available (like, e.g., support vector machines or gradient boosting), but the key factor for a successful application is rather the proper selection and representation of the right variables for the investigated problem (the focus of our work) than the choice of the learning algorithm (Domingos 2012). Experience with the selected method and its characteristics is also crucial for reliable and reproducible results, which is an important argument for the application of ANNs in our use case. Even though many previous studies have shown the potential of this technique in forecasting and prediction applications, a proper implementation and validation as well as an accurate data pre-processing is necessary to achieve reliable results (Adya and Collopy 1998). ANNs may be viewed as a method for non-linear function approximation. In this paper, feed forward networks are used. These are composed of several layers of neurons. A first layer (input layer) describes the independent variables which are used to explain the phenomenon. These neurons are connected by weights θ_1 to a further layer (hidden layer), which in turn is connected to the output $h_\theta(X)$ (or a further hidden layer) by the weights θ_2. The hidden layer is thus in turn the input for the following layer. This pattern can be repeated any number of times (any number of hidden layers), each with any number of neurons within the layers. A three-layer feed forward ANN is defined by:

$$h_\theta(X) = \theta_2 \tanh(\theta_1 X). \quad (1)$$

The hidden neurons and, optionally, the output neurons transform their weighted sum of inputs by means of an activation function (usually the hyperbolic tangent).

$$f(X) = \tanh(X) = 1 - \frac{2}{e^{2X} + 1}. \quad (2)$$

The structure of an ANN is shown in Fig. 4. To be able to perform a function approximation, the ANNs are trained with training patterns (input x_k, output y_k represent the training pattern k). The randomly initialized parameters (weights) are determined using an iterative error back-propagation process to find a solution for mapping the input vector onto the dependent output. ANNs are non-convex optimizations so each training process with the same data can lead to different results (local minima). To avoid using only one randomly bad solution, many ANNs with random initializations of the weights are trained simultaneously and the performance is assessed based on validation data which is not used for adjusting the weights. Therefore, the training patterns are split into a set on which the ANNs are actually trained, I_t and a set of validation patterns, I_v to estimate the out-of-sample performance. Therefore, we split the available training data into 80% actual training patterns and 20% for validation. The final results are then reported based on the performance of the models on an independent test data set which is not used for adjusting the weights nor for model selection. During training, the approximation quality of the ANN is evaluated by calculating the training and validation error functions

$$\varepsilon_t \equiv \frac{1}{2}\sum\nolimits_{k \epsilon I_t} \left(h_\theta(x_k) - y_k\right)^2 \text{ and } \varepsilon_v \equiv \frac{1}{2}\sum\nolimits_{k \epsilon I_v} \left(h_\theta(x_k) - y_k\right)^2. \quad (3)$$

To avoid the problem of overfitting (learning noise in the data), a cross-validation is performed. We use an early stopping approach (stop training when error on the validation set increases) to obtain ANNs with good generalization capabilities. The two most important hyperparameters to be determined are the number of hidden layers and their respective number of hidden neurons. No clear rules exist on how to determine their optimal number, as this depends on the problem domain, the available input factors and the sample size. Experimenting with different topologies can hence lead to good results. Applying methods such as early stopping against overfitting permits the use of larger networks without considerable differences in performance but at the expense of computation time. In our example, good results are obtained with two hidden layers of 50 and 25 neurons, respectively. The training can be parallelized on a computing cluster or by using GPUs, which are especially suitable for larger ANNs.

5.2 Data Cleansing and Variable Importance

Since ANNs are sensitive to outliers, we perform a data cleansing before the actual training process is started. For this purpose, a small preprocessing three-layer ANN including all variables shown in Table 1 is trained to a local minimum on the whole training data. Subsequently, every data set for which $|h_\theta(x_k) - y_k|$ is greater than a threshold value c is removed. In this example, the threshold value c is defined as the 95% quantile of the errors, this means that 5% of the data are removed. A manual analysis of the identified outliers reveals that in the case of outliers with higher residual values than expected, optional equipment (e.g., additional cooling or tool storage equipment) had been installed after production and hence subsequent to the specification of the leasing contract. This led to a higher initial value (above the invoiced original list price) and thus, also to a higher residual value. In the case of outliers with lower residual values than expected, the cars' overall condition (e.g., accidents) had not been properly reported in the data filtered by this approach. As we aim for accurate residual value predictions for accident-free vehicles without additional installations, these outliers had to be excluded from our analyses.

Besides the explanatory power of the different factors (see Sect. 4.2), we are also interested in their predictive power within an ANN environment. Compared to interpretable linear models, assessing the importance of a variable within an ANN approach is less straightforward.

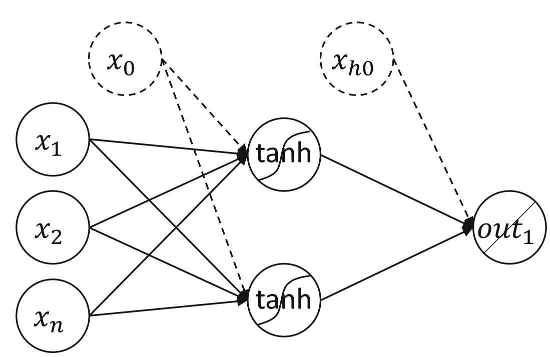

Fig. 4 ANN (three-layer feedforward network)

This issue represents the tradeoff between inference and prediction. However, the available data/factors and their dependencies may differ tremendously for other leasing-related applications or even different market segments. This means that having at least a profound idea about the importance of individual factors in a specific ANN forecasting application is required. This should also help to make the results of the complex optimization model more comprehensible. In order to assess the usefulness of incorporating different variables into the system, we propose that input perturbation ranking (Breiman 2001) should be implemented. For this reason, we again include the ten most frequent vehicle type classes in our data and train an ANN to a local minimum using all available input factors from Table 1, external factors from Table 2, a time factor and monthly dummies. The trained ANN is subsequently used to calculate the output for the same data n times, whereby n is the number of incorporated input factors. Each time, one of the input factors is "destroyed" by randomly shuffling the values of this input. This approach eliminates possible relations between the factor in question and the output, while maintaining statistical properties such as the mean value and standard deviation. Ranking is then performed based on the resulting in-sample error, in this case the root-mean square error (RMSE) (Eq. 4), which the ANN produces with the destroyed input.

$$RMSE_n = \sqrt{\frac{1}{m}\sum_{k=1}^{m}\left(h_\theta(x_{n,k}) - y_k\right)^2}. \tag{4}$$

The higher the error, the greater is the importance of this factor in the model. The importance score is hence defined as the model error with a specific "destroyed" factor divided by the maximum error over all factors, such that the most important factor is assigned a value of 1. Table 3 shows 10 of the most important inputs ranked in descending order.

The baseline performance with all correct input factors is an RMSE of 0.06114059. As expected, the factors "age" and "mileage" have the largest influence on the results of the model. A relevant observation is that many factors which are only internally available (such as "financing type", "distribution center" or "initial list price") are also important for the predictive performance of the models. All external factors are ranked at the bottom part of the list and show no important influence on the resulting RMSE of the model. This supports the observation stated in Sect. 4.2 that within our sample from 2011 to 2017, these factors neither have explanatory nor predictive power after taking vehicle-specific characteristics into account. Therefore, these insights again underline the importance of collecting and using exclusive, internal data in order to improve decision support in the leasing business.

6 Forecasting Application

A forecasting application in the presented business context might be used for at least three different purposes. One case is to estimate the current market value of a used vehicle in order to support dealers in negotiations on the used car market. Although external factors can influence the attainable price in this case, we have shown that during our sample period from 2011 to 2017, none of the tested factors have explanatory and/or predictive power for used car market prices. Another case is to forecast future market values for a given used car in order to answer questions such as: "What price can we expect from a given used car next year?" This is especially important for risk management purposes because realistic expectations about attainable prices on different time horizons influence the necessary provisions for currently running leasing contracts. The third application may answer the question about future residual values of vehicles at the point in time when leasing contracts are specified, which supports decision makers in determining appropriate leasing rates at the beginning of a contract.

In order to simulate the first case, all transactions from the years 2011 to 2013 were used to construct the initial models, using all input factors from Table 1, monthly dummies and the general time factor. The subsequent 6 months of data were used for testing purposes. The models were then retrained with the initial data and the new data of the subsequent 6 months. The next 6 months of data were then used for repeated testing. The results in Table 4 show the improvements in the forecasting accuracy of the ANN model compared to a regularized linear model. An ensemble average of 30 different ANNs with random weight initializations (resulting in different local optimization minima) is used to mitigate potential forecasting errors of single models. For the linear benchmark, we use a ridge regression approach. The regularization parameter is selected by a naïve grid search and the best performing model on a validation set is used.

Table 3 Feature importance

Factor	RMSE	Importance
Age	0.18670350	1
Mileage	0.10002972	0.5357678
No. of gears	0.08053335	0.4313436
Initial list price	0.07457451	0.3994275
Financing type	0.07097613	0.3801543
Distribution center	0.06793025	0.3638403
Vehicle type age	0.06675006	0.3575191
Engine capacity	0.06654379	0.3564143
Additional equipment price	0.06652828	0.3563312
Horsepower	0.06614927	0.3543012

Table 4 Forecasting accuracy for current market values: RMSE for ANN model and ridge regression

Period	ANN	Linear
2014/1	0.07403902	0.08272359
2014/2	0.07478254	0.08319453
2015/1	0.07331877	0.0825396
2015/2	0.07562336	0.08428427
2016/1	0.07326041	0.08350813
2016/2	0.07443271	0.08617191

Table 5 Forecasting accuracy for future market values: RMSE for ANN model and ridge regression

Period	ANN (with t)	Linear (with t)	ANN (without t)	Linear (without t)
2014/1	**0.07403902**	0.08272359	0.0751566	0.08405203
2014/2	0.07738575	0.08410964	**0.07653743**	0.08534023
2015/1	0.0770185	0.0839343	**0.07636575**	0.08659457
2015/2	0.0816638	0.08615005	**0.07740517**	0.08799502
2016/1	0.08367484	0.08551692	**0.07874524**	0.0903501
2016/2	0.09278381	0.08765334	**0.0796895**	0.08937356

The ANN outperforms the linear approach over each testing period due to its ability to learn non-linear interdependencies in the data at the expense of interpretability. Especially in the case of ANNs, it is crucial to understand the influence of the input factors on forecasting capability. Time-dependent input factors are a major issue in this respect. ANNs are suitable for interpolation tasks where information is actually available to learn from. In the practical application considered here, we face the problem of two independent variables which are constantly increasing over time, namely the age of a vehicle type and the general time factor. Hence, in a real world application over time, models which incorporate these factors must be able to extrapolate. The second use case describes the problem of using the models to predict future market values without the possibility of retraining the models for every new decision to be made. Table 5 shows the results for the testing periods from 2014 to 2016 using forecasting models which are only trained on data from 2011 to 2013.

With regard to the investigation of extrapolation capabilities, we use models trained with and without time-dependent factors. The results show an overall increase in uncertainty for later time frames. The best performance (values highlighted in bold) for the first half-year is achieved by the ANN model which incorporates the time factor and vehicle type age. Later forecasts are more accurate without including time-dependent factors. The problem of ANNs with respect to extrapolation can be observed by comparing the ANN model to the linear model when both models include time-dependent factors. The uncertainty of the ANN model increases faster in regions outside the distribution of the training data. In the second half of 2016, even the linear model outperforms the ANN approach. While the linear model benefits from including time factors in all time frames, the ANN model only benefits from these factors in the first half year. This applies, even though it is evident from Table 3 that at least the age of the vehicle type is one of the factors with the highest in-sample predictive power. The general handling of time-dependent factors in leasing business forecasts thus depends mainly on the time horizon concerned and the market context. In our application, the time factors can be beneficial only for a small time frame. If these factors have a clear (linear) trend, it might be reasonable to adjust the non-linear models externally by, e.g., a linear adjustment of the interpolation results. Extrapolation within the framework of ANNs can produce misleading results, however.

The third use case is the forecast of residual values for specific vehicles at the beginning of a leasing contract. Again, all data from the first 3 years (2011 to 2013) are used for training the models (excluding time-dependent factors). All leasing contracts that are concluded during the subsequent 6 months are assessed by these models and the forecasts are evaluated when these vehicles are returned (starting in 2015). The results of the latter are shown in Table 6. It can be observed that ANNs also outperform the linear model in all evaluation time frames. Furthermore, the older the vehicles become, the faster uncertainty increases.

Besides the presented benchmarks, the performance improvements achieved using our approach with internal data are indeed economically relevant in the practical application compared to former, simplistic predictions based on data from external service providers for residual value estimations (average accuracy improvement of three percentage points of the original list price closer to the real residual value). This again emphasizes the importance of using one's own internal data in leasing decision support applications. A discussion of the results as well as an outlook for further research are given in the following section.

Table 6 Forecasts for specific vehicles: RMSE for ANN model and ridge regression

Period	ANN	Linear
2015/1	0.06396709	0.07228487
2015/2	0.06782139	0.07600988
2016/1	0.07978839	0.08955229
2016/2	0.0960669	0.1029367

7 Discussion

The challenge of forecasting residual values of vehicles was examined in this paper. An accurate forecast as a substantial part of a larger DSS is crucial for managing the exposure risk of car manufacturers and dealers in the leasing business. A systematic bias in both directions (too high or too low predictions) leads to negative consequences, either for competitiveness or the resale margin. The aim was to establish a purely data-driven approach for forecasting residual values based on information about past transactions. The results indicate that ANNs are well-suited for such noisy and unstructured data. Nevertheless, thorough data preparation and outlier detection is crucial in order to achieve good results. We show how ANNs can be used to preprocess and filter the database and how a forecasting model can be designed based on an ANN approach. ANNs are often criticized owing to their black-box nature. By means of a transparent description of the topology, variable importance and a data cleansing process, it is possible to mitigate this problem and make the results comprehensible and reproducible. ANNs are often only used as an alternative tool to benchmark different methods. Rather than comparing a few different types of machine learning approaches to each other, however, the available data and ANN model specification and training are the key success factors. Thus, one of the main purposes of this study is to investigate the factors which determine the residual value, while ANNs serve as one possible technique to achieve reliable results. Nevertheless, there are many possibilities for improving the forecast results, e.g., by ensembling different model types, further optimizing hyperparameters or using different regularization techniques. Asymmetric cost functions for the learning algorithm which weight different forecast errors according to their respective economic consequences might also be beneficial in order to better account for the particular business problem (Lessmann 2013).

Within our sample from 2011 to 2017 we neither found a significant explanatory nor a predictive influence of externally available (macroeconomic) factors such as the oil price. Contrary to this, the most important factors comprise variables such as the initial list price or financing type, which is internal information only available to the manufacturer. Accordingly, it is much more important to collect and use the data available within the company rather than simply rely on external data and/or service providers. However, our findings are only valid for the sample considered, which excludes major crises or economic shocks. This is a limitation that applies especially to long-term forecasts. More data over a whole business cycle are required to derive valid statements regarding the influence of external disruptive changes in market conditions. Additionally, we also investigated time-dependent factors. A clear downward trend in the residual values was identified with increasing vehicle type age and time. A reason for this may be the declining attractiveness of a particular vehicle type over time, which means that customers tend to buy a newer generation of products. As a result, older vehicle types must be offered at a lower price. Moreover, the seasonal component of the used car market shows lower residual values in December and higher residual values during the first quarter of a year. This empirical observation may be explained, e.g., by dealers trying to meet their sales targets towards the end of the year. Although these observations might be a special phenomenon for the type of vehicles examined in our study, it is a topic for further research investigating these patterns for a broader range of vehicle classes in order to formulate a more general statement.

The forecasting simulation illustrates the different main use cases of the system. The most challenging aspect of a leasing-related application is to properly incorporate the time-dependent factors. In this paper we show that ANNs outperform linear models, even though they are not particularly suitable for extrapolation tasks such as, e.g., the constantly increasing age of vehicle types. Further studies must address this issue more closely in order to compare different extrapolation techniques. Model combinations involving ANNs for the interpolation task and linear adjustments of the results based on the different time factors might further improve long-term forecasts.

In the greater context of an entire DSS, the particular use cases presented in this paper serve as a general example that by using methods and tools from the field of business intelligence, predictive analytics and data science, corporations can obtain valuable, business-critical information from data that is often already (and exclusively) available internally. It also shows that this information, properly prepared and visualized, can support or even induce management decisions and help to monitor the consequences. In the particular case of the DSS presented in Sect. 3, many use cases beyond residual value forecasts have already been realized, from the assessment of individual dealership performance to the measurement of the impact of internal decisions. Another practical example from our project is the simulation of different market scenarios, e.g., the assessment of the car manufacturers' risk exposure if residual values suddenly drop due to an unexpected external shock such as financial crises, new legislations or competitors' decisions. The results of such "stress tests" support the financial/controlling department in the establishment of appropriate provisions to cover these risks.

Further concepts for value-oriented data analysis in this context could include the development of new business models in the leasing business in general. One example could be the implementation of vehicle sensor data in order to permit a calculation of flexible leasing payments depending on intended car use. Customers could then benefit from lower leasing rates due to a reduction in forecast uncertainty. Live sensor data may also be used to assess wear and tear. Additional factors for possible future discussion may include ethical and legal aspects.

One of the major disadvantages of systems such as those presented in this study is that they are usually quite complex, especially for employees/decision-makers with a non-technical background. Understanding the whole process of how results are determined requires a deep technical and mathematical understanding and, most importantly, the necessary time. At this point, complexity may become a problem, as time usually is a scarce factor in daily business, especially in management. Decision makers need to be able to trust the results, especially if important decisions are to be based on them. In an operative, real-life DSS, it is our experience that technology acceptance can be strengthened, e.g., by a clearly arranged data quality assurance dashboard and, in general, reports whose visual appearance is not completely new to the receivers' eye. Subsequently, professional communication of project results, analyses and ultimately, between managers, analysts and developers is inevitable and plays an important role in earning the necessary confidence. Since easy to understand reports can reduce complexity, build up trust and thus, facilitate communication, further research should also concentrate on proper visualization (Köpp et al. 2014) of data and analyses.

8 Conclusion

In the course of this paper, we investigated means to reduce the residual value risk car manufacturers and leasing companies face in their daily business. In order to better understand the factors which determine prices on the used car market, we provided evidence for the influence of internal and external variables. While internal factors like "initial list price" and "financing type" have a strong influence on the residual value, our case study results also show that external economic factors such as the oil price have no significant explanatory or predictive power under normal market conditions. This underpins the importance of exploiting exclusive internal data to realize competitive advantages. The results provide hints to internal variables that are worth looking at more closely in leasing applications. The forecasting approach developed in this paper mainly relies on artificial neural networks, which show superior performance compared to linear models. As demonstrated by three typical applications of residual value forecasts, the accuracy, especially of the non-linear models however, greatly depends on the forecasting horizon. The investigated influence of the time factor can be seen as a general challenge for residual value forecasts in any domain and should therefore receive special attention in future research.

From a more general perspective, it can be concluded that corporations usually have access to large amounts of exclusive, unstructured, unintegrated data, which, properly processed, prepared and interpreted, have the potential to make a difference in daily business or even in important strategic decisions. This potential should not remain unexploited. Nevertheless, the information obtained still relies on humans with expert knowledge to interpret and communicate the results correctly. In a practical environment, close coordination between these experts and decision makers is crucial for the success of such projects.

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