Association for Information Systems
AIS Electronic Library (AISeL)

ICIS 2010 Proceedings

International Conference on Information Systems (ICIS)

2010

DECISION SUPPORT IN CAR LEASING: A FORECASTING MODEL FOR RESIDUAL VALUE ESTIMATION

Stefan Lessmann
Institute of Information Systems, University of Hamburg, lessmann@econ.uni-hamburg.de

Mariana Listiani
Hamburg University of Technology Institute of Software, mariana.listiani@gmail.com

Stefan Voß
Institute of Information Systems, University of Hamburg, stefan.voss@uni-hamburg.de

DECISION SUPPORT IN CAR LEASING: A FORECASTING MODEL FOR RESIDUAL VALUE ESTIMATION

Completed Research Paper

Stefan Lessmann
Institute of Information Systems,
University of Hamburg
Von-Melle-Park 5,
20146 Hamburg, Germany
lessmann@econ.uni-hamburg.de

Mariana Listiani
Hamburg University of Technology
Institute of Software, Technology, and Systems (STS)
Schwarzenbergstraße 95
20173 Hamburg, Germany
mariana.listiani@gmail.com

Stefan Voß
Institute of Information Systems, University of Hamburg
Von-Melle-Park 5, 20146 Hamburg, Germany
stefan.voss@uni-hamburg.de

Abstract

The paper proposes a methodology to support pricing decisions in the car leasing industry. In particular, the price is given by the monthly fee to be paid by the lessee as compensation for using a car over some contract horizon. After contract expiration, lessors are obliged to take back the vehicle, which will then be sold in the used car market. Therefore, lessors require an accurate estimate of cars' residual values to manage the risk inherent to their business and determine profitable prices. We explore the organizational and technical requirements associated with this forecasting task and develop a prediction model that complies with identified application constraints. The model is rigorously tested within an empirical study and compared to established benchmarks. The results obtained in several experiments provide strong evidence for the proposed model being effective in generating accurate predictions of cars' residual values and efficient in requiring little user intervention.

Keywords: Decision Support, Risk Management, Forecasting, Pricing, Automotive Industry

Introduction

Leasing has emerged as a popular means towards financing various types of equipments such as commercial vehicles, office machines and manufacturing devices as well as IT-infrastructure. For example, *Leaseurope,* the European Federation of Leasing Company Associations, amounts new leasing volumes granted through its members in 2008 to 330.1 billion Euro (Leaseurope 2010). Such numbers emphasize the importance of the lease financing sector. The advantages of leasing are manifold and include being able to acquire costly equipment without affecting cash flows. Small and medium sized companies may also find it easier to settle a contract with a leasing agency than to obtain a loan for equipment purposes from their bank, especially at times where banks act increasingly risk-averse. Finally, firms can benefit from topical models of machinery without having to worry about update cycles.

As in other financial industries, risk management plays a key role within the leasing business. Since a leasing contract shares several similarities with a loan, risk management activities include appraising the likelihood of customers failing to pay the agreed fee as well as predicting the loss incurred in the case of default (see, e.g., Schmit 2004). An even more important risk specific to the leasing business is associated with anticipating resale prices. Lessors are obliged to take back the subject of the lease after contract expiration, which will then be sold in the second-hand market. The selling price attainable in this market (i.e., the subject's residual value) governs the leasing rate a company can offer to its customers without risking financial loss on resale. More specifically, overly optimistic estimates suggest a lower leasing rate, which, in turn, will diminish overall profits if the (used) item needs to be sold below its anticipated price after contract expiration. Consequently, leasing agencies are required to forecast residual values as realistically as possible to effectively manage the risk inherent to their business.

The objective of this work is to examine the specific requirements and peculiarities associated with this estimation task in one particular branch of the industry, the car leasing sector. Furthermore, we aim at developing a forecasting methodology that addresses identified challenges, facilitates accurate and reliable predictions of cars' residual values to be generated, and, thereby, supports decision making in the leasing business. The choice of the car leasing industry is motivated as follows: According to Leaseurope (2010), the lease of passenger cars and commercial vehicles is the largest market segment with a 2008 contribution to overall market volume of 58%. Therefore, this industry branch is particularly important from an economical perspective. This view is supported by optimistic growth rate predictions for upcoming years (see, e.g., Barkholz and Sherefkin 2009; Sawyers 2009), especially for emerging economies. For example, the market research agency *Datamonitor* estimates the average annual growth rate of the car leasing market in India to be 28% until 2013 (MarketWatch 2009). In summary, the relevance of the car leasing market suggests that findings obtained for this segment may be regarded as valuable for the industry as a whole. Finally, we motivate our choice by observing that the problems associated with residual value estimation are particularly severe in the automotive sector. For example, results of an analysis of the German market suggest that 33% (~52 billion Euro) of overall revenue is made in the used car segment, whereas this sector's profit contribution was as low as 0.057% in 2004 (Joas 2005); due to the financial crisis, today's situation is most likely worse. The inability to make profit with used cars establishes the need for decision support systems (DSS) to improve decision quality in general and predicting residual values in particular.

Previous work on forecasting (cars') residual values is limited to only a few studies (Lian et al. 2003; Lucko et al. 2006; Prado 2009). This motivates a technology-centered research paradigm to gain insight whether established analytical techniques enable an effective prediction model to be designed and what particular challenges are encountered within this endeavor. In particular, adopting the principles of design science (Hevner et al. 2004), the paper aims at devising an IT artifact in form of a forecasting methodology to address the business problem of estimating cars' residual values.

In pursuing this objective, the paper makes a number of important contributions. First, decision processes in the car leasing business are examined from a business and technological perspective. This sheds light on the particular characteristics and requirements of an important but not sufficiently researched business problem. Second, the IT-artifact developed on the basis of this analysis integrates established techniques from machine learning and nature-inspired computing in a novel way and extends previous approaches to estimate residual values. Third, an empirical study is undertaken to rigorously assess the artifact in a realistic environment and confirm that it effectively solves the problem it is meant to solve. To that end, a large real-world dataset from a leading car manufacturer is employed. Fourth, the study is designed to clarify upon the utility of transaction specific information (i.e., characteristic to one specific contract and leasing subject in particular) in estimating residual values. Such information has not been considered in previous research, but could play an important role in the (car) leasing business. In particular, a common practice in this domain is to base residual value estimates on reference lists published by market research companies. Since they are unable to take transaction specific information into account, examining its utility allows conclusions regarding process organization to be drawn. That is, if the potential of transaction specific information to increase forecasting accuracy can be confirmed, this would evidence a need for company-internal forecasting systems and discourages unduly reliance upon reference lists.

The paper is organized as follows: Organizational and technological requirements in the car leasing business are examined in the next section. The actual forecasting methodology is derived in the third and empirically evaluated in the fourth section. The paper concludes with a summary of key findings in the fifth section.

Requirements Analysis

Effective design requires knowledge about both, the application domain (requirements and constraints) and the solution domain (technical and organizational) (Hevner et al. 2004). Therefore, we begin with examining business processes in car leasing, specifically the selling process, to gain insight into application requirements. Together with technical considerations, these are translated into design objectives to be fulfilled by the forecasting methodology.

Business Perspective

Previous research has shown that objective decision quality, measured by means of, e.g., cost savings or profit increases associated with a business process, can be improved through high-quality DSS (see, e.g., Benbasat and Nault 1990; Lilien et al. 2004; Sharda et al. 1988). In particular, the contribution of DSS comprises changing the (imperfect) process in which decisions are made (Silver 1990). In the focal application, the sanity of pricing decisions is threatened by inaccurate expectations about residual values. Overestimating residual values results in lower leasing rates being offered to customers, but deteriorates profits in the long run. Conversely, underestimating residual values dictates higher leasing rates and may deter customers from accepting an offer. Therefore, expectations about resale prices are an important determinant of pricing decisions in the leasing business. Accordingly, endeavors to support decision making involve providing sales agents with data and methodology to anticipate cars' residual values.

A forecasting model, be it a formal quantitative model or an informal model – possibly a heuristic subconsciously employed by a decision maker – can be considered an information processing unit: it receives as input data concerning the business transaction and the focal vehicle in particular, and processes this data in some fashion to eventually output an estimate of a future state. For the estimate being close to (future) truth, it is essential that the model's internal mechanisms effectively distill generalizable knowledge from the given inputs, and that these themselves are relevant to the problem, i.e., facilitate such an undertaking.

Possible drivers of residual values are manifold. Whereas car brand and model as well as age and mileage are arguably the most important determinants, resale prices might also be influenced by more subtle factors including, e.g., special-equipments, color, type of cushion, etc. The key point is that a rich set of information concerning the subject of the lease is available. Since vehicles are known to enter the used car market after contract expiration, any information that could possibly affect selling prices in this market should be taken into account when estimating residual values to achieve maximal forecasting accuracy. On the contrary, cognitive limitations in processing large amounts of information (see, e.g., Hogarth and Makridakis 1981) are likely to prohibit decision makers from accounting for less obvious drivers of residual values. Instead, they may turn to simple heuristics (Lilien et al. 2004).

One such simple decision heuristic is known as anchoring and adjustment (Tversky and Kahneman 1974). For example, sales agents may ground their estimates of residual values on reference lists published by market research companies like ALG[1], which in this sense represent an anchor. Although of undoubted value, external recommendations inevitably fail to account for information only available within the company (e.g., specific to an individual business transaction and car in particular) and thus suffer the same limitations outlined above.

In addition to not employing the full set of available information, a second source of concern is that decision makers' estimates might be deliberately biased. Specifically, sales agents might be tempted to overestimate residual

[1] http://www.alg.com

values because this facilitates offering more favorable leasing rates to customers, which, in turn, increases the likelihood of a leasing contract being set. Depending upon organizational incentive structures, a decision maker may well prefer (short-term) revenue over profitability in the long run; especially if the organizational unit responsible for the leasing business is different from the one handling returned cars.

The previous considerations motivate a directive approach (see, e.g., Sutherland 2008) towards supporting residual value estimation to make full use of available information, remove prediction bias, make decision makers move away from anchors, and eventually improve the process in which decisions are formed (Arnott 2006; Lilien et al. 2004; Silver 1991). In such scenario, the task of collecting and processing different types of information is left to the DSS, which then provides sales agents a concrete recommendation (i.e., a forecast) of a car's residual value. Compared to an interactive DSS, a normative approach is also desirable because it reduces efforts associated with training users how to master the system. On the other hand, an estimate of residual value is just one ingredient in the business process of negotiating leasing rates and other rental terms with customers. Therefore, the proposed DSS should not unduly circumcise sales agents' freedom in shaping this process, which might otherwise diminish the utility of a directive approach and raise concerns associated with user acceptance (see, e.g., Davis 1989).

Technical Perspective

The task of estimating residual values can be characterized as a regression problem. Given data of past sales, the objective of regression is to approximate a functional relationship between cars' resale prices and observable attributes that capture particular vehicle characteristics. The resulting regression function represents a forecasting model that can be employed to predict residual values on the basis of car characteristics. The attributes are referred to as independent variables in regression terminology, whereas the modeling target is termed the dependent variable.

A large number of regression methods have been developed (see, e.g., Hastie et al. 2009), differing for example in type of functional relationship assumed between dependent and independent variables (e.g., linear versus nonlinear) and the particular way empirical data is employed to construct the function. The classical principle is to minimize the empirical risk of the regression function, in terms of a predefined loss measure, over a given data sample. Clearly, the most well-known representative of this approach is standard linear regression.

In residual value estimation, we face a situation where much and detailed data about vehicles is available, which could potentially be of value for forecasting. The design objective of making full use of such information to boost forecasting accuracy translates into a technical requirement to cope well with a large set of attributes. Some concern has been issued that the classical principle experiences difficulties in such settings. In particular, regression models relying on empirical risk minimization may be unstable when working with a large number of possibly correlated attributes (Vapnik 1995).

The reason for potential reliability problems is that empirical risk is, by definition, measured on the basis of one specific data sample. The ultimate goal of regression is to predict novel cases (not contained in this sample) with high accuracy. A key result of Vapnik's (1995) theory of statistical learning is that the degree to which a model achieves this objective depends not only upon its empirical risk but also upon its complexity. In addition to actual relationships between attributes and the dependent variable, a complex model may also capture random patters peculiar to the specific sample from which it is derived. This problem is known as *over-fitting* and results in poor performance (low accuracy) when the model is applied to predict novel cases. A difficulty with models that employ a large number of attributes is that they are, ceteris paribus, more complex than models with fewer independent variables. Concentrating only on empirical risk when building such models will usually result in over-fitting.

The principle of *structural risk minimization* (SRM) has been developed as a generalization of empirical risk minimization, which avoids over-fitting and is robust towards large attribute sets (Vapnik and Kotz 2006). The essence of SRM is to balance the conflicting goals of low empirical risk and complexity. Whereas an overly simple model may not suffice to accurately approximate intricate patterns in the sample, even if these represent actual relationships, a too complex model may suffer from over-fitting and thus fail to predict novel cases with high accuracy. In order to achieve a favorable trade-off between the two, measurements of empirical risk and complexity should be considered jointly when inferring a regression model from data.

The SRM principle is appealing for residual value estimation. A forecasting method implementing this philosophy facilitates processing a large set of attributes and thus meets the requirement to fully employ all available information concerning vehicles. By explicitly accounting for model complexity, the induction algorithm is in a position to distinguish between informative and non-informative variables and filter out the most valuable pieces of information without rendering the model too complex.

In addition to objectives concerning predictive accuracy, operational feasibility is another requirement any decision support approach needs to fulfill. In practice, this may impose strict technological requirements to ensure that, e.g., the DSS is in line with an organization's IT landscape and complies with clearly defined interfaces to access relevant information from operative or decision-centric data stores. Although being anything but trivial, these aspects are not central to this work and need to be explored in future research. Instead, we focus on decision makers' (i.e., users') needs. The tasks of constructing and applying a forecasting model may easily be perceived as complex, due to the mathematical computations inherent to regression. Therefore, it seems desirable that the forecasting methodology avoids manual intervention in the model building process to the largest degree possible. Moreover, automation reduces efforts associated with instructing and training system users as well as updating forecasting models once new data becomes available or structural changes in the car market suggest a recalibration.

Design of a Forecasting Methodology

The previous analysis has identified two main design objectives: the forecasting methodology should deliver accurate predictions and possess high degree of automation. We strive to achieve the former by employing a regression method that embodies SRM to account for a large set of car-specific attributes. To address the latter, an intelligent tuning agent is devised to carry out modeling tasks users would otherwise have to perform themselves.

Prediction Model

To estimate residual values, the forecasting methodology incorporates *Support Vector Regression* (SVR), which has been proposed by Vapnik (1995) as a learning algorithm in the spirit of SRM. Essentially, this method constructs a linear model, *f*, of the following form:

$$f(\boldsymbol{x}, \boldsymbol{\beta}) = \boldsymbol{\beta} \cdot \varphi(\boldsymbol{x}) + \beta_0 , \tag{1}$$

where the vector $\boldsymbol{x}$ comprises the independent variables, and $\boldsymbol{\beta}, \beta_0$ denote the normal and intercept of the linear regression function, respectively. As a key feature of SVR, independent variables may be transformed in some nonlinear fashion prior to constructing the linear regression function. Due to the transformation, represented by $\varphi(\cdot)$ in (1), SVR is able to account for nonlinear relationships in data. For example, vehicles are known to lose much of their original value in the first years, whereas depreciation stabilizes in later years of usage. This suggests that the relationship between an independent variable 'age' and residual value is not linear. Whereas the approach to transform independent variables could, in principle, be employed in conjunction with any regression method, the particular merit of SVR stems from the fact that the transformation can be performed implicitly by means of a kernel function (Vapnik 1995). This *implicit* transformation makes the concept computationally feasible.

Whereas a detailed discussion of kernel functions, also called kernels, is beyond the scope of this paper (readers are referred to Smola and Schölkopf's (2004) excellent tutorial), three aspects are of particular importance for this research. First, kernel functions facilitate nonlinear regression, but SVR can also perform a linear regression if a linear kernel is used. Second, there are different types of kernel functions (Shawe-Taylor and Cristianini 2004). We consider *linear*, *polynomial* and *radial basis function* (RBF) kernels in this work and formally introduce these in Appendix I. Third, kernel functions may possess (meta-) parameters, which need to be set externally (i.e., by users) prior to constructing a SVR forecasting model. For example, if a user selects a polynomial kernel function to transform independent variables, then s/he has to determine the degree of the polynomial, which, in this respect, represents a meta-parameter of this kernel.

To implement the principles of SRM, SVR employs a novel loss function called ε-insensitive loss for model building. The idea behind ε-insensitive loss is that when fitting the model to sample data (i.e., when minimizing empirical risk), small deviations between the regression function and data points should be ignored, because these might be caused by noise. The representational power of SVR (achieved through kernels) would otherwise allow the model to approximate any peculiarity of the sample with 100% accuracy (i.e., over-fit the sample). To control this risk, the errors to be minimized during model building are defined as data points outside a tube of size ε around the regression function. This principle is illustrated in Figure 1. Whereas the data points in the tube would contribute towards the regression's loss in standard linear regression, they are ignored by the ε–insensitive loss function.

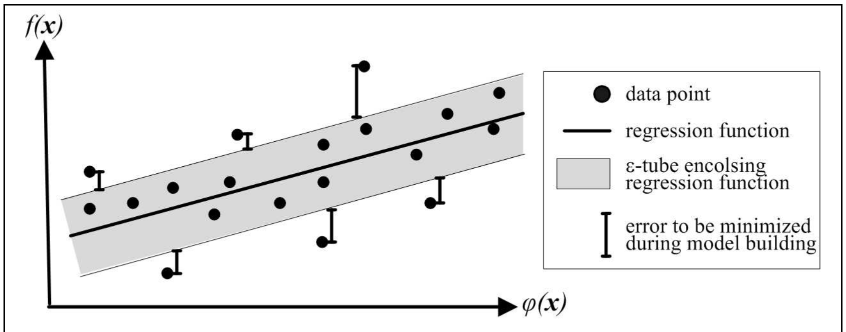


Figure 1. Linear SVR with ε-insensitive loss

In principle, a larger tube implies that the resulting model is less complex since less attention is devoted to deviations of sample data points from the regression function. Accordingly, such a model will fit the sample data less accurately. Therefore, the trade-off between empirical risk and complexity can be controlled through the parameter ε.

In addition, SVR incorporates a second mechanism for penalizing overly complex models. Specifically, the model building process is given an incentive to minimize not only empirical risk, measured by means of ε-insensitive loss, but also the square-norm of the parameter vector $\boldsymbol{\beta}$ (Smola and Schölkopf 2004). Essentially, it can be shown that a regression model's complexity increases with the magnitude of (absolute) parameter values. Consequently, small norm of $\boldsymbol{\beta}$ is desirable since a respective model may be considered simple and is less prone to over-fitting.

The ideas of ε-insensitive loss and minimization of the norm of $\boldsymbol{\beta}$ can be combined to obtain the mathematical program (2), whose optimal solution gives the SVR regression function shown in (1).

$$\min_{\boldsymbol{\beta}} C \cdot \left| y_i - f\left(\boldsymbol{x}_i, \boldsymbol{\beta}\right) \right|_{\varepsilon} + \left\| \boldsymbol{\beta} \right\|_2^2 . \tag{2}$$

Index i refers to individual data points in the sample and C is a constant that allows users to gear minimization either towards empirical risk or complexity, respectively. The ε-insensitive loss between the dependent variable y and model predictions $f\left(\boldsymbol{x}_i, \boldsymbol{\beta}\right)$ is represented by $\left|\cdot\right|_{\varepsilon}$, whereas $\left\|\cdot\right\|_2^2$ denotes the square of the Euclidian norm of $\boldsymbol{\beta}$.

Parameter Selection

A large body of literature emphasizes the importance of tuning meta-parameters of SVR to adapt the method to a particular decision problem (see, e.g., Cherkassky and Ma 2004; Kwok and Tsang 2003; Wang et al. 2003). That is, only appropriate settings for the meta-parameters ε and C, as well as parameters of the kernel function enable high forecasting accuracy to be achieved. The process of identifying such settings can be seen as a search problem in a real space of candidate values and is commonly referred to as model selection (see, e.g., Momma and Bennett 2002).

The standard approach to organize model selection is known as grid-search and involves predefining candidate settings for each meta-parameter and empirically assessing all possible value combinations (see, e.g., Van Gestel et al. 2004). A key advantage of this approach may be seen in its simplicity. However, it suffers severe limitations: First, some user intervention is needed to predefine the set of candidate values. This task is critical since the search is restricted to these values and requires expertise. Second, a fully enumerative search is performed, which is computationally expensive and fails to balance between examining a broad range of candidate values (exploration) and searching intensively in promising regions of the search space (exploitation).

A more advanced alternative involves the use of heuristic search procedures (see, e.g., Chen and Wang 2007; Momma and Bennett 2002; Tay and Cao 2001). In particular, it has been argued that a family of procedures known as *Evolutionary Strategies* (ES) might be particularly suitable for SVR model selection because the model's meta-parameters are all positive real values and ES work well with this type of decision variables (Gijsberts et al. 2010). Therefore, we pursue the path initially suggested by Friedrichs and Igel (2005) for discrete prediction tasks (i.e., classification), and employ ES for tackling the model selection problem in residual value estimation. An additional benefit of ES stems from the availability of sophisticated self-tuning mechanisms (Beyer and Schwefel 2002; Hansen and Ostermeier 2001). Heuristic search procedures, in general, also exhibit meta-parameters akin to those of SVR. Consequently, to avoid simply exchanging one parameter tuning problem for another, it is crucial that the model selection mechanism is self-adaptive. Whereas not even ES fully comply with this requirement, they fulfil it to a large extent, i.e., better than possible alternatives.

ES can be characterized as iterative, direct, randomized search procedures, which mimic the principles of neo-Darwinian evolution theory (Beyer and Schwefel 2002). They operate on a collection of individuals, each of which represents a candidate solution to the problem, i.e., a vector of candidate values for SVR meta-parameters. The solution quality of such an individual is assessed by constructing a SVR model with the meta-parameters the individual embodies, and measuring the resulting model's forecasting accuracy. To mirror Darwinian principles, the collection of individuals is termed population, whereas solution quality is referred to as fitness. Let M be the number of individuals in the population. Striving to increase fitness, in each iteration of the algorithm (generation), $N>M$ novel individuals (offspring) are generated by means of partially stochastic variation of existing (parent) individuals. For example, with some probability, the value of a SVR meta-parameter may be in-/decreased by a random number. The M fittest members of the offspring population will then form the novel population,[2] and this loop of variation and selection is repeated until a termination criterion is met.

The process of tuning SVR meta-parameters by means of ES is illustrated in Figure 2, where p_i denotes one out of n SVR parameters and $N(0,\sigma_i)$ represents a random number drawn from a normal distribution with zero mean and standard deviation σ_i.

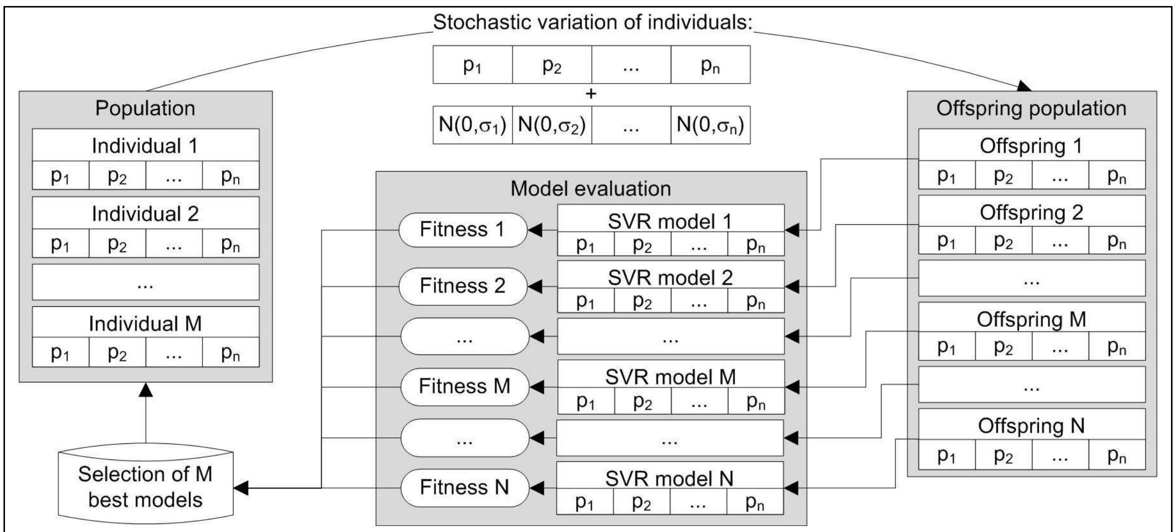


Figure 2. Model selection with ES tuning agent

Evaluation

The principle aim of evaluation is to determine how well a designed IT artifact fulfills quality criteria related to functionality, completeness, consistency, accuracy, performance, reliability and usability, as well as

[2] Alternatively, one can combine offspring and parent population prior to selecting M fittest individuals for the novel population. This way, an individual is given a chance to survive multiple generations (Beyer and Schwefel 2002).

implementability and organizational fit (Hevner et al. 2004). In the focal case, the IT artifact consists of a methodology to construct a forecasting model for residual value estimation. In accordance with standard practices in forecasting (see, e.g., Winklhofer et al. 1996), we emphasize accuracy and performance criteria and study their fulfillment by means of an experimental evaluation. In particular, the accuracy of the model's predictions is taken as key indicator of its merit.

Hypothesis Development

In order to verify that the proposed model fulfills the main design objectives of being effective in producing accurate predictions and efficient in its resource consumption in general and the avoidance of human intervention in the forecasting process in particular, four hypotheses are developed to guide the empirical evaluation.

The proposed methodology incorporates ES to calibrate SVR parameters and thereby adapt the method to a given task. ES is expected to contribute to model effectiveness (by identifying predictive parameter values) and efficiency (through performing the search autonomously and in a resource preserving fashion). Model selection could alternatively be performed by means of grid-search. To justify our design decision, we thus need to show that:

H1: ES dominates grid-search as a model selection mechanism.

To conceptualize domination, we detail *H1* as follows:

H1a: A SVR model parameterized by ES shows forecasting accuracy at least as high as a SVR model resulting from grid-search.

and

H1b: ES requires a smaller amount of computer resources than grid-search.

and

H1c: ES requires little human intervention when performing the model selection task.

Turning attention to the artifact as a whole, a necessary condition for it being of value is that the task of estimating residual values truly requires a formal (quantitative) forecasting model. Otherwise, potential bias of decision makers' forecasts (see above) could probably be corrected more effectively by, e.g., modifying organizational incentive schemes. Therefore, we distinguish between two types of information that could affect residual values: information that human decision makers would most naturally employ in their personal predictions (i.e., brand, model, age, mileage) and information very specific to a particular sale (e.g., type of customer, intended vehicle usage, car's special equipment, etc.) they would likely ignore. These two categories of independent variables are termed *standard domain variables* (SDV) as opposed to *transaction specific variables* (TSV). Then, we strive to demonstrate that:

H2: Forecasting models that employ TSV in addition to SDV are more accurate than models restricted to SDV.

With regard to the previous argumentation, confirming *H2* is important to evidence the necessity of using a formal (quantitative) model for residual value estimation. If such evidence is found, then the merit of the particular forecasting methodology proposed in this work has to be verified. To that end, a benchmark is needed against which model predictions may be compared to. Due to employing a large amount of data in the empirical evaluation (see below), consideration of expert judgments is infeasible. On the other hand, research in the application domain is limited, so that no standard model for residual value estimation can be identified in the literature. Consequently, we turn to what may be seen as the most natural benchmark and compare the novel model's predictions with forecasts generated by a *multivariate linear regression model* (MLR). In terms of the type and amount of information employed, the predictions of this model may already be much more sophisticated than those of a field expert. MLR may thus be seen as a challenging benchmark. However, restricting the effect of covariates on residual value to be linear and additive, the way MLR computes forecasts is still "reasonably close" to how a human decision maker would perform the task, which further supports its choice. Therefore, to demonstrate the effectiveness of the proposed forecasting model, it will be important to confirm that:

H3: Employing identical variables, residual value estimates of the novel model are more accurate than those of a MLR benchmark model.

A plausible explanation for the presumably superior performance of the proposed forecasting model is that it distills valuable information from the independent variables over and above those that MLR is capable of extracting. Since a major difference between the two is that our model facilitates nonlinear relationships between covariates and the dependent variable to be discerned, we hypothesize that:

H4: The proposed model performs akin to MLR if restricted to be linear.

Experimental Setup

The data to be used within the empirical study has been provided by a leading global car manufacturer. The dataset comprises 124,386 cases, each of which represents one vehicle that was sold in the used car market. All vehicles are of the same car model, which can be considered upper-class. The precise type of model has to be concealed for confidentiality reasons. The selling price in the used car market is expressed as percentage of a vehicle's original list price, and serves as dependent variable in this study. To build a forecasting model, each vehicle is characterized by a set of 176 attributes (i.e., independent variables). The large number of variables can be explained by the fact that many attributes are discrete and have been encoded by means of binary dummy variables, a standard preprocessing operation in data analysis (see, e.g., Crone et al. 2006). A high-level description of the variables is given in Table 1.

The merit of a forecasting model is assessed in terms of *root mean squared error* (RMSE), which has been suggested as meaningful accuracy measure for this application by the car manufacturer. In order to compute RMSE, and error measures in general, a hold-out sample of 'fresh' data is needed. Using dedicated evaluation data simulates a real-world scenario where the forecasting model is employed to predict residual values for cases disjoint from those used to construct the model in the first place. Different experimental schemes facilitate such realistic assessment of model performance, including, e.g., cross-validation or bootstrapping (see, e.g., Hastie et al. 2009). Since our dataset is relatively large, a split-sample setup is appropriate for this study. In particular, a sample of 37,316 examples (30%) is randomly drawn from the dataset and reserved for evaluation (test set), whereas the remaining cases (training set) are used for model building.

Table 1. Independent variables

Description	No. of variables*	Scaling level	Variable group
Age	3	continuous	SDV
Mileage	1	continuous	SDV
Customer variables	21	discrete	TSV
Production year	6	discrete	TSV
Engine type	24	discrete	TSV
Lacquering/color	29	discrete	TSV
Type of cushion	15	discrete	TSV
Special equipment	77	discrete	TSV

*A value greater than one indicates that multiple variables belong to the group of, e.g., Age variables.

Empirical Results

In order to check the validity of *H1*, we begin with a comparison of ES versus grid-search as model selection mechanisms. To that end, a subset of 30% is randomly drawn from the training data to serve as validation partition.[3] Both procedures are then invoked with the configuration listed in Appendix II to construct SVR-based forecasting models (with different meta-parameter settings) on the remaining training cases and to assess their performance on

[3] Drawing an additional "hold-out" sample is important because SVR parameters would otherwise be optimized on the test data. As a consequence, SVR would be granted an unfair advantage over MLR and performance of the former would be overestimated in later comparisons.

the validation set. The parameters delivering highest forecasting accuracy and respective RMSE values are reported in Table 2. There and in the following, results are separated for models using only SDV and those that in addition incorporate TSV. The analysis embraces three types of kernel functions to widen the scope of the comparison.

Model selection aims at identifying one single parameter setting that works best for a given forecasting task. Therefore, to contrast (search) effectiveness of ES versus grid-search, it is appropriate to compare the performance of the "best" models each competitor has produced. Table 2 reveals that ES delivers similar or slightly better performance in terms of RMSE across all kernel functions in both settings. The high level of consistency is appealing and provides strong evidence in favor of *H1a*.

One might be tempted to call for a formal test to verify statistical significance of results. During the search for effective parameters, ES and grid-search have constructed and assessed hundreds of individual forecasting models (see below). Therefore, one could theoretically employ a paired *t*-test or its nonparametric counterpart to check whether the models derived by ES show, on average, significantly higher performance than models based on grid-search. However, such comparison would put ES in an advantageous position since grid-search is constrained to a predefined search-space and has no possibility to trade-off exploration and exploitation objectives. As a consequence, it will inevitably visit some solutions (i.e., forecasting models) with very low performance. Therefore, any statistical test on the basis of the population of models developed by ES and grid-search, respectively, would be severely biased and offer misleading advice.

Table 2. Results of the comparison of ES vs. grid-search

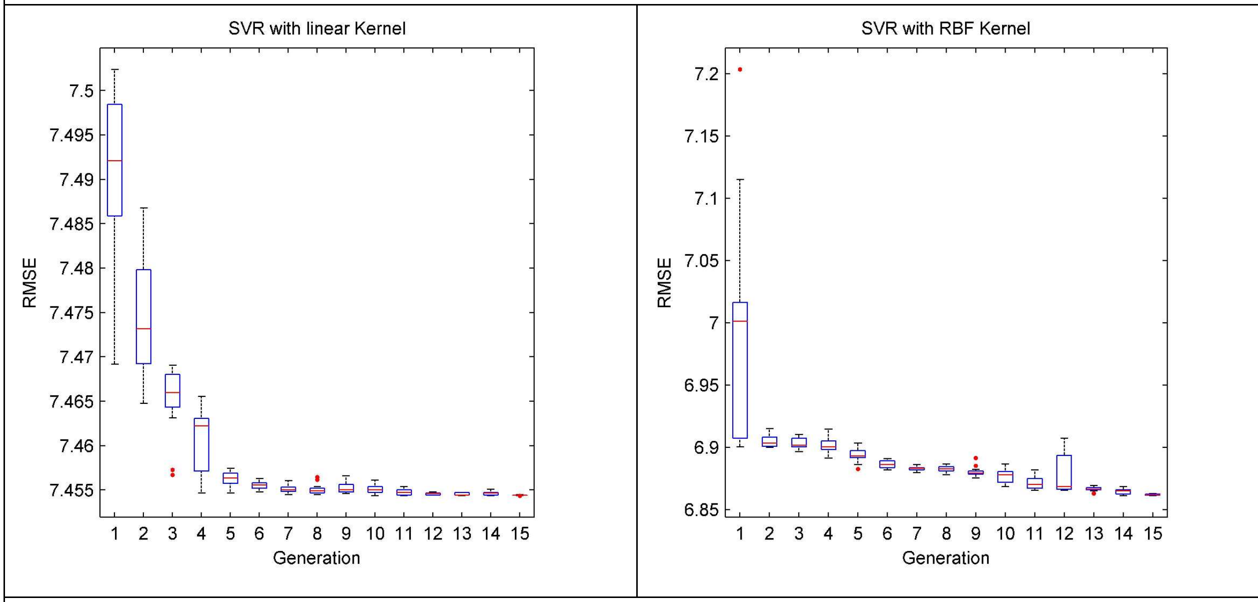
Setting 1: Forecasting models restricted to SDV					
	SVR kernel	Minimal RMSE	Parameters		
			C	ε	Kernel*
Grid-search	Linear	7.45	16,384.00	8.00	-
Grid-search	Polynomial	6.97	512.00	8.00	3-5
Grid-search	Radial	6.88	512.00	1.00	8.00
ES	Linear	7.45	112.69	10.03	
ES	Polynomial	6.97	111.14	7.67	5
ES	Radial	6.86	197.72	2.93	12.18
Setting 2: Forecasting models employing SDV and TSV					
Grid-search	Linear	6.25	256.00	4.00	
Grid-search	Polynomial	6.20	0.125	1.00	2
Grid-search	Radial	6.07	64.00	1.00	0.0156
ES	Linear	6.24	182.71	6.42	
ES	Polynomial	6.18	128.45	4.82	3
ES	Radial	6.06	110.96	3.42	0.01

*The column reports the value of the parameter γ in the case of the RBF kernel and *d* (degree) for a polynomial kernel (see Appendix I for details).

Verification of *H1b* is complicated by the fact that (search) efficiency of ES and grid-search is tied to the number of parameter settings that are evaluated before a (sub-)optimal configuration is identified. In the case of grid-search, this number is fixed and depends upon the a priori specified search space. In other words, the efficiency of grid-search is in direct control of the researcher, which clearly impedes an objective comparison with ES. There seems to be no way to resolve this dilemma. All we can do to shed some light upon efficiency issues, is grounding our specification of the search space on established recommendations from the literature and findings concerning parameter interaction (Cherkassky and Ma 2004; Kwok and Tsang 2003; Wang et al. 2003). The resulting configuration is shown in Appendix II. Depending upon SVR kernel, between 280 and 418 models are constructed and assessed by grid-search. The respective number of ES is 183, which results from setting ES strategy parameters as suggested by Beyer and Schwefel (2002) and Gijsberts et al. (2010).

By these definitions, ES always builds (much) less models and is trivially more efficient. However, contrary to grid-search, ES allows for controlling resource usage in a more direct fashion. Whereas the former is bound to explore the full predefined search-space, ES may be terminated once it becomes apparent that no further performance improvements are attainable. In particular, the search behavior of ES is explored in Figure 3.

Setting 1: Forecasting models restricted to SDV



Setting 2: Forecasting models employing SDV and TSV

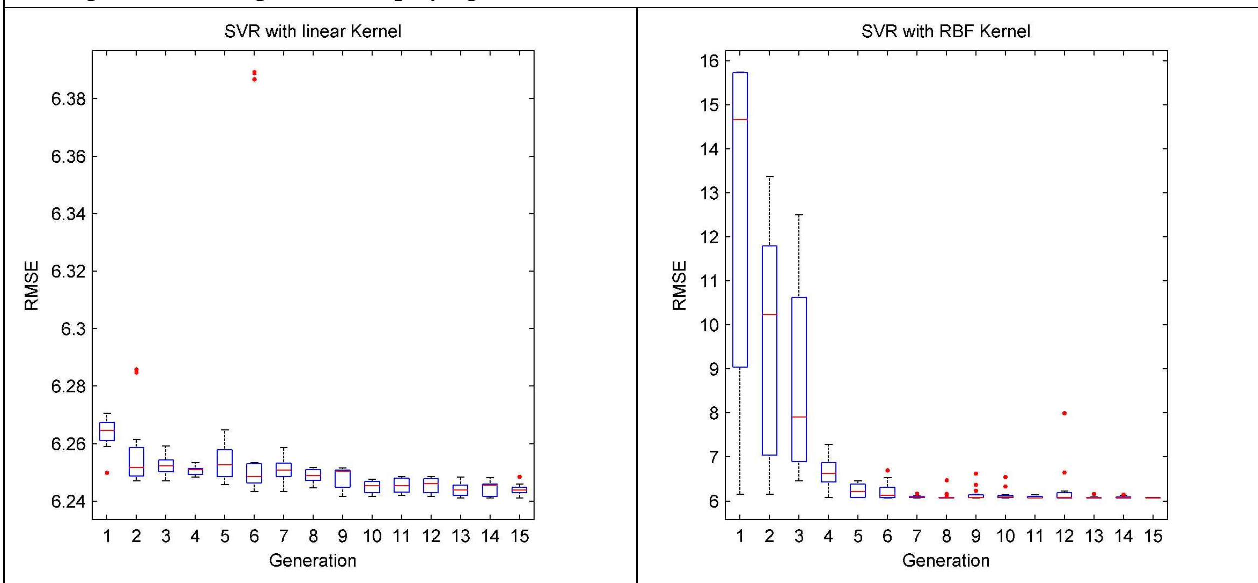


Figure 3. Development of forecasting accuracy across ES generations

Figure 3 depicts the distribution of RMSE among all forecasting models constructed in a given generation by means of box-plots for SVR with linear and RBF kernel. Results for the polynomial kernel function are not included since Table 2 suggests that RBF is a more appropriate (nonlinear) kernel. Figure 3 indicates that ES succeeds in continuously improving performance (i.e., reducing RMSE) throughout successive generations. This holds true for both kernel functions and is consistent across experimental settings. Furthermore, there is little if any need to further increase the number of generations, which has been set to 15 in this experiment. On the contrary, it seems well feasible to further reduce the number of generations, and thereby increase ES efficiency. This is because the ultimate task of ES is to identify a single "best" setting for SVR parameters and this setting (i.e., with minimal RMSE) is commonly found before generation 15. Moreover, an earlier termination of ES is supported by observing that the net increase in performance in later generations is rather limited (see Figure 3). Overall, this justifies accepting *H1b* because a) executing ES for 15 generations is already much cheaper than conducting a grid-search with specification as employed in this study, b) both procedures yield forecasting models with comparable accuracy, and c) there is reasonable support for the feasibility of further reducing resource consumption for ES.

Finally, one may ask whether a computer-intensive search for SVR parameter settings is necessary at all. Some insight on this issue may be gained from Figure 3. In the first generation, ES constructs forecasting models with default parameters. More specifically, some parameters are initialized randomly, whereas the heuristic of Cherkassky and Ma (2004) is used wherever applicable. Performance variations among these models are substantial, especially for nonlinear SVR models with RBF kernel. In addition, the standard deviation of RMSE observed during grid-search (Table 3) may be taken as an indicator for the relevance of tuning SVR parameters. Remembering that tuned models achieve RMSE between six and seven (Table 2), the standard deviations shown in Table 3 indicate that forecasting accuracy varies considerably with different parameter settings. This confirms that model selection is indeed important for the application considered here.

Table 3. Standard deviation of RMSE during grid-search

Setting 1: Forecasting models restricted to SDV		
	SVR kernel	RMSE standard deviation
Grid-search	Linear	3.82
Grid-search	Polynomial	4.73
Grid-search	Radial	4.29
Setting 2: Forecasting employing SDV and TSV		
Grid-search	Linear	4.40
Grid-search	Polynomial	5.44
Grid-search	Radial	4.37

With respect to *H1c*, both grid-search and ES require some user intervention to configure the search mechanism. In the former case, candidate values for all meta-parameters of the prediction method need to be specified, and the above results evidence that their choice is critical to the success of model selection. In the case of ES, most meta-parameters are tuned in a self-adaptive manner (see, e.g., Hansen and Ostermeier 2001). However, some exogenous strategy parameters have to be determined. One such setting concerns the particular manner in which a novel population is formed from candidate solutions. Two alternative strategies termed (μ, λ) and $(\mu + \lambda)$ are available (see, e.g., Beyer and Schwefel 2002). Both have been tested empirically but have been found to deliver identical results.[4] The setting of this option does therefore not require particular attention. In a similar fashion, the results of Figure 3 indicate that another ES strategy parameter, the maximal number of populations is not critical; unless set to a very small number, any value will allow ES to identify suitable meta-parameter settings. This leaves only two strategy parameters to be determined by users, the number of individuals per population and the parent-offspring

[4] The previous as well as all following results are based upon $(\mu + \lambda)$ selection.

ratio, which determines the number of variations of a single (parent) individual to produce offspring. These have been set to default values in this study (3 and 4, respectively). No dedicated tests have been conducted to examine the sensitivity of ES with respect to these two settings. However, the above results (as well as subsequent ones) do not indicate that a tuning of these two parameters is necessary. In particular, default settings suffice to achieve appealing results substantially better than those of possible alternatives. Therefore, it may be concluded that ES is robust towards settings of its external strategy parameters and requires little user intervention.

Having confirmed the appropriateness of the design choice to embed ES as parameter tuning agent into the proposed methodology, we may proceed with exploring its effectiveness. To that end, the accuracy of the model's forecasts is compared to those of the MLR benchmark model. As detailed above, concerns regarding the appropriateness of empirical risk minimization, the standard approach to build MLR models, for settings with large number of independent variables have been issued (Vapnik 1995). To address these and striving to construct a challenging benchmark, we conduct an additional optimization of MLR in the experimental setting with all variables. In particular, a stepwise regression is undertaken, which entails building a sequence of MLR models adding one variable at a time. This delivers a collection of 176 MLR models, whose appropriateness can be assessed in terms of R^2, the coefficient of determination. The model which performs best in this experiment is then used as benchmark. With respect to the two main ingredients of the proposed methodology, ES and SVR, the abbreviation ES/SVR is used in the following to refer to a respective forecasting model. Results of the comparison are shown in Figure 4, whereby the ES/SVR model employs a RBF kernel, which has given highest accuracy in previous experiments.

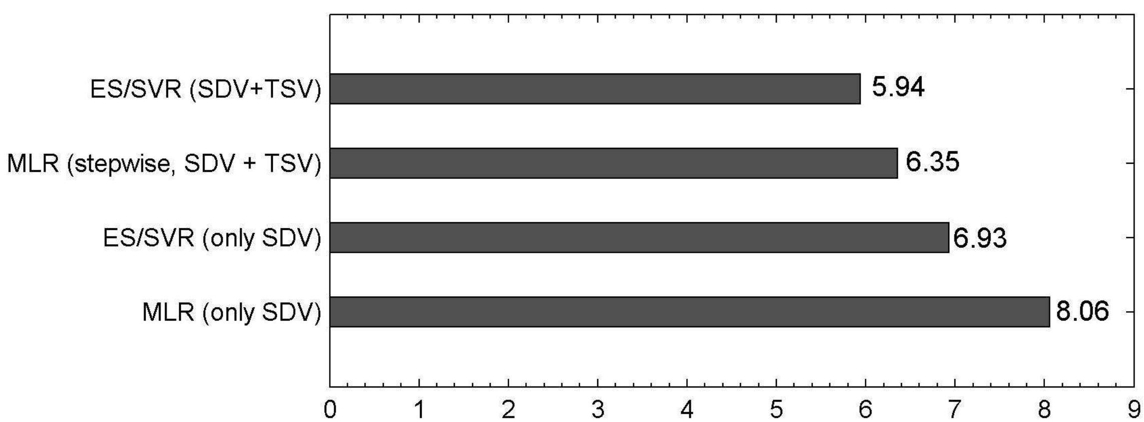


Figure 4. Comparison of the ES/SVR vs. MLR in terms of RMSE on test data

Figure 4 enables a number of important conclusions to be drawn. First, we note that considering TSV when building a forecasting model is beneficial. Models that have access to this type of information show lower RMSE, irrespective of the type of model. For ES/SVR, a similar trend has been observed during the model selection experiment. In the case of MLR, the utility of TSV can also be verified by a formal test since the model incorporating only SDV is a restricted version of the one with all variables included. For such nested models, the F-test can be used to evaluate the statistical significance of the additional variables (i.e., TSV), while controlling for SDV (Allen 1997). The test is based upon sample size, i.e., the test set containing 37,316 cases, the R^2 values of the full and restricted model (0.85 c.f. 0.77), and their respective degrees of freedom (175 c.f. 3). The (empirical) F-value of 116.07 suggests that TSV is indeed highly significant (p-value < 0.001). Overall, these results allow accepting *H2*.

Concerning the competitive performance of the ES/SVR model and MLR, Figure 4 indicates that ES/SVR's forecasts are more accurate, independent of the particular set of variables. Specifically, RMSE is reduced by 6.5% in the setting with all variables, whereas a reduction of 14.0% is achieved when relying entirely on SDV. It is arguable whether these figures suffice to accept *H3*. In general, it would be desirable to check this hypothesis in a formal manner by employing a statistical test. However, this study does not facilitate such an undertaking because it is restricted to a single dataset. On the contrary, hypothesis tests require a sample of observations (e.g., RMSE values of ES/SVR and MLR across several datasets). We discuss this limitation in detail below. However, for the data employed here, the consistency and magnitude with which ES/SVR outperforms the MLR benchmark model provides reasonable evidence for the former being more accurate.

Next, it is of interest to reason what factors enable the improvement in forecasting performance and why it is particularly exposed in the setting that employs only SDV. Whereas a fully comprehensive analysis of these issues is left to future research, the following discussion may offer some insight.

SDV captures information concerning cars' age and mileage. It is plausible that their relationship with the dependent variable, the vehicle's selling price in the used car market, is nonlinear since new cars loose much of their original value in the first year(s) of usage. Having higher representational power, the ES/SVR model can approximate such nonlinear development more accurately than MLR, which could explain the reduction of RMSE. Though, it has to be considered that the data used here refers to sales of an upper-class car model. In general, residual values for such models decrease not as rapidly as in the case of middle- or low-class cars. Consequently, the relationship between age/mileage variables and the dependent should still be "moderately" linear. This is confirmed by the MLR model achieving a high R^2 of 0.77. One may speculate that the proposed forecasting methodology outperforms MLR with even larger margin when using data from less prestigious car models.

If the full set of variables is considered, MLR and ES/SVR can capitalize from a large source of additional information to predict residual values more accurately. The fact that ES/SVR outperforms MLR with smaller margin could be explained by the additional variables reducing the relative importance of SDV, which, because of being, in tendency, nonlinearly related with the dependent, give ES/SVR an advantage. However, that would imply that the relationship between variables from the TSV category and residual values is moderately linear. Otherwise, ES/SVR would have the same advantage and could be expected to reduce RMSE over the MLR model by a margin, similar to the SDV-only setting. Technical consideration might offer some support for this assertion. Since variables in the TSV group are all encoded as binary "dummy" variables, a linear forecasting model should be able to extract most of the information they embody.

If it is true that performance differences between the ES/SVR model and MLR can be explained by nonlinear relationships in the data, ES/SVR's advantage should vanish if the component to capture nonlinearity is removed. In particular, exchanging the RBF kernel function with a linear kernel can be expected to diminish the ES/SVR model's performance, which is the essence of *H4*. Indeed, a ES/SVR model with linear kernel and SDV achieves RMSE of 8.27 (c.f. 6.93 with RBF kernel), whereas incorporation of TSV improves this figure to 6.39 (c.f. 5.94 with RBF kernel). This is roughly the level of performance attained by the MLR model (see Figure 4),[5] which supports the view that the appealing performance of the proposed methodology is to a large extent due to its ability to account for nonlinearity in the data and indicates that this capability is crucial for residual value estimation.

Discussion

The empirical analysis has shown that the ES/SVR model outperforms the MLR benchmark under different experimental conditions in terms of predictive accuracy. In particular, evidence in favor of all hypotheses has been found. This confirms that the proposed forecasting methodology provides operationally accurate estimates of vehicles' residual values and succeeds in supporting actual prediction decisions in car leasing.

In principle, this result is valid only for the dataset employed in the study. For example, external validity may suffer from the data being restricted to one brand and one particular type of car. This problem is insurmountable for the time being and more (empirical) experience with other datasets is highly desirable. On the other hand, there may be no need to judge generality too pessimistically. As argued above, MLR may be considered a challenging benchmark for this dataset from an upper-class car model. Thus, the forecasting accuracy observed in this study is encouraging.

However, to truly establish that the designed artifact "effectively addresses the problem it was meant to solve" (Hevner et al. 2004), it is important to examine the relationship between increases in forecasting accuracy and objective improvements of decision quality. In other risk management contexts, one may assume that a direct link

[5] We did not conduct any further analysis to examine the differences between MLR and a linear ES/SVR model. Noting that both models, besides being linear, still differ considerably (e.g., with respect to employed loss function and underlying estimation principles), it seems natural that they do not perform exactly akin.

between accuracy and profitability does exist. In the credit business, for example, regulatory frameworks such as the *Basel II* capital accord emphasize the importance of forecasting financial risks and reward accuracy with less conservative capital requirements (see, e.g., Crook et al. 2007). In (car) leasing, accurate estimates of residual values reduce the risk of losing money on resale and guide sales agents in their decision making processes so as to focus on long term profits. Therefore, it is plausible that increases in the accuracy of residual value forecasts contribute to the individual performance of sales agents and the process of negotiating contractual terms as a whole.

Established theories of information system effectiveness offer some additional support for this assertion. In particular, the question to what extent and in which circumstances DSS improve performance in decision outcomes has attracted much research (see, e.g., Benbasat and Nault 1990; Sharda et al. 1988; Todd and Benbasat 1999). With respect to the influence of technology on users' performance, the concept of task-technology fit (TTF) has been identified as an important moderator, especially if use of the technology is not voluntarily (Goodhue 1995; Goodhue and Thompson 1995). The artifact designed in this work lacks several features of a fully-functional forecasting support system (see, e.g., Fildes et al. 2006). On the other hand, many of these may be dispensable for a directive DSS whose only task is to recommend residual values without human intervention (Sutherland 2008). Therefore, the artifact may be accepted as core component of a forecasting support system. Since a normative DSS policy requires users to strictly follow the system's recommendations, use of the system is indeed mandatory. Consequently, TTF may be considered an important determinant of improvements in decision outcomes. Although there has been no research to establish the constituents of TTF for a forecasting support system, it seems intuitive that the accuracy of its predictions is a key driver of TTF. If accepting this proposition, then previous research (see, e.g., Dennis et al. 2001; Lilien et al. 2004) would generally suggest that higher forecasting accuracy (higher TTF) does improve actual decision quality. However, future research is beneficial to explore in more detail the effects of forecasting methodology and predictive accuracy on actual performance in leasing processes. This could, for example, involve observing decision makers in doing their business and interviewing them on their practices to estimate residual values, or examining this issue by means of questionnaires.

The merit of the designed artifact could also be challenged from a technological angle. Exchanging either the prediction model, the tuning agent, or both, would yield a different forecasting methodology. Does this question the significance of the proposed approach? We reiterate that previous research in forecasting residual values is scarce. Lian et al. (2003) strive to predict auction-prices by means of a time-series approach, whereas Lucko et al. (2006) and Prado (2009) use SDV together with some macroeconomic variables in an ordinary regression framework. These procedures differ in terms of employed information and methodology notably from the one proposed here. This justifies our decision to develop a novel methodology on the basis of identified business requirements as well as established and carefully selected methods. In this sense, the ES/SVR model may be seen as an initial yet crucial step towards developing accurate estimation models. Given the empirical results observed, it seems justified to consider the artifact a "satisficing solution" (Simon 1996). However, we explicitly encourage future research to refine and extend our methodology. For example, employing a collection of diverse prediction models instead of a single one and averaging their forecasts has been found to work well in other settings (see, e.g., Ngo-Yel and Dutt 2009; Perols et al. 2009) and could also be useful for residual value estimation.

Finally, one may question whether black-box forecasting models are appropriate at all; specifically, whether decision makers would trust their predictions. Issues of model transparency and comprehensibility have been discussed extensively in the literature and are considered desirable if not mandatory in many applications (see, e.g., Martens and Baesens 2010). For the leasing business, we have argued the suitability of a normative DSS for residual value estimation. Such approach does not require decision makers gaining insight into the mechanisms that eventually lead to system forecasts. As outlined above, given that predictions are sufficiently accurate, strictly following system recommendation may actually be key to increasing performance of the overall business process (Lilien et al. 2004). Moreover, there is often a trade-off between forecasting models' expressive power and transparency (Lessmann and Voß 2009). The empirical results observed here suggest that powerful, nonlinear models are needed for residual value estimation, which further substantiates the view that black-box forecasting models are acceptable for the focal application. If their use is considered problematic in a particular case, they may still be employed together with rule extraction procedures, which can (re-)introduce model comprehensibility ex post (see, e.g., Baesens et al. 2001; Setiono et al. 2006).

In summary, the proposed forecasting methodology as a whole as well as the selection of individual components and their respective features are neither indisputable nor immutable. Clearly, there is need for future research to further explore features as well as constraints of the developed approach and identify potential for further improvements from technical and especially organizational perspectives. The designed artifact will serve as reference point for such endeavors, either as highly challenging benchmark for novel residual value prediction models to be developed, or as prototype to study, e.g., operational feasibility and user acceptance in real-world decision contexts.

Conclusions

We set out to support decision making in the car leasing industry by generating accurate estimates of leasing subjects' residual values. To effectively address the specific requirements encountered in this application, a tailor-made forecasting methodology has been developed. Incorporating a state-of-the-art prediction method from the field of statistical learning allows considering a large number of variables in the estimation, and this has been confirmed to increase forecasting accuracy. To free users from the laborious and complex task of adapting the prediction method to a particular forecasting task and simplify the approach's adoption in real-world decision processes, an evolutionary tuning algorithm has been employed to calibrate the prediction method with little human intervention. The effectiveness of the overall methodology to generate accurate estimates of cars' residual values in general as well as the appropriateness of individual model components has been confirmed by means of empirical experimentation.

The results observed during the evaluation of the proposed forecasting tool are encouraging and establish its utility for the particular application considered in this research. Clearly, empirical results do not warrant any conclusions regarding the methodology's suitability for residual value estimation tasks in other leasing contexts. However, an important finding of our study may be seen in the fact that it establishes the value of transaction specific information for forecasting. The availability of this type of information at the lessor's side is a general characteristic of any leasing business. The more complex the leasing subject, the more data will be available to describe its particular features, which, in turn, may affect its residual value. Therefore, an implication of this research for the whole leasing industry is that the predictive utility of specific knowledge about equipments to be given for lease should be examined.

Moreover, if the utility of transaction specific information in other applications can be confirmed, a broader implication is that forecasting tasks associated with estimating residual values need to be performed within the company. Only an internal forecasting solution can take very specific characteristics of a leasing subject into account and capitalize on the predictive information contained therein. In this respect, our findings suggest that leasing agencies should not exclusively rely upon reference lists of residual values when estimating resale prices of equipment. A preferable solution is to employ such reference prices alongside other indicators and transaction specific characteristics in particular within an internal forecasting support system.

In summary, decision makers are well advised to review business processes associated with negotiating contractual terms and leasing rates in particular to examine the degree to which residual value estimates make full use of available information. This may be considered a necessary condition for achieving maximal accuracy in this business critical forecasting task. The selection of an appropriate methodology for generating predictions can be seen as another precondition. Unlike other financial industries, the leasing sector faces few governmental regulations concerning the organization of an internal risk management. In particular, no restrictions concerning the transparency of decision support tools are imposed. Consequently, a wide range of estimation methods including sophisticated procedures can in principle be applied to aid decision making. Potential concerns of users and reservation to work with complex black-box forecasting tools are a threat to the success of respective systems, but should not be insurmountable within a normative DSS strategy. Moreover, our results have shown that the ability to account for nonlinear patterns in data may be crucial in leasing contexts (i.e., to capture the instationary depreciation developments).

The particular methodology developed in this work evidences that the technology to fulfill key application requirements is readily available. State-of-the-art estimation principles facilitate a large number of equipment characteristics (i.e., independent variables) to be processed. Powerful modeling procedures such as SVR are demonstrably successful in distilling predictive information from such variables including complex, nonlinear interactions with residual values. Evolutionary tuning agents enable the forecasting task to be performed in a widely automated manner and help to achieve operational feasibility.

Appendix I: SVR Kernel Functions

Building a SVR forecasting model requires an optimization problem to be solved (see (2) above). It turns out that the input data vectors, $\boldsymbol{x}_i$, enter the mathematical program only in form of scalar products (Smola and Schölkopf 2004). As a consequence, if the data is to be transformed in some nonlinear fashion, only the scalar product of the transformed input vectors is needed. A kernel, k, is a function that facilitates computing this scalar product between two vectors implicitly without actually computing the transformation. The particular kernel functions employed in this work are illustrated in Table 4, whereby $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ are two different data points in a sample and scalars d and γ are meta-parameters for the polynomial and RBF kernel function, respectively.

Table 4. SVR kernel functions

Linear	$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \boldsymbol{x}_i \cdot \boldsymbol{x}_j$
Polynomial	$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = (\boldsymbol{x}_i \cdot \boldsymbol{x}_j + 1)^d$
RBF	$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\gamma \left\lVert \boldsymbol{x}_i - \boldsymbol{x}_j \right\rVert^2\right)$

Appendix II: Grid-Search Model Selection Configuration

Table 5 reports the candidate values for each SVR meta-parameter to be considered during grid-search. The values are based upon findings associated with parameter interaction (Cherkassky and Ma 2004; Kwok and Tsang 2003; Wang et al. 2003), the recommendations of Hsu et al. (2003), and considerations related to computational feasibility. The overall number of SVR models to be built and assessed during model selection follows from empirically testing all possible combinations of the given parameter values.

Table 5. Configuration settings for grid-search

		No. of SVR candidate models	SVR meta-parameters		
			C	ε	Kernel function*
Grid-search	Linear	418	$2^{-6}, 2^{-5}, \ldots, 2^{15}$	$2^{-9}, 2^{-8},\ldots,2^{9}$	
Grid-search	Polynomial	280	$2^{-6}, 2^{-3}, \ldots, 2^{15}$	$2^{-9}, 2^{-6},\ldots,2^{9}$	2, 3, …, 6
Grid-search	RBF	392	$2^{-6}, 2^{-3}, \ldots, 2^{15}$	$2^{-9}, 2^{-6},\ldots,2^{9}$	$2^{-15}, 2^{-12}, \ldots, 2^{3}$

*The column reports the value of the parameter γ in the case of the RBF kernel and d (degree) for a polynomial kernel.

References

Allen, M.P. *Understanding Regression Analysis*, Plenum Press, New York, 1997.

Arnott, D. "Cognitive biases and decision support systems development: A design science approach," *Information Systems Journal* (16:1), 2006, pp 55-78.

Baesens, B., Setiono, R., Mues, C., Viaene, S., and Vanthienen, J. "Building Credit-Risk Evaluation Expert Systems Using Neural Network Rule Extraction and Decision Tables," in: *Proc. of the Intern. Conf. on Information Systems,* V.C. Storey, S. Sarkar and J.I. DeGross (eds.), New Orleans, LA, USA, AIS, 2001, pp. 159-168.

Barkholz, D., and Sherefkin, R. "Low rates, more leasing to boost volume," *Automotive News* (84:6388), 2009, pp 24-24.

Benbasat, I., and Nault, B.R. "An evaluation of empirical research in managerial support systems," *Decision Support Systems* (6:3), 1990, pp 203-226.

Beyer, H.-G., and Schwefel, H.-P. "Evolution strategies – a comprehensive introduction," *Natural Computing* (1:1), 2002, pp 3-52.

Chen, K.-Y., and Wang, C.-H. "Support vector regression with genetic algorithms in forecasting tourism demand," *Tourism Management* (28:1), 2007, pp 215-226.

Cherkassky, V., and Ma, Y. "Practical selection of SVM parameters and noise estimation for SVM regression," *Neural Networks* (17:1), 2004, pp 113-126.

Crone, S.F., Lessmann, S., and Stahlbock, R. "The impact of preprocessing on data mining: An evaluation of classifier sensitivity in direct marketing," *European Journal of Operational Research* (173:3), 2006, pp 781-800.

Crook, J.N., Edelman, D.B., and Thomas, L.C. "Recent developments in consumer credit risk assessment," *European Journal of Operational Research* (183:3), 2007, pp 1447-1465.

Davis, F.D. "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly* (13:3), 1989, pp 319-340.

Dennis, A.R., Wixom, B.H., and Vandenberg, R.J. "Understanding fit and appropriation effects in group support systems via meta-analysis," *MIS Quarterly* (25:2), 2001, pp 167-193.

Fildes, R., Goodwin, P., and Lawrence, M. "The design features of forecasting support systems and their effectiveness," *Decision Support Systems* (42:1), 2006, pp 351-361.

Friedrichs, F., and Igel, C. "Evolutionary tuning of multiple SVM parameters," *Neurocomputing* (64), 2005, pp 107-117.

Goodhue, D.L. "Understanding user evaluations of information systems," *Management Science* (41:12), 1995, pp 1827-1844.

Goodhue, D.L., and Thompson, R.L. "Task-technology fit and individual performance," *MIS Quarterly* (19:2), 1995, pp 213-236.

Gijsberts, A., Metta, G., and Rothkrantz, L. "Evolutionary Optimization of Least-Squares Support Vector Machines," in: *Data Mining,* R. Stahlbock, S.F. Crone and S. Lessmann (eds.), Springer, Berlin, 2010, pp. 277-297.

Hansen, N., and Ostermeier, A. "Completely derandomized self-adaptation in evolution strategies," *Evolutionary Computation* (9:2), 2001, pp 159-195.

Hastie, T., Tibshirani, R., and Friedman, J.H. *The Elements of Statistical Learning*, (2 ed.), Springer, New York, 2009.

Hevner, A.R., March, S.T., Park, J., and Ram, S. "Design science in information systems research," *MIS Quarterly* (28:1), 2004, pp 75-105.

Hogarth, R.M., and Makridakis, S. "Forecasting and planning: An evaluation," *Management Science* (27:2), 1981, pp 115-138.

Hsu, C.-W., Chang, C.-C., and Lin, C.-J. "A Practical Guide to Support Vector Classification," Working Paper, *Department of Computer Science and Information Engineering, National Taiwan University*, Taiwan, 2003.

Joas, A. "Systemprofit Automobilvertrieb 2015 – Die Agenda für profitables Wachstum der Markenkanäle," Industry report, *Mercer Management Consulting*, München (in German), 2005.

Kwok, J.T., and Tsang, I.W. "Linear dependency between epsilon and the input noise in epsilon-support vector regression," *IEEE Transactions on Neural Networks* (14:3), 2003, pp 544-553.

Leaseurope. "Leasing Facts & Figures 2008," Accessible at http://www.leaseurope.org/index.php?page=key-facts-figures. Date of last access: 24th of August 2010.

Lessmann, S., and Voß, S. "A reference model for customer-centric data mining with support vector machines," *European Journal of Operational Research* (199:2), 2009, pp 520-530.

Lian, C., Zhao, D., and Cheng, J. "A Fuzzy Logic Based Evolutionary Neural Network for Automotive Residual Value Forecast," in: *Proc. of the Intern. Conf. on Information Technology: Research and Education,* N. Ansari, F. Deek, C.-Y. Lin and H. Yu (eds.), Newark, NJ, USA, IEEE Computer Society, 2003, pp. 545-548.

Lilien, G.L., Rangaswamy, A., Van Bruggen, G.H., and Starke, K. "DSS effectiveness in marketing resource allocation decisions: Reality vs. perception," *Information Systems Research* (15:3), 2004, pp 216-235.

Lucko, G., Anderson-Cook, C.M., and Vorster, M.C. "Statistical considerations for predicting residual value of heavy equipment," *Journal of Construction Engineering and Management* (132:7), 2006, pp 723-732.

MarketWatch "Indian operational leasing market presents enticing opportunity," *Automotive* (9:1), 2009, pp 6-7.

Martens, D., and Baesens, B. "Building Acceptable Classification Models," in: *Data Mining,* R. Stahlbock, S.F. Crone and S. Lessmann (eds.), Springer, Berlin, 2010, pp. 53-74.

Momma, M., and Bennett, K.P. "A Pattern Search Method for Model Selection of Support Vector Regression," in: *Proc. of the 2nd SIAM Intern. Conf. on Data Mining,* R. Grossman, J. Han, V. Kumar, H. Mannila and R. Motwani (eds.), Arlington, VA, USA, SIAM, 2002.

Ngo-Yel, T., and Dutt, A. "A Study on Efficacy of Ensemble Methods for Classification Learning," in: *Proc. of the Intern. Conf. on Information Systems*, Phoenix, AZ, USA, AIS, 2009.

Perols, J., Chari, K., and Agrawal, M. "Information market-based decision fusion," *Management Science* (55:5), 2009, pp 827-842.

Prado, S. "The European Used-Car Market at a Glance: Hedonic Resale Price Valuation in Automotive Leasing Industry," Economix Working Paper 2009-22*, Université de Paris Ouest Nanterre La Défense*, Paris, 2009.

Sawyers, A. "Rising residuals encourage leasing," *Automotive News* (84:6377), 2009, pp 8-8.

Schmit, M. "Credit risk in the leasing industry," *Journal of Banking & Finance* (28:4), 2004, pp 811-833.

Setiono, R., Baesens, B., and Mues, C. "Risk Management and Regulatory Compliance: A Data Mining Framework Based on Neural Network Rule Extraction," in: *Proc. of the Intern. Conf. on Information Systems*, Milwaukee, WI, USA, AIS, 2006.

Sharda, R., Barr, S.H., and McDonnell, J.C. "Decision support system effectiveness: A review and an empirical test," *Management Science* (34:2), 1988, pp 139-159.

Shawe-Taylor, J., and Cristianini, N. *Kernel Methods for Pattern Analysis*, Cambridge University Press, Cambridge, 2004.

Silver, M.S. "Decision support systems: Directed and nondirected change," *Information Systems Research* (1:1), 1990, pp 47-70.

Silver, M.S. "Decisional guidance for computer-based support," *MIS Quarterly* (15:1), 1991, pp 105-122.

Simon, H.A. *The Science of the Artificial*, (3rd ed.), MIT Press, Cambridge, 1996.

Smola, A.J., and Schölkopf, B. "A tutorial on support vector regression," *Statistics and Computing* (14:3), 2004, pp 199-222.

Sutherland, J.W. "Directive decision devices: Reversing the locus of authority in human-computer associations," *Technological Forecasting and Social Change* (75:7), 2008, pp 1068-1089.

Tay, F.E.H., and Cao, L. "Application of support vector machines in financial time series forecasting," *Omega* (29:4), 2001, pp 309-317.

Todd, P., and Benbasat, I. "Evaluating the impact of DSS, cognitive effort, and incentives on strategy selection," *Information Systems Research* (10:4), 1999, pp 356-374.

Tversky, A., and Kahneman, D. "Judgment under uncertainty: Heuristics and biases," *Science* (185:4157), 1974, pp 1124-1131.

Van Gestel, T., Suykens, J.A.K., Baesens, B., Viaene, S., Vanthienen, J., Dedene, G., De Moor, B., and Vandewalle, J. "Benchmarking least squares support vector machine classifiers," *Machine Learning* (54:1), 2004, pp 5-32.

Vapnik, V., and Kotz, S. *Estimation of Dependences Based on Empirical Data*, (2 ed.), Springer, New York, 2006.

Vapnik, V.N. *The Nature of Statistical Learning Theory*, Springer, New York, 1995.

Wang, W., Xu, Z., Lu, W., and Zhang, X. "Determination of the spread parameter in the Gaussian kernel for classification and regression," *Neurocomputing* (55:3-4), 2003, pp 643-663.

Winklhofer, H., Diamantopoulos, A., and Witt, S.F. "Forecasting practice: A review of the empirical literature and an agenda for future research," *International Journal of Forecasting* (12:2), 1996, pp 193-221.