Value Based Pricing meets Data Science: A Concept for Automated Spare Part Valuation

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Abstract. Turning data into value is an exciting challenge for Data Science in times of an exponential growing amount of data. Maintenance, Repair and Overhaul companies are facing pricing related decision problems on a daily basis. The industry sits on vast amount of data. Due to lacks of transparency in the surplus part market and missing concepts to efficiently use internal data, existing information is not used exhaustively to improve data-based part utilization decisions. An early-stage concept for automated spare part valuation which classifies pricing data before applying appropriate valuation methods is presented and hereby combines methods from multiple disciplines. Information from heterogeneous sources is aggregated, transformed and then supports machine learning methods to automatically determine a Fair Market Value for surplus spare parts. Handling incomplete historical data sets as well as validating the calculated Fair Market Value are some of the challenges which become visible.

Keywords: Automated Value Determination, ETL, Data Classification, Spare Parts, Fair Market Value

1 Introduction

'We are drowning in information but starved for knowledge.' stated author John Naisbitt in his book Megatrends in the year 1984 [1]. Until today, decision makers still complain in a very similar way about 'drowning in data while thirsting for information' [2]. As this is a general problem, it's especially true for market participants with a vast number of different products, for example the aircraft spare parts industry. The UK's Royal Airforce alone is managing around 685.000 line items [3], the largest commercial airplane Airbus A380 consists of around 2.5 million individual parts[1]. The aircraft parts industry is an especially interesting example since aircraft maintenance has to face high safety regulations but also operate in a very short timeframe to avoid very expensive aircraft downtime. Maintenance Repair and Overhaul (MRO) companies, especially in the aircraft industry, are constantly confronted with managing the logistics of spare parts. An inexpensive repair and maintenance in a timely manner requires an efficiently

[1] Airbus Press Office 2017: Facts & Figures, June 2017

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organized material supply. It cannot always be resorted to new parts, either for cost reasons or because certain parts are not available on the market. Additionally, constant pulling and replacing of parts leads to a high number of used parts in stock which not always have a direct use, in other words they are surplus. The market for aircraft surplus spare parts is characterized by a great number of different products but just a few market participants. Transactions are done via e-mail or telephone. Although trading platforms are listing offers for some parts, prices are rarely published. The compartmentalized structure of traders and MRO companies in the aircraft industry may be one reason why there is still no end-to-end auction based market place for surplus parts. Valuating spare parts on the market or in stock in this environment is done today in a time consuming and error-prone manual manner by industry experts.

There are several ways to determine a price as foundation for the part utilization decision, including auction based market places and prediction models based on historical data. As soon as context based value information is needed for internal decision making, external determined prices fail to include company-specific information and don't provide a sufficient basis for decision-making. Predicting a value based on historical data however may work well for market players with a huge amount of structured and high quality historical data. In this paper, we propose a concept for combining methods from multiple disciplines with the goal of automated part valuation. The aircraft industry is used as an example. This work addresses problems of the MRO industry in general. Existing pricing approaches which had been already discussed in [4] are shortly described in Section 2.1. In cooperation with a large aircraft MRO provider, we gained insights in existing spare part utilization processes which are described in Section 2.2. In Section 3 Pareto Principle and Product Lifecycle are used to classify pricing data which is a basis for an extension of the developed system architecture for automated spare part valuation (ASPV) of [4]. Section 3 closes with approaches for handling the validation of the resulting values. Section 4 summarizes this work and gives an outlook for what will be discussed during following research.

2 State of the Art of Pricing and Surplus Part Supply Chain

This section gives an overview about existing pricing approaches and the surplus spare part supply chain to understand the need for a part's value as basis for the utilization process.

2.1 Pricing

It has been shown that price has the greatest impact on a company's earnings before interest and taxes [5]. Existing literature provides approaches for pricing. Before proceeding to automatically finding a surplus part's value, a short overview about the underlying terminologies is given. According to [6], '*Price* in business market is what a customer firm pays a supplier for its product offering'. Furthermore, [7] state, '*Value* in business markets is the worth in monetary terms of the technical, economical service and social benefits a customer company receives in exchange for the price it pays for a market offering'. Pricing approaches can be categorized into three different groups [8]:

Cost Based Pricing uses data from cost accounting and for example considers original purchase price and internal costs (e.g. repairing) to determine a selling price. It doesn't take the competition or market into account and is therefore considered as the weakest approach.

Competition Based Pricing observes price levels of the competition and uses market prices for orientation in price setting but dismisses company-internal information such as inventory or repair costs of defective spare parts.

Value Based Pricing uses a predefined value as the basis for determining the price. As only value based pricing takes company internal information into account, this approach is now described in more detail to discuss its potential to serve as a foundation for decision making and price setting.

This work focuses on a business to business secondary market for surplus parts which mainly differentiates between the following more granular value terms. *Base Value* is considered as the economic value and assumes balanced supply and demand [9] as well as completely informed market participants and thus is considered as a hypothetic value [10]. *(Current) Market Value* is defined as determined value after manual analysis [10] or the 'most likely trading price' and is used synonymously with Fair Market Value [9]. [11] state that the *Fair Market Value (FMV)* is '(..) the price at which the property would change hands between a willing buyer and a willing seller when the former is not under any compulsion to buy and the latter is not under any compulsion to sell, both parties having reasonable knowledge of the relevant facts'.

Still, many companies are not able to benefit from Value Based Pricing. One obstacle is that the value has to be determined before it can be used as an argument for pricing [8]. Value Based Pricing and value estimation methods are often related to product introductions in primary markets. State-of-the-art literature about Value Based Pricing takes the customer point of view for value determination. Common methods are surveys or conjoint analysis [12]. This is applicable to this scenario in a limited way only. Conducting surveys for this large quantity of different products seems to be a disproportionate effort. Also, as soon as context based values are needed, external determined prices fail to include company-specific information and don't provide a sufficient foundation for a company's decision-making. Therefore, an approach is needed which includes company internal information and is feasible to a large number of parts.

2.2 Understanding the Spare Part Supply Chain

As pointed out in [13], products at the end of the traditional supply chain may be surplus but still have value. As shown in Figure 1, surplus parts are stored, depending on their value.

Expert interviews with a large MRO provider showed that parts with value but no internal demand will be put on a trade stock and sold to the surplus market via direct sale or auction. From the same surplus market, parts could be bought (B). If there is internal demand they are stored in a pool stock for (future) replacement (R). The pool stock could also be filled by parts pulled out of the operations, such as an aircraft or production facility (P). If they have no value at all, they will be scrapped. Because of the fact that parts circulate in a loop but not return to the manufacturer, this process is called Alternative Closed Loop Supply Chain Process.

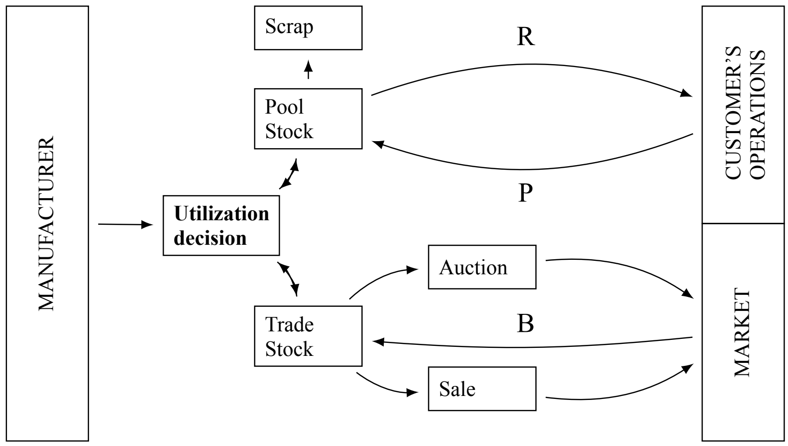

Figure 1. Alternative Closed Loop Supply Chain Process from a MRO point of view

Studies have shown that simple disposal of parts which have failed or appeared to have failed is a major cost contributor within the whole supply chain [13]. In this situation, reverse logistics are important from an economic[2] and ecological[3] point of view. [13] also points out, that extra revenues are realized if there is an ability to liquidate parts with value in secondary markets. MRO companies therefore need to estimate a value as characteristic parameter and foundation for price derivation in order to support internal decision-making processes.

3 Framework for Automated Spare Part Valuation

From characteristics of the surplus market, an overview of relevant pricing literature and value definitions, the following research goals result:

- Design a framework in order to automatically determine a FMV for surplus spare parts and present it to the end user in a meaningful way (*ASPV framework* in following).
- Find a way to prepare data as foundation for automated valuation of surplus spare parts.
- Validate the calculated FMV.

The resulting ASPV framework should be able to determine a part's FMV under consideration of the company's specific situation. The calculated value contains

[2] Valuable parts will not be disposed but could be used or sold.
[3] Probably fewer parts will be disposed if the value is recognizable.

information as displayed in Table 1. The variables are categorized by time (historic and current) and by point of view (company-internal and -external).

Table 1. Variables for FMV calculation

Time	*Internal*	*External*
Historic	Purchase price, offer price, selling price	Original launch price
Current	--	Market price

We suggest a combination of a set of data analytics methods to transparently determine and present a FMV. Based on the results from [14], proposing prediction methods for determining prices for the used car market, an application of prediction methods seems to be promising in order to evaluate secondary market items. There is a wide variety of machine learning methods, from simple Linear Regression Models to Neural Networks which may perform differently in this specific scenario[4].

The ASPV framework differs from state-of-the-art Value Based Pricing methods as shown in Table 2. State-of-the-art Value Based Pricing and value estimation methods are related to product introductions in primary consumer markets. The proposed ASPV framework focuses on business to business secondary markets in the MRO industry. State-of-the-art Value-Based Pricing focuses on an individual consideration of a small number of products which is an obvious scope for pricing related customer surveys and conjoint analysis. On the contrary, this work aims to automated valuation of thousands of different products from multiple variables (see Table 1), present the valuation in a transparent way and in a second phase increase objectivity in contrast to the status quo results from manual value determination.

Table 2. Differentiation from state-of-the-art Value Based Pricing methods

Dimension	*State-of-the-art Value Based Pricing*	*ASPV framework*
Target	Primary markets	Secondary market
Audience	B2C	B2B
Scope	Small number of products	Thousands of products
Automation	Individual consideration	Automated valuation

3.1 Classification of Pricing Information

As Value Based Pricing is effort intensive, it should not be used on all products. To address the effort issue, we propose a rule-based segmentation of the products based on their need for an approximation on the one side or for exact value determination on the other side. To reduce complexity in the classification stage we prefer this rule-based approach over machine learning.

[4] An extensive overview can be found in 15. Hastie, T., R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* Springer Series in Statistics, 2009.

[16] take a closer look at the Pareto principle which led to a classification of products into A, B and C groups. The 'A' group (the 'vital few'), consisting of approximately 20% of the attributes (surplus spare parts in this case), accounts for 80% of the phenomenon (value in this case); the 'B' group, i.e. the next 30% of the items, accounts for 10% of the phenomenon, and the 'C' group (the 'trivial many'), which contains 50% of the items, accounts for also 10% of the phenomenon. Given that, [17][5] recommend the following procedure:

- **Classification –** Find attributes for sorting products into A, B and C groups,
- **Differentiation –** set differentiation policy for each class,
- **Allocation –** allocate (pricing) effort according to classification and differentiation.

Based on the Pareto principle and illustrated in Table 3, category A parts which make about 20% of the parts but are responsible for 80% of the inventory's value would be valuated via the following ASPV framework. Category B and C parts which only contribute a combined 20% of the value but 80% of quantity could be just valued via market data. If competition based pricing is not feasible because of a lack of data, there is no alternative option than using any internal price information as basis for the FMV.

Table 3. Classification prior to choosing valuation method

Category	*Amount*	*Value*	*Method*
A	20%	80%	Valuation via ASPV framework
B	30%	10%	Competition Based Pricing
C	50%	10%	Competition Based Pricing

Another perspective on product importance is by classification into stages of a product lifecycle. [18] gives an overview of a product's lifecycle progress in four phases, beginning with an introduction phase where the amount of sold products grows slowly. The following growth phase is characterized by even more rising sales. Due to market saturation or introduction of improved products, sales reach a plateau and later on decline until obsolescence. [19] extend this concept and state that the number of new products and the demand for remanufactured products or spare parts is positively correlated but also delayed in time. As spare parts are removed some time later from operations, the number of parts on the surplus market peaks after the maturity phase of new parts (see Figure 2).

To refine the allocation of parts, the consideration of the part's product lifecycle is helpful. Products wander through a product lifecycle which is characterized by a dependence from product value to demand and distribution on the market. The value of the parts is very dependent on the product lifecycle and therefore the demand of the underlying operations. Nevertheless, the product lifecycle of the new part can be an estimate of the demand for the spare part and therefore an indicator for the part's importance for valuation.

[5] Quoted from 16. Grosfeld-Nir, A., B. Ronen, and N. Kozlovsky, *The Pareto managerial principle: when does it apply?* International Journal of Production Research, 2007. **45**(10): p. 2317-2325..

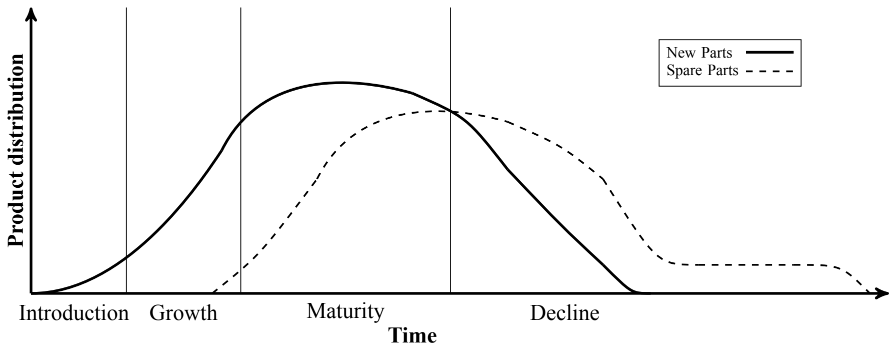

Figure 2. Product lifecycle based on [19]

As extension to the procedure of [17] and in the context of this scenario, the following procedure is therefore recommended:

- **Classification –** Find attributes for sorting products into A, B and C groups,
- **Differentiation –** set differentiation policy for each class,
- **Refine –** differentiate further by putting in perspective of product lifecycle,
- **Apply –** use ASPV framework for A parts and competition based pricing for B and C products,
- **Revise –** repeat process regularly based on improved data.

3.2 ASPV Framework

Even with a smaller number of parts for valuation, the process from raw data to information is a walk through the jungle of data analytics methods. An extension to the existing Extract Transformation and Load (ETL) process of [20] is proposed to address the particularities of pricing data and provide a system for method evaluation. The system architecture of the ASPV framework is visualized in Figure 3.

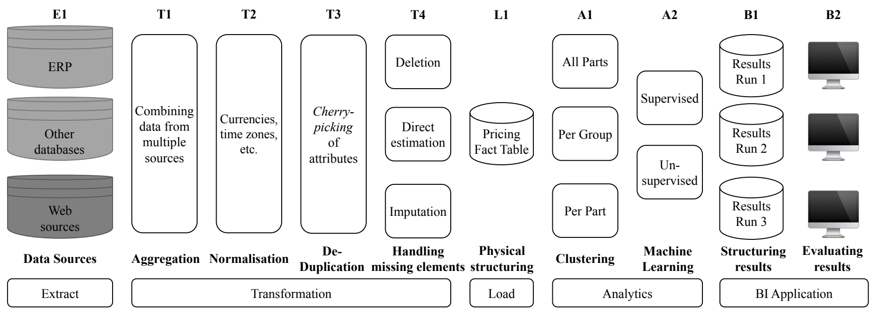

Figure 3. ASPV framework

The first step is the extraction of raw data from available data sources which include internal ERP systems, other internal databases and web sources from trading platforms

(E1). Every data source contains complementary pricing information, that is why data pre-processing is of high importance prior to applying machine learning methods. Extracted data is now aggregated (T1) and subsequently normalized concerning currencies, time zones etc. (T2). The resulting datasets containing pricing information are now uniquely distinguishable by the combination of part number and date.

	partNo	partDate	partGroup	purchasePrice	offerPrice	sellingPrice	originalLaunchPrice	marketPrice
1	(string)	(datetime)	(string)					(double)
2	(string)	(datetime)	(string)				(double)	
3	(string)	(datetime)	(string)	(double)				
4	(string)	(datetime)	(string)		(double)			
5	(string)	(datetime)	(string)			(double)		

1	(string)	(datetime)	(string)	(double)	(double)	(double)	(double)	(double)

Figure 4. Deduplication of aggregated data

As there are usually multiple pricing points per part, duplicative datasets are combined (T3) as shown in the example in Figure 4. Multiple incomplete datasets are combined to one complete dataset. In case of multiple available data, aggregation or selection methods need to be selected according to the business process environment. Still missing elements need to be handled (T4). Two simple and widely used concepts are listwise and pairwise deletion. In case of listwise deletion a complete record is deleted when at least one attribute is missing. This might be the quickest and most effortless approach but also loses much data. Pairwise deletion on the other hand doesn't always ignore incomplete datasets but considers records with connected attributes. Consider the following example: the correlation between attribute A and attribute B is calculated. Pairwise deletion takes all records (including incomplete) into account where attribute A and B still exist. A detailed overview about handling missing data methods is given in [21]. The result of the preceding transformation is a clean pricing fact table (L1) which is the basis for applying analytics methods. Now parts are combined in clusters of different size (A1). Clustering depends on the underlying characteristics of the parts, e.g. number and size of part groups. Machine Learning methods can then be applied on different aggregation levels (A2). Resulting is a FMV per part number and part date (B1). Finding a suitable machine learning method depends on the underlying data structure. The framework's performance can be evaluated by repeatedly running the process in multiple combinations from E1 to A2 and comparing the results (B1) in B2.

3.3 The Challenge of Validation

After collecting the results, the question of validation still stands out. In which combination of methods does the ASPV framework determine a good or correct FMV as target variable? Which FMV is the best or what is the target number of the FMV? We propose a two-step process for using the ASPV to find a FMV: First, automate the valuation process, second increase objectivity of the automated valuation to improve the status quo.

Supervised machine learning methods could be used to automate the valuation process. Predicted FMVs are validated with a subjective opinion of a domain expert. By that the prediction model will be trained to deliver the same quality as the domain expert.

To realize a substantial contribution to existing approaches the ASPV has to be more objective than the domain expert. The FMV should be in context to the input data which are the basis for FMV calculation. In reality, that might lead to choosing a value between reference values such as purchase and selling price. As this seems straightforward for validation, the question may arise, why taking all the effort and complicated models to calculate a FMV to, in the end, simply taking a mean value as reference. Achieving higher objectivity could be realized by deriving a model which leads to a FMV-based decision which contributes most to the overall business profitability. A FMV-based decision which achieves a more profitable business leads to the conclusion that this FMV was correctly determined regarding the definition given by [11]. This determination could be done by comparing time periods before using the FMV and periods while using the FMV for decision making. The challenges coming with this approach are:

1. Separating the FMV from its exogenous influence factors such as
   (a) macroeconomic factors like overall economic growth,
   (b) general profitability within the industry sector,
   (c) general market conditions,
2. and then again, handling emerging missing values which might prevent this separation.

The third approach is not only the most complicated to realize but also the most objective.

4 Conclusion and Outlook

To find methods to determine a surplus spare part's value, existing pricing literature was analyzed. As Cost Based and Competitive Based Pricing are not applicable, Value Based Pricing is the right approach to find a Fair Market Value. The concept of the ASPV framework is an expansion of Value Based Pricing for manual value determination in primary markets to automated valuation in secondary markets.

The vast amount of different parts makes an automated part valuation inevitable. This is impeded by missing data and a non-transparent market structure. A generic ASPV framework for reliable value determination of spare parts enables companies to recognize a part's value right away and leads to a more sustainable use of parts. Due to the information gain, it would lead to a more efficient market overall. In the end, an automated value determination prevents bad part utilization decisions and could lead to a more efficient and sustainable use of surplus material. The concept for automated spare part valuation is a promising alternative for value determination and pricing in secondary markets and thus may serve as a foundation for building a generic surplus part trading platform to overcome market transparency issues if the obstacles of validation are overcome.

An early-stage blueprint of a framework for automated spare part valuation which serves as a guide for segmenting pricing data and aligning software layers from data aggregation to transformation, analytics and evaluation has been provided (research question 1). Future research has to deal with refining the alignment of the methods for segmentation of pricing data (research question 2) by benchmarking the approach against competitive concepts such as mean estimation, a k-nearest neighbors clustering, Bayesian Personalized Ranking or approaches without segmentation. Also the methods for predicting a FMV (research question 3) must be evaluated with real world data. Only experiments with real world data are able to give us an insight on whether a solution based on machine learning is even applicable to find a FMV.

References

1. Naisbitt, J. and J. Cracknell, *Megatrends: Ten new directions transforming our lives*. 1984, Warner Books New York.
2. Neely, A. and Y. Jarrar, *Extracting value from data–the performance planning value chain.* Business Process Management Journal, 2004. **10**(5): p. 506-509.
3. Eaves, A.H. and B.G. Kingsman, *Forecasting for the ordering and stock-holding of spare parts.* Journal of the Operational Research Society, 2004. **55**(4): p. 431-437.
4. Wickboldt, C. and N. Kliewer. *A framework for value-based pricing in aircraft surplus markets*. in *MKWI Conference 2016*. 2016.
5. Hinterhuber, A., *Towards value-based pricing—An integrative framework for decision making.* Industrial Marketing Management, 2004. **33**(8): p. 765-778.
6. Anderson, J.C., J.B. Thomson, and F. Wynstra, *Combining value and price to make purchase decisions in business markets.* International Journal of Research in Marketing, 2000. **17**(4): p. 307-329.
7. Anderson, J.C. and J.A. Narus, *Business marketing: understand what customers value.* Harvard business review, 1998. **76**: p. 53-67.
8. Hinterhuber, A., *Customer value-based pricing strategies: why companies resist.* Journal of Business Strategy, 2008. **29**(4): p. 41-50.
9. Kelly, D.B., *Forecasting aircraft values: An appraiser's perspective.* Air-finance annual, 2008.
10. Ackert, S., *Basics of Aircraft Market Analysis.* Aircraft Monitor, 2012.
11. Mercer, Z.C. and T.S. Brown, *Fair Market Value vs. The Real World.* Business Valuation Review, 1999. **18**(1): p. 16-25.
12. Anderson, J.C., D.C. Jain, and P.K. Chintagunta, *Customer value assessment in business markets: A state-of-practice study.* Journal of Business-to-Business Marketing, 1992. **1**: p. 3-29.
13. Blumberg, D.F., *Introduction to management of reverse logistics and closed loop supply chain processes.* 2004.

14. Voß, S. and S. Lessmann, *Resale Price Prediction in the Used Car Market.* Tristan Symposium VIII, 2013.
15. Hastie, T., R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* Springer Series in Statistics, 2009.
16. Grosfeld-Nir, A., B. Ronen, and N. Kozlovsky, *The Pareto managerial principle: when does it apply?* International Journal of Production Research, 2007. **45**(10): p. 2317-2325.
17. Ronen, B., I. Spiegler, and N. Kozlovsky, *The use, misuse and abuse of the Pareto principle.* Working paper, 2005.
18. Blythe, J., *Essentials of marketing*. 2008: Pearson Education.
19. Östlin, J., E. Sundin, and M. Björkman, *Product life-cycle implications for remanufacturing strategies.* Journal of cleaner production, 2009. **17**(11): p. 999-1009.
20. Kimball, R. and M. Ross, *The data warehouse toolkit: the complete guide to dimensional modeling*. 2011: John Wiley & Sons.
21. Allison, P.D., *Missing data. Series: Quantitative applications in the social sciences.* Thousand Oaks. CA, 2002.