Solving the supplier selection problem with a data-driven total cost of ownership model: Cost prediction case study

Jan Spreitzenbarth and Heiner Stuckenschmidt

Data and Web Science Group, University of Mannheim, Germany

Keywords: Total cost of ownership, procurement, artificial intelligence, uncertainty

Topics: Sourcing and supplier selection, big data & analytics, cost prediction

Word count: 7.917

Abstract

The goal of this research is to understand more clearly lifecycle costs of supplier selection using methods of artificial intelligence (AI) with a total cost of ownership (TCO) model. AI is a key technology for procurement and its usage is still in its infancy (Schiele, 2017). Only few have successfully integrated AI methods into their operations and across their supply chains (Hazen et al., 2014, Schoenherr and Speier-Pero, 2015). This constitutes a research opportunity on how AI increase the performance of procurement and evaluation of suppliers (Chae et al., 2014, Sanders, 2016, Hülsbömer, 2017, Nguyen et al., 2017).

The research question is how to reduce uncertainty in order to provide better information for selecting the right supplier, which in turn adds value to the organization. A case study is conducted in the automotive industry with three distinct data sets over the lifecycle mainly in electronics and connectivity. Exaptation, extending existing solutions to novel problems is a recognized and valid way to contribute (Gregor and Hevner, 2013, Evermann et al., 2017). Concepts are drawn that are applied in IT, chemicals, aerospace, and the military. Naïve algorisms are evaluated as baselines for quality of cost prediction based on nomination data and particularly data of change requests since they often lead to price increases (Bode and Peters, 2016). In addition, cost breakdowns are considered, as they are applicable during several phases of the lifecycle (Hellen, 1963). In particular, regression trees and Bayesian optimization seem prone to deal with uncertainty inherit in supplier selection (Brochu et al., 2010, Jain et al., 2014). Contribution is two-fold: The work makes uncertainty measureable within the TCO framework. Furthermore, the research indicates that at AI models are able to reduce uncertainty inherit in supplier selection - at least to a large degree than the naïve baselines and standard regression.

1. Motivation and introduction

AI is a research area that attempts to design mechanisms allowing machines to develop intelligent behavior. It is a key technology for procurement and its usage is still in its infancy (Schiele, 2017). For instance, the Volkswagen (VW) Group Procurement Strategy 2025 stresses the potential of AI to optimize processes and structures (Volkswagen AG, 2017) and more generally in the automotive industry from sales, production to engineering and supply chain management (Hofmann et al., 2017).

Procurement can be defined as the acquisition from an external source at the best possible cost to meet the needs in terms of quality, quantity, time, and location and must consider conflicting targets with time, cost, and quality constraints (Van Weele and Eßig, 2014). The procurement process can be divided into requirement analysis, supplier selection, and continuous monitoring. Supplier selection takes into account one or several evaluation factors, for instance, TCO tries to capture all costs related to the purchase. While well researched, even minor improvements to the supplier selection process may save millions to the financial bottom line (Pal et al., 2013). Since the depth of value creation has decreased in many organizations over the last decades, procurement is an important factor for the overall profitability (Monczka et al., 2002. For example, in 2016, Porsche had a sourcing volume of about 5.8 billion Euro and the VW Group of 166.5 billion Euro (Porsche AG, 2017, Volkswagen AG, 2017).

Potential applications of AI in procurement are summarized below along the procurement process embodied by the stakeholders, goals, strategy, and recent research focus. Particularly relevant use cases of this research are highlighted in bold script.

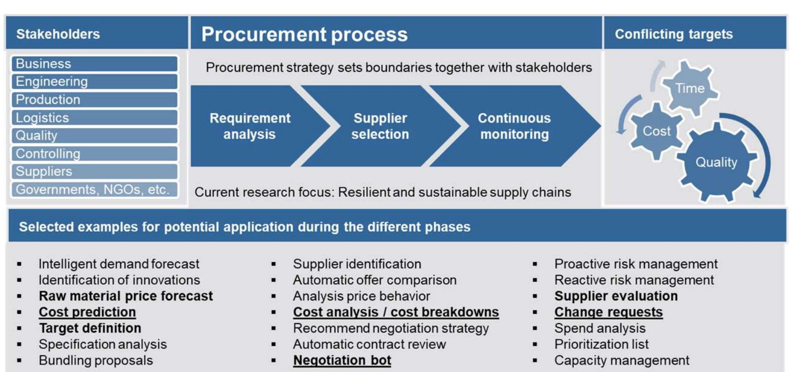

Figure 1: AI in procurement (extended from Van Weele and Eßig, 2014 and Sander, 2017)

Next to ensuring quality and quantity of supply, an important performance indicator of procurement is cost savings often measured as its direct contribution to the financial bottom-line called procurement result that is usually differentiated to mere cost avoidance (Nollet et al., 2008). There are several approaches to forecast savings usually conducted by controlling to set challenging targets for procurement. These are bottom-up calculation, top-down, i.e. "3 % are always possible", benchmarking, and classifying products in terms of their importance and their maturity, for example battery packs likely have a different behavior than standardized, well-known parts such as screws or fasteners.

When considering the difference between the approved target or budget and the nomination value after negotiation and nomination decision, the formula to measure the cost prediction and procurement result interestingly can be denoted in the same way.

$$\text{Cost prediction deviation and procurement result} = \sum_1^n \left| 1 - \frac{Nomination\ value}{Target/\ b\ udget} \right| * \frac{1}{n} \qquad [1]$$

If there is a cost prediction deviation of merely 2 to 3 %, this is means for an organization such as Porsche an uncertainty 400 to 600 million Euro; for the VW Group this accounts to 3 to 5 billion Euro. Strategically, the goal is to reduce this to 0 %. Uncertainty means a situation, in which something is not known, or something that is not known or certain (Cambridge Dictionary, 2020). The higher the uncertainty, the more likely cost prediction deviation is to increase, or put in other words, the difference of estimation and reality is the uncertainty at that particular point in time. If the formula above is generalized for all cost predictions along the lifecycle, this leads to the following:

$$\text{Cost prediction deviation} = \sum_1^n \left| 1 - \frac{Estimated\ value\ in\ the\ future}{Value\ at\ time\ of\ consideration} \right| * \frac{1}{n} \qquad [2]$$

Research question: How to reduce uncertainty in supplier selection with AI methods?

The remainder of this paper is organized as follows: In Section 2, an overview of related work is provided. In the subsequent chapter, a framework for modelling TCO is laid out and the methodological concept described. The empirical evaluation in Section 4 comprised of a case study in the automotive industry built on different data sets. Lastly, the findings are summarized and opportunities for further research are outlined.

2. Related literature

Being able to predict the future behavior is an important business capability (Houy et al., 2010, Evermann et al., 2017). Relevant literature is at the intersection between AI, TCO, and procurement research. Related research for all three areas is rather scarce. However, there is some research in two of the respective areas. For example, AI methods have been applied to automated negotiation that is an interesting field with promising results (Oliver, 1996, Moosmayer et al., 2013, Chou et al., 2015). Furthermore, the TCO concept is widely applied in procurement, for example at the German automotive manufacturers Daimler and MAN, German chemical company BASF, US-based communication company Alcatel, the defense industry and the armed forces (Degraeve et al., 2004, Krawitz, 2004, Albrecht and Wetzel, 2009). In general, the research is related to operations research, supply chain management, and systems engineering.

2.1 Artificial intelligence methods

AI is a strong research stream from human-machine interaction, ethical considerations, to practical application, for example of chatbots and experts systems, evolutionary algorithms, and machine learning (Galbusera et al. 2019). Previous research suggest that AI methods are prone to dealing with uncertainty inherit in the supplier selection problem (Degraeve et al., 2004); in particular, regressions trees and Bayesian optimization (Brochu et al., 2010, Jain et al., 2014). These two methods are illustrated below.

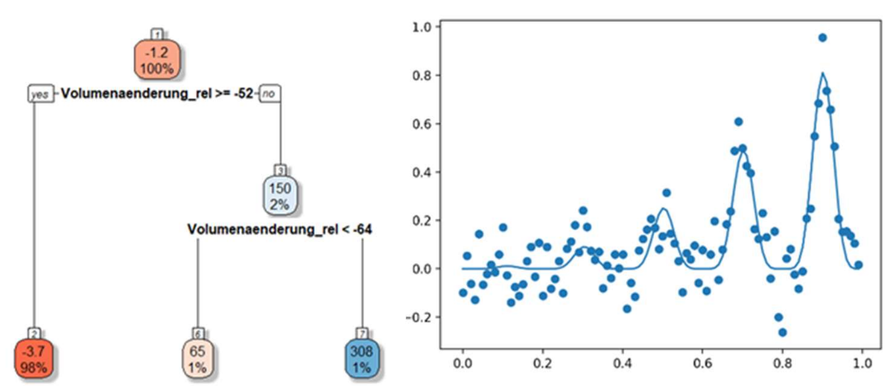

Figure 2: Decision trees (own illustration in R) and Bayesian optimization (Bishop, 2006)

Decision tree models are nested if-else conditions where the paths from root to leaf represent the rules. Their interpretability is more distinct. However, this is often at cost of accuracy with strategies such as bagging or boosting to overcome this weakness (James et al., 2017). Decision tress are called regression trees when the target variable can take continuous values such as real numbers in contrast to classification with discrete labels (Bishop, 2006).

Bayesian optimization builds a surrogate for the objective, tries to quantify uncertainty and uses an acquisition function defined from this surrogate to decide where to sample to (Wang et al., 2016). Thereby, a prior is set over the objective function and is combined with evidence to get a posterior function. This permits a utility-based selection, which can take into account both exploration with high uncertainty and exploitation that offer improvement over the current best observation.

Lastly, there is a strong research stream of AI dealing with uncertainty and forecasting, for example of supply chain demand (Huber and Stuckenschmidt, 2020), which is an important variable for procurement as the volume needed to be purchased to fulfill customer demand. Probability is an important tool to account for this, yet, in actual applications there is often uncertainty regarding the probability values themselves. There is a distinction between two types of uncertainty, dissonance and nonspecificity. Dissonance pertains to probabilistic uncertainty while nonspecificity can be described as increasing with the number of alternatives in a decision situation in the Dempster-Shafer theory (Sundren and Karlsson, 2013).

2.2 Total cost of ownership

The TCO model tries to capture all relevant costs associated to the purchase. For cost prediction in procurement, uncertainty may be seen a noise that makes the supplier selection difficult. While uncertainty is decreasing as the actual requirements of the purchase are more clearly understood, the ability to influence costs is decreasing as well.

There are several estimation methods available from cost engineering, mainly expert judgement, analogies, parametric models, and combinations hereof (IBM Developer Works, 2007). Cost engineering can be defined as systematic approach to manage cost throughout the lifecycle (Hollmann, 2014). Cost prediction is the best estimate at a particular point made with a degree confidence for which research has shown that simple methods are preferable to complex methods (Armstrong, 2001, Stamelos et al., 2003). While the terms estimation and prediction is often used interchangeably, there is a difference in meaning. An estimator uses data to guess a parameter, e.g. a constant in a mathematical function while a predictor uses the data to approximate a value not included in the data where forecasting is probabilistic statement, usually over a long time scale (Armstrong, 2001). The rate at which the accuracy typically improves as requirements specificity increases is known as the Cone of Uncertainty illustrated in the graph below.

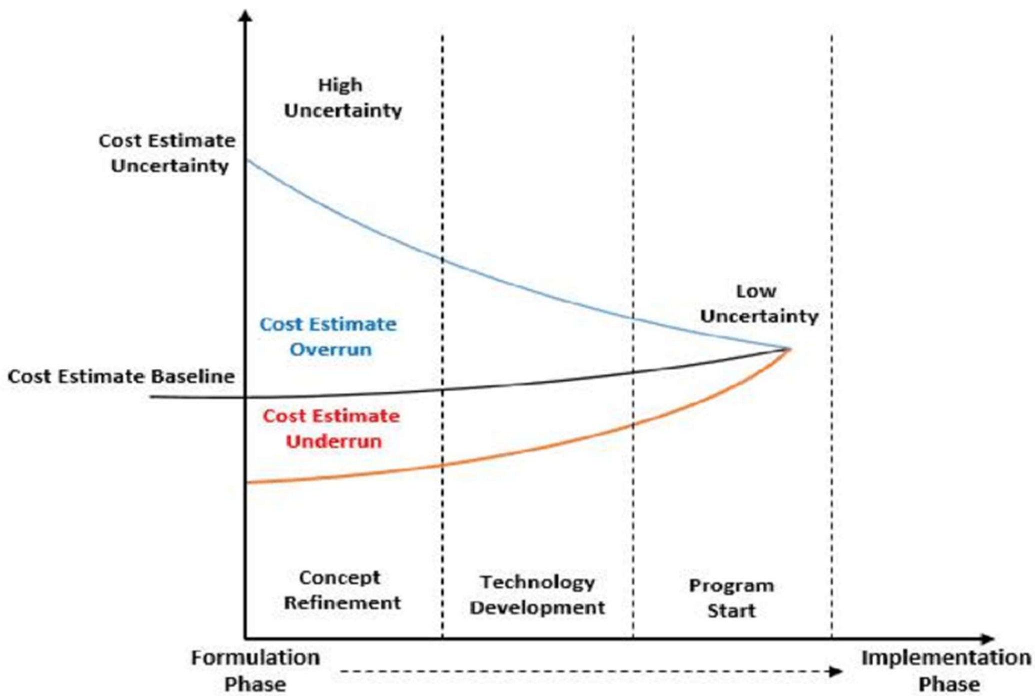

Figure 3: Cone of Uncertainty (Government Accountability Office, 2009 in Gohardani, 2017)

Lastly, there is an important distinction for controlling purposes between direct costs that can be directly attributed to the cost item and indirect costs such as sales and general expenses. To breakdown costs is an important tool to understand the costs associated with the purchase. Costs are broken down mainly in three types: Materials costs such as purchased parts, raw materials, and logistics costs; production costs such as machine costs, labor costs, and manufacturing overhead; and lastly sales and general expenses including profits (Bumb et al., 2008, Albrecht and Wetzel, 2009). Thereby, the main cost drivers are examined such as display size for the cost of display or run-time upkeep of a server while also considering relevant cost factors that are influenced by the decision, for example quality and logistics costs for displays or energy consumption by servers.

2.3 Supplier selection

A supplier selection framework must deal with conflicting targets, explainability, and robustness against manipulation. As not all variables are clearly defined at time of nomination, there is much inherent uncertainty involved in the supplier selection decision. How can this uncertainty be reduced? There are several reviews of supplier selection and evaluation including pre-qualification of potential partners. The selection methods use the knowledge and experience of the decision makers. The extraction of hidden knowledge is an important tool to address such uncertainty and AI methods may a good tool to account for this (Jain et al., 2014). Operations research offers different methods and techniques to support procurement decision-making. This includes multi-criteria decision aid, problem structuring approaches, and mathematical programming models (de Boer et al, 2001). Generally, evaluation criteria are of mixed nature, quantitative and qualitative criteria that conflict one another and vary from one purchase to the other (Lyès et al., 2003). Multi-criteria decision-making seems superior over traditional cost-based only approaches. In fact, research suggests that the main evaluation today is quality, secondly delivery and service, and only thirdly the price (Ho et al., 2010).

Today, procurement in many industrial organizations such as Volkswagen but also for instance IBM is often divided in direct procurement that focuses on materials that are built in the resulting products such as brakes, tires, or batteries and indirect procurement that focuses on internal demand such as construction, marketing, or logistics (Volkswagen AG, 2017, IBM, 2020). Direct materials are often clustered into different product categories, for instance at IBM, so-called global category managers are leading material groups, devising supplier strategies across different brands or divisions.

The data sets examined in the empirical evaluation in Chapter 4 are to a large extent split into these two groups where different internal processes and regulations are applied. Budget and target is used interchangeable as the approved budget for a requisition also called tender. There are two main sourcing types, forward sourcing enables an early involvement of a serial production supplier in the development and global sourcing where the demands of different projects are bundled and the current suppliers challenged (Arnold, 1995, Monczka et al., 2003). In general, procurement deals with conflicting targets with controlling functions, but must also balance the needs of the relevant stakeholders such as quality, production and logistics as outlined in the introductory part.

An overview of related studies of AI, TCO, and procurement is provided below:

Table 1: Overview of related studies AI, TCO, and Procurement

Author, year	**Main result of the study**
Ellram, 1995	Examined eleven companies using TCO concepts in purchasing proving the importance of the concept.
de Boer et al., 2001	Proposed a framework that takes into account the diversity of procurement and covers all phases in the supplier selection process from initial problem definition, over the formulation of criteria, to the selection problem among the qualified suppliers.
Cavalieri et al., 2004	Applied parametric and neural network for the estimation of the manufacturing costs of brake disks by an Italian manufacturer. Confirmed the validity of neural networks with yet with no clear superiority.
Degraeve et al., 2004	Demonstrated how to use with mixed-integer optimization for procurement with a case study of selecting airlines for 56 destinations at US communication company Alcatel obtaining TCO savings of 19.5 %.
Bumb et al., 2008	Reported how TCO is applied at German chemical company BASF at the example of pump systems, whereby a low offer price does not necessarily lead to the order but rather the consideration of individual boundary conditions.
Pal et al., 2013	Reviewed supplier selection criteria concluding that it is important to harmonize qualitative and quantitative criteria. Categorized selection methods including AI that copes well with the complexity and uncertainty in supplier selection.
Jain et al., 2014	Showed that machine-learning techniques work well for evaluating criteria at the pre-qualification stage of supplier selection and its inherent uncertainty in general.

3. Methodology

3.1 Problem description

The problem can be visualized by examining the procurement process from an early phase until the end of life of a product or service (de Boer et al., 2001). It may be possible to look at only a sub-set of the overall process to break down the problem into manageable pieces. Starting with an early phase where the technical concepts are defined and thereby most of the costs defined (Krawitz, 2004, Dehen and Feldhusen, 2008). A target or budget is approved and concrete requirements are described. A tender is set-up with a bidder's list. Offers are received and technically evaluated. Finally, prices are negotiated among qualified suppliers and a supplier proposed for nomination.

Important mile stones in automotive are the project approval, the technical evaluation, the nomination itself, the start of production (SOP) and the end of life (EOL). The timing is given as an observed approximate that may vary widely across industries and categories. As an example, pricing in an arbitrary unit of three suppliers is provided. Cost influence, uncertainty, and cost occurrence is illustrated (Cavalieri et al., 2004) as described in literature on TCO in Chapter 2.2. Now, which supplier should be selected?

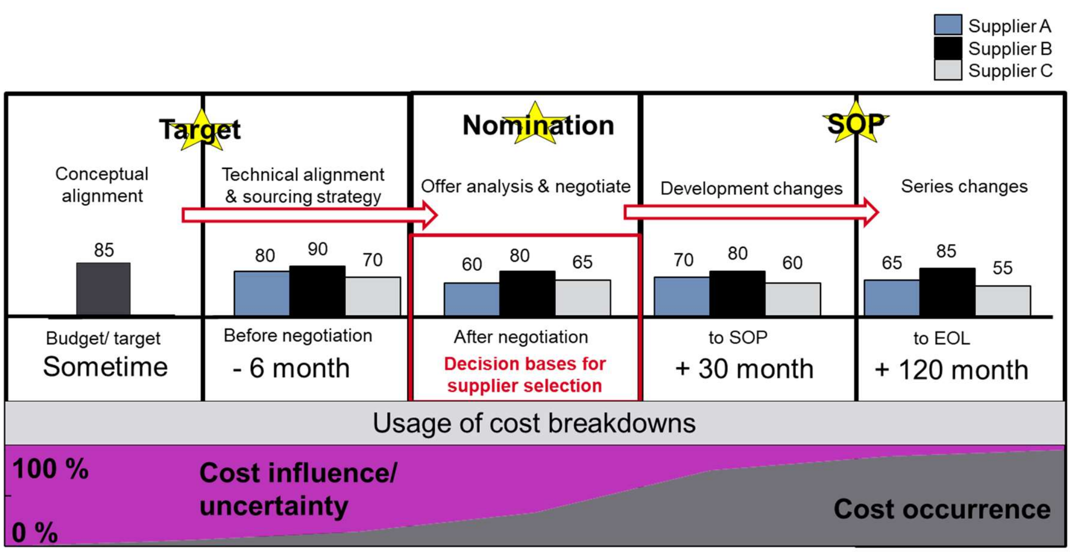

Figure 4: Cost prediction break down of the life cycle (own illustration)

Research goal: Provide better decision-making basis for supplier selection with AI

As shown above, there are several applications during the lifecycle: Cost planning, the prognosis of negotiation performance, e.g., for setting targets of a negotiation bot, considering change request and industrialization in supplier selection and business plans. While all these applications may be interesting, focus is put on the closer problems to the supplier selection with the rationale that the closer problems are seemingly easier to solve. With the knowledge and methods derived, the farer problems such as predicting costs to EOL 10 years in the future can be tackled in an incremental manner.

3.2 Concept

Extending existing solutions to novel problems also called exaptation is a recognized and valid way to contribute (Gregor and Hevner, 2013, Evermann et al., 2017). In a case study in the automotive industry, a baseline for cost prediction deviation is established and different methods evaluated against the baseline. For TCO, all related costs should be considered (Ellram, 1995, Bumb et al., 2008, Albrecht and Wetzel, 2009). A simple TCO formula includes serial production costs, indirect costs, and development costs with the objective to minimize total cost of ownership over the entire lifecycle.

To formalize, the following equation is proposed:

$$\text{TCO}=V*(P+Cc-Cs)+Co+\ Cd+\ E \qquad [3]$$

V = *Volume of actual units*

P = *Price per unit including logistics*

Cc = *Change induced cost per piece*

Cs = *Savings per piece*

Co = *Overhead costs as indirect costs*

Cd = *Development costs as one-time costs*

E = *Error term*

The target is best-estimated price per unit considering change induced costs and savings. Yet, there is also intercorrelations, most prominently of volume where the price per piece can change significantly (Paulson, 1976, Cavalieri et al., 2004). Some costs can be directly influenced; others such as production facilities are more or less pre-defined.

Furthermore, external factors such as earthquakes or force majeure can influence costs. Ultimately, there are yet unknown factors that difficult to be accounted for ex-ante.

Research design: Case study of cost prediction with three related data sources

Thereby, it is important to differentiate between value, price, and cost (Foussier, 2006). Often the actual cost is unknown while price an indicator of value as it is smaller or equal than the perceived value by the customer. Thus, cost estimation may be evaluated against the actual nomination value as proxy for the actual costs as there is no ground truth.

3.3 Other concepts

So far, no directly comparative study has been identified in literature. One the one hand, the lack of quantitative comparative studies provides a research opportunity. On the other hand, the results can only be compared with the baseline, which might be complemented with standard regression analysis. There are, however, several benchmark studies for cost estimation, for example of the empirical validation of software cost estimation models (Kemerer, 1987, Laderia, 2002). In addition, there are commercial applications of estimation, predicting, and forecasting in various forms and tools (Cavalieri et al., 2004, 4cost, 2020, Siemens, 2020). Furthermore, there are heuristics and expert judgments that try to forecast, for instance, the cost development during production, which results in the often seen three times 5 % yearly cost reduction per piece in business plans. In addition, controllers use target costing to monitor and direct variable costs. Cost engineers use cost breakdowns to verify the change costs during the life cycle of the project and use brown-field analysis (Ellram, 1995, Degraeve et al., 2004). Lastly, different methods of supplier selection and evaluation aim to provide a decision basis for dealing with uncertainty.

On a different note, there is a concurrent concept called total economic impact method, which tries to capture other factors as well in particular the impact on potential revenue. This seems compelling, yet, this method has not gained the popularity of the TCO model in research and practice (Nguyen et al., 2017). This could be due to the underlying complexity. Due to resource constraints, focus is laid on the costs that are more easily measureable. It could be interesting to analyze selected examples with this framework, for example, premium sound systems or premium tires.

4. Empirical evaluation

4.1 Data and preconsideration

The data includes nomination data of direct material and indirect materials, several linked and unlinked systems on tracking and evaluation change requests and cost breakdowns. Yet, there is not consistent data source with a unique identifier through the lifecycle making it challenging to match the data of different databases. As the company under consideration is a German company, most data is in German that is translated when needed. Firstly, to gain a better understanding of the characteristics, a pre-study was conducted on indirect materials as most other data is on direct materials, e.g. brakes. This provides the possibility to make analogies between direct and indirect products. As further investigation, it would be interesting to conduct the analysis in other organizations and industries. Indirect materials are normed globally as eCl@sses for master data and semantics (eCl@ss e.V., 2020). The naïve baseline is simply always predicting the average value of the training set, while the other classifiers predict the training set average of the known characteristics of the test set. More complex algorisms could be combinations, regression, and more refined AI trained models that may find relationships within the data previously unknown (Pal et al., 2013) and thus better prediction models.

Naïve baseline = $Target * average\ savings$ [4]

Simple classifier Y = $Target\ * average\ savings\ of classifer\ Y$ [5]

Multiple classifier YZ = $Target * weighted\ savings\ of\ classifers\ YZ$ [6]

Step 1: Visualize and clean data of missing and wrong values, e.g. negative savings. There are in total 2.157 data points from the years 2015 to 2018. The data is randomly split into 70 % training set and 30 % test set. The average procurement performance measured against the best bid as lowest technical verified offer is 11 % and average procurement result measured against the target or budget is 9 %.

Step 2: Calculation of averages for procurement performance and result for all classifiers. Calculation of expected values for each instance with deviation from actual.

Table 2: Baseline modelling with relative accuracy score

Performance metrics		Naïve baseline	eCl@ss	Supplier	Tender type	Cost type	Team	Budget container	Year	Duration
Procurement performance (vs- best bid)	Worst	79%	74%	**70%**	86%	86%	86%	86%	86%	86%
	Standard deviation	9%	8%	**7%**	11%	11%	11%	10%	11%	11%
	5 % hits in %	36%	58%	**76%**	38%	38%	38%	50%	38%	38%
	10 % hits in %	70%	81%	**88%**	64%	66%	65%	71%	64%	67%
	20 % hits in %	91%	93%	**96%**	87%	87%	87%	89%	87%	88%
Procurement result (vs. target)	Worst	**90%**	**90%**	95%	99%	99%	99%	99%	99%	99%
	Standard deviation	10%	10%	**7%**	13%	13%	13%	13%	13%	13%
	5 % hits in %	23%	50%	**72%**	55%	51%	52%	67%	51%	57%
	10 % hits in %	84%	74%	**85%**	70%	70%	72%	79%	68%	72%
	20 % hits in %	91%	93%	**96%**	87%	87%	87%	89%	87%	88%
Relative score		0.93	1.06	1.21	0.95	0.94	0.95	1.05	0.93	0.97

Shown are the worst estimations of each classifier, their standard deviation (SD) and correct prediction within a 5 %, 10 %, and 20 % margin. For each indicator, the best result is marked in bold script. For better comparison of the relative strength of the classifiers, all indicators are combined into a relative score. In particular, eCl@ss, supplier, and budget perform well while temporal classifiers such as sourcing duration do not yield good predictions.

Step 3: Combining different classifiers to gain a combined model of different classifiers, which is weighted by relative score with the rationale that information of each classifier add to the information gain of the combined model. Interestingly, the combination of two or more classifiers led only to somewhat better results than a simple classifier. Furthermore, the relatively strong classifiers eCl@ss and supplier did not perform better but even worse than other combinations of classifiers.

Table 3: Combination of different classifiers with relative accuracy scores

Performance metrics		Supplier plus eCl@ss	Supplier plus budget	Supplier plus tender type	Supplier plus cost type	Supplier plus team	Supplier plus year	Supplier plus duration	Supplier plus budget & eCl@ss
Procurement performance (vs. best bid)	Worst	**61%**	58%	57%	57%	57%	58%	57%	**54%**
	Standard deviation	6%	**5%**	6%	6%	6%	6%	6%	5%
	5 % hits in %	41%	58%	58%	57%	58%	57%	57%	51%
	10 % hits in %	79%	84%	86%	86%	85%	86%	85%	84%
	20 % hits in %	**98%**	**98%**	**98%**	**98%**	**98%**	**98%**	**98%**	**98%**
Procurement result (vs. target)	Worst	83%	**88%**	**88%**	**88%**	**88%**	**88%**	**88%**	91%
	Standard deviation	**5%**	6%	6%	6%	6%	6%	6%	7%
	5 % hits in %	44%	59%	60%	60%	60%	60%	59%	65%
	10 % hits in %	**89%**	83%	86%	86%	85%	86%	84%	86%
	20 % hits in %	**98%**	97%	97%	97%	97%	97%	97%	95%
Relative score		0.94	1.00	1.01	1.01	1.01	1.01	1.01	1.00

To conclude, a good cost model needs a good idea and statistics to demonstrate its credibility. Accuracy is measured in terms of the deviation between predictions and actual in the test set. The simplest way to calculate accuracy is the absolute deviation, which is the calculated value divided by the actual value times 100 %. A relative accuracy metric to account for error size is the magnitude relative error (MRE) and its average value, the mean magnitude relative error (MMRE) (Lee et al., 2002). As an example, for early software cost estimation an acceptable target value for MMRE is 25 %, denoting that in average a project may be estimated with a relative error of 25 % (Laderia, 2002).

4.2 Nominations and intersection

In total, 19.127 data points from the years 2012 to 2019 from production materials of a standardized nomination database are included. Firstly, data is visualized and cleaned of missing and wrong values. Average savings as baseline are calculated for savings and performance for different product types. Afterwards, the performance in terms of cost prediction deviation is measured and the results visualized. The data can be viewed in three dimensions: Part, supplier, and factory level. The meta data is similar to the pre-study in the preceding chapter: Each tender has their unique identification number, the previously mentioned product type, lead buyer and their organizational unit, information about the product, nominated supplier now with their production facilities, pricing information, temporal information about the nomination date and the sourcing duration. There are two main sourcing types, forward sourcing and global sourcing as described in the Section 2.3 on supplier selection. Pricing information can be further divided into the planned volume and price per piece, one-time costs and negotiated cost reduction during serial production to account for learning effects (Lung, 2018). The data is most closely related with the supplier-selection process, which must be documented well for compliance reviews but also due to its impact to the triple bottom line of the organization (Elkington, 1994, Porsche AG, 2016).

An intersection analysis was conducted to illustrate how the data sets overlap and to gain an understanding of impact of change requests on pricing. An example is provided below of the product category electrical system such as generators. It is interesting to denote that the change requests after SOP have a stronger in this case positive on pricing.

Table 4: Intersection analysis of the data sets at the example of electrical systems

Supplier	Nominations #	Change requests #	Impact on pricing%	CBDs #
A	8	1	- 10	2
B	79	19	- 10	21
C	16	4	- 6	3
X	27	5	- 13	3
Y	43	1	- 2	3
Sum	**173**	**30 (22 after SOP)**	**- 10 (- 11)**	**32**

As nomination data is sensitive, nomination volume is not shown and under the acronym supplier X several suppliers with a small revenue share are aggregated. Change requests after SOP are highlighted in brackets. Lastly, the number of cost breakdowns for this supplier in this product category is provided.

4.3 Change requests

For change requests, several databases were merged including with 1.586 data points up to date. Thereby, the data of the last four years was structured and cleaned from missing or anomaly data with a 70 % and 30 % split into training and test set. When matching their relative change of volume to price separating between before nomination, before and after SOP, the following picture shows as could be expected a wider spread at a later point in the process as well as higher relative prices.

A change request is symbolized by a point on the data plot in Figure 5 that represents the relationship between relative volume and price change. They are categorized by the time at which they are evaluated marked with different coloring. The lines mark up the upper and lower bound in which 70 % of the values fall for better readability. Expected would be an S-shaped where the learning curve lead to lower costs and strong changes in capacity change would lead to higher costs (Lung, 2018). This shown the interdependence between volume and price per unit discussed in the methodological concept in Section 3.2. Most change requests with a strong dip in volume, naturally lead to a strong increase in price. For better illustration, they not includes the graph. For change management, it is relevant to understand whether to timing of the change before nomination, after nomination and after SOP is in fact statistically significant.

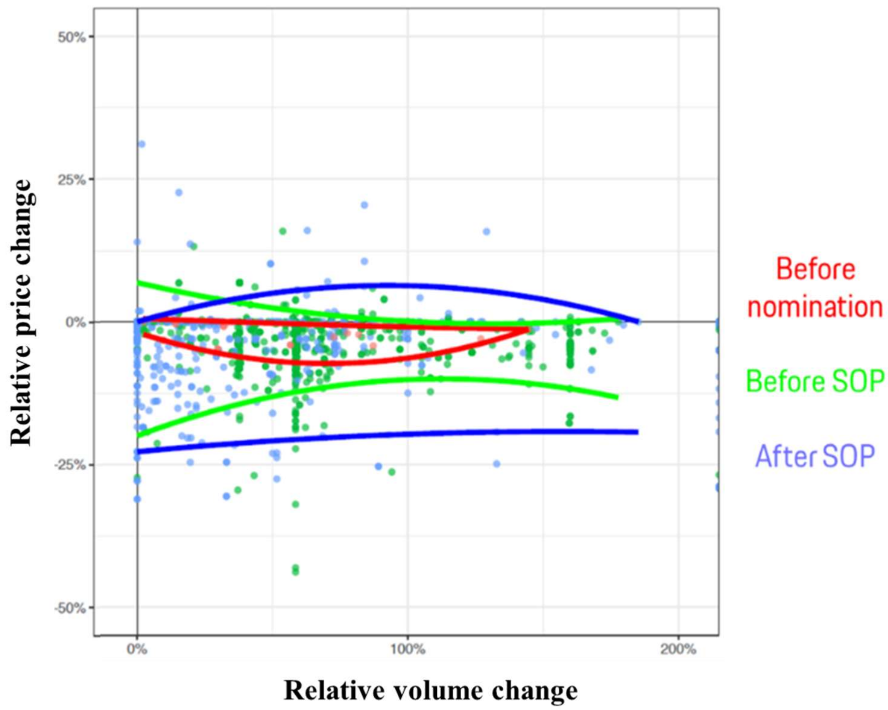

Figure 5: Relationship between change of volume and price during life cycle (own illustration)

Change costs are depended upon characteristics such as type, supplier, time, and budget that may be used as classifiers. If it were possible to capture these costs better, this could provide a data basis to select the supplier with the lowest TCO as in the example described in the problem description in Section 3.1. Thus, the data set includes information on the part and related vehicle project, the nomination with nominated supplier, the intended change and timing and particular volume change as a key cost driver, and the resulting approved changes in the price per part. Summary statistics of the data is provided below for further reference mainly in original German language.

For change requests, as an example the automotive sector tries to cope with this problem through late assignments, modularization, project purchasing with a focus on actively managing change requests, top change rounds at board level and global sourcing after a few years of series production. Furthermore, German automotive manufacturer Daimler allow changes only at certain times during the development process (Albrecht and Wetzel, 2009). In order to synchronize and the procurement and development activities it is important create responsibilities, reflect and focus as well as discipline, reach measurability, and ensure adequate product maturity (Bode and Peter, 2016).

4.4 Cost breakdowns

Should cost analysis or also called reverse price analysis allows a company to compare the proposed price to a price built-up consisting of different components, for instance, material costs, labor rates, or freight costs (Hellen, 1963, Monczka et al., 2002). Up to date, a data set of about 200 projects from the years 2015 to 2020 with cost breakdowns mainly in the area of electronics and connectivity has been created.

Firstly, the data is cleaned and normalized. Initial analysis is conducted in order to verify data consistency. Most importantly, information is added about the main costs drivers of the calculated projects. Afterwards, generic and class-specific models can be created. Lastly, the information is visualized to the stakeholders of the analysis.

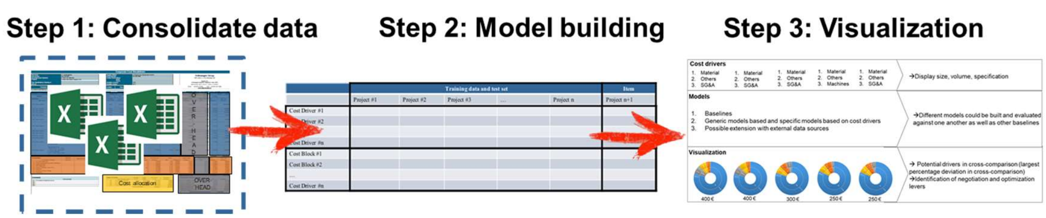

Figure 6: Process to build models and visualize cost breakdowns (own illustration)

Cost breakdowns are especially valuable often used over several phases of the lifecycle (Hellen, 1963). Thus, they are used to supplement the nomination and change requests data. They typically contain meta data about the project again about the part, the supplier, and the production facility. As the word suggests, cost can be broken down as described in the Chapter 2.2 total cost of ownership in materials costs such as purchased parts, raw materials, and logistics costs; production costs such as machine costs, labor costs, and manufacturing overhead; and lastly sales and general expenses including profits.

So-called green-field cost breakdowns are utilized in an early phase for target setting. During the tender process, buyers receive supplier-specific brown-field cost breakdowns reflecting the specific circumstances to validate offers and augmentative support for negotiation (Krawitz, 2004, 4cost, 2020, Siemens AG, 2020). After nomination, the plausibility of delta costs induced by technical changes can be verified with cost breakdowns. However, the information provided by the supplier may be intentionally incorrect as it might be used against them. Whereas, suppliers can also be seen as coproducers in a value network since they can provide production factors such as know-how due to limitations of internal resources, strategic focus or simply cheaper (Stamelos et al., 2003, Roser et al., 2009). Once a supplier is selected, the two parties enter a de-facto partnership. The supplier benefits, if the buyer is doing well and vice versa because re-qualification costs are usually too high to change suppliers for running projects. Thus, some organizations have established an open book policy that calculation is open to all partners aiming to strengthen long-term relationships that are profitable for all parties.

4.5 Summary

In the Table 5 below, the results of the baselines and different methods are provided. Regression analysis is also applied for comparison, next to the naïve baselines as described in the Chapter 4.1 on data and preconsideration as well as the AI methods described in the Chapter 2.1. Further references can be drawn from numerous applications of cost estimation from tool and consulting providers such as 4Cost and Siemens (4Cost, 2020, Siemens AG, 2020) to benchmark studies in cost estimation, for instance 25 % as acceptable MMRE for software estimation, and also the Cone of Uncertainty whereupon during different stage of the product life-cycle different accuracy should be expected.

Table 5: Preliminary summary of results of the different methods

Data set	Naïve baseline			Logistic regression			Regression trees			Other methods, e.g. Bayesian optimization		
	Mean	SD	MMRE	Mean	SD	MMRE	Mean	SD	MMRE	Mean	SD	MMRE
Nominations												
Change requests	**-3.2**	**6.4**	**32 %**	**-4.0**	**3.7**	**21 %**	**-3.7**	**2.6**	**17 %**			
Cost breakdowns												

Next steps:

- Train and optimize models, e.g. bagging or boosting
- Compare with others methods and studies, i.e. 25 % MMRE considered good for early software cost estimation (Laderia, 2002)
- Plug the results in the TCO equation [5] described in the concept in Chapter 3.2

5. Discussion and conclusion

Supplier selection is complex and must deal with a high degree of uncertainty. The results show that cost prediction is challenging but feasible. It is puzzling that despite much uncertainty and unknown factors, organizations still seem to have a general good understanding of costs. Thus, it would be interesting to learn more about the knowledge hidden in decision-makers, controlling and cost engineering professionals. It is therefore important for procurement organization to invest in an early phase. AI seems to be a good way to tackle this. AI in procurement is still in its infancy, there is much research potential on how AI may provide further supply chain insights (Chae et al., 2014, Sanders, 2016, Hülsbömer, 2017, Nguyen et al., 2017).

Thereby, the TCO framework should be extended since several factors are not fully considered that account for the uncertainty. Based on the results of the empirical evaluation in the previous chapter, the Figure 4 has been extended with the quality of cost estimation during the different stages of the lifecycle. It is marked in dark green for the relatively strong results on nomination and light green for decent results for predicting based upon targets in pre-study as well as for the change request data. The more farer away problems are remain uncolored, as these sub-problems temporal farer away from the supplier selection hold for further research where cost breakdowns could be applied but also data on target commitment and industrialization not considered in this research.

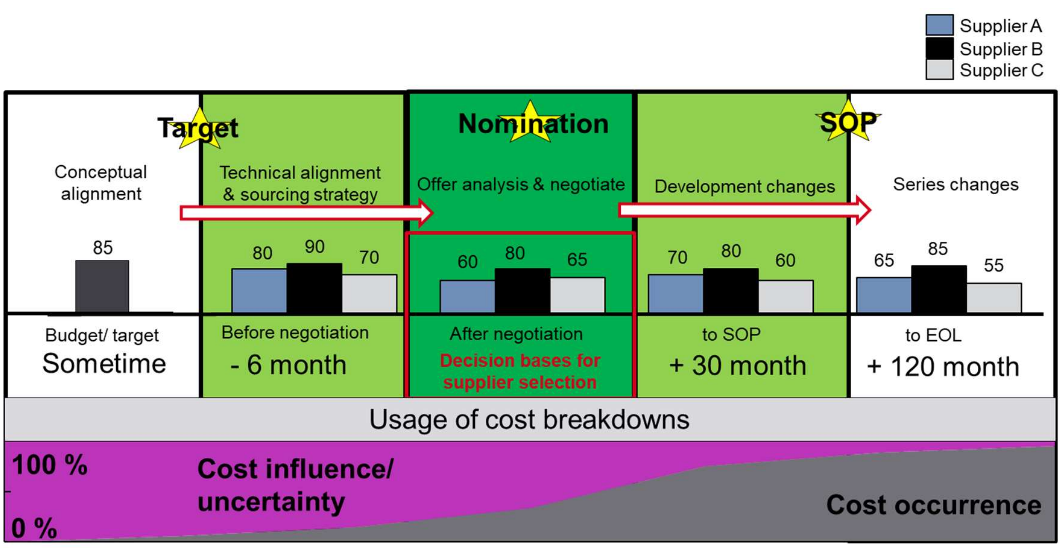

Figure 7: Summary of case study of empirical evaluation (adapted from Figure 4)

Thirdly, change requests should be handled in with specific attention as they often lead to price increases after initial nomination (Bode and Peters, 2017). The study suggests that even if change requests can also have a positive effect on pricing, change requests are not that hard to predict and could in fact be considered in the supplier selection. For this, the decision-making parameters and supplier selection frameworks must be expanded, that should be an interesting extension of this research in the future.

Procurement is often criticized as one-sided focused on costs. What if procurement is not measured by savings but by overall profitability? A supplier selection framework must deal with conflicting targets, explainability, and robustness against manipulation. Yet, most supplier selection frameworks in theory and industry are focused on costs, use generic ratings for quality, and time factors that seem difficult to make objectively measureable. While this is a case study in a single company with related databases, the same analysis may be conducted for other business units with similar challenges and datasets. The application of the TCO model is well described in automotive, chemical, IT, and aerospace and defense industry with high costs per piece. It would be interesting to learn more about applications, for example, in fast moving consumer goods.

A framework could be built upon the total economic impact method described as competing concept to TCO in the chapter of the related literature (Nguyen et al., 2017) utilizing the expert knowledge from the involved stakeholders as crowd-funding (Surowiecki, 2004), i.e. engineering, production, logistics, and sales. In this way, the stakeholders are more actively involved in the decision and must justify their assessment in terms of related costs and sales potential, which could be reviewed and tracked by controlling. A study could benchmark this framework against traditional frameworks based upon the lowest verified bidding price. A database could be set up that, if constructed without bias, could make time and quality to a large degree measureable.

Yet, since this requires much involvement and time commitment by the stakeholders, this may not applied for every decision. Already today, in some organizations standard requisitions are handled by catalogues and specialized providers (Hofmann et al., 2017, Sander, 2017). A negotiation bot could be applied for these while buyers focus on providing oversight, error handling, parameter tuning, and ensuring quality and quantity of supply for production (Oliver, 1996, Moosmayer et al., 2013, Chou et al., 2015).

Author's background and acknowledgements

The author is an external doctoral student in the Data and Web Science Group at the University of Mannheim under the supervisor of Professor Heiner Stuckenschmidt. He holds a bachelor degree in international management from Simpson College and a master's degree in production and operations management from the Karlsruhe Institute of Technology. His master thesis focused on cost estimation of embedded software in cooperation with IBM.

Currently the author works as a buyer in the Porsche Smart Mobility unit. Special thanks to my manager Thomas Pichler for his guidance, corporate sponsor Joachim Scharnagl, Dr. Frank Czymmek of the VW AutoUni, and Endowed Chair of Procurement Christoph Bode at University of Mannheim.

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