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A machine learning-based Biding price optimization algorithm approach

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ABSTRACT

Trading companies of used product market are struggling to gain customers attentaion and to sell the products. The aim of this research is to develop a mechanism that can maximize the sale of products while considering profit implications. The literature review classifies the procurement mechanism. Given the limited-supply nature, that also includes unpredictable quality levels and a procurement mechanism that perceives the company offering prices to suppliers on a single-item basis. The academic literature has not covered such a mechanism. Techniques like those that improve the required bidding strategy are reviewed and considered fit to be included in the support tool as the procedures intention to maximize an objective function depending on the bidding price and contain the probability of winning the auction and the profit made from the proceeding, the motivation laid on the approach that predicts the probability. It is determined that this assembles a Response to Reverse Request for Quotation that meets the assumptions of a First-Price Sealed-Bid(FPSD) auction that potentially includes a hidden reservation price.

1. Introduction

According to Aristotle viewpoint, 'The whole is greater than the sum of its parts. However, this might be true in many cases, not necessarily if one considers the market for used spares and parts. In such an environment, the reverse can be observed. For example, a car that is written-off after an accident and consecutively transferred to the scrapyard, sometimes even for a fee, does not hold much value as a hole, but once dismantled, its components can yield returns. After all, the rusty cliché of, 'One man's trash is another man's treasure', is the basis of an entire industry concerned with second-hand durable goods and parts. Inherently such markets are faced with two key issues. Firstly, they can be as fragmented as the number of individual consumers; the primary traders have sold to (Van Cayseele, 1993). Secondly, the assets are always reallocated between agents whose appraisal of the product is sufficiently different (Bond, 1982; Awan et al., 2022). Both properties bear the fundamental principle that to match supply and demand, a considerable amount of searching and screening is needed. This is particularly the case, because the wear and tear make the valuation of almost every traded item unique, even if it was formerly produced in larger quantities. Such dynamics potentially pose barriers that prevent

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the emergence of various organized suppliers (Grossman and Miller, 1988). Furthermore, according to Akerlof (1970) and his theory about the 'Market for lemons', an adverse selection caused by the asymmetric information of buyer and sellers, should in fact lead to a collapse of such markets. Nevertheless, these problems, especially the valuation problem, can be overcome by the mechanisms of auctions, as they allow for the remake of prices for each and every transaction in accordance with the current market situation (Mcafee and McMillan, 1987). Hence, the industry for used parts and goods has always reverted to the numerous forms of auctions and auction-like transactions. Moreover, the Internet has reinforced these modus operandi while making it more accessible to a much broader business-to-consumer and business-to-business audience (Teich, Wallenius and Wallenius, 1999). The trading company for which this research is conducted, bases its business exactly on the exploitation of the appraisal gap. More specifically, it buys used car engines solely from suppliers in the United Kingdom (UK) to sell them onto customers oversees. Henceforth, the used-parts market at hand does not only permit a suppliers' mark-up but also allows the trading company to profit. By economic theory this should not be the case. But with global trade, such additional revenue from physically separated markets is possible, especially when exports go into less wealthy countries where fewer people can afford new cars (Lacourbe, 2016). In fact, by having expanded onto the global stage, the Engine Export Company (EEC) is faced with a demand they cannot currently match. On first look, this could be because demand genuinely exceeds supply. However, as a preliminary examination shows, see Figure-1, the suppliers reject a majority of all web based procurement offers made by the EEC. As a result, revenue is foregone and customer loss could occur because of the unsatisfactory service. Consequently, this study investigates and aims to solve the demonstrated and undecided business problem.

Having established the company's operations, it has become clear that the imbalance between a successful and unsuccessful procurement stems from the suppliers' acceptance of the proposed offers. As the offers are solely made on a price signal, it is self-evident that the acceptance probability is likely to be a function of the purchase price. It can also be assumed that a higher price is more likely to win the offer. But by convention, an incline of these costs leads to a decline in profit. Hence, it can be further assumed that the acceptance probability inclines when profit declines. Additionally, as the offers are made on an item base and the retail prices per item are fixed, the only alternative to solve the company's business problem of too few accepted offers, is to alter the offer price. Therefore, the objective of this study is as follows. Establish an item-based method that optimizes the purchase price subject to maximizing the offer-acceptance-probability and the profit, so that more engines can be procured. It is clear that this article aims for a multi-objective optimization tool that assist dynamic and flexible procurement pricing for a company in a used-parts market. The objective is just not try to increase the number of accepted offers by changing the decision variable for underpriced items, but it should also adjust over-priced ones.

1.1. Main contribution of this research to the literature

To the best of our knowledge, the academic literature does not hold any specific information on neither the procurement of such markets nor on any procedures that optimize the pricing for it. Such novelty may make for a good academic contribution, though, to classify the underlying mechanism first and to then derive the correct optimization techniques from the existing literature is a thorough exercise.

To solve the underlying problem an approach was chosen that combines a machine learning technique with a metaheuristic. At first,a time series data of the companies having offers are model by logistic regression. This allows the acceptance probability to be calculated for any given item on any price level. Consecutively, a Genetic Algorithm that incorporates the model is used to determine the optimal purchase price by optimizing the multi-objective constraints.

The remaining of this research is organized as follows; brief literature review is provided in section 2.Section 3 explained the underline approaches in more details. Analysis and findings are presented with critical discussion in section 4. Section 5 concludes this research with suggestions for further research and decision-making advice.

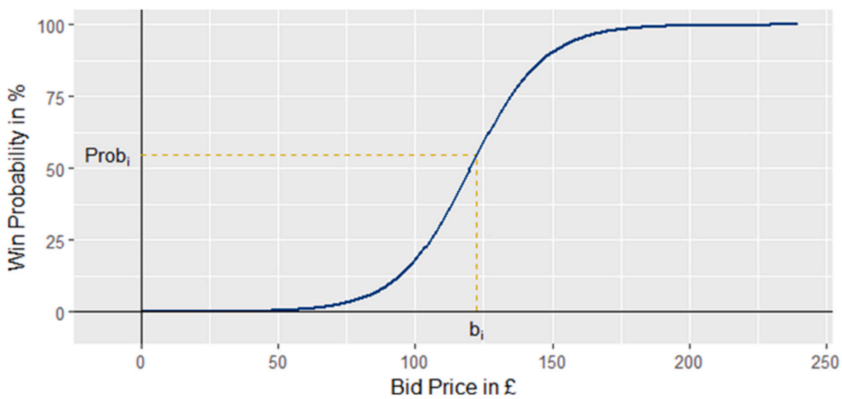


Fig. 1. Presents an exemplary distribution function.

2. Brief literature review

This section aims to define the procurement pricing mechanism set out in the first section by gathering sufficient knowledge from the academic literature. Moreover, the acquired theories and techniques are further scrutinized to develop a better working understanding of how to enhance the instrument. This occurs with emphasis on the constraints and limits that may influence the finding of a feasible and satisfying approach.

2.1. Online-based pricing: A market framework

In the late 1990s and early 2000s the commercial use of the internet as a market place bloomed for the first time. With it came a surge of academic interest and literature that studied the newly developed practices of buying and selling goods and services. In this period, academics established market frameworks that enabled them to classify these procedures. The work of (Guttman and Maes 1998; Li et al., 2020) concentrated especially on the association of buyer(s) and seller(s), as it is regarded as the fundamental principal in understanding and optimizing the systems that bring the two sides together (Whinston, Stahl and Choi, 1997; Li et al., 2020; Feng et al., 2021). It is for that reason that this work follows their outlined market framework to generally position the mechanism the EEC is using to purchase engines from its suppliers. Table-1 gives an overview of their suggestion.

> It becomes apparent that the discrepancy is made upon the number of agents involved in either side of the transaction. Thus, a closer look at the EEC case regarding the number of buyers and sellers on their procurement side is obligatory. If the buying side is considered, transactions that only include one buyer can clearly be disregarded. Alone an ad hoc online search revealed numerous companies that compete with the EEC for buying used engines. Likewise, it can be assumed that there are many private purchasers. The last point shall not be underestimated as several of the EEC suppliers are scrapyards that also sell parts to hobby mechanics and others.

Consequently, a negotiation face-to-face or over the internet where bargaining determines the price (Teich et al., 1999; Kumar et al., 2022), is not appropriate to classify the mechanism. Similarly, a reverse auction where one of many sellers tries to be selected by one buyer according to their bidding price and other criterion (Beall et al., 2003), is not suitable either. It is now established that only many buyers can be considered, though, from here the classification is not that straight forward and a further investigation of the selling side is needed. With 45 potential suppliers registered with the company one could be let to believe that it must be a many-to-many transaction and therefore, a market. Yet, it is not the number of sellers that decides but more precisely the number of sellers who trade the same or similar item or product (Guttman and Maes, 1998; Awan et al., 2022). This shift in focus toward the nature of the article combined with the trading of used parts leads to a broadening of the investigation. It could be argued that because the company is effectively retailing engine types to their customers, their replenishment of suitable engines is more likely to be an exchange market (Awan et al., 2022). As an engine type, marked by the engine code, represents a certain production line, that in many instances has produced the engine over several years, a higher volume of such engines is available and it is most likely distributed across many sellers. Online applications for such markets are common and could be like any generic comparison website.

On the other hand, the argument can be made that because the engines are used, the valuation of the sellers and buyers is not only related to the product attributes but also to the state of the product and its comparable specifics. In that case, auctions are the mechanism most favorable to remake the price (Mcafee and McMillan, 1987; Awan et al., 2022). Furthermore, studies about the online auction platform "ebay", a mainly Consumer-to-Consumer orientated setting, show that used-items from the same production line, overall and for used-cars, can perform significantly different due to quality uncertainty (Dimoka, Hong and Pavlou, 2012; Muthitachareon, Barut and Saeed, 2014). As a result, it is concluded that the procurement system under investigation should be classified as an auction or auction-like procedure. For the continuation of the study, two assumption are drawn from this sub-section.

Assumption 1. The suppliers have more than one buyer for each engine

Assumption 2. The EEC procurement system is an auction or auction-like procedure.

3. Methodology

In this research the argumentation of Krishna (2002); Liu and Wang (2010) and Feng and Wang 2022 is followed. When N potential buyers bid on an item, every single bidder i assigns his own independent bid price bi. Amongst with all others is independently but identically located on an increasing distribution function F. The interval of this function is $[0, w]$ and has a non-negative real line $[0, \infty]$, with the notation of $w = \infty$ and the assumption that the expected bid price

$$\mathrm{E}[\mathrm{bi}] \text{ is}, 0 \leq \mathrm{E}[\mathrm{bi}] \leq \infty.$$

Therefore, the bidders' conditional probability of winning the auction depending on the bid price can be formulated in Eqn-1 as:

$$Probi(\mathrm{win}|bi) \tag{1}$$

As bidding is a competitive matter and the item only being available once, the result is dependent on the bids of other bidders. Therefore, the payoffs for the submission of bidder i are presented in Eqn-2:

$$\boldsymbol{\pi}_{-}(i) = \{\ vi - bi\ if\ bi > \ \max j \neq i$$

$$bj = 0 \ if \ \mathrm{bi} < \max j \neq i \tag{2}$$

with vi being bidder $i's$ estimate of the item, where $maxj{\neq}i\, bj$ is the highest bid of the other participants. A profit πi is only realized if the bidding price exceeds any other bid. It needs to be noted that with the assumption of an independent private item valuation per bidder and $vi < w$, some part of the distribution function can suffer an individual negative πi when the bid is successful. This holds two interesting implications that are visualized in Figure −2.

> Firstly, under the strategical assumption that a bidder would not bid $bi > vi$ and if $Probi\ (win|vi) < 1$, some part of the function cannot be utilized and uncertainty at any price level prevails. Secondly, if competitors have a valuation of $vj < vi$, the profit for any given price level is always $\pi j{<}\pi i$. Also, if the first implication is considered, it can lead to profit simply not being achievable (e.g. πk). Consequently, a bidder's options during the auctions are likely to be limited. However, it can be argued that if the valuation vi is of a not strictly and direct monetary nature, the bidder could surpass his appraisal when bidding, so that $bi > vi$. In that case, a negative profit could also be considered in the bidding strategy.

An example for such a behavior could arise, if for instance, a customer orders several machines at once and needs to receive the export at a certain delivery date. If the company cannot deliver one of the appliances in time because it lost all then the available RRRFQs, the customer could be inclined to not purchase appliances with the company again. Such a loss can hardly be priced in to the valuation of single items, as it would require extensive knowledge about future revenues from that customer and a churn prediction explicitly suited for this case. In conclusion, in this applied setting with many lower value items that have lesser impact on overall profitability, it could be valuable to include the possibility of bids exceeding the financial valuation.

Finally, we look at how the bidder maximizes his outcome in the discussed FPSB. In principal, the bidder is faced with a trade-off between two contradictory objectives that are both determined by his bidding price. On the one hand, he aims to maximize the likelihood of winning the auction and securing the item by setting a high bidding price. On the other hand, he attempts to exploit the greatest possible profit by paying the lowest possible bidding price. With the former he could only achieve an unsatisfactory or no profit, with the latter his chance of obtaining the item is low if not existent at all. In this setting and under the elaborated assumptions, Mcafee and McMillan (1987) and Che and Gale (1996) suggest, that in order to determine the bidding equilibrium, the objective for bidder i is to select a bid price that is subject to maximizing his own expected profit. This can be formulated as:

$$\mathrm{bi,Opt} = \mathrm{argmaxbi}\{\mathrm{Probi}\ (\mathrm{win}|\mathrm{bi}\ )[\mathrm{vi}\ -\ \mathrm{bi}\ ]\} \tag{3}$$

Curve [1] in Figure-3 with an optimal bidding price of bi gives a visualization of Eqn-3.

As (Liu and Wang 2010; Yang et al., 2021) point out, the above method implies that the bidder's preference is equal for both, winning and profit. This might not be the case for all bidders under our assumptions. One might prefer winning over profit or vice versa. Then the formula introduced in eqn [2]. can be adjust for such modification by using the weighted product method, or in other words a Cobb-Douglas utility function. Their model is represented in Eqn-4:

$$\mathrm{bi,Opt} = \mathrm{argmaxbi}\{[\mathrm{Probi}\ (\mathrm{win}|\mathrm{bi}\ )]\boldsymbol{\alpha}[\mathrm{vi}\ -\ \mathrm{bi}\ ]\boldsymbol{\beta}, \propto, \boldsymbol{\beta} > \ 0, \boldsymbol{\alpha} + \boldsymbol{\beta} = 1\} \tag{4}$$

A hypothetical outcome of such an adjustment can be seen in graphs [3,2] in Fig. 3. An $\propto = 0.25$ and $\boldsymbol{\beta} = 0.75$ was chosen for curve [3] and the exact opposite for curve [2]. Both graphs are based on the underlying input of curve [1]. As can be observed, an $\propto > 0.5$ leads to a higher optimal bidding price biw. It should be noted that in both methods an above-mentioned and hypothesized negative profit would never be part of the optimal solution. However, this can be integrated with an approach which is introduced by the author. Instead of maximizing a single objective function (OF), the problem can be formulated as a linear combination of objectives, see Azadeh et al. (2012) and Li et al., 2020 for a similar approach. To combine the conditional probability of winning with the profit on equally weighted terms, it is necessary to normalize the profit equation first which is given in Eqn-5:

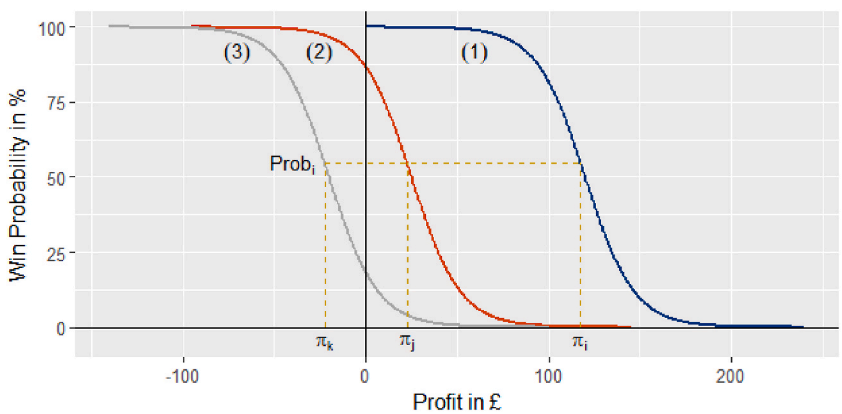


Fig. 2. Profit and the probability of winning an auction.

$$\pi iN(bi) = 1 - bivi \tag{5}$$

With both functions being in the interval of [0,1] and conditional or dependent on the bidding price, a third OF can be introduced in Eqn-6:

$$bi, Opt = \text{argmax}bi\{Probi\ (win|bi) + \boldsymbol{\pi} iN(bi)\} \tag{6}$$

This proposed function will create a pareto-front similar to the graphs in Figure-2 that holds an optimal solution. It also allows for the possibility of lose and the introduction of a probability threshold as a constraint to push the optimization towards either objective.

3.1. Related work

If the optimal bid price is to be determined, we are faced with one main problem. This is not the revelation of the monetary valuation but the prediction of the win probability. In the literature, there are three main strands of methods that aim to solve this problem. The two earlier approaches were reviewed by Vicky and Cassaigne (2000). One uses statistical models and the other one is expert based(Li et al., 2020). The first one requires historical bidding data which is centered around the knowledge of the other participant's bids (Friedman, 1956; Gates, 1967). This information is used to model the distribution function to then determine the appropriate strategy. In the second approach, no historical data is required. The win probability is established for different scenarios using input from human experts.

The third method strand was introduced by Lawrence (2003). It utilizes machine-learning that takes the bidders history of previous bid transactions to directly learn associations of features that can determine the winning probability. This approach claims superiority over the other two in cases where information about the competitor's behavior is not or hardly available, or where experts can barely cover all scenarios (Lawrence, 2003). As is later shown, neither is the information about other bidders' behavior available in this case nor is expert input feasible for the hugely diverse amount of bidding items. Though, the data that is accessible, holds the bidding outcome and numerous other features that can help the prediction. In conclusion, the machine learning approach is believed to be the most reasonable method and is chosen to calculate the wining probability. The selected method that then eventually solves the multi-objective maximization is introduced in the methodology section.

3.2. Formulation of research hypotheses

With the information gathered in this literature review, the research hypotheses are formulated as follows.

H1. The inclusion of information about suppliers significantly improves the accuracy of the winning probability prediction.

H2. On average, the winning probability of won bids is higher than of lost ones.

H3. The supporting tool adjusts for underpriced and over-priced offers alike.

H4. The supporting tool increases the number of winning bids compared to the original quantity. H5: Objective function [4] can enhance the results of objective function [2].

H6. The supporting tool that optimize the bidding strategy returns a higher profit than the original.

H7. Objective function [5] performs better than objective function [2,4].

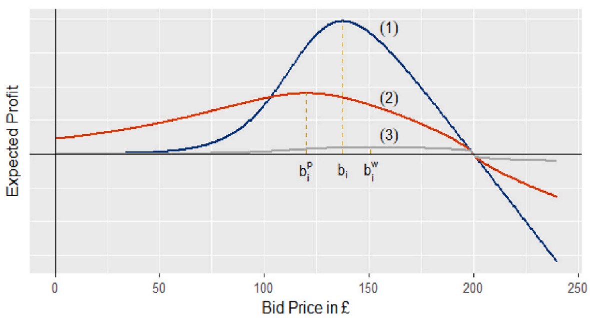


Figure —3. Expected profit functions.

4. METHODOLOGY and DATA

The entire attempt of enhancing the bidding strategy evolves around the machine learning approach that predicts the wining probability. Therefore, this section starts with a remodeling of the price optimization, so that not just the bidding price but also other features used in the prediction can be integrated into the OFs. Subsequently, the process of gathering and preparing the data is described.

4.1. Feature vector in the bidding price optimization

Before remodeling the OFs, we must be aware what type of prediction is needed, as this influences the formulation and the data gathering. It was already introduced that the EEC holds numerous records of offers made to their suppliers including the suppliers' responses. That means that a binary outcome can be assigned to each bidding item which makes it possible to use prediction via classification. The process trains algorithms on instances of data whose class membership is known in order to recognize feature patterns that are then used to classify new instances (Alpaydin, 2010; Feng and Wang 2022). In fact, the algorithms calculate the probability of that instance being member of that class and the binary decision of belonging to either is made on reaching a pre-set threshold. The following reformulation is based on the notations and work of Lawrence (2003). Their starting point is the definition of a set of random-variables. The variables represent features that are included with every bidding item. The notation for M non-prime variables is Xm, $m = 1, \ldots, M$ and the price offered is denoted as Xp. If all features are combined, the feature vector is created as outlined in Eqn-7:

$$\boldsymbol{X} = [Xp, X1, \ldots, XM] \tag{7}$$

The notation for each bidding item can be written as $n = 1, \ldots, N$ and thus a vector that includes the feature values for every item can be returned as express in Eqn-8:

$$\boldsymbol{x}n = [xp_n, x1\ n, \ldots, \mathrm{xM_n}] \tag{8}$$

For historical bidding items, the outcome of the auction also needs to be included. This target variable is denoted as wn and holds a binary label of (win or loss). Any historical bidding item can therefore be expressed by Eqn-9:

$$Bn \equiv [\boldsymbol{x}n, wn]wn \in [win, loss] \tag{9}$$

Having already clarified that the probability of winning the bid should be dominantly dependent on the offer price, the function is reformulated to Eqn-10:

$$Prob\left(win \middle| \boldsymbol{X} = \boldsymbol{x}_{-}(n)\ \right) \tag{10}$$

The objective functions [2,4,5] can now be remodeled and [6] is incorporate as given in Eqn.(11)–(13):

$$\text{‘xp,Optn} = \text{argmaxxpn}\{\text{Prob}(\text{win}|\mathbf{X} = \mathbf{x}\text{n})[\text{vn} - \text{xpn}\ ]\} \tag{11}$$

$$\widehat{\text{x}}\text{p,Optn} = \text{argmaxxpn}\{[\text{Prob}(\text{win}|\mathbf{X} = \mathbf{x}\text{n})]\boldsymbol{\alpha}\ [\text{vn} - \text{xpn}\ ]\boldsymbol{\beta}\ ;\ \propto, \boldsymbol{\beta} > \ 0, \boldsymbol{\alpha} + \boldsymbol{\beta} = 1\} \tag{12}$$

$$\widehat{\text{x}}\text{p,Optn} = \text{argmaxxpn}\left\{\text{Prob}(\text{win}|\mathbf{X} = \mathbf{x}\text{n}) + \left[1 - \text{xpnvn}_{/}\right]\right\} \tag{13}$$

4.2. Theoretical framework

Before any data is gathered, it is vital to better understand under which philosophy the research is conducted and thus, which collection method is required. In this regard,following the suggestion of Saunders et al. (2016) the underline research is based on the philosophy of pragmatism.According to Saunders et al. (2016, p.144) "For a pragmatist, research starts with a problem, and aims to contribute practical solutions that inform future practice", the way this is done is "by considering theories, concepts, ideas, hypotheses and research findings not in an abstract form, but in terms of the roles they play as instruments of thoughts and action, and in terms of their practical consequences in specific contexts." So far, this work has adhered to this philosophy, but which collection methods are appropriate? It is stated that in pragmatism qualitative or quantitative data can be used, if the method is well-founded, relevant and reliable. But what is the difference between them? Table-2 gives insights into the main differentiation. From there it becomes clear that the only reasonable data can be of quantitative nature. This is because the elaborated machine learning algorithm and the optimization procedure require statistical interference and numerical comparisons.

Table 1
Market framework.

BUYERS			
SELLER		ONE	MANY
	ONE	NEGOTIATION	AUCTION
	MANY	REVERSE AUCTION	MARKET

Table 2
Comparison of Qualitative vs Quantative Research.

	Qualitative	Quantitative
Conceptual	Concerned with understanding phenomena from an in- formant's perspective	*Concerned with discovering facts about phenomena*
	Assumes a dynamic and negotiated reality	*Assumes a fixed and measurable reality*
Methodological	Data are collected through participants observations and interviews	*Data are collected through measuring things*
	Data are analyzed by themes from descriptions by informants	*Data are analyzed through numerical comparisons and statistical interferences*
	Data are reported in the lan gauge of the informant	***Data are reported through statistical analyses***

4.3. Computational Environmnet, Data pre-processing and classification

This study is conducted on a problem of a specific company. Thus, the main source of data is the company itself. Having received a backup of their database, the first task was to find out which parts of it hold relevant information. Due to discretion, not all tables and columns can be revealed. Those tables from which data was retrieved are shown in Fig. 7.1 in Appendix A. For the data collection, the software MySQL Workbench was used. The significant parts of SQL code that were programmed to manipulate and retrieve the data are illustrated in Figure A2 in Appendix B. The most important table is labelled as 'tracker' and contains information on all uploaded engines that either have received offers or could still receive offers. Amongst some system details, it holds information about the engine VRM, the engine code, the make, model, engine capacity, supplier ID, offered price, the date it was added and the bidding status per item. It is therefore the main source on historical bidding records that are required for training the machine-learning algorithm. Interestingly, the table is kept as a log and otherwise unique items can have more than one entry. The difference between them is their status. The values of this column have their own table, their explanations can be seen in Appendix A. Logically, the latest entry and therefore, the latest status of each item is most interesting to this research because it let us distinguish the eventual outcome of the offer. Consequently, the last entry of each item was transferred into a new table. The next step was to sub-set the records according to their status. From the ten possible values only items marked as 'Offer', 'Accepted Quote', 'Rejected' and 'Checked Out' were chosen. All others are either not applicable because they do not hold information on the bidding process or data is not available. Additionally, only the columns that were mentioned earlier were selected. After the data was inspected a rather large proportion of missing values became apparent. Especially, the engine attributes such as make, model, engine size and some of the prices were not complete. Also, the company's valuation of the engines or in other words their retail price was not given. Though, other tables also hold information on the features. In the 'engine_match_log' information about all sorts of engines are merged according to engine codes and VRM data and it also includes a potential offer price column. As this table is also a log, a new table was created in the same manner as with the previous one. Additionally, information about the same attributes and the retail price can be found in the 'purchases engines' table. It was now possible to merge the three tables on the VRM column as this is the unique identifier for every item. Moreover, in the table 'customer_engine_codes_prices' the company keeps a recent price list with all retail prices they offer or have charged their customers. The prices are listed for each engine code, model, which in this case is the make and customer ID. It was noted that in some cases there are differences between prices that have the same engine code and model. Therefore, a new table was created that includes every unique combination of engine code and model and its respective average price. This allows to merge the data from this table with the information from the tracker table on the engine code. With all four tables merged and originally missing values replaced with data from the other tables, a second inspection was conducted. Yet again, most data were still missing. However, most information that was not there is considered to be vital for the machine-learning algorithm(Wang et al. (2022). In particular, the engine attributes were mostly effected. Fortunately, this information is too some extent publicly accessible. But because there are more than 4900 records, it was decided to obtain it on bulk from a third party. This could have either been done with help from some private entities. Both ways were encountered. Though, the UK Vehicle Data Ltd was the only one that kindly provided it. After this data had been integrated into the database under the table name 'engine_attributes', it was checked for consistency in accordance with already existing values. This set of information can also be merged with the tracker table on VRM. Finally, the last SQL query brings the data from all five tables together which constitutes the data collection process.

Algorithms for the pursuit of modelling the machine learning application and also, for the optimization process, we follow the suggestion of 'Knowledge Discovery in Databases' (KDD) established by Debuse et al. (1999). Where possible and for an easier understanding, some steps are presented together. We take the liberty too slightly alter the sequence of some early steps to suit the project. The last two stages are presented in the subsequent section.

4.3.1. Problem specification and computational environment

The problem specification has already been established partly. However, it is vital that the gathered data undergoes a thorough examination in terms of reliability and validity. From the collection, we retrieved most fields more than once from different tables and because almost all of them had missing values, a methodology for consolidating them was in order. But before this could be done some noise in the data needed to be addressed. Table 7.1 in Appendix B summaries each retrieved field with its type, number of missing values, the number of unique values and an example of their field semantic. For the remainder of the work the coding language R with the software package R-Studio was used for all operations including the data preparation, modelling and optimization process.

4.3.2. Feature selection and feature construction

Any feature selection aims to reduce dimensionality and overfitting of the model (Guyon and Elisseeff, 2003; Wang et al., 2022) which in turn makes it more accurate. It should be performed on the results of statistical analysis. The main tool for it is to assess the correlation between attributes and the target field, and the correlation amongst attributes. Firstly, when building classification models, a correlation between the target and the features is crucial because otherwise no predictive relationship can ever evolve. That means that in a classification the stronger the correlation the more import the attribute (Zhu and Wu, 2004). Thus, features with a correlation value close two zero can be discarded. Secondly, fields that highly correlate with each other should be reduced to one field only (Senliol et al., 2008). However, this method and most algorithms only work on numerical values. Therefore, another pre-processing step that either omits or transforms the symbolic fields is required first. For attributes with unique values in every row, a correlation cannot be achieved and thus, the fields' ID' and 'vrm' were omitted. For all others, the transformation is done by 'one-hot encoding'. It creates new fields for each unique value of an unordered categorical field so that each field only contains binary values of $Xm\in\{0,1\}$. This was performed on the dataset which in case of the fields' Fuel Type', 'Transmission Type' and 'bid_status_success' lead only to an overwrite of the literals. For example, a win from 'bid_status_success' became 1 and a loss became 0. The attributes' supplier_ID' and 'make' were separated as described. But because this approach will effectively increase the dimensionality by $n-1$ unique values, it is not advised to be used on fields with too many literals (Alpaydin, 2010). It is not to the knowledge of the author that any maximum is established, but by rule of thumb less dimensions are always preferable. Hence, before the one-hot encoding took place, instances with unique values that had a frequency of less than one percent were recoded to the value 'others'. The resulting dataset incorporates 48 attributes of which 24 and 17 relate to the 'supplier_ID' and 'make' respectively. The correlations, see Table 7.4 in Appendix C, reveal five notable observations that influence the feature selection. Firstly, all correlations with the bidding outcome are relatively weak and range between -0.15 and 0.33. Secondly, the attributes that relate to the feature 'make' are omitted from the dataset because of an overall weak correlation with the bid status as the box-whisker-plot in Fig. 3.1 suggests. Thirdly, this is not the case for the features linked to the suppliers' where the inter-quartile range is larger, see Figure -4.

Number four, the features' Purchase Price' and 'Retail Price' with a value of 0.96 are highly, positively correlated with each other. Thus, one of the features should be ignored. However, this decision should be based on the introduced theory. That means the 'Purchase Price', which effectively is the offered bid price, is the only sensible option and should be chosen. Yet, the final observation reveals a correlation of -0.1 between the bidding outcome and the purchase price. This could imply that higher bidding prices are more correlated with unsuccessful bids which would go against the theory. But as explained, the items are unique to a certain extent and have their own valuation. Because of that, auctions can be won on small absolute bidding prices where the items valuation in absolute terms is small. Therefore to establish a generalized relationship for the machine learning approach, the absolute values cannot be considered.

Wang et al. (2022) overcame the problem by normalizing the price based on the company's valuation of the item. In our case it is perfectly plausible to assume that the retail price as revenue is the company's valuation. Thus, the example can be followed and the new feature 'Bid Price' is construct as: $Xp = PurchasePriceRetailPrice$ When checking up on the correlation of this newly established field, which is only 0.02, another obstacle arises. According to Zhu and Wu,2004; Chen et al., 2021) such a weak relationship, significant or not, is problematic because it will not serve as a strong predictor in the classification. Hence, any alternation of the bidding price in order to optimize the OF might not be sensitive enough which could lead to implausible extreme solutions. To hedge against such an outcome, another feature that also includes the bidding price could potentially enhance the prediction. As suggested in the discussion that progresses around Fig. 2, the profit, as a function of the offer price and revenue, can also be associated with the probability of winning the auction. Yet, an integration of an absolute profit has the same problem as the integration of an absolute bid price. But including this as a normalized feature yields a high correlation of -0.94 with the normalized bid price which is also problematic. Interestingly, when correlating the absolute profit on the bidding status it is of the same magnitude as the correlation of the retail and purchase price on the same field. All three absolute values might not hold individual information on a single items relationship in that auction, but the pattern that emerges might capture a relationship that is generally inherent for all the procurement auctions. One could hypothesis that the suppliers cost for acquiring an engine might over-proportionately increase with an increase of their valuation for the item. That would mean their willingness-to-sell decreases which in turn increases their reservation price. In this setting, it is plausible that absolute higher values in the aforementioned fields capture this effect. Since these auctions can only be successful where the bidding price at least exceeds the reservation price, an integration of this information seems legitimate. Because

Table 3
Pre-processed datasets for the machine learning models.

Dataset				
	1	*2*	*3*	*4*
Feature				
Supplier_ID X_S		•		•
Fuel Type X_1	•	•	•	•
Transmission Type X_2	•	•	•	•
Year of Manufacture X_3	•	•	•	•
Engine Capacity X_4	•	•	•	•
Profit X_π			•	•
Bid Price X_p	•	•	•	•
bid_status_success W	•	•	•	•

these fields, including the 'Bid Price', are interacting, the attribute that correlates the least with the 'Bid Price' should be chosen. In conclusion, the profit is selected and calculated in Eqn-14:

$$X\pi = \text{RetailPrice} - \text{PurchasePrice} \tag{14}$$

Finally, the machine learning algorithms are trained, tested and evaluated on four different datasets. The features included are shown in Table 3. It should be noted that the feature vector has slightly changed. The suppliers' feature includes 24 fields and is combined under *XS* and a second price feature $\boldsymbol{X\pi}$ is introduced.

4.3.3. Sampling, evaluation process and data balancing

Any machine learning algorithm needs to be trained before being deployed onto unseen data. To guarantee that their quality is satisfactory they need to be validated. Therefore, a randomized subset of the original data is set aside. The sampling ratio for the split was chosen at three quarters whereas the larger one with 3285 records is used for training. The balancing of the data would be deemed to be not necessary as the target classes with 57.32% losses and 42.68% wins is acceptable, see Figure-1. However, there is a balancing technique that can synthetically create new instances. By doing so, the diversity of numerical values can potentially be increased.

This is interesting because one plausible explanation for the weak correlation of the normalized bidding price with the auction outcome could be, that the price was poorly heuristically set and does not meaningfully enough account for differences between items. In this dataset, there are 523 different engine types which likely have prices that are almost equally differentiated. Additionally, the differences in quality that arise due to individual wear and tear imply that engines from the same type can have a different appraisal which potentially leads to a further price differentiation. However, the company only offered 55 different absolute prices or 302 normalized ones respectively for 4446 items. Therefore, creating the extra records could have the effect similar to a feature construction which usually aims to give the algorithm a more versatile and decisive input (Guyon and Elisseeff, 2003).

4.4. Machine learning algorithms

Recently Zhu et al. (2023) examined the influence of different sEMG pre-processing methods and algorithms on prediction findings. The author suggested an enhanced PCA approach based on the kernel method for dimensionality reduction to remove duplicate information and constructed a model (CNN + LSTM) to forecast the knee joint angle to generate feature values that indicate gait characteristics. Chen et al. (2021) described a unique gait pattern recognition method for lower limb exoskeletons based on Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). The authors attached an Inertial Measurement Unit (IMU) to the exoskeleton to capture motion data for LSTM-CNN input. Furthermore, the CNN layer is utilized to extract features and the LSTM layer is used to handle temporal sequences.Similarly, Liu et al., 2020 used deep learning to complete complicated tasks on a prototype biomimetic soft robot operated by Shape Memory Alloy (SMA) with light weight and multi-motion capability.

Most recently, Wang et al. (2022) proposed an integral subject-adaptive real-time Locomotion Mode Recognition (LMR) approach for a lower limb exoskeleton system based on GA-CNN. The LMR approach is a hybrid of Convolutional Neural Networks (CNN) and Genetic Algorithm (GA)-based multi-sensor information selection that operates on the Bayesian optimization principle. Feng et al. (2021) briefly explained monarch butterfly optimization and provides insights the implementation of the MBO algorithm in future research. Furthermore, Li et al. (2020) proposed a new stochastic optimizer based on the natural oscillation mode of slime mold. SMA has several new features, including a unique mathematical model that uses adaptive weights to simulate the process of producing positive and negative feedback of a slime mold propagation wave based on a bio-oscillator to form the optimal path for connecting food with excellent exploratory ability and exploitation propensity. Feng and Wang (2022) developed a binary moth search algorithm based on self-learning (SLMS) to solve an NP-hard combinatorial optimization problem with many diverse applications, the 0–1 multidimensional knapsack problem (MKP), in order to increase population diversity and improve MS's global search ability. The inventor of SLMS outlined a self-learning flight straightly operator to make any individual learn from anyone better than themselves, not simply the world's greatest.

The synthetic minority oversampling technique (SMOTE) that is able to achieve this was introduced by Chawla et al. (2002). The general idea is to use the k-nearest-neighbor clustering algorithm to retrieve information about the k-neighboring instances of each record in the respective class (Batista et al., 2004). A new instance is created in accordance with this cluster. We use the R package 'DMwR' to perform SMOTE on the training dataset only. There are eight different training sets which consist of the four previously mentioned sets with and without SMOTE.

4.4.1. Classification algorithms

According to Lawrence (2003) and Wang et al. (2022) the main requirement for the classification algorithm is that it "easily generates the win probability as a function of *xpn*, given fixed nonprice features $x1\ n, \ldots, xBn$." After reviewing the possibilities, they also point out that the Naïve Bayes classifier (NBC) is well-matched for the task. This is the case because it always considers all inputs for the calculation. For instance, a decision tree does not likely do the same because it might find other rules where the price is not needed for the calculation. Using a neural network holds similar uncertainties. However, we propose a second option and train a logistic regression (LR) which fits the requirement.

4.4.2. 4.4.2. Naïve Bayes classifier

This method is based on the Bayes theorem (Rish, 2001) express in Eqn-15,

$$P(C = i|X = x) = P(X = x|C = i)P(C = i)\ P(X = x) \tag{15}$$

where $P(C = i|X = x)$, with X as a vector of inputs, denotes the probability of this instance occurring. As $P(X = x)$ does not depend on C it is assumed constant and the focus is on the evaluation of $P(X = x|C = i)$ which is the conditional probability of observing $X = x$. Given the class label the NBC makes the assumption that the input values are conditionally independent. Lawrence (2003) are again followed and because of the independence they can remodel it into a normalized probability per item that is required for the optimization as given in Eqn-16:

$$Prob\ (\mathrm{win}|xpn, x1n, \ldots, xMn\ ) = \widetilde{P}(win|xn\ )\ \widetilde{P}(win|xn) + \widetilde{P}(loss|xn) \tag{16}$$

4.4.3. Logistic regression

Likewise the NBC, the logistic regression estimates the probability of a binary response from a set of inputs. As conventional in regression, the categorical target is the dependent variable and the features are independent variables. According to Alpaydin, 2010, it is based on a sigmoid function that incorporates the features and coefficients and is written as Eqn-17:

$$P(Y = win) = F(xn'\boldsymbol{\beta}) = 1\ /\ \left(1 + e^{-(x^{n^{\sim}}\beta)}\right) \tag{17}$$

With the binary dependent variable y, the probability equation rearranged to suit the specific problem, we get Eqn-18:

$$Prob(win|xn'\ \boldsymbol{\beta}) = 1 \Big/ \left(1 + e^{-\left(x^{n^F}\beta\right)}\right) \tag{18}$$

which can now be integrated into the OFs. It is to be noted that, one of the supplier fields had to be dropped as otherwise the 'dummy variable trap' occurs.

4.4.4. Genetic algorithms and the optimization application

According to Scrucca's (2013) the Genetic Algorithm (GA) is, "[that they] are stochastic search algorithms which are able to solve optimization problems [...], both for continuous (whether differentiable or not) and discrete functions." Because of the use of classification algorithms, our OFs are either hardly or not differentiable and a deterministic approach is not feasible. In this situation, evolutionary algorithms such as the GA provide a good alternative to find high-quality solution (Coello et al., 2007; Wang et al., 2022). The GA is inspired by biological principles and like nature it evolves a population consisting of several individuals to become more well suited for their purpose. Only certain individuals, those that are deemed the fittest, can reproduce while the others cannot transfer their genetics. The reproduction is done by crossover, meaning that an offspring will have genetic information of both parents. But naturally an alternation of the genetic make-up occurs in the form of mutation. Like their predecessors, the individuals of this newly created population undergo a fitness test and the reproduction starts again. This yields a stronger generation with every iteration.

To suit the GA to a specific problem, a value of the decision variable becomes an individual that by succeeding in competition with its peers can breed a better solution. The key is the computation of the fitness that renders the contest possible. It is determined by calculating the OF with those individual values in the population. Therefore, the key is the integration of the study specific objective functions into the GA. For completeness, this demands a slight adjustment to the OF, as it must incorporate changing bidding price levels caused by the iterative GA calculations. That means instead of using the static *xpn*, a sequence of *xp*,1, …, *xp*,*I* with *I* prices is defined as *xp* which assess the win probability as follows in Eqn-19:

$$P(win|xp;\ x1\ n, \ldots, xMn\ ) \equiv [P(win|xp, 1;\ x1\ n, \ldots, xMn\ ), \ldots, P(win|xp, I\ ;\ x1\ n, \ldots, xMn\ )] \tag{19}$$

Thus, $P(win|xn)$ from the OFs [7] [8,9], is rewritten to $P(win|xp; x1\ n, \ldots, xMn)$.Following the suggestion of Lawrence (2003) on the reformulation. To finally run the GA optimization approach, we use the peer reviewed R-package' GA' by Scrucca (2013). The option that needs a binary input of the decision variable is selected. This has two reasons. Firstly, the search is easier and more efficient

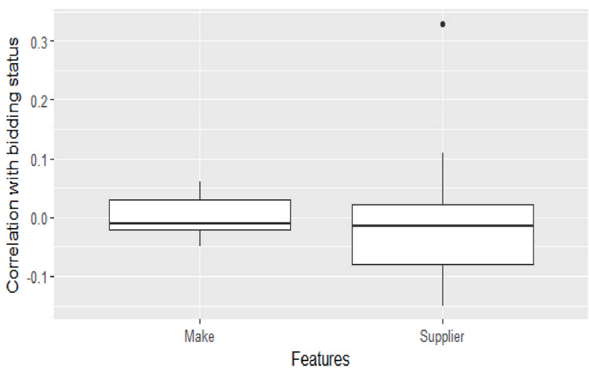


Fig. 4. Correlation with bidding status for make and suppliers.

because binary can only be translated to integer-values. Secondly, only natural numbers are required, assuming that the bidding price is always greater or equal to zero. With the highest bidding price in the dataset being £1,000, the number of binary places could be kept at ten but to allow for possible excess another one was added which equates to a maximum bidding price of £2047. For creating the initial population, selection, crossover and mutation, the pre-set parameters are used. That is, a random population is generated. The individuals allowed to reproduce are chosen by nonlinear-rank selection which ranks the individuals according to their fitness. The crossover of the parent's genes (binary places) is done by a single-point swap illustrated in. Finally, the mutation follows a uniform random replacement of genes. Other such mechanisms are not considered as the search space is relatively small and the chosen ones should suffice. As for the other parameters, the population size is set to 20 and the algorithm stops once it reaches 40 generations. It also keeps the best two values, known as elitism, and carries them into the next generation in case they do not get selected. A chart of this GA optimization process is shown in Figure- 5. In Appendix E three pieces of code are provided to demonstrate how the GA application is implemented. As the code needs to be adjusted for the respective algorithm, Figure A3 and Figure A4 show this implementation for a LR and NBC respectively. Additionally, the former illustrates the code for OF [7] and latter for [8]. For function [8], an $\boldsymbol{\alpha}$ is set to 0.75 and $\boldsymbol{\beta}$ to 0.25 which favors a higher win probability over profit. Fig. 7.5 includes OF [9]. Note that in this case because of the linear combination of profit and probability, the profit needs to be normalized so that both objectives are equally weighted. Also, the search space was tilted towards achieving a probability of equal or greater 50%. After all, the company struggles to procure enough engines. If an individual scored at or above the threshold its fitness is calculated by the addition of probability and normalized profit. If it scores less but greater than zero profit the fitness equals the probability and otherwise the fitness is zero (see Fig. 5).

5. Empirical results and discussion

After thoroughly establishing the theory and methodology of our proposed application, the subsequent section analyses its performance, verifies the hypotheses and discusses the results from an academic and applied perspective. Firstly, the algorithms are evaluated and the two best performing ones are chosen to be tested in the application. Secondly, the average win probabilities of the winning and losing bids are compared. Thirdly, the results of the GA optimization for the three OFs and two algorithms are presented and analyzed.

5.1. Algorithm evaluation

The performance analysis of the algorithm happens on the test dataset, where the models predict the target field outcome which can then be compared with the actual class. This assessment can take on four different results that depend on which class is labelled as true. A win in the auction and thus a value of one in the field 'bid_status_success' is set as true. The outcome of the comparison is either a True Positive (TP) where it was predicted as true and is actually positive, or a True Negative (TN) where both conditions are false, or a False Negative (FN) where it was predicted as negative but is actually true and last, it can also be a False Positive (FP) which is the opposite of a FN. All comparisons from the test records are collected in a contingency table. From there, numerous performance metrics

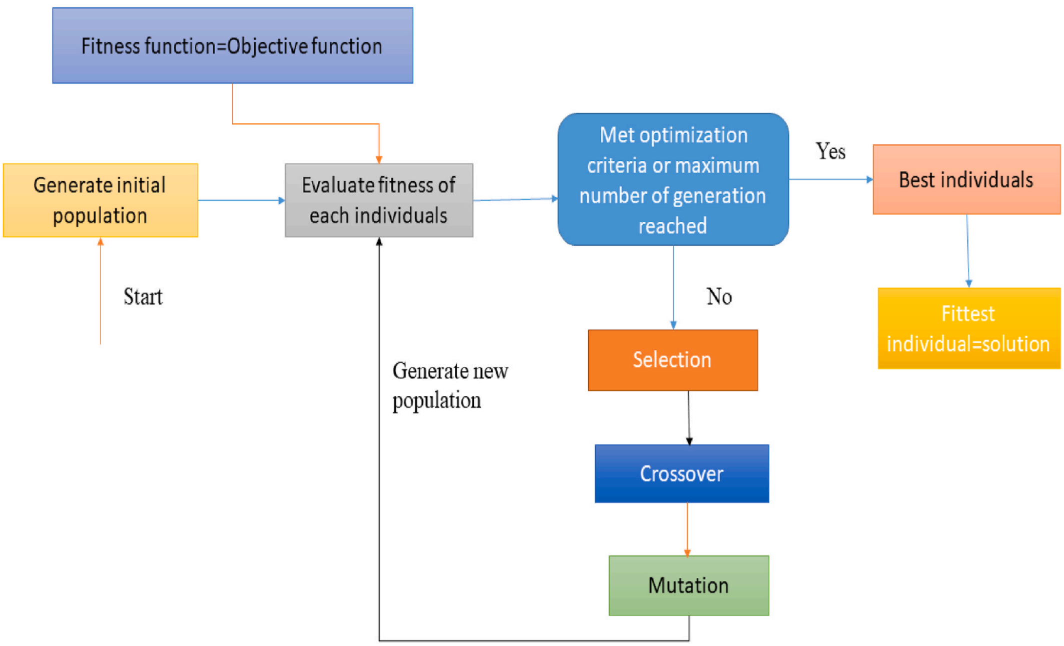


Figure —5. Flow chart of genetic algorithm optimization.

that assess the algorithm can be calculated. Which measure to choose, is highly dependent on the objective of the project and the costs of misclassification (Powers, 2011). Consequently, the focus needs to be on two things. Firstly, the accuracy (ACC) of the algorithm needs to be sufficiently high enough. An accuracy that is only as good as the no-information-rate, which is in this case the frequency of losses (57%), would only be as good as a random prediction on a large sample that assumes that this portion of the records contains this fraction of the negative tuples (Lawrence, 2003). The measure is calculated as Eqn-20,

$$\mathrm{ACC} = \frac{\sum \mathrm{TP} + \sum \mathrm{TN}}{\sum \mathrm{Positives} + \sum \mathrm{Negatives}}. \tag{20}$$

Secondly, the true positive rate (TPR) or sensitivity needs to be high while the false omission rate (FOR) needs to be low. Their calculation is presented in Eqn-21 and Eqn-22:

$$\mathrm{PR} = \frac{\sum \mathrm{TP}}{\sum \mathrm{Positives}} \tag{21}$$

$$\text{and } FOR = \frac{\sum \mathrm{FN}}{\sum \mathrm{FN} + \sum \mathrm{FN}} \tag{22}$$

The reasoning for both measures is that if the algorithm misses too many TPs, it effectively too often predicts a positive probability of less than 50% for instances with a TP condition. The algorithm should rather overstate the positive probability, as otherwise a change of the bidding price needs to be more severe to push it towards an acceptable threshold where winning the auction becomes likely. If this is not the case, the optimized bid price will incur overstated costs and it is probable that the supplier gets offered too much for the item. The downside is that because of the exaggerated probability the offered price might not be enough and the auction is lost. However, this might only lead to long-term costs that are hard to measure, as elaborated in the introduction. Conclusively, to consider an algorithm as feasible, it needs to score a sufficiently high accuracy and needs to perform better on the FPR and FOR than other algorithms that also score an adequate ACC.

As can be seen from Table-4, there are stark performance differences between the algorithms. Especially, models that were trained on the datasets enhanced by the SMOTE technique, score an average accuracy of only 58% whereas the others mange an average of 64%. It can therefore be concluded that in cases where SMOTE was used to create more levels for the numeric features, so that the inputs are more decisive, has not worked. This has potentially two reasons. Firstly, the algorithm is overfitting and did not learn the underlying relations but only the training examples, or secondly, the data was distorted because of the technique. With only an average of 59% accuracy for all algorithms on the respective training datasets, it is more likely that the latter applies. This is consistent with the study of Batista, Prati and Monard (2004) who state that SMOTE is less prone to overfitting than other balancing methods, however, it may distort the underlying trends.

The second observation is that the LR algorithms perform higher or equally well than the NBC models on every dataset in terms of accuracy. On the other hand, the former is outperformed by the latter on the TPR and FOR by 22% more and seven percent less on average respectively. As elaborated, missing to predict the winning bids is problematic but so is an insufficient accuracy. Hence, both algorithm types should be tested on the optimization application and because the four best performing models include both sorts this is possible. Interestingly, each algorithm type achieves near identical results on dataset two and dataset four. Since, the benefits of including another price dependent variable is explained in the methodology and even if it only covers a very small part of variability, it is concluded that the LR and the NBC trained on dataset four are considered for the optimization. Lastly, it can be observed that the performance of the algorithms trained on datasets that include the supplier features is better than without them. Yet, this is not enough evidence to conclude that the supplier attributes are statistically relevant to the prediction, just like the first hypothesis suggests. Therefore, the coefficients and p-values of the logistic regression from dataset four are examined and can be found in Appendix F in

Table-4
Performance evaluation algorithm.

Algorithm	Dataset	SMOTE	ACC in %	TPR in %	FOR in %
LR	1	no	60	19	40
NB	1	no	60	22	40
LR	1	yes	60	23	40
NB	1	yes	55	27	42
LR	**2**	**no**	**70**	**55**	**29**
NB	**2**	**no**	**67**	**78**	**22**
LR	2	yes	66	45	33
NB	2	yes	46	99	13
LR	3	no	59	19	40
NB	3	no	59	31	39
LR	3	yes	58	21	41
NB	3	yes	56	30	41
LR	**4**	**no**	**70**	**55**	**29**
NB	**4**	**no**	**67**	**78**	**22**
LR	4	yes	66	44	34
NB	4	yes	48	98	10

Table 5
GA application distortion.

GA Application	No. Zero Price	∑ Profit	Ø Probability	ØProbabilityOriginal	Bid Status Win	Bid Status Loss
LR (XII)	16	£2429	64%	87%	14	2
NBC (XII)	74	£42,265	100%	33%	13	61
LR (XIII)	0	£0	NA	NA	NA	NA
NBC (XIII)	71	£40,158	100%	32%	13	58
LR (XIV)	49	£7614	56%	83%	40	9
NBC (XII)	63	£36,347	100%	34%	13	50

Table A5. It is evident that not all supplier coefficients are statistically significant on their own. But a second Wald-test was conducted to find out if the entire set of dummy variables and thus, the supplier feature as a hole is significant. The hypothesis under H0 is that all supplier coefficients are equal zero whereas H1 is that they are not equal. The test result has been presented in Fig. 6. The p-value is zero which means that H0 gets rejected on the one percent significance level and that we can confirm our first hypothesis that the supplier feature is statistically significant as a predictor for the bidding outcome. Similar results were achieved by Lawrence (2003), where they showed for a standard RFQ that the relationship to the buyer influences the acceptance of the bidding price.

5.2. Comparison of Winning Probabilities

When considering the winning probabilities of the bid items one should always bear in mind that it measures the likelihood that this event, a win in the auction, occurs, given its price level and non-price features. That means it is always possible that there are items which, 'against all odds', are still a win or vice versa a loss. However, in that situation the underlying prediction either does not cover the relationship correctly or there are other influencing relationships that are not covered by the attributes. It is for that reason that the prediction decisions between the two classes is set to 50%. Thus, it is preferable that the number of such instances is kept comparatively low for either outcome. Projected onto a distribution of the probabilities for wins and losses, this should mean that the ideal spreading is skewed either way with actually won bids having a higher average win probability than the losses. Furthermore, the former should be above 50% and the latter below. Fig. 4.2 illustrates the distribution for the computed win probability for either case and both algorithms. It is evident that both models adhere to the above remarks. Consequently, hypothesis H2 is confirmed.

There are other interesting implications that can be drawn from analyzing the distributions. Firstly, the LR probability mean of 42% somewhat recollects the underlying class distribution of 43%. Additionally, it has a much higher proportion of bids under 50%. On the other side, the NBC is the opposite and has a larger number predicted above the threshold. Both observations are along the lines of the performance measures introduced in the previous sub-section, meaning that the LR potentially misses more winning bids than the other model. However, the skewed NBC distribution illustrates well that the weaker accuracy stems from a higher amount of falsely discovered winning bids. If this happens around the 50% threshold this might be acceptable, though in this situation the overstatement of the probability might even be more severe and could cause problems. Notably, with the NBC there is also a larger number of instances predicted between 85 and 95%.

5.3. Bidding price optimization

Before we can derive any conclusions which of the proposed Genetic Algorithm application works best and if the performance is good enough to be applied at the company, one needs to be aware that an actual test scenario for this application is hardly feasible and goes beyond the scope of this dissertation. This is because the supporting tool ultimately aims to suggest a bidding price for items which are not yet auctioned. To assess its performance with higher certainty, it would take a larger sample where the application and also the company's pricing strategy is applied in the procurement process. For now, the analysis is based on assumptions and logical reasoning and must be conducted on the prepared test dataset where its outcome is compared with the original data.

5.3.1. Comparison of bid prices

A good starting point in this assessment is the evaluation of the prices that were computed by the GA application. This allows to detect any errors caused by either the machine learning or genetic algorithms before any false conclusions are drawn from collective

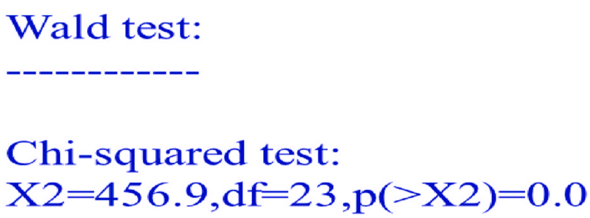


Fig. 6. Wald-Test result on Supplier Feature Importance.

measures. As shown in the theoretical part, it is expected that the supporting tool potentially adjusts for over- and underpriced items alike. Because the EEC is faced with the problem that the bids are too often rejected the intuition is that on average the proposed prices should go up. To test this, the computed optimal price is compared with the original price and by normalizing the metric an overall relationship can be established. Furthermore, this method potentially makes it possible to spot any outliers that are by logic not tolerable. The calculation is carried out with the following Eqn-23:

$$\delta = \frac{(\text{OriginalPrice} - \text{OptimalPrice})}{\text{OptimalPrice}} \tag{23}$$

The interpretation of δ is that when it is negative the original price is that percentage less of the optimal price. It marks a cautious bidding strategy. Vice versa it is as considered aggressive. Fig. 7.6 in Appendix G shows the price comparison for all six applications. The mean of the normalized price difference ranges between −2.3 and 2494.7%. The careful strategy seems acceptable but any other application adopted an aggressive plan. Even the second lowest suggests that the original prices are too high by 292,5% on average. Such proposal is highly doubtful. Having a closer look at all graphs it becomes apparent that they heavily tail-out towards the positive values. The outliers obviously influence the mean immensely. This can only appear if the computed price is far less than the original. The question is why does the application calculate such low prices. There are two possibilities, either the GA ran into an arbitrary point (Coello Coello, Lamont and Veldhuizen, 2007) or the included algorithms produce perverse results when the bid price gets altered. It appears that the former is not the case but after investigating the lower price levels a problem with the algorithms is detected. To demonstrated the problem, Table 4.2 summarizes the occurred distortion for computed prices that were set to zero. The following major observations stay out. Firstly, the supporting tools that use the NBC are far more effected. For these algorithms, the comparison of the original probability with the one at the lower price level suggests an increase, that is, the probability rises from roughly 30 to 100% when the price drops. Moreover, most bid items effected are originally losses which makes this tendency the more critical. This behavior goes against the entire theory on FPSB auctions that assume a higher price is associated with a higher win probability.

A further investigation shows that this relationship persists and 45 to 69% of all bidding items throughout all NBC applications are affected. The reason for this occurrence could lie in the strong assumption of independence of any two features given the target class. If the conditional independence is violated this can lead to perverse results (Domingos and Pazzani, 1997). On the other side, even if the assumption is not met, Zhang (2004) shows, that the results can still be good. That potentially means that the distortion could have come from the weak correlations of all predictors with the bidding status, especially in case of the bidding price. The misinterpretation of the underlying relationships, are also likely to be the reason why the NBC had a higher average probability among all items. In conclusion, this argumentation cannot be brought to a close but we can certainly dismiss all support tools that incorporate the NBC.

The second major observation from Table 5 is that there is also distortion in the applications using the LR. However, in this case the drop in probability goes together with the decreased price. That is not a surprise as the coefficient for the normalized bid price is positive, see Table A5 in Appendix F. Though, from the same table it becomes apparent that other attributes also highly contribute towards the probability and that even without the price the probability can be high. This is not necessarily troublesome because the features capture valuable relationships. For instance, bid item 227 comes from supplier 72 and the engine was manufactured in 1989, almost 30 years ago. Both these attribute values make an auction win more likely. For the age, this is plausible because the quality of an

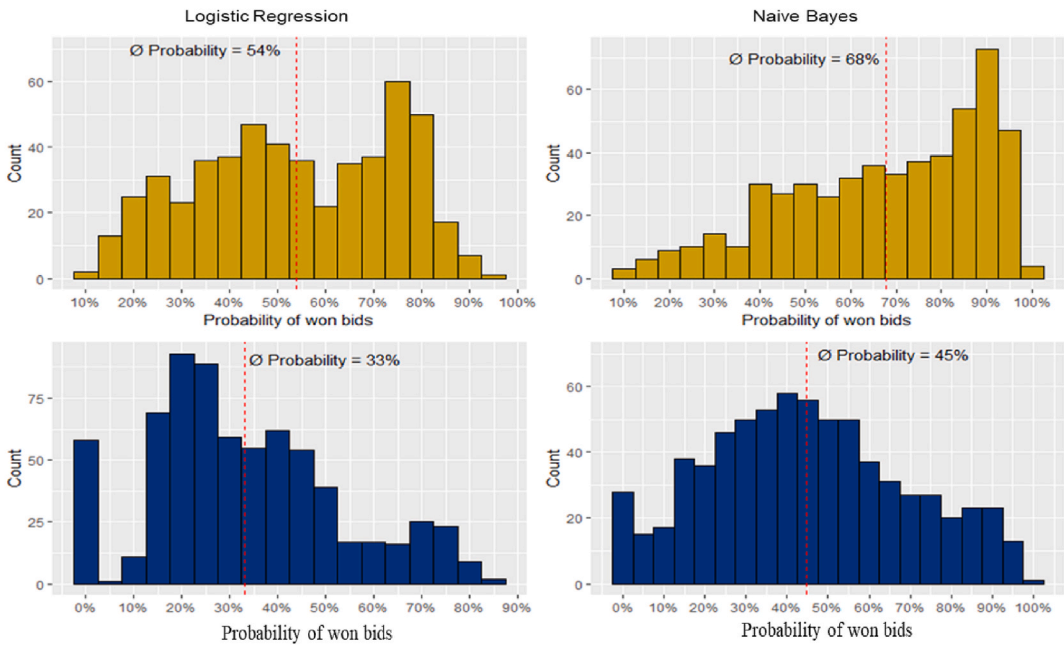


Figure −7. Comparison of winning probabilities.

engine simply decreases over time. As for the supplier, the model potentially captures a comparatively low supplier's reservation price or the fact that other bidders might value items less from this source. We wish to exploit all three associations so that any original overpricing of this item might be corrected. Therefore, handling this problem is important and can be done by either the application itself, for instance the one that uses OF (*XIII*) or by other means. To achieve a better comparability, all further investigations have those items with a zero computed price recoded back to their old attributes. Practically speaking, this would act like a supporting tool that has a similar default setting if it were to set a bid price equal to zero. Figure-7 stipulates the adjusted price comparison and it is evident that the means are smoothened. The supporting tool that uses OF (*XIII*) (STXIII) still seems to have the most reasonable repricing. However, as Table-6 shows, STXIII does lift the prices for most originally lost items but also lowers many. Application (*XIV*) (STXIV) on the other hand pushes the price upwards for 86% of all losses but it also does this for many won instances. Almost all offers are reduced when application (*XII*) (STXII) is in use (see Fig. 8).

Generally, the reduction of lost item prices goes against theoretical and practical implications because the suppliers would only be more inclined to reject the offers. It seems that the item based OFs created by the tools that use profit multiplied by probability, have maxima that tend to prefer profit over probability for the given data. A look at the functions of bid item 719 and 840 in Figs. 9(a) and 10 (b) echoes the circumstance and both these tools yield a reduced price in comparison to the other application Figs. 9(b) and 10(a) provide a clear picture. The cause for the similar but less severe problem in STXIV is different and is explained by the introduced inaccuracies in the classification model. For example, if a loss is misclassified its probability exceeds 50%. The GA then runs the pareto front optimization instead of only maximizing the probability. This together with the occasionally overstating of non-price features, leads to items with lower prices. Because the objective of the tool is to increase the number of successful offers, we are more inclined to prefer the bid price setting of ST-XIV. Lastly, hypothesis H3 can be confirmed because all tools adjust for over- and underpriced items alike.

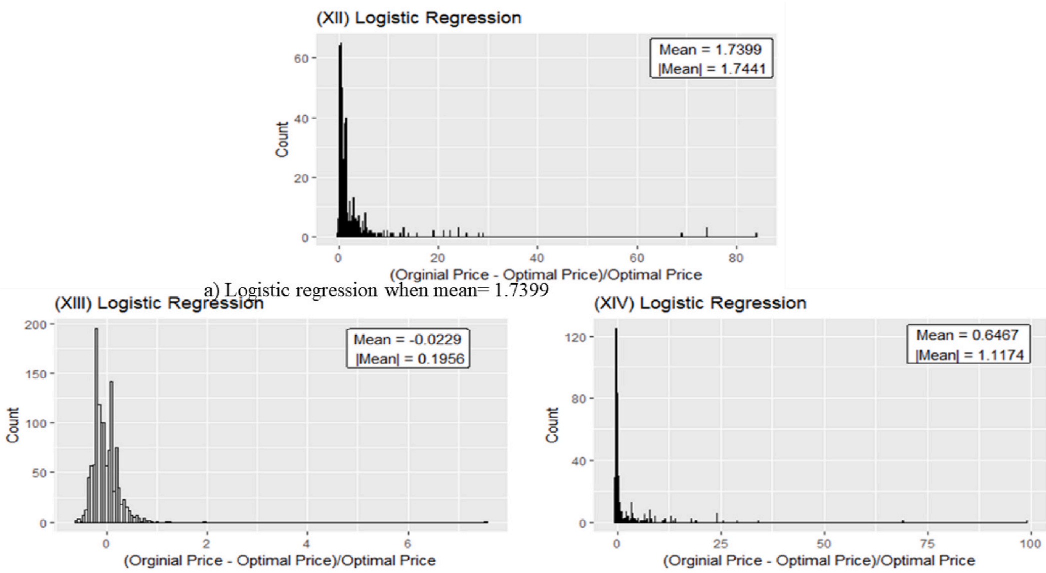
through logistic regression having mean 1.7399,0.0229 and 0.6467 in a,b and c.

5.3.2. *Support tool assessment*

For the final verdict, the applications need to be compared on the impact they have on the number and likelihood of won-bids and the subsequent profit. As explained, it is not possible to test the tools and therefore, we must assume that only offers that exceed a probability of 50% are likely to win and can be classified as such. This is the same assumption made for assessing machine learning models. Misclassification aside, this approach is plausible considering that the study objective is to increase the number of winning offers while reaching the maximum profit doing so.

The first observation from Table-7 is that apart from one application the number of winning offers can be increased. Thus, hypothesis H4 can only partly be verified. With this result and together with the price analysis, it is concluded that ST-XII is not considered any further as it misses the objective. Based on this it is possible to confirm hypothesis H5 that stipulates that the objective function used in ST-XIII can in this case enhance the result of OF- (*III*).

Answering the two remaining hypothesis that also answer which application to choose is more problematic. As can be seen, the profit generated at the 50% probability threshold is greater for ST-XIV than for ST-XIII and both exceed the original, though, this is reversed for the expected profit. Also, the ST-XIV has less expected profit than the original dataset. This circumstance becomes plausible given that the average probability and the average price is much higher for the ST-XIV. Comparatively, it is questionable if



a) Logistic regression when mean= 1.7399

b) Logistic regression when mean= -0.0229

c) Logistic regression when mean= 0.6467

Figure −8. Adjusted comparison of original prices with computed optimal prices.

Table 6
Number and direction of Bid Price changes according to Bid Status.

Bid Status	Test Dataset	Price Change	STXII	STXIII	STIV
Win 520		increase	19	246	325
		decrease	501	274	195
Loss	699	increase	23	491	604
		decrease	676	208	95

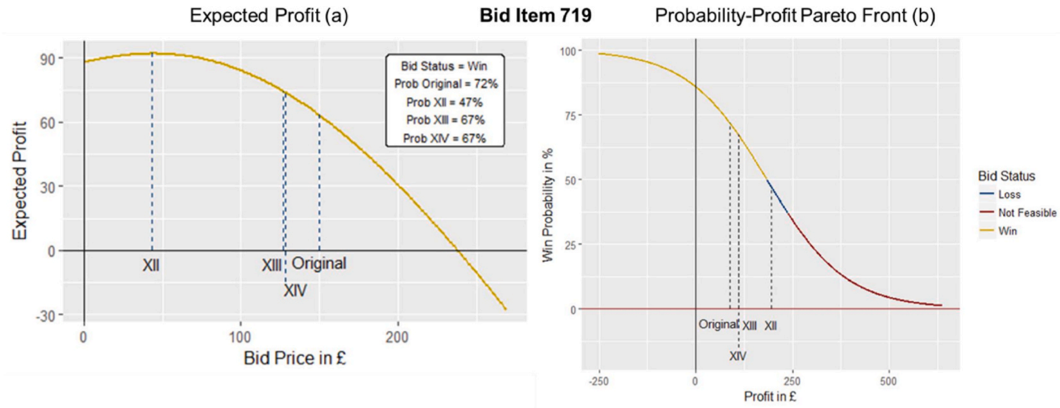


Fig. 9. Expected profit and probability of wining Bid Item 719.

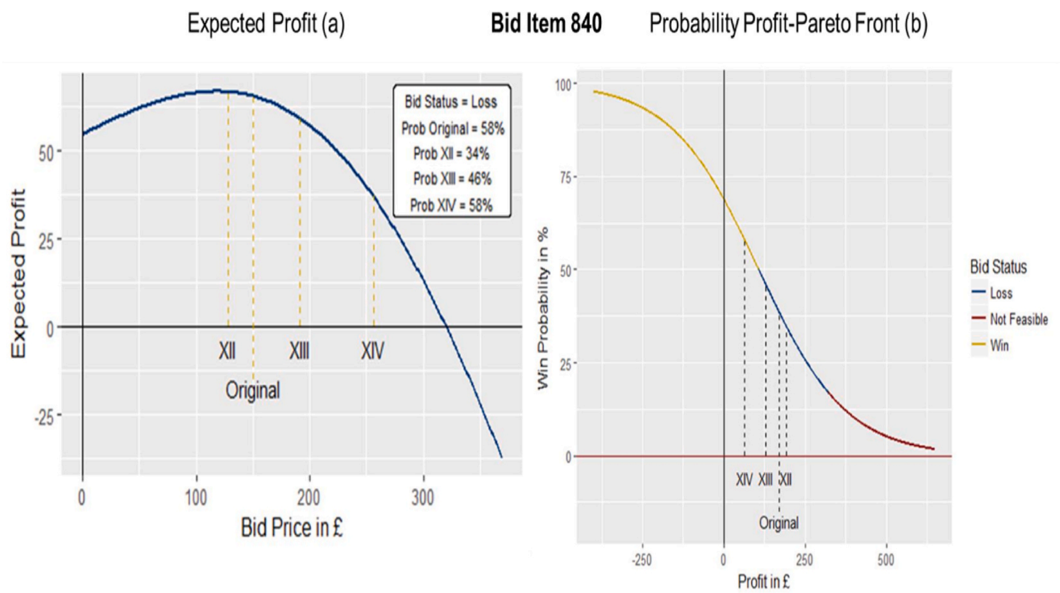


Fig. 10. Expected profit and probability of winning Bid Item 840.

Table −7
Wins, Probabilities and Profit of the three Support Tools.

Metric	Test Dataset	STXII	STXIII	STXIV
Bids above 50%	416	151	458	864
Bids below 50%	803	1068	761	355
Ø Win Probability	42%	30%	44%	50%
Ø Price	£165	£101	£179	£206
∑ Expected Profit	£46,170[2]	£59,243	£47,504	£35,411
∑ Profit above 50%	£35,042	£24,104	£46,311	£62,040
Min. Profit	£ −156	£ 39	£21	£ −160
Max. Profit	£800	£777	£345	£584

the subtle change in average price and probability of the ST-XIII would yield enough returns. Especially, given that the same application, lowers the price for 29% of items that were originally lost. To be more certain about this decision, another factor should be considered. The standard techniques of bidding enhancement always need to assume that the buyer's valuation can be represented by direct monetary terms (Milgrom and Weber, 1982). However, when supply chain security and, as in our case, a business expansion needs to be considered this becomes hard to account for. Consequently, it is valuable that the bidding strategy can be optimize along a pareto front which allows to set a threshold of certainty. For instance, Fig. 7(b) shows that the other two applications could not reach this aspired result. Given these findings, we can conclude that hypothesis H6 can be verified, as both applications can return higher profits under the stipulated assumptions. For hypothesis H7 we are inclined to declare that OF-(VI) works the best for the case at hand. Though, this dissertation attempts to suggest a solution which could be applied to this real business situation. Therefore, on a practical note a combination of both support tools could be deployed. ST-XIII could be used on cases that are less strategic, whereas ST-XIV covers items where more certainty is in order. If done correctly this approach might yield more returns than a single support tool by itself.

6. Conclusion and implication

In this investigation, we were faced with a trading company in the used-product market that struggles to acquire enough engines to sell them onto their international customers. The goal was to find an application that enhances the number of successful transactions while taking profit into account. Given the limited-supply nature that also includes different levels of quality and a procurement mechanism, that sees the company offering prices to suppliers on a single-item base, it was concluded that this assembles a Response to Reverse Request for Quotation, that meets the assumptions of a First-Price Sealed-Bid auction, that potentially includes a hidden reservation price. Such a mechanism has not been covered by the academic literature.

Although, techniques like those that enhance the bidding strategy were reviewed and deemed fit to be included into the support tool. Because the goal of the study is to maximize an objective function that is dependent on the bidding price and contains the likelihood of winning the auction as well as the profit made from the proceeding, the emphasis was placed on the approach that forecasts the probability. We chose machine learning methods to determine the probability directly from prior bidding data that contains non-price variables because information on competitors' bidding prices is not available. This potentially makes the objective function not differentiable. Lawrence 2003; Yeng et al., 2021; Feng and Wang 2022),are mainly followed for the machine learning part, who tries to solve this by creating bins for different price levels for which they runs the calculation separately(Kumar et al. (2022).

Because of the larger price range and more diverse items, we developed a novel approach that solves the objective function with an evolutionary optimization using a Genetic Algorithm. The three different objective functions yielded dissimilar results. The common approach that equally weights profit and probability gave the highest expected profit but had a stark reverse effect on the number of potentially procured engines. Thus, it's done the least well. In the second one, we were able to empirically show for the first time that the mathematically proven enhancement of the same objective function proposed by Liu and Wang (2010) does lead to the hypothesized results. A higher number of products would be purchased and profit would also increase. Thirdly, the objective function developed here assembles a linear-combination rather than a multiplication of probability and product which maximize a pareto front between the two. Additionally, a preference about the winning probability is included. This function debatably worked the best and can potentially expand the number of successful offers by approximately 100% while increasing profit by 34%. The results must be taken with attention because the application yet needs to be tested in the real environment Awan et al. (2022). Moreover, the underlying machine-learning model only performs moderately because the bidding price data does not follow an item-based strategy but rather a general and not differentiated price list. As a result, some form of alteration can be detected in the prediction. Though, in conclusion, the application has shown that it can assist in solving the company's business problem. Moreover, this combinatorial machine learning and genetic algorithm approach to preferential optimal bid pricing would add a novel method to the academic literature that can be applied to a range of other similar auction problems.

6.1. Future research work

An automated warning system might potentially negotiate the consequences. Otherwise, a test of the support tool on a subset of real offers allows the prediction model to be retrained with a more differentiated and hence more decisive pricing input. Another area of study and development could look into whether changing the parameters in the two final objective functions can yield more optimization. An iterative computation for a smaller number of parameter values and a successive comparison could be used as a starting point.Furthermore,one can extend the proposed method to privacy protection related problems.For example, implimentaion of machine learning techniques in constructing dummy query sequences to protect location privacy and query privacy in location-based services.Similierly, A Basic Framework using machine learning for privacy protection in personalized information retrieval should be need to be done on priority basis.

Declarations

Ethics approval and consent to participate

This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of data statement:

All results reported in this research was carried out in R-studio computational environment. Details about data are well explained in data section of this manuscript and files and tables are presented in supplementary material.

Yousaf Ali Khan; I.M. Ashraf: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data. </p>

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Saleem Ahmad: Conceptualization, Formal analysis, Resources, Supervision, Writing – original draft. **Sultan Salem:** Investigation, Software, Visualization, Writing – original draft. **Yousaf Ali Khan:** Conceptualization, Data curation, Formal analysis, Investigation, Writing – review & editing. **I.M. Ashraf:** Data curation, Formal analysis, Funding acquisition, Resources, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e20583.

Abberavations

EEC	Engine Export Company
RRR	Response to Reverse Request
FPSD	First-Price Sealed-Bid
KDD	Knowledge Discovery in Databases
SMOTE	Synthetic Minority Oversampling Technique
GA	Genetic Algorithm
LR	Logistic Regression
OF	Objective Function

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