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Base price determination for IPL mega auctions: A player performance-based approach

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Abstract. Indian Premier League (IPL) is the most popular T20 domestic league in the world. An essential aspect of this league is the "Mega-Auction", which is of focus in this study. The mega auction occurs once every three years, and it is found that the auction process is inefficient as the time taken is long ($\sim$2 days). This is because players specify their base price. Thus, this study focuses on the efficiency of the auction process and addresses it by prescribing the base price for players. The base prices are prescribed such that they are as close to the actual auction price of a player. Accordingly, in the past, only two mega auctions occurred in 2014 and 2018, and both are considered in this work. Here, a two-stage algorithm to determine the base prices of players is proposed. In the first stage, K-Means clustering is used to group players. The base price for players allocated to a cluster is proposed using a developed assignment logic in the second stage. An empirical demonstration of the proposed algorithm indicates that the auction process has been made efficient as the time taken decreases by $\sim$17.6% and $\sim$31.1% for Indian and foreign players, respectively.

Keywords: IPL, mega-auction, base price, clustering

1. Introduction

Sports analytics is a field that applies analysis techniques to past performance data that can provide a competitive advantage to an individual or a team. It became famous following the release of the film Moneyball in 2011. The global sports analytics market was valued at $42.76 million in 2018, and it is projected to hit $6.376 billion by 2026, growing at a CAGR of 40.40% from 2019 to 2026 (Allied Market Research, 2019). There are two types of sports analytics: (1) on-field and (2) off-field. On-field analytics deals with tracking and monitoring a player's performance on the field to predict future performance, strengths, weaknesses, and injuries. This can improve the performance of a team or an individual in a game. Off-field analytics deals with the business side of sports, where a sports organization or a team owner finds patterns or insights in data that could improve their revenue or competitive advantage. This assists in making critical strategic decisions that can improve the profitability of the sports organization.

Cricket, a globally popular team sport, has also incorporated sports analytics in recent times (Kargal, 2021). Currently, the three-game formats at the international level are Test Matches, One-Day Internationals, and Twenty20 (T20). T20 is the newest and shortest version of the three formats. This format of 20 overs per side was introduced in 2005 by the International Cricket Council (ICC). A typical T20 match is for three hours, bringing in new audiences due to its shorter duration. As the game is fast-paced, it demands skill sets like power-hitting, skilful bowling, and outstanding fielding. Therefore, T20

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has had the highest incorporation of analytics (ICC, 2022).

T20 games are played at the international level and in several leagues worldwide. The Indian Premier League (IPL) is one of the most famous annual Twenty20 cricket leagues. IPL began in the year 2008. It was founded by then BCCI vice-president Lalit Modi seeing the popularity boom of T20 in India when the national team won the ICC World T20 (TNN, 2013). The IPL has a global audience, and it is currently the most-watched cricket league in the world (India Today, 2021).

At present, the IPL has eight teams, each representing an Indian city. In the league phase, each team plays against the other twice in a round-robin fashion, and the top four qualify for the playoffs. The playoffs then decide the two teams that will face each other in the IPL Finals, and the winner is crowned "IPL Champions" for that year. IPL is a franchise-based tournament that invites private firms to own them. Investors see value in investing in the tournament as they believe that IPL will continue to grow, given that it is a source of entertainment to millions (Business Today, 2021).

The different franchises will have to create squads for participating in the IPL. The squad creation is through the IPL auction, an exciting part of the tournament. The BCCI conducts the auction to select players from a pool of Indian and overseas players for the eight franchises. The BCCI ensures a fair auction by setting a cap on the budget for all the participating franchises before the auction. In the 2021 IPL auction, the budget for each franchise was Rs. 85 crores. Additionally, a franchise must spend at least 75 percent of the budget. The budget may or may not get revised before an auction. A franchise can have players ranging from 18 to 25 in their respective squads. However, a squad must have at least 17 Indian players and at most 8 overseas players. The Indian players are categorized as capped and uncapped based on whether they have represented their country or not.

We have two types of IPL auctions – mini-auction and mega auction. A mega auction takes place once every three years, while mini auctions are held every year in those three years. In a mini-auction, every franchise has the right to retain or release any number of players. Nevertheless, in a mega auction, a franchise can only retain a maximum of five players by a combination of direct retention and Right To Match (RTM). Direct retention allows a team to retain a maximum of three players before the auction. RTM is another option to retain a player by matching the highest bid amount by another team during the auction. Teams that have already retained three players by direct retention can use two RTM cards, while teams with less than three can opt for three RTM cards. Each team can retain a maximum of 3 capped Indian players, 2 overseas players, and 2 uncapped Indian players.

The IPL auction is a one-day or a two-day long event, depending on whether it is a mini or mega auction that year. Before the process, an initial list of players who register for the auction will be shortlisted based on the lists provided by each franchise. Players come in sets on the first day of the auction. The auction starts with marquee players who are top performers in T20 cricket. This lot is followed by separate lots of batsmen, all-rounders, wicketkeepers, fast bowlers, and spinners. Each of these lots contains both capped and uncapped Indian players and overseas players. Once these players have been presented in the auction, the eight franchises can select a set of players from the remaining unsold players by the end of the first day. These players will go under the hammer the next day as part of the accelerated bidding process. Before such a long process, an important aspect is that the base price of players must be decided. The base price ranges between Rs. 20 Lakhs to Rs. 200 Lakhs. Players can decide upon their base prices, but they must be carefully chosen considering their performance history and recent form. Else they might risk getting unsold (Katewa, 2021).

This study aims to assist the auction process of IPL by suggesting a player's base price. For the suggestion of the base price, past IPL performance data are utilized. If the suggested base price is as close to the actual auctioned price, then the auction duration is shortened. Moreover, since the base price is suggested based on past IPL performance, it will ensure that good-performing players have improved base prices, while players with average performance (even if they are big names in the sport) have a base price adjusted based on recent performance.

The following section presents a literature review related to the problem. Section 3 discusses the problem of focus in detail. The methodology to address the focused problem, along with an illustration, is presented in Section 4. The illustration is done using real-life data collected from past IPL tournaments. Hence, the results from the illustration are also presented in the same section. The paper concludes in Section 5, where the significance and limitations of this work, along with the future scope, are presented.

2. Literature review

Since the new millennium, data analytics has taken over nearly every sport at almost every level (Navarro, 2020). There have been several studies on the analysis of sports. A study by Apostolou and Tjortjis (2019) attempted on predicting the performance of individual soccer players based on the previous season's data. In the game of soccer, another research, Pantzalis and Tjortjis, 2020, studied two fundamental cases of sports analytics: team performance prediction and player performance prediction. Here, advanced statistics are used on the previous season's data for prediction.

Plumley et al. (2018) analyse the competitive balance in the English Football League system using the Herfindahl Index of Competitive Balance (HICB). The study identified that "English Premier League" stands out as the least balanced league in English football among the four leagues. Coluccia et al. (2018) attempt to financially evaluate a goalkeeper of a Series A-League club using an option-pricing model. Mu (2016) proposes an Analytical Hierarchy Process (AHP) for selecting the Golden Ball winner. This is applied to the 2014 FIFA Golden Ball selection, and the potential winners are suggested based on their attack, defence, and fair play performance. Easton & Newell (2019) took an altogether different problem of fantasy sports and analysed whether daily fantasy sports are gambling or not.

Coming to cricket, a study by Anik et al. (2018) does performance prediction of players in ODI cricket using machine learning algorithms. Studies by Barot et al. (2020), Kapadia et al. (2020), and Senevirathne and Manage (2021) focus on predicting the outcome of a game, specifically in limited-overs cricket. Jayanth et al. (2018) proposed a model for match outcome prediction, team structure analysis, and player recommendation systems. Support vector machine (SVM) is used for ranking the players and k-means clustering is used for the player recommendation system. Wickramasinghe (2020) uses the naive bayes approach to predict the winner of an ODI match and achieves its highest accuracy of 85.71% using the univariate feature selection method. Davis et al. (2015) introduce a new metric for player evaluation called "expected run differential" in T20 cricket.

The niche area of the auction in IPL has been studied from time to time. Dey et al. (2014) designed a model based on Analytical Hierarchy Process (AHP) and Artificial Neural Network (ANN) for estimating players' prices in IPL. First, AHP measures the weights of the attributes responsible for player price estimation, and following that ANN is used to forecast the player price with the weights calculated by AHP.

Chauhan et al. (2018) focus on applying operations research to the concept of IPL auction. The objective of this research is to use operations research in player valuation. Various methods are used to develop the model, such as performance-based index, hedonic pricing, ordinary least squares regression technique, and AHP-ANN model. The Performance-Based Index combines batting, bowling, and wicket-keeping skills to form one index and quantify their performances to find the price they deserve. The Hedonic Pricing model considers the internal and external factors in developing the valuation. The Least Square Regression model accounts for the players' experience, performance, and characteristics to evaluate the players. The AHP-ANN model assists in handling the complexity and selecting the attributes for player price calculation.

Rani et al. (2020) focused on applying various machine learning algorithms to predict the bid price of a player participating in an IPL auction. The bid price for a player is estimated using a player's past performance parameters. The machine learning algorithms in the paper are Decision Tree Regressor, K-Nearest Neighbours (KNN), Linear Regression, Stochastic Logistic Regression, Random Forest Regressor, and Support Vector Regression (SVR). SVR and Linear Regression stood out for giving the best results.

The study by Das et al. (2021) shows how a modified hedonic model and a robust machine learning technique, i.e. XGBoost Learning, can be efficient in the price prediction of players in an IPL auction. This modified hedonic model extends the classic hedonic model, which aims to find the coefficients of independent variables and output a new price for cricketers.

Till now, the research in IPL auctions is all about predicting a player's bid price. The study by Kansal et al. (2014) addresses the base price prediction in IPL auctions. The study predicts the base price of players in IPL using the data mining technique. Several predictive models have been built to predict a player's selection in the Indian Premier League based on each player's past performance. The data used consists of playing factors from all the two formats of the game, namely ODI and T20 cricket. The playing factors such as average, strike rate, number of wickets, catches, etc., were utilized to predict the selection of batsmen, bowlers, and all-rounders in the teams. The core idea of the study is to assign players to a base group among a set of fixed five base groups. The base groups range from Rs. 30 Lakh to Rs. 200 Lakh. Data mining tools were used to predict the base price group for players. Three algorithms are applied, namely decision tree, naïve Bayes, and Multi-Layer Perceptron (MLP), on the data set to predict the base price of players. The algorithms are applied to batsmen, bowlers, and all-rounder data set, respectively. For the batsmen dataset, the highest accuracy is shown by MLP, which is 94.18%. Similarly, for bowlers and all-rounders datasets, the highest accuracies are shown by MLP, and they are 94.44% and 97.95%, respectively. The study concludes that MLP had shown the best accuracy for any category of players.

Kansal et al. (2014) can be considered the basis for this study. However, in this current study, the scope for base price prediction is far more extensive than the one addressed by Kansal et al. (2014). This is because the study by Kansal et al. (2014) only assigns players to base groups based on past performance. In this work, the past performance of players is used to arrive at a specific base price for the player in the current auction. This base price is also expected to be closer to the actual auction price of the player. Moreover, new base groups may be created using the arrived base prices if required.

3. Problem formulation

The IPL Auctions are the forum where different franchises engage in an open bidding process to acquire players for creating the respective squads. In this auction, the base price for players is declared before the auction process. A player's base price is the price at which a franchise starts bidding for that player. The base price range is between Rs. 20 Lakhs to Rs. 200 Lakhs. The large range is because of the different types of players: Overseas and Indian players being auctioned. Overseas players are non-Indian citizens who represent different national teams across the globe. These overseas players can set their base price within the given range. Indian players are Indian citizens playing at the international level as part of the Indian National Team and/or playing domestic cricket in India as part of different state associations. The Indian players who have represented the country as a part of the country's international team are called "Capped players", while those who have not been are called "Uncapped players". The base price of Indian players is communicated to the BCCI by the players themselves (Sportskeeda, 2021). Currently, the base price for uncapped players can be one of the following: Rs. 20 Lakhs, Rs. 30 Lakhs, or Rs. 40 Lakhs. In the case of capped players, the base price can be Rs. 50 Lakh, Rs. 75 Lakh, Rs. 100 Lakh, Rs. 150 Lakh, and Rs. 200 Lakh, (Malvania, 2019). To the best of our knowledge, no source in the open forum specifies how the base prices are determined for the different players by the BCCI.

The different franchise bid for players in the bidding process, and bids increase by Rs. 5 Lakh for every bid till Rs. 100 Lakh. After Rs. 100 Lakhs, the bid increases by Rs. 10 Lakh till Rs. 200 Lakh. Beyond Rs. 200 Lakh, the increase is by Rs. 20 Lakh for every bid till Rs. 1000 Lakh. After Rs. 1000 Lakhs, bids increase by Rs. 50 Lakh till the player gets sold. (Cricbuzz, 2018)

The above IPL auction is an extravagant event, and it is of two types: "Mega-auction" and "Mini-auction". More than 500 players will go under the hammer in a mega-auction, and around 300 players can be expected in a mini-auction. A franchise uses the mega auction to completely rebuild their squad, except for a few retained players who are retained. Mini auctions are meant to fill small gaps in the existing squad of a franchise's team. A mini-auction can be conducted in a day, while mega-auctions take double the time to get completed, excluding the time taken by franchises to get prepared before those two days. BCCI has two entire days before the IPL to conduct the mega auction. However, from an IPL management perspective, auction conduct time can be considerably reduced if the base price for the player is as close to the actual selling price. Thus, determining an ideal base price would translate to a reduction in the number of bids for a player. This can drastically reduce the total time taken for an auction. From an IPL management perspective, the determination of base price for a player is more imperative than determining the actual auctioned price for the same player. This is because, player auction prices are driven by non-tangible factors such as "Player Popularity", "Franchise Requirements", etc. Hence, an error in determining the auction price would drastically affect the revenue streams.

Therefore, this study aims to bridge the gap in determining the base prices for players in an analytic and data-driven fashion. To this end, an algorithm to predict the base price close to a player's auctioned price is proposed. The proposed algorithm uses past IPL performance and auction data of players. The core of this proposed algorithm consists of two stages, the first is clustering, and the second is base price prediction. Players are grouped into clusters in the clustering stage based on their overall IPL experience. After this clustering, the base price of a player participating in an upcoming mega auction is determined using a developed assignment logic. This assignment logic identifies a similar player within the same cluster as the current player by utilizing past IPL performance characteristics. Once a similar player is identified, the previous year's auction price of this similar player is assigned as the base price for the current player. The above algorithm is explained in detail in the subsequent sections.

4. Methodology and illustration

4.1. Algorithm

To determine the base price, an algorithm with two stages is proposed. The first stage of the algorithm focuses on clustering players of the auction. The second stage determines the base price for players, within a cluster, by using a developed assignment logic.

Past mega-auction data is utilized in the clustering stage to create player clusters based on "IPL experience". In this study, IPL experience is quantitively measured as the total number of balls a player has bowled and/or faced irrespective of their role (Batsman, Bowler, All-Rounder, or Wicketkeeper). This IPL experience is computed for the duration after the past mega auction and until the current mega-auction. This implies that the IPL experience for a mega-auction conducted in 2018 is computed using 2015, 2016, and 2017. This is because the previous mega auction occurred in 2014. In IPL history, only two mega auctions have occurred. One in 2014 and the other in 2018. Hence, in the clustering stage, clusters are created based on the IPL experience for 2014.

For 2014, "n1" players auctioned are grouped into "k" clusters based on the IPL experience computed from the data of 2013, 2012, and 2011. Here, intuitively, the IPL experience indirectly captures the different player types. For determining the k-clusters, a K-Means clustering is adopted. This is a non-hierarchical clustering technique, and k-clusters are created such that the total intra-cluster variance is minimal. Say,

$P = \{\mathrm{p} \mid \mathrm{p}$ is a player auctioned off in the past IPL mega Auction (here it is the 2014 IPL auction), and $1 \leq \mathrm{p} \leq \mathrm{n}_1\}$

$Z = \{\mathrm{z} \mid \mathrm{z}$ is a cluster of players auctioned off in the past IPL mega Auction (here it is the 2014 IPL auction), and $1 \leq \mathrm{z} \leq \mathrm{k}\}$

$\mathrm{PE_p}$ – Past IPL Experience of a player-p in IPL seasons before the past mega auction (here it is from 2011 to 2013)

$\mathrm{AP_p}$ – Auction Price for player-p in the past IPL mega Auction (here it is for the 2014 IPL mega Auction)

$\mathrm{C_z}$ – Centroid of a cluster-z

$\mathrm{A_{pz}}$ – Assignment of player-p to cluster-z for the past mega auction (here it is 2014 IPL mega Auction)

where $A_{pz} = \begin{cases} 1, \ if \ z = argmin_j \left\| PE_p - C_z \right\|^2 \\ \qquad 0, \ otherwise \end{cases}$

Then, the objective of minimizing total intra-cluster variance can be computed as given in (1)

$$Total\ Intra - Cluster\ Variance = \sum_{z=1}^{k} \sum_{p=1}^{n} A_{pz} \left\| PE_p - C_z \right\|^2 \quad (1)$$

K-Means clustering is a nonhierarchically clustering technique, and the following procedure is adopted to identify the ideal number of clusters-k.

Say,

$X = \{\mathrm{x} \mid \mathrm{x}$ is a player in the training set and $x \in P\}$

$Y = \{\mathrm{y} \mid \mathrm{y}$ is a player in the testing set, and $y \in P$, such that $\mathrm{Y\text{-}X} = \{\}\}$

$\mathrm{AP_x}$ – Auction Price for player-x in the training set

$\mathrm{AP_y}$ – Auction Price for player-p in the testing set

Then, since three possible player roles exist, the algorithm is set to have a minimum of 3 clusters (initial value for k is 3). "k" is then increased up to 14, because after 14 clusters less than five players will be allocated to different clusters which are undesirable for the next stage of the algorithm. For each value of k, the following procedure is followed to identify the players in each cluster.

Step-1: Split the past IPL mega auction data in an 80:20 ratio, where 80% of the dataset goes into the training set-X and the remaining 20% goes into the testing set-Y.

Step-2: Apply K-Means clustering on the training set-X and assignment logic on the testing set-Y.

Step-3: Calculate the ratio of the number of correct predictions and the total number of predictions. A prediction is said to be correct when the predicted auction price for a player (in Y) is less than or equal to the actual auction price for the player (in P).

Step-4: Repeat the above three steps a large number of times (say 100 times) and compute the average of ratios calculated in Step-3.

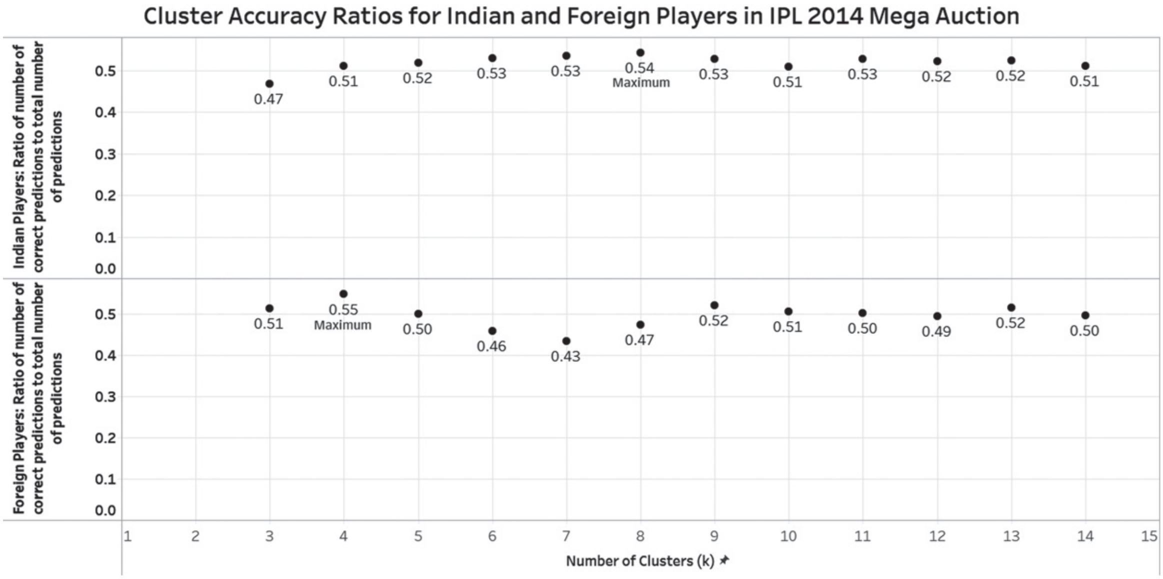

Fig. 1. Cluster accuracy ratios for Indian and Foreign players in 2014 IPL mega auction.

The results from the above algorithm are plotted as a graph as shown in Fig. 1, with the number of clusters on the x-axis and the average of the ratios on the y-axis. The number of clusters which has the maximum average ratio is the ideal number of clusters for the data set at hand.

By adopting the above procedure, "n1" players who appeared in the past IPL mega auction can be grouped into k-clusters based on the past IPL experience "PE_p". Using the identified clusters, in the second stage of the algorithm, the base price for players being auctioned in the current mega auction is assigned based on player attributes. Player attributes refer to the different measurable performances such as the number of balls faced, fours scored, wickets taken by a player, etc. These attributes enable the algorithm to identify similar players and assign base prices accordingly. For the base price assignment, a rule-based approach is developed. The assignment stage of the algorithm consists of 5-steps.

Say,

$Q = \{$q | q is a player to be auctioned in the current mega auction (here it is 2018 IPL mega auction), and $1 \leq q \leq n_2\}$ $L = \{$l | l is an attribute of a player's performance, and $1 \leq l \leq 14\}$

CE_q – Current IPL Experience of a player-q in IPL seasons between the past and current mega auctions (Here it is from 2015 to 2017)

BP_q – Base Price for player-q in the current mega auction (here it is 2018 IPL mega auction)

CA_{qz} – Assignment of player-q to cluster-z for the current mega auction (here it is 2018 IPL mega auction)

VA_{lp} – Value of attribute-l for player-p

VA_{lq} – Value of attribute-l for player-q

Then the 5-steps in the assignment stage of the algorithm are as follows:

Step-1: Player-q is assigned to a cluster-z such that the Euclidean distance between "C_z" and IPL experience "CE_q" is minimal.

Step-2: Within the assigned cluster-z, player-q is matched to the nearest similar player-p. This is achieved by minimizing the Euclidean distance (given in (2)) across all attributes.

$$Euclidean\ distance = \sqrt[2]{\sum_{l=1}^{14} \left(VA_{lq} - VA_{lp}\right)^2} \quad (2)$$

Note: If the player-q is already in cluster-z as player-þ based on $PE_{þ}$, then the above matching is conducted after removing player-þ from the cluster. This is done to ensure that the mapping is unbiased.

Step-3: AP_p for player-p is assigned as the BP_q for player-q.

Step-4: Repeat Steps 1 to 4 for all the n2 players in set-Q.

Once the above procedure is completed, the base prices for all the players being auctioned will be available for the IPL management. Therefore, the proposed two-stage algorithm can be summarised as:

Clustering stage (Stage-1): Create clusters using IPL experience from the immediate past mega auction.

Assignment stage (Stage-2): Allocate current players being auctioned to previously determined clusters by using IPL experience. Identify the most similar player within the allocated cluster, and assign their auction price as the base price for the current player.

Both accuracy and efficiency need to be verified to establish the utility of the proposed algorithm. The accuracy of the proposed algorithm can be measured by comparing the actual IPL auction price and the proposed base price for a player. If the proposed base price is less than or equal to the actual auction price, then the algorithm is accurate. Efficiency can be established by calculating the difference between the number of actual bids and the number of bids when the base price equals the one suggested by the algorithm. The above difference must be positive or zero for the algorithm to be efficient. This indicates that the algorithm has saved time by proposing a base price closer to the actual auction price than the existing policy for assigning a base price.

4.2. Data collection and pre-processing

To demonstrate the two-stage algorithm proposed for base price determination, primary data is collected from “cricsheet.org” and web scrapped from “iplt20.com”. From the two websites, two data sets are obtained. The first data set, obtained from “cricsheet.org”, contains ball-by-ball information on every IPL match played from 2008 to 2017. The second dataset from “ipl20.com” contains the auction information of players sold in two (2014 and 2018) IPL mega auctions. Snapshots of the above two datasets are presented respectively in Tables 1 and 2.

The ball-by-ball information in the first dataset is processed to consolidate three-year values, before the respective mega auction, for each player’s attribute. Hence, for a player being auctioned in 2014, consolidation consists of values in each attribute for the years 2011, 2012, and 2013. Similarly, for the 2018 mega auction, consolidation in each attribute is for the years 2015 to 2017. Here, attributes are the characteristics that best depict a player’s performance. The chosen 14 attributes and their descriptions are presented in Table 3. The 14 attributes are chosen as they are (1) commonly referred to when introducing players during an IPL game, and (2) they capture player characteristics. The processed first data set is merged with the auction data for the respective mega auctions. This generates a data set, henceforth referred to as “Player Dataset“, which is utilized by the algorithm. A snapshot of the player dataset is provided in Table 4. The player dataset consists of 149 Indian players, out of which 76 and 73 are the number of players sold in the mega auction of 2014 and 2018, respectively. Additionally, there are 69 Overseas players, out of which 33 and 36 are the number of players sold in the mega auction 2014 and 2018, respectively. The above data processing is carried out through a developed python script.

4.3. Demonstration

The player dataset created in the previous subsection is utilized to demonstrate the proposed algorithm’s workability and establish its effectiveness. Here, the player dataset is separated into Indian and Foreign players, and the algorithm is implemented separately for the two types of players. This is because the base price of Indian and Foreign players is significantly different in IPL. Accordingly, for the split datasets, the mega auction conducted in 2014 is utilized to create the clusters at the clustering stage of the proposed algorithm. A plot of player experiences (PE_p) for 76 Indian and 33 Foreign players is presented in Fig. 2 and Fig. 3, respectively. With this, the clustering stage is executed, and the accuracies for the different number of clusters are presented in Table 5. The ideal number of clusters for Indian players is 8, and that of Foreign players is 4. The number of players in each of these clusters is presented in Table 6.

At the 2018 mega auction, 73 Indian and 36 Foreign players were auctioned. These players are assigned to the 8 Indian clusters and 4 Overseas clusters based on their experience (CE_q) in the IPL seasons from 2015 to 2017. It is interesting to note that the number of clusters for Indian and Foreign players differs. A possible reason for this could be the squad requirement (at least 17 players must be Indian, and at most 8 players are Foreign). There is a larger and more closely associated pool of Indian players. Thus, a franchise may be more liberal when bidding for Indian players. On the contrary, a franchise may be more cautious in picking a foreign player because both the number of available slots and the number of available players are lesser.

Next, the base price for each player is determined by identifying similar players based on the attributes.

Table 1
Sample ball-by-ball data obtained from cricsheet.org

Match ID	Inning	Batting team	Bowling team	Over	Ball	Batsman	Non-striker	Bowler	Is it a super over	Wide runs	Bye runs	Leg bye runs	No-ball runs	Penalty runs	Batsman runs	Extra runs	Total runs	Player dismissed	Dismissal kind	Fielder	Year
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	1	1	SC Ganguly	BB McCullum	P Kumar	0	0	0	1	0	0	0	1	1				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	1	2	BB McCullum	SC Ganguly	P Kumar	0	0	0	0	0	0	0	0	0				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	1	3	BB McCullum	SC Ganguly	P Kumar	0	1	0	0	0	0	0	1	1				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	1	4	BB McCullum	SC Ganguly	P Kumar	0	0	0	0	0	0	0	0	0				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	1	5	BB McCullum	SC Ganguly	P Kumar	0	0	0	0	0	0	0	0	0				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	1	6	BB McCullum	SC Ganguly	P Kumar	0	0	0	0	0	0	0	0	0				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	1	7	BB McCullum	SC Ganguly	P Kumar	0	0	0	1	0	0	0	1	1				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	2	1	BB McCullum	SC Ganguly	Z Khan	0	0	0	0	0	0	0	0	0				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	2	2	BB McCullum	SC Ganguly	Z Khan	0	0	0	0	0	0	4	0	4				2008
60	1	Kolkata Knight Riders	Royal Challengers Bangalore	2	3	BB McCullum	SC Ganguly	Z Khan	0	0	0	0	0	0	4	0	4				2008

Table 2
A sample data on player-wise auction price in previous mega auctions

Player name	Auction year	Country	Auction price
A Ashish Reddy	2014	Indian	20,00,000
A Choudhary	2018	Indian	30,00,000
A Dananjaya	2018	Overseas	50,00,000
A Mishra	2014	Indian	4,75,00,000
A Mishra	2018	Indian	4,00,00,000
A Nehra	2014	Indian	2,00,00,000
AB Dinda	2014	Indian	1,50,00,000
AD Nath	2018	Indian	1,00,00,000
AD Russell	2014	Overseas	60,00,000
AG Paunikar	2014	Indian	20,00,000

The base price for a player in the 2018 mega auction is set to be the auction price of a similar player in the 2014 mega auction. The similar players identified for 73 Indian and 36 Foreign players are presented in Table 7. Table 7 also provides the proposed base price for 73 Indian and 36 Foreign players and their actual base and actual auction prices in the 2018 mega auction. The implementation of the proposed algorithm is through a developed python script.

From Table 7, out of 73 Indian players and 36 Foreign players:

- The algorithm has improved the base price for 54 Indian players and 21 Foreign players, i.e., the predicted base price is less than or equal to the actual auction price for these players. Therefore, the base price is not higher than the actual auction price for ∼74% of the Indian players and

Table 3
List of player attributes considered in this study

S. no	Attribute	Attribute description
1	Total_runs	Total runs scored by the player
2	0s	Total number of dot balls faced by the player
3	Running	Total number of ones and twos run by the player
4	4s	Total fours scored by the player
5	6s	Total sixes hit by the player
6	Dots_bowl	Total number of balls bowled by the player without conceding runs
7	Wides	Total wide balls bowled by the player
8	No_balls	Total no balls bowled by the player
9	Runs_conceded	Total number of runs that the opposing side have scored while the player was bowling, excluding any byes, leg byes, or penalty runs.
10	Extra_runs_conceded	Total number of runs that the opposite side have scored through wides and no balls
11	Wkts	Total number of wickets taken by the player
12	Bowled	Total number of wickets taken when the player's legitimate delivery hit the stumps
13	Caught	Total number of wickets taken when the ball is caught by either the player who bowled or the fielder, after the opponent player hits the ball
14	Boundaries_conceded	Total number of fours and sixes scored by the opposing side while the player was bowling

$\sim$58% of the Foreign players. This indicates the accuracy of the algorithm.

- Among the 54 players, the algorithm underpredicted the base prices for 21 Indian players and 5 Foreign players, i.e., the predicted base price is less than the actual base price and actual auction price. For the remaining 33 players, the new predicted base price is improved compared to the actual base price.
- The algorithm has decreased the time taken for the entire auction process by $\sim$17.6% and $\sim$31.1% for Indian and Foreign players, respectively. The time taken for the auction process is calculated in terms of the number of auction calls. The actual time taken for Indian and Foreign players is 1237 and 494, respectively. If the proposed base prices were used, the time taken is 1019 and 340 for Indian and Foreign players, respectively. This decrease in the time taken proves the efficiency of the algorithm.
- A deeper analysis of the 19 Indian players whose proposed base price is higher than their actual auction price indicates the following:

  - Out of the 19 players, 10 were uncapped players, and 9 were capped players.
  - The uncapped players have performed well, and hence they are matched with players with reputations and higher auction prices. However, all uncapped players have gone either at their base price or very low incremental prices.

Furthermore, the results obtained for the 2022 Mega Auction through the proposed algorithm are presented in Annexure 1 (2022 mega auction data was unavailable at the time of submission). From Exhibits 1 and 2 (in Annexure-1), the following observations are made for the 72 Indian and 38 Foreign players auctioned in 2022:

- The algorithm has improved the base price for 44 Indian players and 22 Foreign players, i.e., the predicted base price is less than or equal to the actual auction price for these players. Therefore, the base price is not higher than the actual auction price for $\sim$61% of the Indian players and $\sim$58% of the Foreign players. This indicates the accuracy of the algorithm.
- The algorithm has decreased the time taken for the entire auction process by $\sim$34.4% and $\sim$27% for Indian and Foreign players, respectively. The time taken for the auction process is calculated based on the number of auction calls. The actual auction calls for Indian and Foreign players are 1317 and 621, respectively. If the proposed base prices were used, the auction calls would be 864 and 453 for Indian and Foreign players, respectively. This decrease proves the efficiency of the algorithm.

Table 4

A sample data on the consolidated three-year values, before the respective mega auction, for each attribute of a player

Name	Auction year	Balls faced	Total runs	0s	Running	1s	2s	4s	6s	Balls bowled	Dots bowled	Wides
A Ashish Reddy	2014	118	160	38	80	51	13	11	6	203	65	7
A Choudhary	2018	20	25	4	15	13	1	1	1	101	42	6
A Dananjaya	2018	0	0	0	0	0	0	0	0	0	0	0
A Mishra	2014	163	173	76	91	69	11	19	1	974	370	10
A Mishra	2018	78	61	42	41	33	4	2	2	750	246	23
A Nehra	2014	20	12	13	8	6	1	1	0	504	183	10
AB Dinda	2014	21	11	13	7	7	0	1	0	540	207	22
AD Nath	2018	28	20	14	16	10	3	1	0	0	0	0
AD Russell	2014	40	58	14	28	16	6	3	3	138	38	3
AG Paunikar	2014	57	49	40	13	9	2	9	0	0	0	0

No. of	Runs balls	Extra runs conceded	Total runs conceded	Wickets conceded	Bowled	Caught	Boundaries conceded	4s conceded	6s conceded	Country	Role	Price
2	298	9	307	14	4	7	36	21	15	Indian	Bowler	20,00,000
1	137	7	144	5	0	5	19	13	6	Indian	Bowler	30,00,000
0	0	0	0	0	0	0	0	0	0	Overseas	Bowler	50,00,000
6	1113	16	1129	53	9	29	114	65	49	Indian	Bowler	4,75,00,000
2	972	25	997	32	4	15	108	65	43	Indian	Bowler	4,00,00,000
2	706	12	718	22	4	17	103	76	27	Indian	Bowler	2,00,00,000
8	756	30	786	30	6	23	113	88	25	Indian	Bowler	1,50,00,000
0	0	0	0	0	0	0	0	0	0	Indian	All-rounder	1,00,00,000
1	225	4	229	1	0	1	35	29	6	Overseas	All-rounder	60,00,000
0	0	0	0	0	0	0	0	0	0	Indian	Wicket keeper	20,00,000

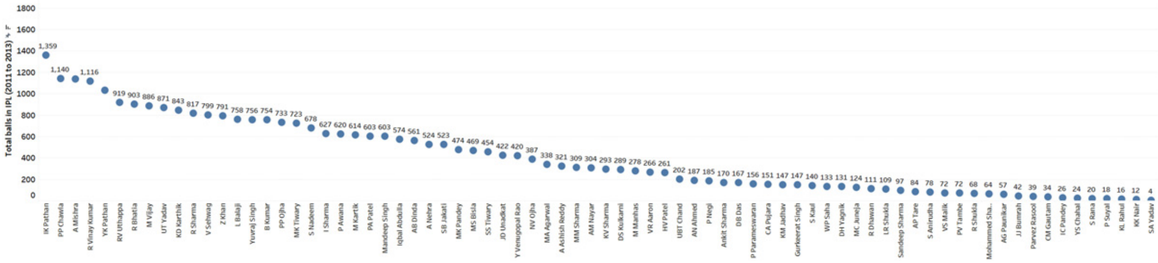

Fig. 2. Indian players IPL experience (from IPL 2011 to IPL 2013).

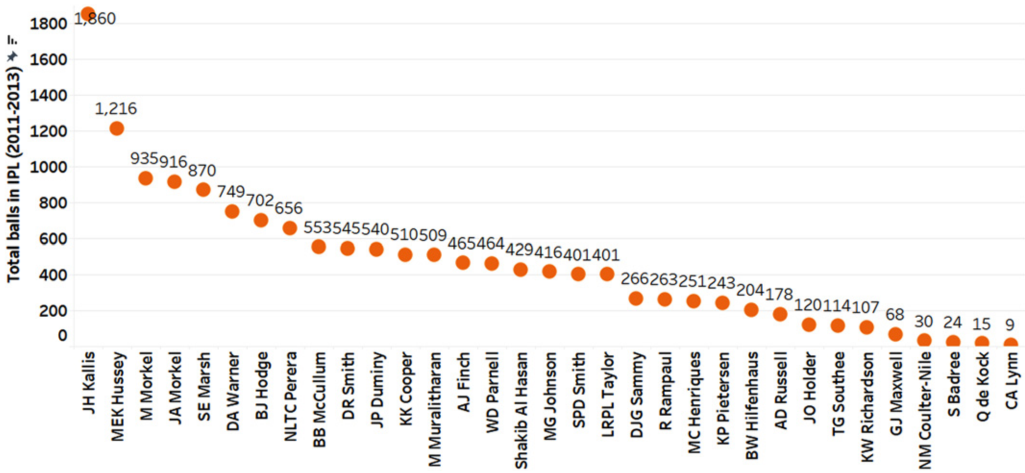

Fig. 3. Foreign players IPL experience (from IPL 2011 to IPL 2013).

Table 5
Summary of the number of clusters and the accuracies for Indian and Foreign players

Number of clusters (k)	Accuracy for Indian players	Accuracy for Foreign players
3	0.4668	0.5143
4	0.5097	**0.5486**
5	0.5172	0.4999
6	0.5289	0.4593
7	0.5338	0.4343
8	**0.5430**	0.4743
9	0.5265	0.5214
10	0.5093	0.5057
11	0.5266	0.5028
12	0.5212	0.4943
13	0.5231	0.5161
14	0.5112	0.4975

The demonstration for the 2022 mega auction further strengthens the reliability of the proposed model.

Therefore, from the above demonstration, it is evident that the proposed algorithm assists in predicting the base price for the players in an auction.

5. Conclusion

This study focuses on the problem of base price determination for an IPL mega auction. The problem is addressed from the perspective of improving

Table 6
Summary of number of Indian and Foreign players in the cluster

Cluster number for Indian players	Number of Indian players auctioned in 2018 mapped to that cluster	Cluster number for Foreign players	Number of Foreign players auctioned in 2018 mapped to that cluster
0	12	0	17
1	14	1	0
2	5	2	14
3	0	3	5
4	7	Only 4 clusters for foreign players	
5	20		
6	10		
7	5		

the efficiency of the auction process by reducing the time of the auction. Accordingly, the study proposes a two-stage algorithm for base price prediction. The first stage of the algorithm is clustering. The second stage is a developed assignment logic. The players are clustered into groups at the clustering stage based on the IPL experience. The IPL experience is computed based on the number of balls a player has played (batsman have faced and bowlers have bowled) in the time frame of three years between the previous two IPL mega auctions. The clusters are formed using the K-Means clustering technique. Next, the players about to be auctioned in the current IPL mega auction are assigned to the determined clusters by computing their IPL experience in the IPLs between the previous mega-auction and the current mega auction (three IPL years). After this assignment, the second stage of the algorithm is utilized. In this stage, the players assigned to the clusters are matched to the closest player in that cluster based on IPL performance. Once the closest player has been matched, the previous mega auction's actual price is allocated as the base price for the player in the current auction.

The proposed two-stage algorithm is demonstrated using real-life IPL data. The mega-auction data is collected for the past two mega-auctions in 2014 and 2018. The player performance is computed from data collected for IPL matches between 2011 to 2018. Using the above data, two performance measures for the proposed algorithm are estimated. The first is accuracy, and the second is efficiency. Here accuracy refers to the ability of the algorithm to arrive at a base price that is not higher than the actual auction price of the player. The efficiency refers to the ability of the algorithm to reduce the auction time by suggesting a base price that is as close to the actual auction price of the player. Accordingly, from the demonstration, it is evident that the proposed approach has an accuracy of $\sim$74% and $\sim$58% for predicting the base price of Indian and Foreign players, respectively. Moreover, the algorithm decreases the time taken for the auction process by $\sim$17.6% and $\sim$31.1% for Indian and Foreign players, respectively. Analysis of the 2022 mega auction data aligns with the results of the 2018 mega auction.

Therefore, from the demonstration, it is evident that the proposed algorithm effectively addresses the concern of base price determination. Nevertheless, it is also evident that accuracy ($\sim$74%) needs attention. As there are only three past IPL mega auctions as references for this study, the concrete establishment of accuracy and efficiency is not yet possible. Moreover, to the best of our knowledge, this is the first study that focuses on base price determination. This is in contrast to the present practice where the players themselves set the base price in IPL. Thus, it is believed that future work can focus on improving accuracy. Further, the current work is suitable only for determining the base price for players with IPL experience. It is not applicable for new entrants without IPL experience. Therefore, to address these concerns, experience from other sources (T20 leagues in other countries for foreign players and domestic T20 leagues for uncapped Indian players) can be explored. Additionally, future work may also consider the exploration of modelling the IPL as a Vickrey auction so that true player values may be determined.

Table 7

Proposed base prices, actual base & auction prices and algorithm efficiency for players participating in 2018 IPL Mega Auction

S. no	Player	Country	Identified most similar player	Actual base price (in million Rupees)	Proposed base price (in million Rupees)	Actual auction price (in million Rupees)	Actual time taken for auction	Time taken with the proposed base price
1	A Choudhary	Indian	AN Ahmed	3000000	3000000	3000000	0	0
2	A Mishra	Indian	UT Yadav	15000000	26000000	40000000	15	7
3	AD Nath	Indian	Parvez Rasool	2000000	9500000	10000000	16	1
4	AM Rahane	Indian	YK Pathan	20000000	32500000	40000000	10	4
5	AP Tare	Indian	AG Paunikar	2000000	2000000	2000000	0	0
6	AS Rajpoot	Indian	S Kaul	3000000	4500000	30000000	29	26
7	AT Rayudu	Indian	Mandeep Singh	5000000	8000000	22000000	21	15
8	Ankit Sharma	Indian	AN Ahmed	2000000	3000000	2000000	0	0
9	Anureet Singh	Indian	A Nehra	3000000	20000000	3000000	0	0
10	Avesh Khan	Indian	VS Malik	2000000	2000000	7000000	10	10
11	BB Sran	Indian	HV Patel	5000000	4000000	22000000	21	23
12	Basil Thampi	Indian	A Ashish Reddy	3000000	2000000	9500000	13	15
13	Bipul Sharma	Indian	HV Patel	2000000	4000000	2000000	0	0
14	DJ Hooda	Indian	JD Unadkat	4000000	28000000	36000000	30	4
15	DL Chahar	Indian	R Shukla	2000000	4000000	8000000	12	8
16	DS Kulkarni	Indian	P Awana	5000000	6500000	7500000	5	2
17	G Gambhir	Indian	YK Pathan	20000000	32500000	28000000	4	0
18	Gurkeerat Singh	Indian	P Negi	5000000	2000000	7500000	5	11
19	HV Patel	Indian	A Nehra	2000000	20000000	2000000	0	0
20	Harbhajan Singh	Indian	PP Chawla	20000000	42500000	20000000	0	0
21	IR Jaggi	Indian	KK Nair	2000000	7500000	2000000	0	0
22	Ishan Kishan	Indian	MA Agarwal	4000000	16000000	62000000	43	25
23	J Yadav	Indian	LR Shukla	5000000	15000000	5000000	0	0
24	JD Unadkat	Indian	VR Aaron	15000000	20000000	115000000	48	43
25	KD Karthik	Indian	Mandeep Singh	20000000	8000000	74000000	27	41
26	KH Pandya	Indian	Yuvraj Singh	4000000	140000000	88000000	56	0

(*Continued*)

Table 7
(*Continued*)

S. no	Player	Country	Identified most similar player	Actual base price (in million Rupees)	Proposed base price (in million Rupees)	Actual auction price (in million Rupees)	Actual time taken for auction	Time taken with the proposed base price
27	KK Nair	Indian	Mandeep Singh	5000000	8000000	56000000	38	32
28	KL Rahul	Indian	Y Venugopal Rao	20000000	5500000	110000000	42	61
29	KM Jadhav	Indian	A Ashish Reddy	20000000	2000000	78000000	29	55
30	KV Sharma	Indian	M Kartik	20000000	10000000	50000000	15	25
31	Kuldeep Yadav	Indian	HV Patel	15000000	4000000	58000000	24	41
32	M Ashwin	Indian	S Kaul	2000000	4500000	22000000	27	22
33	M Vijay	Indian	PA Patel	20000000	14000000	20000000	0	6
34	M Vohra	Indian	MA Agarwal	2000000	16000000	11000000	17	0
35	MA Agarwal	Indian	M Manhas	2000000	3000000	10000000	16	14
36	MK Pandey	Indian	Mandeep Singh	10000000	8000000	110000000	52	56
37	MK Tiwary	Indian	DS Kulkarni	5000000	11000000	10000000	10	0
38	MM Sharma	Indian	R Vinay Kumar	15000000	28000000	24000000	7	0
39	Mandeep Singh	Indian	MA Agarwal	5000000	16000000	14000000	14	0
40	Mohammed Shami	Indian	A Ashish Reddy	10000000	2000000	30000000	15	31
41	Mohammed Siraj	Indian	P Parameswaran	10000000	3000000	26000000	13	27
42	N Rana	Indian	MA Agarwal	2000000	16000000	34000000	33	11
43	NV Ojha	Indian	KV Sharma	7500000	37500000	14000000	9	0
44	P Negi	Indian	M Kartik	5000000	10000000	10000000	10	0
45	P Sahu	Indian	AN Ahmed	2000000	3000000	2000000	0	0
46	PA Patel	Indian	Mandeep Singh	10000000	8000000	17000000	7	11
47	PJ Sangwan	Indian	P Parameswaran	3000000	3000000	15000000	19	19
48	PP Chawla	Indian	M Kartik	10000000	10000000	42000000	21	21
49	R Ashwin	Indian	Iqbal Abdulla	20000000	6500000	76000000	28	45
50	R Tewatia	Indian	Parvez Rasool	2000000	9500000	30000000	31	16
51	R Vinay Kumar	Indian	HV Patel	10000000	4000000	10000000	0	12
52	RA Tripathi	Indian	DS Kulkarni	2000000	11000000	34000000	33	16
53	RD Chahar	Indian	Mohammed Shami	2000000	42500000	19000000	25	0
54	RV Uthappa	Indian	V Sehwag	20000000	32000000	64000000	22	16
55	S Dhawan	Indian	YK Pathan	20000000	32500000	52000000	16	10
56	S Gopal	Indian	PV Tambe	2000000	2000000	2000000	0	0

57	S Kaul	Indian	P Parameswaran	3000000	3000000	38000000	33	33
58	S Nadeem	Indian	VR Aaron	4000000	20000000	32000000	28	6
59	SA Yadav	Indian	A Ashish Reddy	3000000	2000000	32000000	30	32
60	SN Thakur	Indian	VR Aaron	7500000	20000000	26000000	18	3
61	SS Tiwary	Indian	MA Agarwal	5000000	16000000	8000000	6	0
62	STR Binny	Indian	JD Unadkat	5000000	28000000	5000000	0	0
63	SV Samson	Indian	Mandeep Singh	10000000	8000000	80000000	40	44
64	Sachin Baby	Indian	AN Ahmed	2000000	3000000	2000000	0	0
65	Sandeep Sharma	Indian	Z Khan	5000000	26000000	30000000	25	2
66	T Natarajan	Indian	YS Chahal	4000000	2000000	4000000	0	4
67	UT Yadav	Indian	Z Khan	10000000	26000000	42000000	21	8
68	V Shankar	Indian	CM Gautam	4000000	2000000	32000000	28	32
69	WP Saha	Indian	Mandeep Singh	10000000	8000000	50000000	25	29
70	Washington Sundar	Indian	LR Shukla	15000000	15000000	32000000	11	11
71	YK Pathan	Indian	R Bhatia	7500000	17000000	19000000	14	2
72	YS Chahal	Indian	UT Yadav	20000000	26000000	60000000	20	17
73	Yuvraj Singh	Indian	Mandeep Singh	20000000	8000000	20000000	0	14
74	AJ Finch	Foreign	DR Smith	15000000	45000000	62000000	26	9
75	AJ Tye	Foreign	DJG Sammy	10000000	35000000	72000000	36	19
76	B Stanlake	Foreign	TG Southee	5000000	12000000	5000000	0	0
77	BA Stokes	Foreign	BJ Hodge	20000000	24000000	125000000	45	43
78	BB McCullum	Foreign	DA Warner	20000000	55000000	36000000	8	0
79	BCJ Cutting	Foreign	KP Pietersen	10000000	90000000	22000000	11	0
80	C Munro	Foreign	KW Richardson	5000000	10000000	19000000	19	9
81	CA Lynn	Foreign	KP Pietersen	20000000	90000000	96000000	38	3
82	CH Gayle	Foreign	DA Warner	20000000	55000000	20000000	0	0
83	CJ Jordan	Foreign	GJ Maxwell	10000000	60000000	10000000	0	0
84	CR Brathwaite	Foreign	KP Pietersen	10000000	90000000	20000000	10	0
85	CR Woakes	Foreign	KW Richardson	20000000	10000000	74000000	27	37
86	DA Miller	Foreign	NLTC Perera	15000000	16000000	30000000	10	9
87	DJ Bravo	Foreign	JA Morkel	20000000	24000000	64000000	22	20
88	DT Christian	Foreign	DJG Sammy	10000000	35000000	15000000	5	0
89	GJ Maxwell	Foreign	NLTC Perera	20000000	16000000	90000000	35	39
90	Imran Tahir	Foreign	NLTC Perera	10000000	16000000	10000000	0	0
91	JC Buttler	Foreign	DR Smith	15000000	45000000	44000000	17	0
92	JJ Roy	Foreign	KP Pietersen	15000000	90000000	15000000	0	0
93	JP Duminy	Foreign	Shakib Al Hasan	10000000	28000000	10000000	0	0

(*Continued*)

Table 7
(*Continued*)

S. no	Player	Country	Identified most similar player	Actual base price (in million Rupees)	Proposed base price (in million Rupees)	Actual auction price (in million Rupees)	Actual time taken for auction	Time taken with the proposed base price
94	K Rabada	Foreign	KW Richardson	15000000	10000000	42000000	16	21
95	KA Pollard	Foreign	JA Morkel	20000000	24000000	54000000	17	15
96	KS Williamson	Foreign	Shakib Al Hasan	15000000	28000000	30000000	10	1
97	MA Starc	Foreign	R Rampaul	20000000	9000000	94000000	37	49
98	MG Johnson	Foreign	JP Duminy	20000000	22000000	20000000	0	0
99	MP Stoinis	Foreign	JP Duminy	20000000	22000000	62000000	21	20
100	Mohammad Nabi	Foreign	R Rampaul	5000000	9000000	10000000	10	2
101	Mustafizur Rahman	Foreign	M Muralitharan	10000000	10000000	22000000	11	11
102	NM Coulter-Nile	Foreign	BJ Hodge	15000000	24000000	22000000	6	0
103	PJ Cummins	Foreign	NLTC Perera	20000000	16000000	54000000	17	21
104	Q de Kock	Foreign	DR Smith	20000000	45000000	28000000	4	0
105	SR Watson	Foreign	JA Morkel	10000000	24000000	40000000	20	8
106	SW Billings	Foreign	MC Henriques	10000000	10000000	10000000	0	0
107	Shakib Al Hasan	Foreign	NLTC Perera	10000000	16000000	20000000	0	0
108	TA Boult	Foreign	JP Duminy	15000000	22000000	22000000	10	4
109	TG Southee	Foreign	JP Duminy	10000000	22000000	10000000	6	0

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ANNEXURE-1

Exhibit 1: Proposed base, actual & auction prices and algorithm efficiency for Indian players auctioned in the 2022 IPL Mega Auction

S. no	Player	Country	Identified most similar player	Actual base price (in million Rupees)	Proposed base price (in million Rupees)	Actual auction price (in million Rupees)	Actual time taken for auction	Time taken with the proposed base price
1	Mohammed Shami	Indian	MM Sharma	20000000	24000000	62500000	0	0
2	WP Saha	Indian	SS Tiwary	10000000	8000000	19000000	6	0
3	J Yadav	Indian	STR Binny	10000000	5000000	17000000	24	9
4	V Shankar	Indian	KV Sharma	5000000	50000000	14000000	49	43
5	VR Aaron	Indian	PJ Sangwan	5000000	15000000	5000000	0	0
6	Gurkeerat Singh	Indian	STR Binny	5000000	5000000	5000000	66	60
7	DL Chahar	Indian	Sandeep Sharma	20000000	30000000	1.4E+08	11	26
8	AT Rayudu	Indian	KV Sharma	20000000	50000000	67500000	0	0
9	S Dube	Indian	STR Binny	5000000	5000000	40000000	31	6
10	RV Uthappa	Indian	SV Samson	20000000	80000000	20000000	29	11
11	S Singh	Indian	R Vinay Kumar	2000000	10000000	2000000	34	39
12	Jagadeesan	Indian	Gurkeerat Singh	2000000	7500000	2000000	48	43
13	KM Asif	Indian	S Gopal	2000000	2000000	2000000	0	0
14	Deshpande	Indian	RA Tripathi	2000000	34000000	2000000	0	0
15	SN Thakur	Indian	UT Yadav	20000000	42000000	1.08E+08	35	24
16	K Ahmed	Indian	UT Yadav	5000000	42000000	52500000	42	31
17	C Sakariya	Indian	AS Rajpoot	5000000	30000000	42000000	51	52
18	KS Bharat	Indian	Gurkeerat Singh	2000000	7500000	20000000	0	0
19	Kuldeep Yadav	Indian	P Sahu	10000000	2000000	20000000	7	17
20	KL Nagarkoti	Indian	Basil Thampi	4000000	9500000	11000000	8	0
21	Mandeep Singh	Indian	A Choudhary	5000000	3000000	11000000	0	0
22	Lalit Yadav	Indian	Kuldeep Yadav	2000000	58000000	6500000	37	6
23	Praveen Dubey	Indian	Anureet Singh	2000000	3000000	5000000	8	0
24	SN Khan	Indian	Gurkeerat Singh	2000000	7500000	2000000	0	0
25	RV Patel	Indian	SN Thakur	2000000	26000000	2000000	2	0
26	SS Iyer	Indian	AM Rahane	20000000	40000000	1.23E+08	18	19
27	N Rana	Indian	Harbhajan Singh	10000000	20000000	80000000	32	42
28	UT Yadav	Indian	PJ Sangwan	20000000	15000000	20000000	14	9
29	AM Rahane	Indian	MK Tiwary	10000000	10000000	10000000	13	2
30	M Shahrukh Khan	Indian	N Rana	4000000	34000000	90000000	0	0
31	S Dhawan	Indian	AM Rahane	20000000	40000000	82500000	26	15
32	RD Chahar	Indian	Harbhajan Singh	7500000	20000000	52500000	0	0
33	H Brar	Indian	Gurkeerat Singh	2000000	7500000	38000000	36	5
34	Prabhsimran Singh	Indian	R Vinay Kumar	2000000	10000000	6000000	10	26
35	Sandeep Sharma	Indian	PP Chawla	5000000	42000000	5000000	9	0
36	Avesh Khan	Indian	STR Binny	2000000	5000000	1E+08	22	0
37	KH Pandya	Indian	P Negi	20000000	10000000	82500000	11	4
38	DJ Hooda	Indian	STR Binny	7500000	5000000	57500000	3	0

(*Continued*)

ANNEXURE-1

(*Continued*)

S. no	Player	Country	Identified most similar player	Actual base price (in million Rupees)	Proposed base price (in million Rupees)	Actual auction price (in million Rupees)	Actual time taken for auction	Time taken with the proposed base price
39	MK Pandey	Indian	MM Sharma	10000000	24000000	46000000	57	28
40	K Gowtham	Indian	Mohammed Shami	5000000	30000000	9000000	0	0
41	S Nadeem	Indian	P Sahu	5000000	2000000	5000000	23	11
42	AS Rajpoot	Indian	PJ Sangwan	2000000	15000000	5000000	11	15
43	M Vohra	Indian	MA Agarwal	2000000	10000000	2000000	22	20
44	Ishan Kishan	Indian	YK Pathan	20000000	19000000	1.53E+08	40	30
45	M Ashwin	Indian	A Mishra	2000000	40000000	16000000	18	0
46	JD Unadkat	Indian	YK Pathan	7500000	19000000	13000000	50	29
47	M Markande	Indian	Basil Thampi	5000000	9500000	6500000	8	0
48	Basil Thampi	Indian	PJ Sangwan	3000000	15000000	3000000	6	4
49	Anmolpreet Singh	Indian	MA Agarwal	2000000	10000000	2000000	0	0
50	HV Patel	Indian	PP Chawla	20000000	42000000	1.08E+08	15	15
51	KD Karthik	Indian	YK Pathan	20000000	19000000	55000000	33	29
52	M Lomror	Indian	Gurkeerat Singh	4000000	7500000	9500000	55	6
53	S Kaul	Indian	Mohammed Siraj	7500000	26000000	7500000	32	17
54	KV Sharma	Indian	Basil Thampi	5000000	9500000	5000000	0	0
55	P Krishna	Indian	UT Yadav	10000000	42000000	1E+08	0	0
56	D Padikkal	Indian	KK Nair	20000000	56000000	77500000	32	22
57	YS Chahal	Indian	Harbhajan Singh	20000000	20000000	65000000	30	30
58	R Ashwin	Indian	Harbhajan Singh	20000000	20000000	50000000	11	0
59	R Parag	Indian	STR Binny	3000000	5000000	38000000	0	0
60	N Saini	Indian	UT Yadav	7500000	42000000	26000000	0	6
61	KK Nair	Indian	Gurkeerat Singh	5000000	7500000	14000000	0	0
62	KC Cariappa	Indian	RA Tripathi	2000000	34000000	3000000	0	0
63	K Yadav	Indian	M Ashwin	2000000	22000000	2000000	42	31
64	Washington Sundar	Indian	R Ashwin	15000000	76000000	87500000	45	35
65	RA Tripathi	Indian	KD Karthik	4000000	74000000	85000000	0	0
66	Abhishek Sharma	Indian	STR Binny	2000000	5000000	65000000	20	0
67	B Kumar	Indian	DS Kulkarni	20000000	7500000	42000000	0	5
68	T Natarajan	Indian	Kuldeep Yadav	10000000	58000000	40000000	14	0
69	Kartik Tyagi	Indian	Mohammed Shami	2000000	30000000	40000000	0	0
70	S Gopal	Indian	KV Sharma	2000000	50000000	7500000	9	13
71	Priyam Garg	Indian	NV Ojha	2000000	14000000	2000000	39	6
72	J Suchith	Indian	Anureet Singh	2000000	3000000	2000000	23	23

Exhibit 2: Proposed base, actual & auction prices and algorithm efficiency for Foreign players auctioned in the 2022 IPL Mega Auction

S. no	Player	Country	Identified most similar player	Actual base price (in million Rupees)	Proposed base price (in million Rupees)	Actual auction price (in million Rupees)	Actual time taken for auction	Time taken with the proposed base price
1	L Ferguson	Foreign	Shakib Al Hasan	20000000	20000000	1E+08	17	0
2	DA Miller	Foreign	KS Williamson	10000000	30000000	30000000	4	9
3	A Joseph	Foreign	K Rabada	7500000	42000000	24000000	13	4
4	JJ Roy	Foreign	SW Billings	20000000	10000000	20000000	8	0
5	DJ Bravo	Foreign	GJ Maxwell	20000000	90000000	44000000	15	0
6	CJ Jordan	Foreign	CR Woakes	20000000	74000000	36000000	22	0
7	M Santner	Foreign	AJ Tye	10000000	72000000	19000000	12	0
8	AF Milne	Foreign	CJ Jordan	15000000	10000000	19000000	13	0
9	MR Marsh	Foreign	CR Brathwaite	20000000	20000000	65000000	0	5
10	DA Warner	Foreign	DJ Bravo	20000000	64000000	62500000	0	0
11	Mustafizur Rahman	Foreign	PJ Cummins	20000000	54000000	20000000	1	0
12	TL Seifert	Foreign	CJ Jordan	5000000	10000000	5000000	30	40
13	L Ngidi	Foreign	CJ Jordan	5000000	10000000	5000000	29	3
14	PJ Cummins	Foreign	GJ Maxwell	20000000	90000000	72500000	0	5
15	SW Billings	Foreign	Mohammad Nabi	20000000	10000000	20000000	0	5
16	TG Southee	Foreign	CJ Jordan	15000000	10000000	15000000	0	10
17	Mohammad Nabi	Foreign	DT Christian	10000000	15000000	10000000	39	44
18	L Livingstone	Foreign	JJ Roy	10000000	15000000	1.15E+08	29	3
19	K Rabada	Foreign	SR Watson	20000000	40000000	92500000	37	27
20	J Bairstow	Foreign	AJ Finch	15000000	62000000	67500000	40	40
21	NT Ellis	Foreign	C Munro	7500000	19000000	7500000	53	48
22	IC Porel	Foreign	CJ Jordan	2000000	10000000	2500000	0	0
23	JO Holder	Foreign	JP Duminy	15000000	10000000	87500000	31	0
24	E Lewis	Foreign	JJ Roy	20000000	15000000	20000000	9	0
25	TH David	Foreign	CJ Jordan	4000000	10000000	82500000	23	23
26	J Archer	Foreign	TG Southee	20000000	10000000	80000000	0	0
27	DR Sams	Foreign	AJ Tye	10000000	72000000	26000000	0	0
28	RP Meredith	Foreign	CJ Jordan	10000000	10000000	10000000	47	47
29	FA Allen	Foreign	CJ Jordan	7500000	10000000	7500000	0	0
30	JR Hazlewood	Foreign	AJ Tye	20000000	72000000	77500000	27	0
31	S Rutherford	Foreign	CR Brathwaite	10000000	20000000	10000000	0	0
32	J Behrendorff	Foreign	B Stanlake	7500000	5000000	7500000	38	43
33	S Hetmyer	Foreign	SW Billings	15000000	10000000	85000000	0	0
34	TA Boult	Foreign	TG Southee	20000000	10000000	80000000	0	10
35	JDS Neesham	Foreign	CJ Jordan	15000000	10000000	15000000	30	40
36	N Pooran	Foreign	DT Christian	15000000	15000000	1.08E+08	0	5
37	M Jansen	Foreign	AJ Tye	5000000	72000000	42000000	54	42
38	AK Markram	Foreign	C Munro	10000000	19000000	26000000	0	0