МАТЕМАТИЧЕСКОЕ МОДЕЛИРОВАНИЕ

MATHEMATICAL MODELING

UDC 519.833, 519.863
https://doi.org/10.37661/1816-0301-2026-23-2-80-93

Received | Поступила в редакцию 01.04.2026
Accepted | Подписана в печать 07.05.2026
Published | Опубликована 30.06.2026

Application of Tullock Contest Success Function to transaction fee optimization in high-throughput networks

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Abstract

Objectives. This paper investigates the feasibility of applying a Contest Success Function (CSF) to optimize priority fee expenditures in blockchain networks utilizing priority fee auctions. We analyze the model's ability to describe the relationship between "effort" (bid amount) and the probability of successful transaction inclusion.

Methods. We conducted an experiment to compare the efficiency of the canonical CSF model (Tullock contest strategy) against a baseline strategy – a simple average of the target percentile derived from historical data. Both strategies utilized context gathered from historical datasets to generate bid proposals for the subsequent block. Performance was evaluated based on two primary metrics: the average effort (mean bid size) and the success rate (the percentage of bids successfully landing within the target percentile). The experiment comprised a total of 632 rounds of bid generation.

Results. The experimental trials yielded performance metrics indicating that the canonical CSF model is well-suited for cost optimization in priority fee auctions. Specifically, strategies with decisiveness parameters $R = 10$ and $R = 20$ demonstrated the most favorable results. Furthermore, a positive correlation was observed between the decisiveness parameter R and the strategy's performance; a decrease in the value of R led to a corresponding decline in the strategy's efficiency for cost optimization.

Conclusion. The experimental results demonstrate the overall effectiveness of the canonical CSF for optimizing priority fee expenditures. This approach is particularly relevant for sectors with rapidly advancing blockchain integration, most notably financial services, investment management, and trading. However, it is worth noting that the proposed methodologies are agnostic to specific implementations or projects; they are applicable to any network that implements a transaction prioritization mechanism via additional fees. There remains significant scope for further research, including the introduction of novel performance metrics, the use of more specialized datasets, and the investigation of different historical context window sizes for the model.

Keywords: blockchain, Contest Success Function, Tullock model, percentile, game theory, non-cooperative game, auction, conflicts

For citation. Bokun A. G. *Application of Tullock Contest Success Function to transaction fee optimization in high-throughput networks*. Informatika [*Informatics*], 2026, vol. 23, no. 2, pp. 80–93 (In Russ.). https://doi.org/10.37661/1816-0301-2026-23-2-80-93.

Conflict of interests. The author declares of no conflict of interest.

Применение функций успеха в соревновании для оптимизации транзакционных сборов в сетях с высокой пропускной способностью

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Аннотация

Цели. Целью работы является исследование возможности применения модели описания зависимости вероятности победы от приложенных усилий для оптимизации затрат на приоритетную отправку транзакций в сетях с аукционом приоритезирующих комиссий. Анализируется способность модели описывать взаимосвязь между некоторым «усилием» (в данном случае предложенной ценой) и вероятностью успешного включения транзакции в блок.

Методы. В рамках исследования был проведен эксперимент, где сравнивалась эффективность математической модели CSF (Contest Success Function, функция успеха в соревновании) в каноническом виде (модель Таллока) и конкурирующая стратегия – получение простого среднего по целевому процентилю на исторических данных. Для работы двух стратегий был собран контекст из исторических данных, на основании которого модели делали свои предложения ставок на следующий блок. Оценка была проведена по двум критериям: среднее значение приложенных усилий (средний размер ставки) и процент попаданий в целевой процентиль. Всего было проведено 632 раунда, когда участвующие стратегии предлагали свои ставки.

Результаты. Получены показатели по проведенным испытаниям. Эти данные позволяют сказать, что CSF в каноническом виде подходит для задач оптимизации затрат на участие в приоритезирующих аукционах. Стратегии с параметрами эффективности $R = 10$ и $R = 20$ продемонстрировали лучшие результаты. Кроме этого, было замечено, что с уменьшением параметра эффективности R падает и эффективность стратегии в решении задачи оптимизации.

Заключение. Исходя из полученных результатов можно сделать вывод об общей эффективности CSF в каноническом виде для оптимизации затрат на приоритезирующие комиссии. Данный подход будет особенно полезен в областях, где активно развивается работа с блокчейном. В первую очередь это сфера работы с финансовым и инвестиционным капиталом, а также трейдинг. Однако стоит отметить, что предложенные методики никак не привязаны к конкретным реализациям или проектам. Они будут работать в любых сетях, которые имплементируют механизм приоритизации пропуска транзакций через дополнительные сборы. В дальнейшем остается пространство для углубления исследований: введения новых характеристик оценки эффективности стратегий, использования более специализированных наборов данных, изменения размера контекста исторических данных для модели.

Ключевые слова: блокчейн, Contest Success Function, модель Таллока, процентиль, теория игр, бескоалиционная игра, аукцион

Для цитирования. Бокун, А. Г. Применение функций успеха в соревновании для оптимизации транзакционных сборов в сетях с высокой пропускной способностью/ А. Г. Бокун // Информатика. – 2026. – Т. 23, № 2. – С. 80–93. – https://doi.org/10.37661/1816-0301-2026-23-2-80-93.

Конфликт интересов. Автор заявляет об отсутствии конфликта интересов.

Introduction

Today, blockchain networks are gaining increasing institutional adoption, not merely as investment vehicles or stores of value, but as robust infrastructure for payment processing. Consequently, transaction processing speed has become one of the most critical performance characteristics of modern networks. Projects such as The Solana blockchain network (Solana network) and The Open Network (TON) place a significant emphasis on throughput, specifically modifying consensus algorithms and imposing rigorous hardware requirements on node operators. Another instrument for accelerating transaction finalization is the use of priority fees. The network allows the sender to pay an additional fee to increase their probability of winning the auction for transaction inclusion in the upcoming block. Since network validators are incentivized to prioritize transactions with higher priority fees, users can significantly expedite the execution of their transactions.

The mechanism of these auctions, in turn, creates a complex problem: achieving a desired inclusion percentile[1] typically requires higher fee expenditures to ensure timely transaction processing. This problem can be addressed by framing the auction as a contest – a game-theoretic model where participants compete for a prize by exerting efforts. Contest models are employed across diverse fields, ranging from real estate leasing to conflict studies. In these models, the magnitude of the effort exerted directly influences a participant's probability of winning. The mechanism that formalizes this relationship between the probability of winning and the effort expended is the Contest Success Function (CSF), which serves as a cornerstone of such game-theoretic frameworks.

Most existing research on CSF, ranging from foundational texts to contemporary studies, focuses on applying these models to macro-level problems in economics and strategic conflict. The base concept of the CSF originally emerged from efforts to describe the behavior of large economic agents competing for existing resources. In particular, Gordon Tullock’s seminal works explore the rent-seeking behavior of such agents [1]. Other research in this field extends the application of CSF to issues of various economic spheres: from taxation to bankruptcy proceedings [2].

[1]A percentile is a value that separates the bottom N% of the data from the rest of the results.

A distinct area of study involves the use of CSF within conflict theory, where it is frequently employed to analyze military engagements [3]. For instance, in the work of V. V. Shumov, the CSF is validated using data from military operations of World War I and World War II [4]. However, it should be noted that the number of publications applying CSF to real-world contemporary economic data remains remarkably small; most existing literature focuses primarily on the theoretical modeling of conflicts, contests, and auctions. The novelty of this research lies in the adaptation of the CSF to the micro-level task of real-time transaction fee estimation.

The objective of this paper is to investigate various functions that describe the relationship between the probability of winning and the effort exerted within a contest model, and to evaluate their practical utility and competitiveness within the Solana network environment.

Fees and Auctions in Solana network

Fees represent a fundamental component of the Solana network. They enable the network to perform load balancing during spikes and lulls in activity, prevent malicious transaction broadcasting intended to congest the network (spam mitigation), and provide economic incentives for validators. The fee structure comprises two distinct elements:

base fee – the mandatory standard charges for transaction processing;

priority fee – optional additional fees paid to increase transaction priority [5].

The base fee is a fixed charge levied on the transaction's originating account (or accounts) for the utilization of network infrastructure and resources. Currently[2], the base fee is set at 5,000 lamports (0.000005 SOL) per transaction signer (typically, there is only one). As previously noted, this fee is static and remains independent of the actual amount of computational resources consumed by the transaction.

The volume of resources required to execute a transaction in Solana network is measured in Compute Units (CU)[3]. Thus, Compute Units serve as a metric for the computational complexity of a transaction. The CU count is determined dynamically through an analysis of the executable program's bytecode. The Solana Virtual Machine (SVM) operates using SBF (Solana Bytecode Format), which is a modified version of the Linux eBPF[4] bytecode. Each SBF instruction has an associated approximate cost in CU; the total transaction cost is the sum of the costs of all operations within its instructions, plus additional overhead (e.g., system calls, Cross-Program Invocation (CPI) operations, and data transmission size).

The incentive structure of the reward system is designed such that it is suboptimal for validators to prioritize transactions with high CU requirements when the base fee remains fixed and uniform for all. To quantify a validator's incentive to include a specific transaction, we propose a metric representing the cost per single CU: *the Compute Unit Price*:

$$cu_{price} = \frac{\sum \phi_n}{cu_{count}}, \quad \phi_n \in \Phi, \tag{1}$$

where cu_{price} is the price per single CU;

[2]Solana Fees in Theory and Practice. Available at: https://tinyurl.com/39z3mz7v (accessed 23.01.2026).
[3]Lifecycle of a Solana Transaction. Available at: https://tinyurl.com/mrxpbhfh (accessed 23.01.2026).
[4]Solana Documentation. Programs. Available at: https://tinyurl.com/2d34z28u (accessed 23.01.2026).

cu_{count} is the total number of CUs consumed by the transaction;

ϕ_n is an element of the set Φ, which includes all transaction-related fees (base fees, priority fees, validator-specific tips, etc.).

To address the issue of CU devaluation in computationally intensive transactions, the priority fee mechanism was introduced as an optional feature. The essence of this mechanism lies in increasing the value of $\sum \phi_n$ from equation (1) by incorporating a new fee component – the priority fee – into the set Φ[5].

Typically, the priority fee is calculated as the product of the total CU count and the desired price per unit of CU (excluding base fees, which are constant). It is specified in microlamports to ensure it can always be represented as an unsigned integer.

The priority fee mechanism only partially addresses the issue of excessive prioritization for lightweight transactions. Certain services, such as Decentralized Exchanges (DEXs), generate a high volume of simple swaps involving specific accounts, which can hinder the inclusion of critical transactions even when they carry high priority fees. To mitigate this, a further optimization was introduced: *local fee markets*[6].

The essence of this mechanism lies in partitioning the network into numerous segments centered around specific accounts (for instance, those belonging to the aforementioned DEXs) and establishing an isolated auction for transaction inclusion within each segment. Consequently, only homogeneous transactions compete against one another, allowing the priority fee mechanism to function with greater precision. Each segment maintains its own execution queue, which ensures the timely delivery of transactions to the validator.

Contest Success Function

In game theory, there is a well-established game-theoretic framework for analyzing conflicts by representing them as contests. A contest is defined as a game in which participants exert effort to secure a specific prize [3]. This model is extensively applied across various fields, ranging from military conflict and economic activity to evolutionary biology.

To model such games, a class of functions is employed that maps the formalized efforts of players to their respective probabilities of winning the competition. These are known as CSF [4].

Let us consider an effort vector G, containing numerical representations of the efforts exerted by players to secure winning in the contest. Furthermore, let each player i have a corresponding win probability p_i.

It is important to note that for a more systematic approach to constructing a CSF, three fundamental axioms have been established [6]. These axioms define the baseline conditions for conducting contest-based games:

Axiom 1. *The win probability $p_i > 0$ if the effort $G_i > 0$. Furthermore, there is no scenario in which a winner is not determined:*

$$\sum_{i=1}^{n} p_i = 1. \tag{2}$$

[5]Solana Fees in Theory and Practice. Available at: https://tinyurl.com/39z3mz7v (accessed 23.01.2026).

[6]The Truth about Solana Local Fee Markets. Available at: https://tinyurl.com/ar4ytw6p (accessed 23.01.2026).

Axiom 2. *For all* $i \in N$*, the probability* p_i *is monotonically increasing in* G_i *and monotonically decreasing in* G_j*, for all* $i \neq j$.

Axiom 3. *For any permutation* π*, the following equality holds:*

$$p_{\pi(i)}(G) = p\left(G_{\pi_1}, G_{\pi_2}, \ldots, G_{\pi_T}\right), \qquad \forall\, i \in N. \tag{3}$$

In summary, the first axiom and condition (2) demonstrate that a CSF (let it be a generic function *f*(*x*) for better representation) satisfies the two fundamental criteria of a Probability Density Function (PDF), namely:

Non-negativity – the function satisfies $f(x) \geq 0$ for all x;

Determinism (Normalization) – the sum of outcomes for all possible x $\sum f(x) = 1$ or $\int f(x)dx = 1$, for continuous sets.

In the context of the CSF, the parameter x represents G_i.

Axiom 2 asserts that a player's win probability increases relative to their own effort and decreases relative to the efforts of other players. Axiom 3 describes a crucial condition for conducting a contest: *anonymity*. This dictates that a player's probability of winning must not depend on their identity or the identities of their opponents; only the exerted efforts should be of consequence.

Furthermore, for the sake of simplicity, let us assume (4) that each game involves a minimum of two players:

$$|G| \geq 2. \tag{4}$$

Consequently, the CSF in its general form [2] can be expressed as follows:

$$p_i = \frac{f_i(G_i)}{\sum_{j=1}^{n} f_j(G_j)}, \qquad \forall\, i = 1, \ldots, n. \tag{5}$$

It can be observed that the CSF incorporates a function f_i, known as the *efficiency function*, which describes exactly how the efforts exerted in the game are distributed. In other words, the presence of an efficiency function allows the abstract model to be adapted to various subject areas and to describe them with greater precision. It is crucial to remember that the efficiency function itself must satisfy the CSF axioms.

A canonical example of the efficiency function can be found in the work of Gordon Tullock [1]. He applied the CSF to the rent-seeking market. His version (6) involves raising the measure of effort to a certain scalar power R:

$$p_i = \frac{{G_i}^R}{\sum_{j=1}^{n} {G_j}^R}, \qquad \forall\, i = 1, \ldots, n. \tag{6}$$

The scalar R how discriminatory the CSF is, it is used to increase the sensitivity of CSF to changing incoming bids. A higher value of R amplifies the advantage of superior bids, making the auction more deterministic, while a lower R introduces a higher degree of stochasticity into the selection process. In other words, in the limit as R approaches infinity, higher bids win with probability 1, otherwise, in the limit as R approaches zero, each bid wins with probability $\frac{1}{n}$ where n is a general number of bids in the auction.

As an alternative that is more sensitive to small variations in effort, the logit model (7) is used [2]. In this case (7), the evaluation incorporates not only a certain scalar but also exponents:

$$p_i = \frac{e^{kG_i}}{\sum_{j=1}^{n} e^{kG_j}}, \qquad \forall\, i = 1, \dots, n. \tag{7}$$

Some functions (8) suggest applying individual efficiency metrics expressed through weights $w_j > 0$ instead of common scalars for each participant. These weights serve as an indicator of an individual player's personal efficiency:

$$p_i = \frac{G_i w_i}{\sum_{j=1}^{n} G_j w_j}, \qquad \forall\, i = 1, \dots, n. \tag{8}$$

In some cases (9), games account for a personal bias coefficient $a_i > 0$:

$$p_i = \frac{G_i w_i + a_i}{\sum_{j=1}^{n} G_j w_j + a_j}, \qquad \forall\, i = 1, \dots, n. \tag{9}$$

Options (8) and (9) are frequently combined with the Tullock efficiency function:

$$p_i = \frac{{G_i}^R w_i + a_i}{\sum_{j=1}^{n} {G_j}^R w_j + a_j}, \qquad \forall\, i = 1, \dots, n. \tag{10}$$

In general, any combinations that do not violate the established CSF axioms are permissible. Occasionally, certain efficiency functions emerge that fall outside the standard CSF framework. For instance, there is a model (11) asserting that the difference in effort is the sole determinant of the game's outcome [2]:

$$p_1 = p_1(\sigma G_1 - G_2), p_2 = 1 - p_1, \tag{11}$$

where σ is a common scalar.

Problem Statement

As previously established, auctions for transaction inclusion in blocks occur permanently within each individual local fee market. A distinctive feature of these auctions is that participants can increase their probability of winning by increasing their bid per CU. In other words, there is a direct correlation between the CU price in a transaction and the probability of that transaction being included in a block.

This scenario presents a classic non-cooperative game, where CSF can be applied to describe the dependence between the proposed price and the probability of success (inclusion in a block). The objective of further research will be to evaluate the overall effectiveness of the CSF in solving the problem of optimal fee calculation. By that we mean determining the minimum CU price required to ensure transaction inclusion with a predefined probability threshold. Subsequently, it is necessary to determine which specific functional form of the CSF provides the most accurate model based on the efficiency metric.

The most effective solution will be defined as the one that maximizes the ratio of the success rate (inclusion within the target percentile) to the average proposed CU price over a statistically significant sample of transactions. This efficiency metric is formalized by expression:

$$h = \frac{c}{B_{avg}} \cdot 10000, \tag{12}$$

where c – the success rate, percentage of transactions successfully included in the target percentile;

B_{avg} – the average predicted CU price (average bid).

Therefore, the coefficient h represents the cost-efficiency of the strategy, measured as the success rate per unit of the average bid. It quantifies the yield of inclusion probability relative to the expenditure per CU.

That is, we have two main tasks:

1. Comparative effectiveness analysis: to evaluate the performance of the CSF in predicting optimal transaction fees relative to a baseline solution (the simple moving average of historical fees).

2. Structural optimization: to conduct a comparative assessment of various CSF configurations (by varying the decisiveness parameter R) to identify the functional form that yields the highest predictive accuracy and economic efficiency (using the criterion (12) for estimation).

Working Model

To reiterate, for the purposes of this task, we define the following parameters:

target percentile – the percentile value is determined arbitrarily (set to 70 % for this experiment) and is calculated across all transactions within a block;

winning in the contest – the inclusion of a transaction into the blockchain block within a target percentile;

measure of effort – the price in microlamports offered per CU in the transaction.

A critical feature of the Solana local fee market auction is that the number of participants is not known in advance. This is a significant challenge for the CSF model, which typically assumes a visible (non-hidden) game. To address this, we propose an historical data analysis approach.

While we lack real-time data on current bidders, the blockchain provides a transparent record of participants and their bids in previous blocks. This allows us to calculate the win probability for a hypothetical incoming bid based on past performance.

The approach is as follows: Let B be a specific incoming bid, and BH be a historical dataset of the T most recent blocks (thus $|BH| = T$). From BH, we extract a subset BH_t of size n (the size may vary) representing the bids data from a specific block t. The probability of winning for bid B in block t can then be calculated using formula:

$$P_t(B) = \frac{f(B)}{f(B) + \sum_{j=1}^{n} f\left(BH_{tj}\right)}. \tag{13}$$

Consequently, to estimate the total win probability of bid B in the current auction, we can use the mean value of the probability estimates derived from past auctions. The estimation of the probability is described by expression:

$$\hat{P}(B) = \frac{1}{T}\sum_{t=1}^{T} P_t(B). \tag{14}$$

A bid B is considered optimal if it is the minimum possible entry bid such that its win probability $\hat{P}(B)$ is greater than or equal to a pre-defined target inclusion probability P_{target}. The formal condition:

$$B_{opt} = argmin_B\{B \mid \hat{P}(B) \geq P_{target}\}. \tag{15}$$

Experimental Design

To test the effectiveness[7] of the win probability predictions, a series of trials will be conducted. In these trials, transaction fees will be calculated using a CSF with various classical efficiency functions. A distinct set of tests will be performed for each efficiency function to evaluate its performance independently.

The trial itself will consist of an auction emulation task within the Solana network. The goal is to predict the CU price (in microlamports) required to reach a specific target percentile in a control block.

[7]According to criterion (12).

A historical data sample BH_w is collected with a window size of $T_w = 20$. Based on this data, a price bid is generated for the subsequent control block using each of the tested strategies. A prediction is deemed successful if the proposed price falls within the specified P_{target} in the control block. Note that no actual transactions will be submitted to the blockchain during this experiment.

It is important to note that the blocks in the historical sample BH_w are not necessarily consecutive; however, they strictly adhere to rule:

$$S'_{i+1} = min\{x \in S, x > S'_i\}, \tag{16}$$

where S' – the set of slot numbers corresponding to the blocks included in the historical sample BH_w;

S – the set of slot numbers corresponding to all available blocks for which historical information is recorded.

The slot number for the control block is calculated using formula:

$$S_c = min\{x \in S, x > max\{x \in S'\}\}. \tag{17}$$

Since participant bias[8] and individual efficiency metrics[9] are irrelevant within the Solana network, the experiment will exclusively utilize the standard Tullock function (6).

The Logit model, on the other hand, proved to be excessively sensitive to minor data fluctuations – a characteristic that is critical, if not fatal, for this specific domain. While this does not imply that the Logit model is fundamentally inapplicable, it clearly necessitates a degree of data preprocessing to be viable.

A naive approach will serve as the competing model for the CSF during the experiment. In this model, the optimal fee is defined as the average fee observed across the historical sample BH_w. To calculate this average, all fees that success fully reached the P_{target} within their respective historical blocks (BH_{wt}) are included. The naive method is formalized by expression (18):

$$B_{opt} = \frac{1}{T_w} \sum_{t=1}^{T_w} \bar{P}_t, \tag{18}$$

where

$$\bar{P}_t = avg[Percentile(BH_{wt}, P_{target})]. \tag{19}$$

[8]From model (9).
[9]From model (8).

In summary, the experiment will consist of two distinct rounds of testing:

– testing the standard Tullock function (6);

– testing the competing (naive) model (18).

Within the round dedicated to the standard Tullock function, multiple sets of trials will be conducted using different values for parameter *R*. These trials are essential because the precise impact of effort (bid amount) on the win probability within the Solana network cannot be determined theoretically. The only reliable method to ascertain which values accurately describe the auction dynamics is through empirical measurement during this experiment.

Results and Data Analysis

A total of 632 trials were conducted. The results regarding the average proposed CU price across the different models and parameters are summarized in table 1.

Table 1

Average Proposed CU Price

Strategy	Decisiveness Parameter (*R*)	Average Proposed CU Price (microlamports)
Naive Percentile Average	–	519780.02
Standard Tullock CSF	0.0625	2483163.84
	0.125	290720.89
	0.25	120003.72
	0.5	99960.52
	1	97516.06
	5	86047.23
	10	83062.10
	15	82042.25
	20	81538.84

The results for reaching the target percentile are presented in table 2. This table also includes the final strategy efficiency metric.

Table 2
Target Percentile Success Rate

Strategy	Decisiveness Parameter (R)	Target Percentile Success Rate (%)	Strategy Efficiency Metric (h)
Naive Percentile Average	–	87.66	1.686
Standard Tullock CSF	0.0625	80.22	0.323
	0.125	71.20	2.449
	0.25	62.03	5.169
	0.5	60.60	6.062
	1	62.82	6.442
	5	63.61	7.392
	10	62.66	7.543
	15	61.55	7.502
	20	61.55	7.548

Fig. 1 illustrates the graph of the predicted CU price values relative to the control block number.

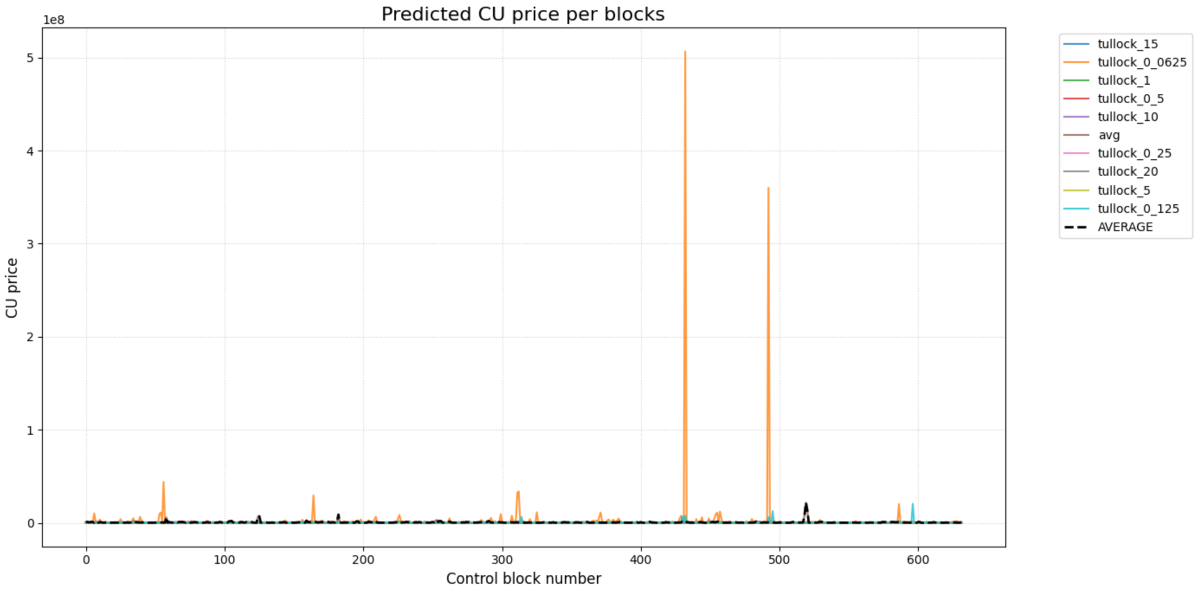

Fig. 1. Plot of the predicted CU price values relative to the control block number

As illustrated in fig. 1, the tullock_0_0625 strategy (Standard Tullock CSF with $R = 0.0625$) produces disproportionately higher CU prices compared to all other evaluated strategies. Due to this significant scale disparity, which obscures the performance of alternative models, this specific plot is omitted from fig. 2 to provide a clearer visual comparison of the remaining results.

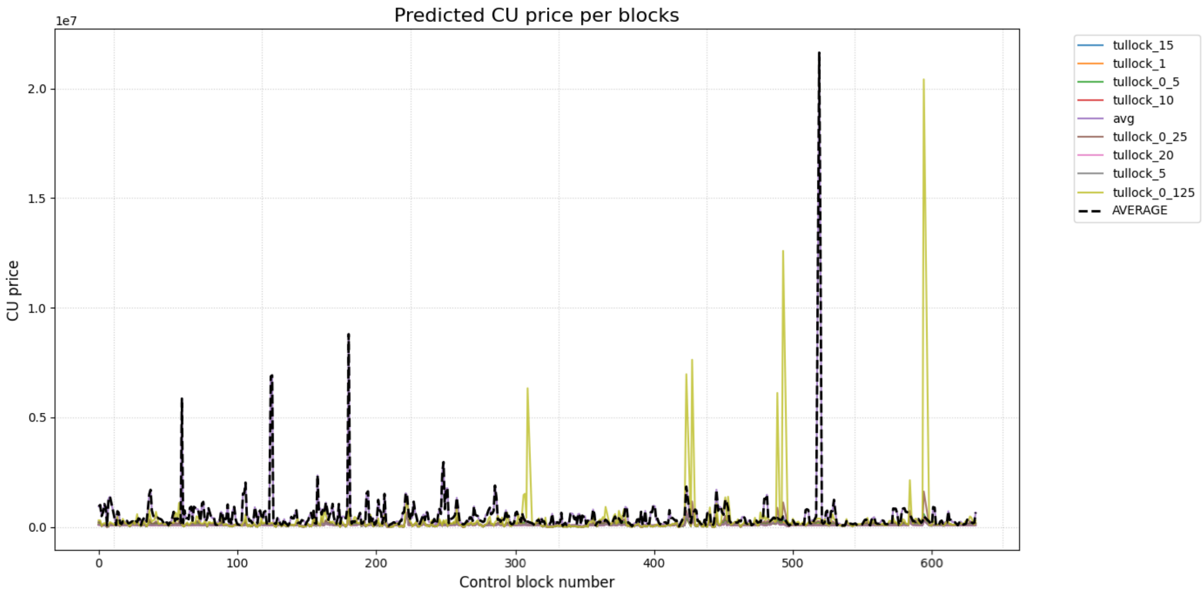

Fig. 2. Plot of the predicted CU price values relative to the control block number (without tullock_0_0625)

The scale of fig. 2 allows for a better assessment of the robustness of each solution to volatility and sudden data fluctuations within individual blocks (e.g., abnormally high auction activity). It is evident that all solutions, except for tullock_0_125 and the simple average (baseline), remain relatively stable. Furthermore, the behavior of tullock_0_125 aligns closely with the expected performance of models characterized by a low R parameter.

Conclusion

The results indicate that the Tullock strategy with a decisiveness parameter of $R = 20$ demonstrated the best[10] overall efficiency. It reduced fee expenditures by more than sixfold, while incurring a 26 % loss in percentile hit accuracy compared to the simple average strategy. In this configuration, the method can be useful for regular users or services that perform a large number of transactions. That is, all those who are not too sensitive to the loss of accuracy and willing to exchange it for savings.

For time-sensitive transactions, we recommend using CSF with $R = 0.125$. This setting provides a higher level of accuracy (16 % loss) while still maintaining a twofold reduction in fees. The parameter value of $R = 0.0625$ proved to be inapplicable for solving this particular problem, as its extreme sensitivity to outlier bids (fee spikes) from other participants led to inconsistent performance.

[10]According to criterion (12).

These findings suggest that the decisiveness parameter *R* serves as a powerful tuning mechanism for model efficiency. It allows the solution to be adapted not only to diverse user requirements but also to be dynamically adjusted based on real-time network congestion and load.

The obtained results allow for the conclusion that the CSF based on the standard Tullock model can successfully compete with the simple average algorithm in terms of CU price prediction efficiency within Solana network auctions. This makes it worthwhile to further explore the prospects of applying such models to optimize transaction costs in networks with similar architectures.

In particular, future research should expand the set of collected metrics by including the mean deviation from the target percentile. Furthermore, data collection should encompass not only standard priority fees but also tips collected by modified validators[11] for the right to include transactions in specialized bundles for accelerated processing.

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[11] e.g., Jito.