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Optimal Sequential Auction Strategies Based on Fuzzy Theory: Postprint

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Abstract

Based on fuzzy theory, the returns of similar items from previous auctions are fuzzily parameterized, and mean-variance is employed to characterize and measure their returns and risks. For these two criteria, a multi-criteria optimization function based on the Cobb-Douglas production function is proposed, thereby constructing a sequential strategy optimization model for sequential auctions based on fuzzy theory. Secondly, a fuzzy simulation algorithm and a multi-criteria 0-1 genetic algorithm are integrated to solve this sequential strategy optimization model. Finally, numerical example analysis compares five sequential strategies with the optimization strategy, demonstrating that the optimal strategy obtained through model solving can achieve higher returns with lower risk.

Full Text

Preamble

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Optimal Sequential Auction Strategy Based on Fuzzy Theory

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Abstract: This paper employs fuzzy theory to parameterize the returns from prior auctions of similar items as fuzzy parameters, and uses a mean-variance framework to characterize and measure both returns and risks. A multi-criteria optimization function based on the Cobb-Douglas production function is proposed for these two criteria, constructing a sequential auction ordering strategy

optimization model grounded in fuzzy theory. Second, by integrating fuzzy simulation algorithms with multi-criteria 0-1 genetic algorithms, we develop a solution method for this ordering strategy optimization model. Finally, numerical examples compare five ordering strategies with the optimized strategy, demonstrating that the optimal strategy derived from the model can achieve higher returns with lower risk.

Keywords: sequential auction; fuzzy theory; optimal strategy; multi-criteria 0-1 genetic algorithm

0 Introduction

With the development of "Internet Plus," online used-car auction platforms have proliferated. In 2014 alone, the online used-car auction market transaction volume reached 350,000 vehicles with a turnover of 19.26 billion yuan. The "Renrenche" online used-car auction platform, established in 2014, rapidly expanded to cover 21 cities with monthly transactions reaching 3,000 vehicles in its first year [**?**]. Used-car auctions represent a typical continuous purchasing environment where auctioneers' primary concern is determining the optimal auction sequence for different items to maximize returns while minimizing risk. This issue has become particularly critical given the industry' s recent explosive growth, making research on sequential auction strategies theoretically significant and practically valuable.

The uncertainty inherent in different ordering strategies stems from four main sources: (a) market dynamics are constantly changing during actual auctions, making it extremely difficult to obtain accurate information about current bidders (valuation distributions, other data); (b) bidders' valuation information and bidding behavior vary across different strategies or scenarios, meaning the same item auctioned at different positions generates different returns and risks; (c) any auction carries the possibility of no-sale, where items remain unsold at auction conclusion; and (d) uncertainty regarding competitive intensity, as auctioneers cannot accurately predict how fierce bidding will be in upcoming auctions. Therefore, strategies formulated based on returns from prior auctions of similar goods can provide valuable guidance for auctioneers.

Due to environmental uncertainty and complexity, different auction sequences for various commodities create numerous possibilities for transaction prices. This is especially true when auctioneers lack current bidder information such as valuation distributions or willingness-to-pay [**?**], making the decision on auction ordering for items of different values a central research focus in sequential auction strategy.

Previous research has identified several common ordering strategies. The most frequent is the "high-to-low" strategy, which auctions items in descending order of value. Conversely, Elmaghraby [**?**] describes a "low-to-high" strategy where

auctioneers prefer to sequence items from lowest to highest value. Between these extremes lie numerous intermediate strategies, such as the "low-high-low" approach that auctions low-value items first to warm up the market [?], and the "high-low-high" strategy designed to attract buyers [?]. To investigate optimal ordering strategies, this paper' s numerical analysis compares the returns and risks of these four strategies.

For auctioneers, the key challenge in sequential auction research is developing ordering strategies that yield higher returns with lower risk. Regardless of the strategy adopted, auction outcomes remain uncertain. Prior research has primarily focused on bidder strategies and purchasing behavior, such as purchase sequencing under budget constraints [?], bidding order decisions [?], and pre-booking choices [?]. However, few studies have applied fuzzy theory to examine how different auction sequences create uncertainty in item returns (maximum bids).

Existing fuzzy theory applications to auction problems have mainly used fuzzy parameters to describe bidding willingness, substituting valuations for revenue or utility analysis [?], or employed fuzzy rough sets to evaluate multi-attribute items [?, ?], without addressing the fuzzification of returns from different auction sequences. This paper defines the return from auctioning an item at a specific position as a fuzzy variable, then derives the uncertain return (mean) and uncertain risk (variance) for that position using the mean-variance model. Fuzzy variables are typically determined from historical data (transaction prices of similar items) [?].

To comprehensively describe the returns and risks of different sequential auction ordering strategies, this paper draws on fuzzy theory methods for handling parameter uncertainty, such as multi-period portfolio return/risk uncertainty studies [?] and fuzzy simulation for parameter uncertainty in economic life assessment [?], to establish an uncertain return-risk optimization model for sequential auction strategies (F-SA model).

To effectively evaluate uncertain returns and risks, we adopt the mean-variance model to assess auctioneer returns and risks under different sequential auction strategies. Given that return and risk are two critical criteria for auctioneers, we employ multi-criteria optimization. Unlike Liu et al. [?], who applied the Cobb-Douglas production function to bidder utility and winning preference selection, this paper uses the function from the auctioneer's perspective to analyze the trade-off between revenue maximization and risk minimization. Building on these foundations, we construct a multi-criteria optimization model for sequential auction ordering strategies based on fuzzy theory and propose a fuzzy simulation-based multi-criteria genetic algorithm (F-MCGA algorithm) to solve it. The numerical analysis specifically compares auctioneer returns and risks across six strategies for multiple items of different values: "high-low," "low-high," "low-high-low," "high-low-high," the strategy from [?], and the optimized strategy.

1 Fuzzy Theory

Given a universe Γ, $\mathcal{P}(\Gamma)$ is its power set, where each element is an event. A credibility measure Cr is a set function on $\mathcal{P}(\Gamma)$ where $\mathrm{Cr}\{\Gamma\} = 1$. Liu and Liu [**?**, **?**] established a complete fuzzy theory by proposing fuzzy variables and expected value operators, providing a theoretical foundation for handling fuzzy variables.

Axiom 1 For the universe Γ, $\mathrm{Cr}\{\Gamma\} = 1$.

Axiom 2 For any events $A, B \in \mathcal{P}(\Gamma)$, if $A \subseteq B$, then $\mathrm{Cr}\{A\} \leq \mathrm{Cr}\{B\}$.

Axiom 3 If C is the complement of event A, then $\mathrm{Cr}\{A\} + \mathrm{Cr}\{C\} = 1$.

Axiom 4 For any combination of events $\{A_i\}$ where $\sup_i \mathrm{Cr}\{A_i\} < 0.5$, we have $\mathrm{Cr}\{\bigcup_i A_i\} = \sup_i \mathrm{Cr}\{A_i\}$.

When Cr is a credibility measure, $(\Gamma, \mathcal{P}(\Gamma), \mathrm{Cr})$ is called a credibility space. When ξ is a fuzzy variable in a credibility space, for the real number set $\mathcal{R}$, we have the following definitions.

Definition 1 If ξ is a fuzzy variable in a credibility space $(\Gamma, \mathcal{P}(\Gamma), \mathrm{Cr})$, its credibility function derived from the credibility measure is $\mathrm{Cr}\{\xi = x\} = \nu(x)$ for all $x \in \mathcal{R}$.

Definition 2 If $(\xi_1, \xi_2, ..., \xi_n)$ is a fuzzy vector in credibility space $(\Gamma, \mathcal{P}(\Gamma), \mathrm{Cr})$, its joint credibility function can also be derived from the credibility measure as $\mathrm{Cr}\{\xi_1 = x_1, \xi_2 = x_2, ..., \xi_n = x_n\} = \nu(x_1, x_2, ..., x_n)$ for all $(x_1, x_2, ..., x_n) \in \mathcal{R}^n$.

Definition 3 Fuzzy variables $\xi_1, \xi_2, ..., \xi_n$ are mutually independent only if their joint credibility function satisfies $\nu(x_1, x_2, ..., x_n) = \min_{1 \leq i \leq n} \nu_i(x_i)$ for all $(x_1, x_2, ..., x_n) \in \mathcal{R}^n$.

Definition 4 If ξ is a fuzzy variable with credibility function ν, then for any real number set B, we have $\mathrm{Cr}\{\xi \in B\} = \sup_{x \in B} \nu(x)$ if $\sup_{x \in B} \nu(x) < 0.5$, and $\mathrm{Cr}\{\xi \in B\} = 1 - \sup_{x \notin B} \nu(x)$ if $\sup_{x \in B} \nu(x) \geq 0.5$.

Definition 5 Assuming $\xi_1, \xi_2, ..., \xi_n$ are mutually independent fuzzy variables, if function f is a mapping from $\mathcal{R}^n$ to $\mathcal{R}$, then the fuzzy variable $f(\xi_1, \xi_2, ..., \xi_n)$ has membership function $\mu(z) = \sup_{x_1, x_2, ..., x_n \in \mathcal{R}} \{\min_{1 \leq i \leq n} \nu_i(x_i) \mid z = f(x_1, x_2, ..., x_n)\}$ for $z \in \mathcal{R}$.

Definition 6 When ξ is a fuzzy variable in a credibility space $(\Gamma, \mathcal{P}(\Gamma), \mathrm{Cr})$, its expected value is $E[\xi] = \int_0^{+\infty} \mathrm{Cr}\{\xi \geq r\} dr - \int_{-\infty}^0 \mathrm{Cr}\{\xi \leq r\} dr$, provided at least one integral is finite.

Definition 7 When ξ is a fuzzy variable with expected value e, its variance can be expressed as $V[\xi] = E[(\xi - e)^2]$.

2 Fuzzy Sequential Auction Ordering Strategy Model

An auctioneer has n items of different values, with the entire auction consisting of T periods (the sequence of the sequential auction strategy). The auctioneer decides to auction item i in period t, where $i = 1, 2, ..., n$ and $t = 1, 2, ..., T$. We define the decision variable $x_{it} \in \{0, 1\}$ to represent whether item i is auctioned in period t. The fuzzy variable ξ_{it} represents the uncertainty associated with this decision, i.e., the uncertain return from selling item i in period t.

The return from auctioning item i in period t is $R_{it} = x_{it}\xi_{it}$. The total auction revenue is:

$$w = \sum_{t=1}^{T}\sum_{i=1}^{n} R_{it} = \sum_{t=1}^{T}\sum_{i=1}^{n} x_{it}\xi_{it} \tag{1}$$

The first term represents the revenue from item i in period t. If the auctioneer chooses to retain item i (not sell), the revenue should be its intrinsic value v_i, which corresponds to the second part of the equation. The third part is the storage cost c_i incurred if item i remains unsold, where $v_i > 0$ and $c_i > 0$. Based on the above analysis, w is a function of x_{it} and ξ_{it}. Assuming fuzzy variables ξ_{it} have a joint credibility function ν_{it}.

From equation (2), we know the total revenue function w is a function of fuzzy variables ξ_{it}, so w is also a fuzzy variable. Through fuzzy simulation, we can calculate the expected revenue $E[w]$ and risk (variance) $V[w]$ of revenue w.

For auctioneers, maximizing return $E[w]$ and minimizing risk $V[w]$ are two primary objectives. We employ the Cobb-Douglas production function to analyze the trade-off between these objectives. Assuming the minimum expected return is a and the maximum acceptable risk is b, the objective function is:

$$f = \left(\frac{E[w]}{a}\right)^{\alpha}\left(1 - \frac{V[w]}{b}\right)^{\beta} \tag{3}$$

where α and β represent the auctioneer' s preference weights for expected return and expected risk, respectively, with $\alpha + \beta = 1$. The fuzzy theory-based uncertain sequential auction ordering strategy model (F-SA model) is formulated as:

$$\max \quad f = \left(\frac{E[w]}{a}\right)^{\alpha} \left(1 - \frac{V[w]}{b}\right)^{\beta} \tag{1}$$

$$\text{s.t.} \quad E[w] \geq a \tag{2}$$

$$V[w] \leq b \tag{3}$$

$$\sum_{t=1}^{T} x_{it} \leq 1, \quad i = 1, 2, ..., n \tag{4}$$

$$\sum_{i=1}^{n} x_{it} = 1, \quad t = 1, 2, ..., T \tag{5}$$

$$x_{it} \in \{0, 1\} \tag{6}$$

To solve the above model (F-SA model), this paper employs the fuzzy simulation algorithm [**?**] to calculate the values of $E[w]$ and $V[w]$, then applies a multi-criteria genetic algorithm (F-MCGA algorithm) to solve the Cobb-Douglas objective function for the multi-criteria problem.

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3 Algorithms

3.1 Fuzzy Simulation Algorithm

Fuzzy simulation can approximate the values of fuzzy variables with membership distribution functions by generating a series of discrete fuzzy vectors. First, randomly generate N vectors $\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_N$. Then calculate their credibility measures $\mathrm{Cr}\{w(\mathbf{x}, \xi) \geq r\}$ and $\mathrm{Cr}\{w(\mathbf{x}, \xi) \leq r\}$. According to Definitions 6 and 7, to calculate $E[w]$ and $V[w]$, we must first compute the credibility measures.

According to Definition 4, we have:

$$\mathrm{Cr}\{w(\mathbf{x}, \xi) \geq r\} = \begin{cases} \max_{1 \leq k \leq N}\{\theta_k \mid w(\mathbf{x}, \mathbf{y}_k) \geq r\}, & \text{if } \max_{1 \leq k \leq N}\{\theta_k \mid w(\mathbf{x}, \mathbf{y}_k) \geq r\} < 0.5 \\ 1 - \max_{1 \leq k \leq N}\{\theta_k \mid w(\mathbf{x}, \mathbf{y}_k) < r\}, & \text{if } \max_{1 \leq k \leq N}\{\theta_k \mid w(\mathbf{x}, \mathbf{y}_k) \geq r\} \geq 0.5 \end{cases}$$

where $\theta_k = \min_{1 \leq i \leq n} \nu_i(y_{ik})$. Similarly:

$$\mathrm{Cr}\{w(\mathbf{x}, \xi) \leq r\} = \begin{cases} \max_{1 \leq k \leq N}\{\theta_k \mid w(\mathbf{x}, \mathbf{y}_k) \leq r\}, & \text{if } \max_{1 \leq k \leq N}\{\theta_k \mid w(\mathbf{x}, \mathbf{y}_k) \leq r\} < 0.5 \\ 1 - \max_{1 \leq k \leq N}\{\theta_k \mid w(\mathbf{x}, \mathbf{y}_k) > r\}, & \text{if } \max_{1 \leq k \leq N}\{\theta_k \mid w(\mathbf{x}, \mathbf{y}_k) \leq r\} \geq 0.5 \end{cases}$$

The fuzzy simulation algorithm then calculates the mean and variance of fuzzy variables. The specific process is shown in Algorithm 1.

Algorithm 1: Fuzzy Simulation Algorithm

1. Set parameters: N (number of random vectors), r (threshold value), and $\theta_0 = 0$.
2. Randomly generate vectors $\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_N$ and calculate credibility measures θ_k for each.
3. For each r, compute $\mathrm{Cr}\{w(\mathbf{x}, \xi) \geq r\}$ and $\mathrm{Cr}\{w(\mathbf{x}, \xi) \leq r\}$ using the above formulas.
4. Calculate $E[w] = \int_0^\infty \mathrm{Cr}\{w \geq r\}dr - \int_{-\infty}^0 \mathrm{Cr}\{w \leq r\}dr$.
5. Calculate $V[w] = E[(w - E[w])^2]$.
6. Return $E[w]$ and $V[w]$.

3.2 Multi-Criteria 0-1 Genetic Algorithm

Following Guo et al. [**?**], who integrated fuzzy simulation with genetic algorithms to solve multi-period portfolio fuzzy problems, this paper integrates fuzzy simulation with a genetic algorithm for multi-criteria 0-1 problems to solve the sequential auction ordering strategy under fuzzy random uncertainty.

The genetic algorithm solution steps are as follows:

a) Initialization: Encode the solution (decision variables x_{it}) into binary chromosome individuals $\mathbf{x}$. Each chromosome must satisfy the constraint $\sum_{t=1}^{T} x_{it} \leq 1$ for all i and $\sum_{i=1}^{n} x_{it} = 1$ for all t. Individuals satisfying all constraints are called valid individuals. Generate n valid individuals to form an initial population of size n.

b) Fitness Function: The fitness function evaluates and selects optimal chromosomes. Unlike [**?**], which directly uses the objective function, we use only the real part of the result for comparison to facilitate calculation:

$$\mathrm{fitness}(\mathbf{x}) = \mathrm{real}\left[\left(\frac{E[w]}{a}\right)^{\alpha}\left(1 - \frac{V[w]}{b}\right)^{\beta}\right]$$

c) Crossover, Recombination, and Selection: Randomly select two individuals from the population, perform multi-point crossover to generate two new individuals, and repeat until $2n$ new individuals are created. Merge with the original population to form a $3n$ population. Filter individuals satisfying constraints into a new population newfarm, calculate their fitness values, select the individual with maximum fitness, duplicate it twice, and replace any two individuals in newfarm (Algorithm 2).

Algorithm 2: Crossover and Selection

1. Randomly select two individuals from the original n population.
2. Perform multi-point crossover on multiple chromosome columns to generate two new individuals.
3. Repeat until $2n$ new individuals are created and merge with the original population to form a $3n$ population.

4. Filter the $3n$ population by constraints to form newfarm.
5. Calculate fitness for each individual in newfarm.
6. Select the highest-fitness individual, duplicate it twice, and replace any two individuals in newfarm.

d) Mutation: Set mutation rate p_m. For each individual, generate a random number $r \in [0, 1]$. If $r > p_m$, mutate any chromosome in the i-th individual to 1; otherwise mutate to 0. Check constraint satisfaction for mutated individuals, and only replace population members if constraints are satisfied (Algorithm 3).

Algorithm 3: Mutation

1. Set mutation rate p_m and generate random number $r \in [0, 1]$.
2. If $r > p_m$, mutate any chromosome in individual i to 1; otherwise mutate to 0.
3. Check constraint satisfaction for the mutated individual.
4. If constraints are satisfied, replace the i-th individual in the population.

e) Termination: Repeat steps (b)-(d) for a predetermined number of generations.

The complete multi-criteria 0-1 genetic algorithm is summarized in Algorithm 4.

Algorithm 4: Multi-Criteria 0-1 Genetic Algorithm

1. Generate n initial individuals satisfying constraints (population farm).
2. Select any two individuals, perform multi-point crossover on multiple chromosome columns until $2n$ individuals are generated, and merge with farm to form a $3n$ population.
3. Filter the $3n$ population by constraints to form newfarm.
4. Calculate the fitness function for each individual in newfarm.
5. Select individuals with higher fitness to duplicate and replace two random individuals in farm.
6. Apply mutation to update population farm chromosomes.
7. Repeat steps 2-6 for the specified number of generations.

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4 Numerical Example

In a used-car auction, an auctioneer has 10 different vehicles to sell through 5 bidding rounds. We characterize fuzzy variables using both triangular and trapezoidal fuzzy numbers.

The 10 vehicles have values $V = [0.8, 1.01, 0.8, 1.1, 0.95, 1.2, 1.3, 0.88, 1.02, 1.5]$ (in hundred thousand yuan). Storage costs are $c = [0.4, 0.6, 0.25, 0.32, 0.2, 0.4, 0.7, 0.6, 0.5, 0.4]$. The auctioneer' s minimum acceptable expected return is $a = 10.5$, maximum acceptable risk is $b = 0.2$, and preference weights are $\alpha = 0.8$, $\beta = 0.2$.

To compare the "high-low," "low-high," "low-high-low," and "high-low-high" strategies, we rank the 10 vehicles into five value tiers: high, relatively high, medium, relatively low, and low .

4.1 Triangular Fuzzy Number Example

The triangular fuzzy numbers for different vehicles across auction periods are shown in Table 2 .

Using fuzzy simulation, we calculate the mean and variance of the fuzzy numbers (Table 3).

Strategy "High-Low" (auctioning high-value items first): The ordering is $(5, 3, 5, 2, 4, 1, 1, 4, 3, 2)$ with objective value $f = 4.067$, expected return $E[w] = 11.47$ (hundred thousand), and risk $V[w] = 0.2876$, which exceeds the risk tolerance $b = 0.2$.

Strategy "Low-High" : Ordering $(1, 3, 1, 4, 2, 5, 5, 2, 3, 4)$ yields $f = 3.4515$, $E[w] = 11.26$, $V[w] = 0.22$.

Strategy "Low-High-Low" : Ordering $(1, 5, 1, 4, 2, 3, 3, 2, 5, 4)$ yields $f = 3.6278$, $E[w] = 11.28$, $V[w] = 0.2224$.

Strategy "High-Low-High" : Ordering $(3, 5, 3, 2, 4, 1, 1, 4, 5, 2)$ yields $f = 3.7309$, $E[w] = 11.58$, $V[w] = 0.2232$.

Strategy from [?]: Ordering $(5, 4, 3, 2, 3, 1, 4, 2, 5, 5)$ yields $f = 2.9355$, $E[w] = 10.555$, $V[w] = 0.2101$.

The **optimal strategy** from the genetic algorithm is $(1, 5, 3, 3, 1, 4, 1, 1, 1, 2)$ with $f = 5.0578$, $E[w] = 11.05$, $V[w] = 0.1556$, satisfying the risk constraint. The convergence curve is shown in Figure 1 [Figure 1: see original paper].

4.2 Trapezoidal Fuzzy Number Example

The trapezoidal fuzzy numbers are shown in Table 4 . Using fuzzy simulation, we obtain means and variances (Table 5).

Strategy "High-Low" : Ordering $(5, 3, 5, 2, 4, 1, 1, 4, 3, 2)$ yields $f = 4.2269$, $E[w] = 10.855$, $V[w] = 0.256$.

Strategy "Low-High" : Ordering $(1, 3, 1, 4, 2, 5, 5, 2, 3, 4)$ yields $f = 4.0339$, $E[w] = 10.695$, $V[w] = 0.2471$.

Strategy "Low-High-Low" : Ordering $(1, 5, 1, 4, 2, 3, 3, 2, 5, 4)$ yields $f = 4.3537$, $E[w] = 11.1$, $V[w] = 0.2595$.

Strategy "High-Low-High" : Ordering $(3, 5, 3, 2, 4, 1, 1, 4, 5, 2)$ yields $f = 2.9355$, $E[w] = 10.555$, $V[w] = 0.2101$.

Strategy from [?]: Ordering $(5, 5, 3, 2, 3, 5, 4, 1, 2, 1)$ yields $f = 4.8995$, $E[w] = 10.69$, $V[w] = 0.1648$.

The **optimal strategy** is $(1, 3, 4, 3, 1, 5, 1, 1, 1, 2)$ with $f = 5.0578$, $E[w] = 11.05$, $V[w] = 0.1556$. The convergence curve is shown in Figure 2 [Figure 2: see original paper].

4.3 Summary

Comparing the four common strategies and the strategy from [**?**] with the optimal strategy reveals that only the optimal strategy keeps risk within acceptable limits; all others exceed the risk tolerance $b = 0.2$.

Both examples demonstrate that fuzzy simulation yields the mean (return) and variance (risk) for each strategy, which are then processed through our multi-criteria 0-1 genetic algorithm. The optimal strategy consistently achieves higher returns under lower risk constraints, with return differences within 1 (hundred thousand) compared to other strategies. This confirms that our approach effectively ensures higher returns at lower risk.

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5 Conclusion

This paper proposes a multi-criteria optimization model for returns and risks, providing auctioneers with superior auction sequencing strategies that guarantee lower-risk returns compared to previous methods focusing solely on revenue maximization. Key conclusions are:

a) We consider both return uncertainty and risk uncertainty, employing multi-criteria optimization with a Cobb-Douglas production function-based objective.

b) We use fuzzy theory to characterize the uncertainty from sequential auction ordering strategies as fuzzy variables, proposing the fuzzy random uncertain sequential auction strategy model (F-SA model).

c) We integrate fuzzy simulation with multi-criteria 0-1 genetic algorithms to develop the F-MCGA algorithm for solving the optimization model.

d) Numerical results demonstrate that the F-SA model yields optimized strategies achieving higher returns with lower risk, meeting auctioneers' multi-criteria requirements and providing practical significance.

The proposed model and algorithm offer a new theoretical perspective on sequential auction ordering strategies and provide decision support for auctioneers.

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