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Integrating Computational Advertising with Guaranteed Display for Enhanced Performance in Wi-Fi Marketing

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***Abstract*—Wi-Fi Marketing effectively engages potential customers by displaying advertisements before granting internet access through public or business Wi-Fi hotspots. However, the increasing number of advertising campaigns complicates resource allocation, necessitating optimized ad placement to achieve campaign goals while minimizing disruptions to the user experience. This paper examines principles of efficient resource allocation in Wi-Fi Marketing, focusing on fairness, demand optimization, and user satisfaction. We propose an allocation model that formalizes advertising contracts between advertisers and publishers managing Wi-Fi infrastructure, incorporating ad supply, ad requests, and contractual terms. The model employs an objective function to balance fairness, penalize unmet requirements, and maximize user engagement, while adhering to constraints such as minimum impressions and resource limits. Additionally, we introduce mathematical formulations to strategically distribute advertisements, ensuring quota fulfillment and catering to diverse audience segments. The proposed framework not only enhances campaign performance but also maintains a seamless and positive user experience. By implementing these principles and the proposed model, Wi-Fi Marketing can effectively manage resource allocation complexities, thereby maximizing the impact of advertising efforts.**

***Index Terms*—Wifi Marketing; Guaranteed Display Advertising; Digital Advertising and Ad Scheduling; Computational Advertising; Campaign Performance Maximization; Resource Allocation in Computer Networks.**

I. Introduction

WI-FI marketing has emerged as a powerful tool for businesses to monetize public Wi-Fi hotspots through advertising. Venue owners can offer premium paid access or advertising-sponsored free access to users [1]. This model is formulated as a three-stage Stackelberg game, where the ad platform's revenue-sharing policy affects Wi-Fi pricing but not advertising pricing. The effectiveness of this approach depends on factors like advertising concentration and user visiting frequency. To optimize ad scheduling, researchers have proposed algorithms that consider Wi-Fi communication constraints and user tolerance for viewing ads [2]. These algorithms aim to maximize user interest in displayed advertisements, potentially increasing revenue for venues and advertisers. Additionally, resource allocation challenges in Wi-Fi networks can be addressed using techniques like the decomposition algorithm to ensure fair distribution of ad impressions across targeted locations.

Wi-Fi marketing presents challenges in resource allocation, fairness, and user satisfaction. Researchers have proposed various approaches to address these issues. Son Anh Ta et al. [3] introduced a Dantzig-Wolfe decomposition algorithm to optimize fairness in ad allocation across targeted locations. Wanru Xu et al. [2] developed a greedy swap algorithm to maximize user interest in Wi-Fi advertisements while considering communication constraints and user tolerance. M. Bateni et al. [4] proposed a stochastic approximation scheme for fair resource allocation in dynamic marketplaces, achieving a balance between seller revenues and buyer fairness. Haoran Yu et al. [1] presented a Wi-Fi monetization model offering premium and advertising-sponsored access, analyzing the economic interactions among stakeholders as a three-stage Stackelberg game. These studies collectively address the multifaceted problem of effective advertising resource allocation in Wi-Fi marketing, considering fairness, demand optimization, and user satisfaction to enhance the effectiveness of this marketing channel.

This paper presents a comprehensive framework for addressing resource allocation challenges in Wi-Fi Marketing. The proposed model formalizes the contractual relationships between advertisers and Wi-Fi publishers, incorporating essential elements such as ad supply, ad requests, and predefined contractual terms. By employing a robust objective function, the model seeks to balance fairness, penalize unmet requirements, and optimize user engagement while adhering to constraints such as minimum impression quotas and resource limitations.

Furthermore, the framework introduces mathematical formulations for the strategic distribution of advertisements, ensuring diverse audience segments are effectively targeted and contractual quotas are fulfilled. These formulations are designed to maximize campaign performance without com-

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promising user experience, thus addressing the dual priorities of advertisers and publishers.

By integrating these principles, the proposed allocation model offers a systematic solution to the complexities of resource management in Wi-Fi Marketing. This approach not only enhances the efficiency and impact of advertising efforts but also upholds a positive and uninterrupted user experience, cementing Wi-Fi Marketing as a sustainable and effective marketing strategy.

II. Related Works

A. Guaranteed Display Advertising

Guaranteed Display Advertising (GDA) is a crucial model in online advertising, allowing advertisers to secure a predetermined number of impressions for target audiences. Recent research has focused on optimizing GDA planning and allocation strategies. Turner [6] formulated the GDA planning problem as a transportation problem with a quadratic objective, developing algorithms for solving large-scale problems. Subsequent studies have proposed adaptive frameworks to improve both contract delivery and user engagement. Cheng et al. [7] introduced an adaptive unified allocation framework that optimizes contract delivery and user interest simultaneously. Fang et al. [8] developed a personalized delivery system that accounts for individual-level constraints and user-ad interactions. Dai et al. [9] proposed a fairness-aware allocation model that balances guaranteed delivery, impression quality, and traffic cost. These advancements have led to significant improvements in contract delivery rates, click-through rates, and overall advertising revenue for e-commerce platforms (Cheng et al., [7]; Fang et al., [8]; Dai et al., [9]).

B. Resource Allocation in Computer Networks

Resource allocation optimization in wireless networks is a crucial area of research for improving system performance. Various approaches have been explored, including cross-layer multiuser optimization (Zhu Han & K. J. R. Liu [10]) and utility-based resource management frameworks (Song & Li [11]). These methods aim to efficiently allocate resources for diverse traffic types with different QoS requirements. In the context of Wi-Fi marketing, a novel mathematical model has been proposed to optimize fairness in campaign allocation across targeted locations (Ta Anh Son et al. [3]). The Dantzig-Wolfe decomposition algorithm is suggested as an effective solution for this large-scale problem. Recent advancements include the integration of deep reinforcement learning with a multi-objective framework to develop periodic product recommendation systems, enabling resource optimization tailored to user preferences and system constraints [12]. Moreover, techniques such as optimistic linear support and user clustering have been combined with multi-objective reinforcement learning to build multi-objective periodic recommendation systems, further enhancing resource allocation efficiency [13]. Other techniques, such as power control, multiple access, and dynamic resource allocation, have also been studied for wireless resource allocation optimization (M. Mehrjoo et al. [14]; Zhu Han & K. J. R. Liu, [10]). These approaches collectively contribute to enhancing the performance of wireless systems, including Wi-Fi networks, and improving resource allocation strategies for various applications.

C. Digital Advertising and Ad Scheduling

Recent research on targeted advertisement distribution and scheduling has explored various approaches to improve ad delivery and effectiveness. Mobile social networks have been utilized for content dissemination, considering user location, mobility, and interests while accounting for resource limitations (Ravaei et al., [15]). In television advertising, combining mathematical programming and machine learning has led to revenue increases of 3-5 % for networks (Souyris et al., [16]). For offline advertising, a system called TARP uses convolutional neural networks to generate viewer demographics and queue scheduling algorithms to display relevant ads on billboards and screens (Malhotra et al., [17]). In the context of IPTV, a 0.502-competitive revenue maximizing scheduling algorithm has been developed to place targeted ads based on comprehensive user profiles derived from TV, broadband, and mobile usage (Kodialam et al., [18]). These advancements aim to enhance ad targeting, increase revenues, and improve viewer experience across various platforms.

III. Problem statement

Within the realm of Wi-Fi Marketing, a common strategy involves presenting advertisements to users prior to granting them internet access via public or business Wi-Fi hotspots. This technique proves effective for engaging potential customers. However, as the volume of advertising campaigns grows, the complexity of resource allocation intensifies. The key challenge lies in optimizing ad placement to fulfill campaign objectives while minimizing disruptions to the user experience.

Wi-Fi Marketing leverages a model where users must view or interact with an advertisement before accessing the internet. This paradigm is characterized by several distinct aspects:

- **Compulsory ad interaction for access:** Users are required to view or engage with an advertisement as a prerequisite to gaining Wi-Fi connectivity. This method ensures direct interaction with users but necessitates strategic ad distribution to maintain a balance between marketing effectiveness and user convenience.
- **Heterogeneous campaigns and audience segmentation:** Advertising campaigns cater to diverse audiences, segmented by factors such as demographics, geographic regions, and behavioral patterns. A dynamic resource allocation framework is critical to delivering relevant advertisements to the appropriate audiences, thereby maximizing campaign impact.
- **Optimization of campaign outcomes:** Ensuring that advertising objectives are met requires a resource allocation mechanism that prioritizes efficient ad delivery while enhancing user engagement.

Consequently, resource allocation in Wi-Fi Marketing centers on the strategic scheduling and delivery of advertisements to achieve campaign goals while ensuring a seamless and positive user experience during Wi-Fi access.

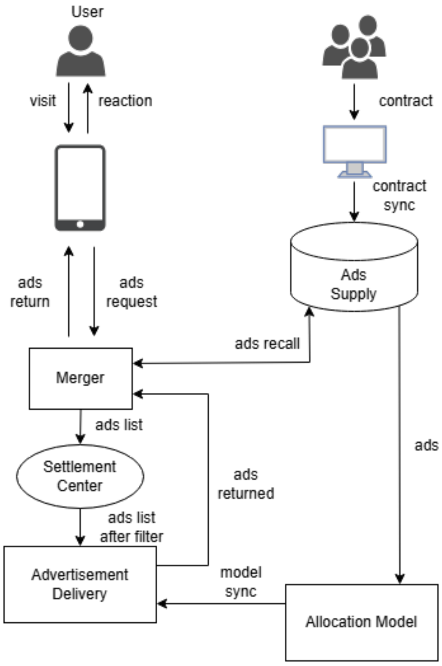

Fig. 1. Overall processing pipeline.

A. Principles of Efficient Resource Allocation

To achieve efficient resource allocation in Wi-Fi marketing, the system must adhere to fundamental principles that ensure fairness, optimize according to demand, and enhance user experience. Below are the key principles aimed at achieving these objectives.

1) Ensuring Fairness and Avoiding Over-Allocation: Fairness in resource allocation ensures that every user or advertisement has a reasonable opportunity for exposure. Additionally, avoiding over-allocation prevents excessive ad repetition, which can irritate users and waste advertising resources.

Suppose x_{ij} represents the resources allocated to advertisement j for user i. The objective is to ensure that the total allocation does not exceed the required limit, expressed as:

$$\sum_{j} x_{ij} \leq d_j, \quad \forall j. \tag{1}$$

where d_j is the maximum limit for the number of advertisements deployed by advertiser j.

To ensure fairness, resources for each advertisement j are allocated based on a priority weight w_j. The allocation model can be optimized using a fairness-maximizing objective function:

$$\max \sum_{i} \sum_{j} p_j \cdot x_{ij}. \tag{2}$$

subject to constraints that prevent exceeding resource limits and maintain fairness among different advertisements.

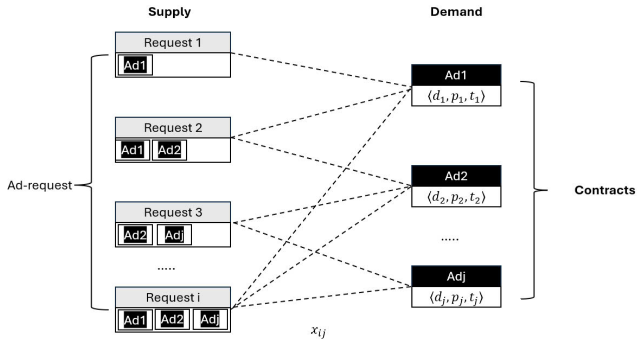

Fig. 2. Contracts between advertisers and publishers.

2) Optimizing Fairness in Resource Allocation: Fairness plays a critical role in ensuring that each advertisement has a reasonable and balanced opportunity for exposure, particularly when multiple campaigns compete for the same advertising space. To achieve fairness, an optimization objective function can be defined as follows:

$$\frac{1}{2} \sum_{i,j \in \Gamma(i)} \frac{1}{\theta_j} \left(x_{ij} - \theta_j\right)^2. \tag{3}$$

Where:

- x_{ij}: The actual amount of resources allocated to advertisement j for user i.
- θ_j: The ideal allocation ratio for advertisement j, representing the desired level of allocation for optimal effectiveness.
- $\Gamma(i)$: The set of advertisements requested by user i.

This objective function minimizes the disparity between the actual allocation x_{ij} and the ideal allocation θ_j, thereby optimizing fairness in resource distribution. A small value of this expression indicates that resource allocation has reached an optimal fairness level, ensuring balanced and reasonable distribution among advertisements.

B. Basic Allocation Model

This model formalizes advertising contracts between advertisers and publishers (the entities responsible for managing Wi-Fi infrastructure). These contracts ensure that advertisements are displayed to users a predetermined number of times within a specific timeframe while meeting additional constraints such as audience segmentation and display duration, as illustrated in Figure 2.

The key components of the model include:

1) *Ad Supply:* This represents a collection of advertisements, $Ad_1, Ad_2, \ldots, Ad_n$, provided by multiple advertisers. Each advertisement has unique requirements for impressions, geographic targeting, and audience segmentation. These requirements often specify the need to reach distinct user groups characterized by specific attributes.

2) *Ad Requests:* Ad requests are user-initiated actions that occur when accessing Wi-Fi services. Each request includes details about the user, the access location, and other contextual attributes, enabling the system to deliver the most relevant advertisements to users.
3) *Contracts:* Contracts between advertisers and publishers define the terms and conditions for advertisement delivery, including:
   - Impression Quota: Specifies the minimum number of times an advertisement must be displayed during a predefined timeframe.
   - Target Audience: Identifies specific demographic or user segments that the advertisement is intended to reach.

1) Advertisement Parameters: Each advertisement Ad_j is characterized by the following parameters:

- d_j: The maximum number of required impressions for advertisement Ad_j.
- p_j: The target audience segment designated for advertisement Ad_j.
- t_j: The timeframe during which advertisement Ad_j must be displayed.

These parameters are represented as a tuple (d_j, p_j, t_j), which serves as the basis for optimizing ad allocation.

2) Objective Function: The resource allocation problem in Wi-Fi marketing aims to optimize the number of ad impressions to maximize revenue for service providers while maintaining user satisfaction. The model satisfies advertising contract requirements, ensures fairness in resource allocation, and considers genuine user interest in advertisements.
The optimization problem is formulated as follows:

$$\arg\min \frac{1}{2} \sum_{j,i\in\Gamma(j)} \frac{V_j}{\theta_j}(x_{ij} - \theta_{ij})^2 - \sum_j p_j \sum_{i\in\Gamma(j)} x_{ij}. \quad (4)$$

where:

- x_{ij}: Represents the allocation of advertisement j to user i.
- θ_j: The ideal allocation ratio for advertisement j, calculated as $\theta_j = \frac{d_j}{\sum_{i\in\Gamma(j)}}$.
- V_j: A weight parameter associated with the importance of fairness for advertisement j.
- p_j: The penalty weight for failing to meet the required impressions for advertisement j.
- d_j: The minimum required impressions for advertisement j.
- s_i: Resource capacity at supply i, estimated from Wi-Fi traffic predictions.

3) Constraints: The model is subject to the following constraints:

1) Minimum Impressions:

$$\sum_{i\in\Gamma(j)} x_{ij} \leq d_j, \quad \forall j. \quad (5)$$

This ensures that the number of impressions for advertisement j does not exceed the required quota d_j.

2) Resource Limits:

$$\sum_{j\in\Gamma(i)} x_{ij} \leq s_i, \quad \forall i. \quad (6)$$

This constraint limits the allocation to the resource capacity s_i at supply i.

3) Non-Negativity:

$$x_{ij} \geq 0, \quad \forall i, j. \quad (7)$$

This guarantees that all allocation variables x_{ij} and penalty terms u_j remain non-negative, consistent with their physical interpretation in resource allocation.

4) Components of the Objective Function: The objective function balances the following three aspects:

1) Fairness in Allocation

$$\frac{1}{2} \sum_{j,i\in\Gamma(j)} \frac{V_j}{\theta_j}(x_{ij} - \theta_j)^2. \quad (8)$$

This term minimizes the deviation between actual allocation x_{ij} and the ideal allocation θ_j, promoting fair resource distribution.

2) Penalty for Unmet Requirements

$$\sum_j p_j \sum_{i\in\Gamma(j)} x_{ij}. \quad (9)$$

This penalizes scenarios where advertisement j fails to meet the required impressions d_j, helping to satisfy contractual obligations.

C. Model for Allocation Application

In the Wi-Fi Marketing system, the resource allocation problem optimizes two campaign types: Domain and Network. Domain ads focus on location-specific content, enhancing personalization, while Network ads extend brand reach regardless of location. The allocation process occurs in two stages: In Stage 1, resources are allocated evenly to ensure fairness between the campaigns. In Stage 2, unused resources are dynamically reallocated to maximize overall revenue. The model uses ratio constraints to adjust priorities and ensure efficient resource utilization.

1) Stage 1: Fair Distribution: In the first stage of the resource allocation model, the system determines the initial allocation of limited resources to Domain and Network campaigns. The goal is to ensure that each campaign has sufficient resources to meet its minimum display requirements, as outlined in contracts, while maintaining fairness in distribution. This initial allocation serves as a foundation for the next stage, where surplus resources can be reallocated to maximize overall revenue. Our new optimization problem is:

$$\arg\min \frac{1}{2} \sum_{j\in D,i\in\Gamma(j)} \frac{V_j}{\theta_j}(x_{ij} - \theta_{ij})^2. \quad (10)$$

s.t

$$\begin{aligned}
&\sum_{i\in\Gamma(j)} x_{ij} \le d_j \quad \forall j. \\
&\sum_{j\in\Gamma(i), j\in D} x_{ij} \le s_i * ratio_i \quad \forall i. \\
&\sum_{j\in\Gamma(i), j\in N} x_{ij} \le s_i * (1 - ratio_i) \quad \forall i. \\
&x_{ij} \ge 0 \quad \forall i, j \in D.
\end{aligned} \tag{11}$$

2) Stage 2: Revenue Maximization: In this stage, the objective is to optimize the utilization of the surplus resources from Stage 1. Specifically, if either the Domain or Network campaign does not fully use its allocated resources, the remaining surplus will be transferred to the other campaign. This approach ensures the maximum efficiency in resource utilization, thereby optimizing the overall revenue of the Wi-Fi marketing system.

Using the solution x^* from Stage 1 as the baseline data, the objective function is redefined to focus on maximizing the use of the remaining resources. The problem, then, becomes one of dynamically reallocating the surplus to maximize total revenue, ensuring the most efficient use of available resources across both campaigns. This leads to the mathematical model, which encapsulates these objectives and constraints.

$$\arg\min -\sum_{j} p_j \sum_{i\in\Gamma(j)} x_{ij}. \tag{12}$$

s.t

$$\begin{aligned}
&\sum_{i\in\Gamma(j)} x_{ij} \le d_j \quad \forall j. \\
&\sum_{j\in\Gamma(i)} x_{ij} \le s_i \quad \forall i. \\
&x_{ij} \ge x^{\star}_{ij} \quad \forall i, j. \\
&x_{ij} \ge 0 \quad \forall i, j.
\end{aligned} \tag{13}$$

IV. Experimental Evaluation

A. Experimental Setup

1) Datasets and evaluation metrics: We analyze data from AWING's advertising platform, encompassing 10,996 supply locations, 128 campaigns, and over 4 million edges within a 100-day timeframe. For simulation purposes, a representative sample of this network is used to reflect the allocation dynamics. To benchmark performance, a linear programming (LP) [19]optimizer is employed, establishing an upper bound for the allocation model and enabling a fair comparison of different optimization methods.

To evaluate the effectiveness of guaranteed display advertising allocation, we focus on two key metrics:

- **Number of allocated clicks**, which measures the total clicks generated through valid allocations. This metric directly reflects the system's ability to meet demand and maximize campaign effectiveness.
- **Over-allocation rate**, defined as the ratio of impressions exceeding the required demand to the total allocated impressions. This metric highlights inefficiencies in resource distribution and the system's capacity to minimize unnecessary surplus.

These metrics provide a comprehensive view of allocation efficiency, balancing campaign performance against resource optimization. By filtering out over-allocated impressions during serving, we ensure the insights remain actionable and aligned with operational goals.

2) Benchmark methods: For benchmarking purposes, we explore and compare three recent methods against our proposed approach in offline allocation experiments:

- SHALE: This method, introduced by Bharadwaj et al [20], is a dual-based optimal algorithm designed for the basic allocation model. It focuses on two main objectives: ensuring distribution fairness and maximizing impressions. Although effective in certain contexts, SHALE does not account for additional complexities that may arise in more nuanced allocation scenarios.
- ALI: Proposed by Fang et al [21], ALI is an allocation model that optimizes the Click-Through Rate (CTR). However, a key limitation of ALI is the lack of a constraint to ensure that the number of impressions allocated does not exceed the demand. Instead, the model incorporates a hyper-parameter known as the learning rate. This parameter is employed during the iterative updates of α to mitigate the risk of overloading, helping to stabilize the process during allocation, but it does not fully eliminate the possibility of exceeding demand limits.

These methods provide a baseline for comparison, highlighting the differences in approach and performance when applied to various allocation objectives. In our experiments, we evaluate the effectiveness of these models against the benchmarks, emphasizing how each addresses specific allocation challenges and their respective limitations. Important parameter values used in our experiments are summarized in Table I.

TABLE I
Summary of Parameter Values

Parameter	Value	Description
v_j	1	Weight of fairness objective
p_j	10	Weight of penalty objective
$t_{\max}$	50	Max iterations for all methods

B. Results

1) Phase 1 - Resource Allocation for Domain and Network Campaigns: In this phase, we independently solve the resource allocation problem for Domain and Network campaigns. The effectiveness of each method is evaluated based not only on the number of allocated impressions but also on over-allocation rates, the number of clicks received, and the L2 distance metric. Tables II and III summarize the results, allowing comparisons of the effectiveness of our method, SHALE, and ALI.

While SHALE achieves similar allocation rates to our method, the slight difference is negligible. However, ALI exhibits significantly higher over-allocation rates of 0.138% and 1.21%, respectively, highlighting its weaker control over resource distribution compared to our method and SHALE.

Regarding clicks, our method demonstrates a significant advantage over SHALE and ALI. On the Network and Domain datasets, our method achieves 3.36% and 3.12% more clicks than SHALE, and 2.83% and 4.13% more clicks than ALI, respectively. These results reflect the ability of our approach to attract more clicks and enhance conversion rates, making a meaningful impact on advertising effectiveness.

In terms of the L2 distance metric, our method achieves the lowest values across both datasets, indicating more even ad distribution. Specifically, for the Network dataset, our L2 distance is 4.57% and 6.2% lower than SHALE and ALI, respectively. Similarly, for the Domain dataset, our method outperforms SHALE and ALI by 2.5% and 5.1%. This demonstrates that our method not only attracts users effectively but also maintains balanced resource distribution.

TABLE II
RESULTS FOR THE NETWORK DATASET.

Method	Allocated Impressions	Over-Allocation Rate	Clicks	L2 Distance
RAP	**943103.70**	**0**	**274934.66**	**1.0534e8**
SHALE	931176.32	0	265984.39	1.1034e8
ALI	935213.18	0.138	267378.21	1.1234e8

TABLE III
RESULTS FOR THE DOMAIN DATASET.

Method	Allocated Impressions	Over-Allocation Rate	Click	L2 Distance
RAP	**35139.03**	**0**	**11434.66**	**6.5764e6**
SHALE	33921.89	0	10980.61	6.7443e6
ALI	34019.32	0.125	11089.34	6.9321e6

2) Phase 2 - Maximizing Surplus Resources: Building on Phase 1, Phase 2 introduces an additional requirement that the solution values must meet or exceed the allocation levels from Phase 1.

In terms of allocated impressions, our method achieves 1,378,242.56, significantly exceeding the values from Phase 1 (943,103.70 for Network and 35,139.03 for Domain). This demonstrates our method's capability to utilize surplus resources effectively, expanding the advertising reach compared to Phase 1.

Regarding clicks, our method achieves 482,384.73 clicks in Phase 2, substantially higher than the 274,934.66 and 11,434.66 clicks from the Network and Domain datasets in Phase 1. This increase highlights the continued optimization of user engagement under evolving conditions.

For the L2 distance metric, our method records 2.4384e9 in Phase 2, ensuring even resource distribution. Although the value is slightly higher than Phase 1 due to the increased resource pool and broader distribution scope, it remains significantly better than other methods, maintaining balance and fairness.

TABLE IV
RESULTS FOR PHASE 2.

Method	Allocated Impressions	Over-Allocation Rate	Click	L2 Distance
RAP	**1378242.56**	**0**	**482384.73**	**2.4384e9**
SHALE	1336895.28	0	454544.39	2.9983e9
ALI	1350677.70	0.112	472737.19	3.0323e9

These results highlight the superiority of our method in maximizing surplus resources while maintaining efficiency, fairness, and user engagement.

V. CONCLUSION

In the field of Wi-Fi Marketing, efficient resource allocation plays a crucial role in optimizing advertising campaign performance while maintaining a positive user experience. By applying fundamental principles such as fairness, demand-based optimization, and enhancing user satisfaction, the resource allocation model proposed in this study has demonstrated its ability to balance advertising objectives with user convenience. The optimized objective functions are designed to ensure that advertisements are distributed effectively, achieve high interaction rates, and fully meet contractual requirements without causing user inconvenience.

The resource allocation model, with constraints on advertising quotas and user satisfaction optimization, not only helps maximize campaign effectiveness but also contributes to minimizing the risks of ad overload, thereby enhancing user trust and satisfaction. The research results indicate that optimizing ad allocation based on the established criteria can significantly improve the performance of advertising campaigns in the current diverse and complex Wi-Fi Marketing environment. In the future, research can be expanded and enhanced by:

- Developing Multi-Objective Models: Build multi-objective optimization models to simultaneously maximize various performance metrics such as ClickThrough Rate (CTR), conversion rate, and user satisfaction.
- Practical Experiments: Implement the proposed models in real-world Wi-Fi Marketing environments to evaluate their effectiveness and adjust the models based on practical feedback.
- Expanding Research Scope: Extend the research to encompass other factors such as advertising timing, and user behavior characteristics to create more comprehensive ad allocation strategies.

These research directions will not only help improve the performance of Wi-Fi Marketing campaigns but also contribute to developing smarter, more flexible, and user-friendly advertising solutions in the future.

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