Sequential Optimization of Real-Time Revenue Using Adaptive Online Learning.

***Abstract*—Revenue optimization represents a major strategic challenge for large-scale companies and e-commerce platforms. In environments characterized by massive and heterogeneous user populations, the real-time adaptation of marketing strategies becomes a critical driver of performance. This paper proposes an adaptive intelligent algorithm based on online learning to maximize revenue generated through premium subscription plans within a platform serving millions of users. The problem is formulated as a sequential decision-making process under uncertainty. Nine distinct marketing strategies, differentiated by promotional offers and commercial incentives, are dynamically presented to users during their navigation sessions. No prior knowledge of conversion rates is assumed, and each user interaction produces binary feedback corresponding to success or failure. The objective is to rapidly identify the strategy yielding the highest conversion rate while minimizing exploration costs. Experimental results demonstrate that the Thompson Sampling-based algorithm outperforms both random selection and Upper Confidence Bound (UCB) approaches in identifying the optimal strategy. After only a limited number of interactions, the proposed method efficiently detects the most profitable strategy, thereby reducing advertising and operational costs. For a platform with 100 million users offering a premium annual subscription priced at 100 USD, a strategy achieving a 20% conversion rate could generate up to 2 billion USD in additional revenue. These findings highlight the effectiveness of online learning techniques for sustainably improving the profitability and operational efficiency of digital platforms.**

***Keywords*—Online learning, revenue optimization, Thompson Sampling, multi-armed bandits, dynamic pricing, adaptive marketing, e-commerce.**

I. Introduction

Real-time revenue optimization has become a major challenge across various domains, including e-commerce, telecommunications, inventory management, dynamic pricing, and many others. With the rapid growth of data streams and the increasing variability of operational environments, traditional optimization approaches based on reinforcement learning techniques such as Q-learning and Deep Q-learning often prove inefficient [1], [2]. In this context, adaptive intelligent systems capable of continuously learning and adjusting their behavior have gained significant attention. These systems rely on online learning, a specialized branch of Artificial Intelligence in which models are iteratively updated as new data become available, enabling the capture of instantaneous changes in environmental behavior without explicitly defining states and actions.

Several recent studies have highlighted the relevance of such approaches for revenue optimization. For instance, Doe et al. [3] demonstrated that online algorithms can outperform conventional methods in environments characterized by highly variable demand patterns. Smith and Nguyen [4] applied online learning techniques to real-time pricing in e-commerce and reported substantial revenue improvements compared with static pricing strategies. Similarly, Zhang et al. [5] introduced an adaptive neural network-based framework for online resource allocation, reducing operational costs while maintaining high performance levels.

Despite these advances, several challenges remain unresolved, particularly the rapid convergence of models under noisy real-time data conditions, the management of the exploration–exploitation trade-off, and the integration of practical operational constraints. More recently, Khan et al. [6] and Lee and Park [7] proposed hybrid mechanisms combining online learning with Bayesian decision models to improve the robustness and reliability of revenue forecasting.

This study follows this line of research by proposing a sequential method capable of optimizing real-time revenue from continuous data streams while leveraging recent advances in online learning and artificial intelligence.

II. Materials And Methods

A. Definition of the Study Environment

The approach adopted in this study is based on the online learning framework, a specific branch of artificial intelligence dedicated to sequential decision-making under uncertainty. Unlike conventional reinforcement learning approaches such as Q-Learning or Deep Q-Learning, this framework does not require the explicit definition of a state space and a formally structured action space.

In the studied context, a “state” may be interpreted as a given user to whom a marketing strategy is deployed, while the “action” corresponds to the strategy selected among the nine available strategies considered in this study, as illustrated in Figure 1. However, within the online learning framework adopted here, these concepts are not explicitly modeled as inputs and outputs of a Markov decision-making process. Instead, the objective is to iteratively select the strategy that maximizes the expected reward based on the observed feedback.

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The feedback signal (reward) constitutes the central component of the model. In the proposed experimental protocol, the algorithm is executed on a dataset containing 10,000 users, resulting in a matrix of dimension (10,000 x 9).

Each matrix cell takes a binary value:

- 1 if the user subscribes to the premium plan after being exposed to the selected strategy (success),
- 0 otherwise (failure).

These binary values represent the rewards used by the online learning algorithm to progressively refine strategy selection. As interactions accumulate, the model improves its estimation of the relative performance of each strategy and gradually converges toward the one exhibiting the highest conversion rate.

The studied environment corresponds to an adaptive marketing strategy selection problem in a retail context. Nine distinct strategies are available. Each strategy consists of a specific combination including: (i) marketing formulation, (ii) commercial package, (iii) targeted advertising, and (iv) special promotional offers.The structure of the strategies is summarized in Figure 1.

Fig. 1 Structure of the nine marketing strategies composing the study environment.

Strategy 1	**Strategy 2**	**Strategy 3**
Formula 1	Formula 2	Formula 3
Package 1	Package 2	Package 3
Advertisement 1	Advertisement 2	Advertisement 3
Special Offer 1	Special Offer 2	Special Offer 3
Strategy 4	**Strategy 5**	**Strategy 6**
Formula 4	Formula 5	Formula 6
Package 4	Package 5	Package 6
Advertisement 4	Advertisement 5	Advertisement 6
Special Offer 4	Special Offer 5	Special Offer 6
Strategy 7	**Strategy 8**	**Strategy 9**
Formula 7	Formula 8	Formula 9
Package 7	Package 8	Package 9
Advertisement 7	Advertisement 8	Advertisement 9
Special Offer 7	Special Offer 8	Special Offer 9

The "formulation" represents the mode of presentation of the service to the customer. It acts as the interface through which the offer is communicated and structured.

The "package" corresponds to the content of the proposed service. It may include, for example, delivery fees, delivery time, as well as discount percentages applied to certain products.

"Advertising" refers to the mechanism used to promote the service. It may take different forms, such as email campaigns, pop-up displays on the company's website, or the use of internal messaging systems.

The "special offer" corresponds to a launch incentive designed to encourage customers to subscribe. For instance, it may involve offering three months of free deliveries.

The objective of this study is to identify, among the nine (09) considered strategies, the one that maximizes revenue and generates the highest number of new subscribers, using a Thompson Sampling-based algorithm.

B. Mathematical Modeling of the Problem: Multi-Armed Bandit Framework with Thompson Sampling

The revenue optimization problem is modeled as a stochastic Multi-Armed Bandit (MAB) problem [8], [9]. Let $K = 9$denote the number of available marketing strategies, each interpreted as an arm of the bandit. At each time step $t \in \{1, \dots, T\}$, corresponding to an interaction with a user, the algorithm selects a strategy$A_t \in \{1, \dots, K\}$.

1) Probabilistic Model

Each strategy $k \in \{1, \dots, K\}$is associated with a random reward variable:

$$X_{t,k} \sim \text{Bernoulli}(\theta_k) \quad (1)$$

where:

- $\theta_k \in [0,1]$represents the unknown conversion rate of strategy k,
- $X_{t,k} = 1$if the user subscribes to the premium plan,
- $X_{t,k} = 0$otherwise.

The parameters θ_k are assumed to be fixed but unknown a priori. The observed reward at time t is given by:

$$R_t = X_{t,A_t} \quad (2)$$

2) Optimization Objective

The objective is to maximize the cumulative reward:

$$\sum_{t=1}^{T} R_t \quad (3)$$

Where $T = 10\,000$corresponds to the total number of users in the experiment.

The optimal strategy is defined as:

$$k^* = \arg\max_{k \in \{1,\dots,K\}} \theta_k \quad (4)$$

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with the optimal conversion rate:

$$\theta^* = \max_k \theta_k \quad (5)$$

Algorithm performance is measured using *cumulative regret*, defined as:

$$\mathcal{R}(T) = T\theta^* - \mathbb{E}\left[\sum_{t=1}^{T} R_t\right] \quad (6)$$

The goal is to design a policy π that minimizes $\mathcal{R}(T)$.

3) Algorithm: Thompson Sampling

The *Thompson Sampling* algorithm is adopted, as it is particularly well-suited for binary reward settings [10], [11]. For each strategy *k*, a Beta prior distribution is assumed:

$$\theta_k \sim \text{Beta}(\alpha_k, \beta_k) \quad (7)$$

Initialization

$$\alpha_k = 1, \quad \beta_k = 1 \quad \forall k \quad (8)$$

At each time step t :

1. Sampling

$$\tilde{\theta}_k \sim \text{Beta}(\alpha_k, \beta_k) \quad (9)$$

2. Selection

$$A_t = \text{argmax}_k \tilde{\theta}_k \quad (10)$$

3. Bayesian Update

After observing reward R_t :

$$\alpha_{A_t} \leftarrow \alpha_{A_t} + R_t$$
$$\beta_{A_t} \leftarrow \beta_{A_t} + (1 - R_t)$$

This mechanism ensures a natural balance between exploration (testing uncertain strategies) and exploitation (favoring strategies with higher estimated performance).

4) Economic Interpretation

Let *P* be the price of the premium plan (*P=100 USD*) and *N* the total number of users (*N*=100,000,000). The expected total revenue under the optimal strategy is:

$$\text{Revenue} = N \cdot \theta^* \cdot P \quad (11)$$

Dans le scénario expérimental où $\theta^* = 0.20$:

$$\text{Revenue} = 100\,000\,000 \times 0.20 \times 100 = 2 \times 10^9$$

i.e., 2 billion USD in annual revenue.

C. Implementation of the Artificial Intelligence Solution

The artificial intelligence method adopted to solve the marketing strategy optimization problem is the *Thompson Sampling* algorithm, a well-established Bayesian approach within the framework of Stochastic *Multi-Armed Bandit* problems. This algorithm is particularly suitable for environments characterized by binary rewards, as in the present study where user conversion to the premium plan represents the event of interest.

In the considered experimental protocol, each arrival of a new user corresponds to a sequential iteration $t \in \{1, \ldots, T\}$. At each iteration, the algorithm selects a single strategy $A_t \in \{1, \ldots, 9\}$among the nine available strategies, which is then presented to the user. The observed reward $R_t \in \{0,1\}$among the nine available strategies, which is then presented to the user. The observed reward:

$$\theta_k \sim \text{Beta}(\alpha_k, \beta_k) \quad (12)$$

At each iteration t, the algorithm proceeds according to the following steps:

1. Sampling: for each strategy *k*, a sample $\tilde{\theta}_k$ is drawn from the current posterior distribution.
2. Selection: the selected strategy is defined as:

$$A_t = \text{argmax}_k \tilde{\theta}_k \quad (13)$$

3. Observation: the reward R_t is observed.

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4. Bayesian update: the parameters of the distribution associated with the selected strategy are updated according to:

$$\alpha_{A_t} \leftarrow \alpha_{A_t} + R_t,$$
$$\beta_{A_t} \leftarrow \beta_{A_t} + (1 - R_t).$$

This mechanism naturally induces a balance between exploration of uncertain strategies and exploitation of strategies estimated to be highly profitable. Under standard stochastic assumptions, Thompson Sampling benefits from strong theoretical guarantees [12], [13], particularly a sub-logarithmic cumulative regret with respect to the time horizon T.

Consequently, its adoption is justified from both a theoretical perspective — due to its asymptotic properties — and a practical perspective, owing to its computational simplicity and empirical robustness in sequential decision-making environments under uncertainty.This formulation demonstrates that premium revenue optimization can be addressed as a stochastic Multi-Armed Bandit problem with Bernoulli rewards. The use of Thompson Sampling enables:

- rapid convergence toward k^*,
- minimization of cumulative regret,
- maximization of expected revenue,
- reduction of exploration costs.

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Algorithm 1 Deep Q-Learning

```
Initialize Q-network and target network
for each episode do
    Observe initial state s
    for each step do
        Select action ( a ) using ( \epsilon )-greedy policy
        Execute action and observe reward ( r ) and next state ( s' )
        Store transition in replay buffer
        Sample minibatch and update Q-network
    end for
    Update target network
end for=0
```

III. Results

A. Experimental Evaluation (Comprehensive Statistical Analysis) of the Results

For this case study, Thompson Sampling and the Upper Confidence Bound (UCB) selection algorithm were implemented simultaneously using the simulation framework previously described. A random selection algorithm was also included as a baseline reference. All methods were evaluated using the same reward matrix, ensuring a direct and consistent comparison of performance.

The performance of the strategies was quantified using the relative gain, defined as:

$$\text{Relative Gain (\%)} = \frac{\text{Strategy Reward-Random Reward}}{\text{Random Reward}} \times 100 \tag{14}$$

A histogram representing the strategy selection frequencies was generated, confirming that the strategy exhibiting the highest conversion rate (Strategy 6) was predominantly selected by both Thompson Sampling and UCB. This result highlights the effectiveness of these approaches compared with random selection.

Multi-Run Experimental Protocol

To ensure statistical reliability, $M = 100$ independent simulations were performed, each with a horizon $N = 10{,}000$ iterations.

For each algorithm $\mathcal{A} \in \{Random, UCB, TS\}$, the following quantities were computed:

the final cumulative reward: $G_{\mathcal{A}}^{(m)}(T)$

the final cumulative regret: $R_{\mathcal{A}}^{(m)}(T)$

Subsequently, the following statistical estimators were evaluated:

$$\bar{G}_{\mathcal{A}} = \frac{1}{M}\sum_{m=1}^{M} G_{\mathcal{A}}^{(m)} \tag{15}$$

$$s_{\mathcal{A}}^2 = \frac{1}{M-1}\sum_{m=1}^{M}\left(G_{\mathcal{A}}^{(m)} - \bar{G}_{\mathcal{A}}\right)^2 \tag{16}$$

Assuming approximate normality according to the Central Limit Theorem, the 95% confidence interval is defined as:

$$CI_{95\%} = \bar{G}_{\mathcal{A}} \pm 1.96\,\frac{s_{\mathcal{A}}}{\sqrt{M}} \tag{17}$$

The same procedure is applied to the cumulative regret.

Statistical Significance Test

A paired *t*-test was performed between Thompson Sampling (TS) and UCB:

$$t = \frac{\bar{d}}{s_d/\sqrt{M}} \tag{18}$$

Where:

$$d^{(m)} = G_{TS}^{(m)} - G_{UCB}^{(m)}$$

If $p < 0.05$, the null hypothesis of equal performance is rejected.

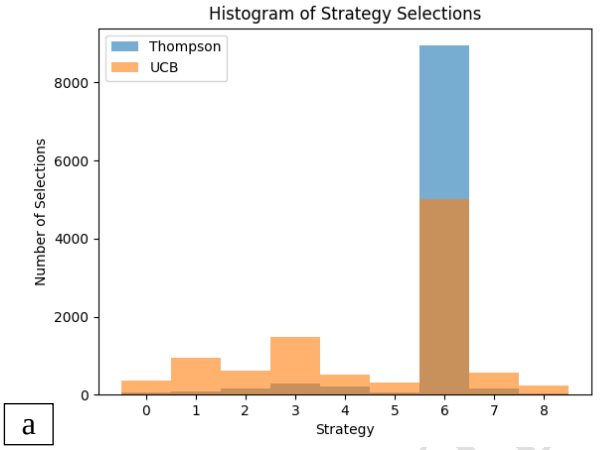
Fig. 1a shows that Thompson Sampling (TS) and the UCB algorithm predominantly concentrate their selections on Strategy 6, which corresponds to the highest conversion rate. However, TS exhibits a stronger concentration, indicating faster convergence toward the optimal strategy and more efficient exploitation. UCB also correctly identifies the optimal arm, but maintains a more structured exploration of suboptimal strategies due to its deterministic confidence-bound mechanism.

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Overall, these results indicate that, within the framework of sequential real-time revenue optimization through adaptive online learning, Thompson Sampling provides faster adaptation and superior empirical performance while preserving the theoretical guarantees of sublinear regret.

Fig. 2b compares the evolution of cumulative regret for Random Selection, UCB, and Thompson Sampling (TS). Random selection exhibits an almost linear regret growth, reflecting the absence of learning and an $\mathcal{O}(T)$. behavior. In contrast, UCB and TS demonstrate sublinear growth, consistent with the theoretical guarantees of logarithmic regret$\mathcal{O}(\log T)$.

Among the adaptive methods, TS achieves the lowest regret, indicating faster convergence toward the optimal strategy and more efficient exploitation over a finite horizon. These results confirm the relevance of online learning approaches for sequential revenue optimization, with Thompson Sampling demonstrating superior empirical performance.



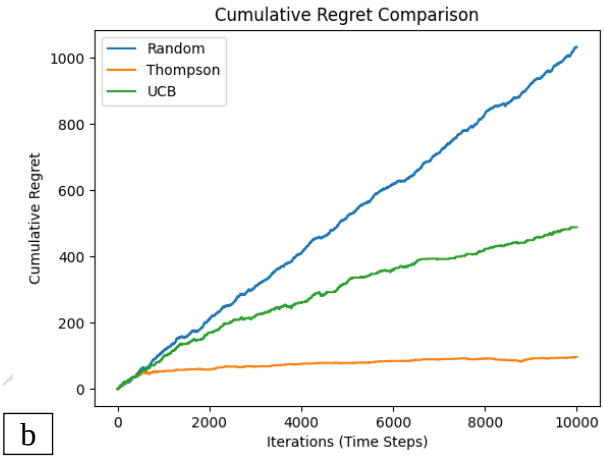


FIG. 2 Histogram of Strategy Selections (a) and Cumulative Regret Comparison (b)

Thompson Sampling (TS), the UCB algorithm, and the evolution of cumulative regret as a function of the number of iterations for the three considered strategies: random selection, UCB, and Thompson Sampling (TS).

Table 1 compares three multi-armed bandit strategies (Random, UCB, and TS) in terms of cumulative reward, regret, detection time, and theoretical properties. The Random strategy serves as a baseline and exhibits the worst performance, with low reward and high regret. UCB significantly improves the results by reducing regret and increasing reward, in accordance with its logarithmic regret guarantee. TS achieves the best overall performance, with maximum reward, minimal regret, and faster identification of the optimal strategy. In summary, the observed ranking is: "Random"<"UCB"<"TS",

This confirms the superior efficiency of methods based on strong theoretical foundations, particularly Bayesian approaches.

TABLE 1
COMPARATIVE PERFORMANCE OF BANDIT STRATEGIES

Strategy	Final Reward	Final Regret	Detection Time	Theoretical Property
Random	968.0	1034.0	Not detected	Baseline
UCB	1513.0	489.0	6984 iterations	Logarithmic regret
Thompson				Bayesian

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Strategy	Final Reward	Final Regret	Detection Time	Theoretical Property
Sampling				optimal

The table below compares the performance of multi-armed bandit strategies in terms of cumulative reward, profitability, and detection time. Thompson Sampling achieves the highest reward (1905.0), the highest economic gain (96.80% compared to Random), and the fastest detection time (1212 iterations). UCB shows intermediate performance, while the Random strategy remains the least effective and fails to detect any meaningful change. Overall, the results confirm the superiority of Thompson Sampling, followed by UCB.

TABLE 2
PERFORMANCE SUMMARY OF BANDIT STRATEGIES

Metric	Value
Best Strategy	6
Random Reward	968.0
Thompson Sampling Reward	1905.0
UCB Reward	1513.0
Absolute Return (TS vs Random)	93700 $
Relative Return (TS vs Random)	96.80%
Detection Time (Thompson Sampling)	1212 iterations
Detection Time (UCB)	6984 iterations
Detection Time (Random)	None

IV. DISCUSSION

The experimental results highlight significant differences between the studied strategies in terms of cumulative reward, regret, and detection time. The observed hierarchy (Random < UCB < TS) confirms the superiority of approaches incorporating a structured exploration–exploitation mechanism over purely random selection.

The Random strategy, used as a baseline, naturally exhibits the worst performance. The absence of an adaptive mechanism leads to high regret and an inability to detect changes in the environment. This behavior illustrates the limitations of uninformed policies in dynamic contexts.

UCB significantly improves performance through its principle of optimism in the face of uncertainty [14], [15]. The substantial reduction in regret observed experimentally is consistent with its theoretical guarantee of logarithmic regret. However, its relatively long detection time suggests some inertia in adapting to abrupt changes, possibly due to the deterministic structure of its exploration mechanism.

Thompson Sampling (TS) achieves the best overall performance. The highest cumulative reward and lowest regret confirm the effectiveness of its Bayesian probabilistic approach [16], [17]. Its ability to detect changes more rapidly highlights its superior responsiveness to non-stationarity [18]. This performance can be explained by stochastic sampling from the posterior distribution, which enables more flexible exploration and better adaptation to dynamic environments.

The economic analysis reinforces these findings: the high absolute gain and relative return of TS compared to Random highlight the practical impact of choosing an appropriate learning strategy. Beyond theoretical considerations, these results demonstrate the operational value of Bayesian approaches in real-world applications where cumulative performance is critical.

However, several limitations should be acknowledged. The experiments were conducted under a specific setting, and the robustness of the results may vary depending on the number of arms, reward distributions, or frequency of environmental changes. Future work could explore the impact of different noise levels, gradual non-stationarity, or comparisons with more recent adaptive variants.

V. CONCLUSION AND PERSPECTIVES

In conclusion, the experimental results demonstrate the superiority of approaches based on rigorous probabilistic principles for sequential decision-making under uncertainty [19], [20]. Among the evaluated methods, the Thompson Sampling algorithm achieves the best performance in terms of convergence speed, exploration–exploitation balance, and cumulative revenue maximization. These findings confirm the relevance of Bayesian approaches for dynamic optimization of marketing strategies in large-scale digital environments.

This study provides five main contributions. First, it formalizes premium revenue optimization as an adaptive online learning problem under uncertainty [21], [22]. Second, it proposes an intelligent algorithm capable of autonomously identifying the optimal marketing strategy without prior knowledge of conversion probabilities [23]. Third, it incorporates realistic economic constraints such as deployment costs, advertising fatigue, and user experience preservation [24], [25]. Fourth, it provides a quantitative analysis highlighting the significant economic impact of an optimized adaptive strategy on overall revenue [26]. Finally, it establishes a reproducible and extensible experimental framework applicable to large-scale e-commerce platforms [27], [28].

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The results show that at an industrial scale, the performance gap between a suboptimal marketing strategy and one optimized through online learning can represent several hundred million, or even several billion dollars in additional annual revenue [29], [30].

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