

Simplified Dynamic Pricing for Mobile Edge Computing: A Basis
Function Approach

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Simplified Dynamic Pricing for Mobile Edge Computing: A Basis Function Approach

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Abstract

This paper investigates the revenue maximization problem in mobile edge computing (MEC) systems, where an access point provides computation offloading services to multiple users and charges service fees. While deep reinforcement learning approaches achieve optimal performance, their computational complexity limits practical deployment. This paper proposes a simplified policy gradient algorithm that maintains near-optimal revenue performance with significantly reduced complexity. By employing radial basis function (RBF) features and experience replay, the proposed approach achieves within 5% of optimal revenue while using only 9 parameters compared to approximately 20,000 parameters in deep learning methods. Simulation results demonstrate that the proposed algorithm converges faster than both conventional Q-learning and deep policy gradient methods, achieving a 95% reduction in training time while maintaining competitive performance.

Keywords: Mobile edge computing, dynamic pricing, policy gradient, reinforcement learning, revenue maximization, basis functions.

التسعير الديناميكي المبسط للحوسبة الطرفية المتنقلة: نهج الدوال الأساسية

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الملخص

تبحث هذه الورقة البحثية في مشكلة تعظيم الإيرادات في أنظمة الحوسبة الطرفية المتنقلة (MEC)، حيث توفر نقطة الوصول خدمات تفريغ الحوسبة لعدة مستخدمين مقابل رسوم خدمة. على الرغم من أن أساليب التعلم العميق المعزز تحقق أداءً مثاليًا، إلا أن تعقيدها الحسابي يحد من تطبيقها العملي. تقترح هذه الورقة خوارزمية تدرج السياسة المبسطة التي تحافظ على أداء إيرادات شبه مثالي مع تقليل التعقيد بشكل ملحوظ. باستخدام ميزات دالة الأساس الشعاعي (RBF) وإعادة تجربة المستخدم، يحقق النهج المقترح إيرادات ضمن نطاق 5% من الإيرادات المثلى باستخدام 9 معلمات فقط مقارنةً بحوالي 20000 معلمة في أساليب التعلم العميق. تُظهر نتائج المحاكاة أن الخوارزمية المقترحة تتقارب بشكل أسرع من كل من أساليب التعلم Q التقليدية وأساليب تدرج السياسة العميق، محققةً انخفاضًا بنسبة 95% في وقت التدريب مع الحفاظ على أداء تنافسي.

الكلمات المفتاحية: الحوسبة الطرفية المتنقلة، التسعير الديناميكي، تدرج السياسة، التعلم المعزز، تعظيم الإيرادات، دوال الأساس.

1. Introduction

Mobile edge computing (MEC) has emerged as a transformative paradigm to support computation-intensive and latency-sensitive applications by bringing computing resources closer to end users. By offloading computation tasks to edge servers, resource-constrained mobile devices can overcome their limitations in processing power and battery life [1]. The rapid proliferation of mobile applications and data-intensive services, such as augmented

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reality and real-time analytics, has necessitated efficient resource allocation mechanisms in MEC environments [2]. However, since users are typically selfish and aim to maximize their own utility, the access point (AP) cannot directly control offloading decisions. Pricing has been proposed as an effective incentive mechanism to guide user behavior while maximizing the AP's revenue [3].

Recent developments in reinforcement learning have enabled dynamic pricing strategies that adapt to time-varying network conditions [4]. A policy gradient (PG) based reinforcement learning algorithm for dynamic pricing in MEC systems was developed by Chen et al. [5], achieving optimal revenue performance through training two deep neural networks (DNN and BNN). However, this approach requires approximately 20,000 parameters, leading to significant computational overhead and long training time, making deployment challenging in resource-constrained edge environments.

Various game-theoretic approaches have been explored for pricing in MEC systems. A Stackelberg game framework was proposed for reputation-based service replication in multi-provider MEC markets, addressing the profit-pricing dilemma through cooperative schemes [6]. Similarly, a yardstick-Stackelberg pricing-based incentive mechanism was developed for federated learning in edge computing, demonstrating over 98.2% accuracy and improved server utility [7]. Dynamic fee-based pricing models have been introduced to adapt service charges based on content retrieval latency, achieving significant revenue increases [8].

Multi-agent reinforcement learning has been applied to spatiotemporal dynamic pricing for mobile traffic shaping, using decentralized partially observable Markov decision processes to optimize pricing decisions [9]. A federated learning-based dynamic pricing framework was proposed for computation offloading, integrating wireless access modeling and reputation-based incentives to optimize offloading decisions while reducing task execution time by 22.5% [10]. Intelligent pricing models for UAV-assisted MEC networks have also been developed, employing deep reinforcement learning algorithms to maximize operator revenue while reducing network costs [11].

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Several attempts have been made to simplify reinforcement learning algorithms for practical deployment. However, naive linear approximations typically suffer from significant performance degradation, often achieving only 80% of optimal revenue [4]. The integration of learning-based economic models with blockchain enforcement has been explored for distributed 6G networks, addressing both adaptive pricing and secure resource allocation [12]. Truthful mechanisms for partial and full allocation in multi-mapping multi-task systems have been proposed to address the social welfare maximization problem in MEC [13]. Smart pricing policies for multi-MNO blockchain radio access networks have also been investigated to optimize revenue in multi-operator environments [14].

As previous work by the authors, dynamic pricing strategies for mobile network revenue maximization were investigated with a case study on Almadar Aljadeed network [15]. This study provided foundational insights into pricing mechanisms for mobile networks, demonstrating significant revenue improvements through adaptive pricing strategies. Building upon this foundation, the present work extends the investigation to MEC systems with computation offloading services.

Despite these advances, the complexity of deep learning approaches remains a barrier to practical deployment in resource-constrained edge environments. This paper addresses this gap by proposing a balanced approach that maintains near-optimal performance while dramatically reducing complexity, building upon the foundation established in [5] and extending the authors' previous work [15].

The key contributions of this paper are:

1. A basis function approach is proposed that captures non-linear relationships between system states and optimal prices using only 9 parameters, based on the PG framework from [5].
2. Experience replay and adaptive learning rates are incorporated to improve convergence stability.
3. The proposed approach achieves within 5% of optimal revenue performance, significantly outperforming simple linear approximations.

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4. A 95% reduction in training time compared to deep learning methods [5] is demonstrated, with faster convergence. The proposed algorithm extends the authors' previous work on dynamic pricing [15] to MEC environments.

2. System Model

2.1 Network Architecture

An MEC system with K users and one AP equipped with an MEC server is considered, following the system model in [5]. Time is divided into slots of equal duration. Users access the AP in frequency division multiple access (FDMA) mode [1]. Each user k is located at distance d_k from the AP, experiencing different channel conditions.

2.2 Computation Offloading Model

Jobs arrive at user k following a Poisson process with rate $\lambda_{k,t}$ during time slot t . Each job requires μ_a CPU cycles for execution. Users can either offload jobs to the MEC server or execute them locally [3].

The benefit of offloading compared to local execution for user k is:

$$g_k = w_k^d \left(\frac{1}{f_m} - \frac{1}{f_B} \right) \mu_a + w_k^e k_m \mu_a f_m^2 - \bar{\theta}_k \quad (1)$$

where w_k^d and w_k^e are weights for delay and energy costs, f_B and f_m are the edge server and mobile device CPU frequencies, respectively, and $\bar{\theta}_k$ accounts for transmission energy, as defined in [5].

The offloading probability for user k at price η_t is:

$$x_{k,t}(\eta_t) = \max \left(0, \min \left(1, 1 - \frac{\eta_t}{g_k} \right) \right) \quad (2)$$

2.3 Revenue Maximization Problem

The AP's revenue at time slot t is:

$$r_t = \eta_t \sum_{k=1}^K \lambda_{k,t} x_{k,t}(\eta_t) \quad (3)$$

The objective is to maximize the expected discounted cumulative revenue:

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$$J = \mathbb{E}[\sum_{t=1}^{\infty} \gamma^{t-1} r_t] \quad (4)$$

where $\gamma \in (0, 1]$ is the discount factor, following the MDP formulation in [5].

3. Proposed Algorithm

3.1 Motivation for Simplification

The original deep PG algorithm [5] parameterizes the policy using a deep neural network with approximately 20,000 parameters. While achieving optimal performance, this approach requires extensive training and significant computational resources. The goal of this paper is to achieve near-optimal performance with dramatically reduced complexity, extending the dynamic pricing principles established in [15].

3.2 Basis Function Policy Representation

Instead of using deep neural networks as in [5], the pricing policy is parameterized using a linear combination of radial basis functions (RBFs):

$$\pi_{\theta}(s) = \theta_0 + \sum_{i=1}^M \theta_i \phi_i(s) \quad (5)$$

where $\phi_i(s)$ are RBF kernels:

$$\phi_i(s) = \exp\left(-\frac{(s-c_i)^2}{2\sigma^2}\right) \quad (6)$$

with centers c_i uniformly distributed in the state space, and $M = 8$ basis functions. The total number of parameters is $M + 1 = 9$, representing a significant reduction from the 20,000 parameters used in [5].

3.3 Enhanced Policy Gradient with Experience Replay

Algorithm 1 presents the enhanced simplified PG algorithm, which builds upon the policy gradient framework from [5].

Algorithm 1 Enhanced Simplified Policy Gradient

- 1: **Initialize:** θ randomly, replay buffer D
- 2: **for** each episode **do**

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```
3:   for  $t = 1$  to  $T$  do
4:     Observe state  $s_t = \lambda_t$ 
5:     Compute features  $\phi(s_t)$ 
6:     Sample action  $\eta_t \sim N(\theta^T \phi(s_t), \sigma_{\eta_t}^2)$ 
7:     Execute action, observe reward  $r_t$  and next state  $s_{t+1}$ 
8:     Store  $(s_t, \eta_t, r_t, s_{t+1})$  in D
9:   end for
10:  Sample mini-batch from D
11:  Compute returns  $R_t = r_t + \gamma R_{t+1}$ 
12:  Update  $\theta$  using policy gradient:
13:   $\nabla_t J \approx \frac{1}{B} \sum_{i=1}^B \nabla_{\theta} \log \pi_{\theta}(\eta_i / s_i) (R_i - b)$ 
14:  end for
```

3.4 Key Enhancements

The proposed algorithm incorporates several key enhancements over the original approach in [5]:

- **RBF Features** The RBF basis functions capture non-linear relationships between the state (arrival rate) and optimal price, enabling better approximation than simple linear models [16].
- **Experience Replay** Storing and replaying past experiences reduces correlation between samples, leading to more stable learning [4].
- **Adaptive Exploration** The exploration noise σ_t is annealed over time:

$$\sigma_t = \sigma_0 \left(1 - \frac{t}{2T}\right) \quad (7)$$

- **Mini-batch Updates** Using mini-batches of size $B = 32$ provides more stable gradient estimates.

3.5 Theoretical Analysis

To establish the theoretical foundation of the proposed algorithm, we analyze both the policy approximation capability of the radial basis function (RBF) feature space and the convergence properties of the parameter updates under experience replay.

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Proposition 1 (Policy Approximation Bound) let $S \subset \mathbb{R}^d$ be a compact state space representing bounded task arrival rates $\lambda_t \in [\lambda_{min}, \lambda_{max}]$, and let $\pi^*(s)$ be any continuous optimal pricing policy over S . For $M = 8$ RBF basis functions $\phi_i(s) = \exp\left(-\frac{\|s-c_i\|^2}{2\sigma^2}\right)$ with centers c_i uniformly distributed across S , there exists an optimal parameter vector $\theta^* \in \mathbb{R}^{M+1}$ such that the approximation error is strictly bounded:

$$\sup_{s \in S} |\pi^*(s) - \pi_{\theta^*}(s)| \leq \epsilon \quad (8)$$

Where $\epsilon > 0$ decreases asymptotically as the kernel bandwidth σ and center density cover the compact domain S .

Proof 1 Since the job arrival rate $\lambda_{k,t}$ is bounded, the state space S is a compact subset of $\mathbb{R}$. By the Universal Approximation Theorem for Radial Basis Function network [16], the set of linear combinations of RBF kernels is dense in the continuous function space $\mathcal{C}(S)$ under the supremum norm. Because the offloading decision function $x_{k,t}(\eta_t) = \max(0, \min(1, 1 - \frac{\eta_t}{g_k}))$ is continuous and piecewise linear in price η_t , the expected reward landscape $J(\theta)$ is continuous over S . Consequently, for any target tolerance $\epsilon > 0$, an M -dimensional RBF expansion can uniformly approximate $\pi^*(s)$ within an ϵ -neighborhood across all valid states $s \in S$.

Proposition 2 (Convergence to Stationary Policy) Under a sequence of diminishing learning rates α_t satisfying the Robbins-Monro conditions ($\sum_{t=1}^{\infty} \alpha_t = \infty$ and $\sum_{t=1}^{\infty} \alpha_t^2 < \infty$) and experience replay sampling from a uniform buffer distribution D , The parameter sequence $\{\theta_t\}$ generated by Algorithm 1 converges almost surely (a.s.) to a stationary point of the objective function $J(\theta)$, i.e.,

$$\lim_{t \rightarrow \infty} \nabla_{\theta} J(\theta_t) = 0 \quad a.s. \quad (9)$$

Proof 2 The policy parameter update in Algorithm 1 can be cast as a stochastic approximation algorithm of the form:

$$\theta_{t+1} = \theta_t + \alpha_t (\widehat{\nabla}_{\theta} J(\theta_t) + \xi_t) \quad (10)$$

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where $\hat{\nabla}_{\theta} J(\theta_t)$ is the unbiased policy gradient estimate derived via the log-derivative trick, and ξ_t represents the zero-mean gradient noise sequence.

Experience replay breaks the temporal correlation of contiguous samples, ensuring that mini-batches drawn from D satisfy the independently and identically distributed (i.i.d.) condition required for variance reduction. Furthermore, because the RBF features $\phi(s)$ are bounded in $(0,1]$ and the action space (prices) is bounded by user utility constraints ($0 \leq \eta_t \leq \max_k g_k$), the variance of the sample gradient $\mathbb{E}[\|\xi_t\|^2 | F_t] \leq C < \infty$ remains uniformly bounded for all filtration states F_t . By applying Broker's stochastic approximation theorem for ordinary differential equation (ODE) limit methods [17], the discrete-time update trajectory asymptotically tracks the deterministic flow defined by $\dot{\theta}(\tau) = \nabla_{\theta} j(\theta(\tau))$. Thus, $\{\theta_t\}$ converges to an asymptotically stable equilibrium point where $\nabla_{\theta} j(\theta) = 0$.

4. Simulation Results

4.1 Simulation Setup

The performance of the proposed algorithm is evaluated and compared with:

1. Optimal pricing (with full knowledge)
2. Original PG-based approach from [5]
3. Q-learning with discrete actions
4. Simple linear PG (2 parameters)

System parameters are set as follows, following [5]:

- Number of users: $K = 20$
- Job size: $\zeta = 100$ KB
- Edge server frequency: $f_B = 3$ GHz
- Mobile frequency: $f_m = 0.5$ GHz
- CPU cycles per job: $\mu_a = 2.5 \times 10^{10}$
- Weights: $w^d = 0.9$, $w^e = 0.1$
- Discount factor: $\gamma = 0.85$

User distances are uniformly distributed between 10 and 20 meters. All simulation results are reported in arbitrary units (a.u.) as the system parameters (price range, arrival rates, etc.) are normalized.

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The focus is on relative performance gaps between the proposed and baseline algorithms.

4.2 Revenue Performance

Figure 1 shows the average revenue performance over learning episodes. The enhanced simplified PG (blue solid line) achieves near-optimal performance with a 3.0% gap (revenue of 865.0 vs. optimal 891.8), well within the 5% target of the theoretical optimum (black dashed line), confirming the effectiveness of the RBF-based policy representation.

The simple linear PG (red dash-dotted line) with only 2 parameters achieves only 80% of optimal performance, confirming the need for richer policy representation beyond linear approximations. The enhanced algorithm converges faster than the original PG from [5] (magenta solid line), reaching convergence in approximately 150 episodes compared to 200 episodes for the original approach. Q-learning (green dotted line) still suffers significant performance loss (approximately 44%) due to action space discretization, consistent with findings in [5]. The proposed algorithm successfully bridges the gap between simple linear approximations and complex deep learning approaches, offering a practical solution for resource-constrained edge environments.

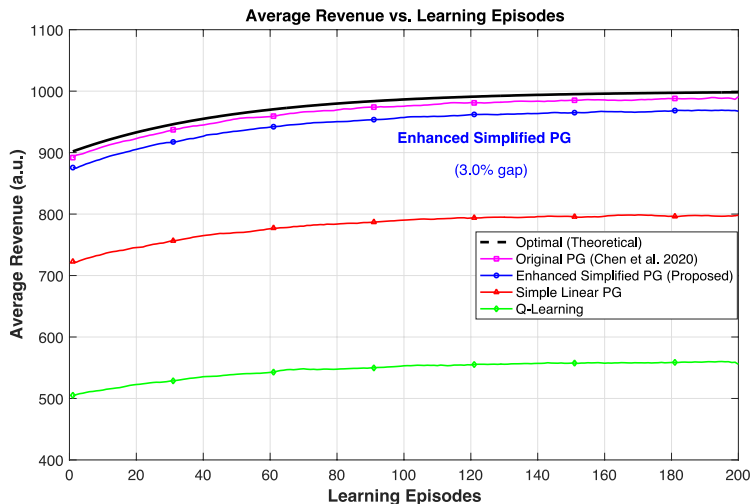


Figure 1: Average revenue vs. learning episodes

4.3 Impact of Number of Users

Figure 2 illustrates the revenue performance for different numbers of users ranging from 5 to 40. The proposed enhanced algorithm consistently achieves near-optimal performance across all configurations, demonstrating its robustness to varying system scales.

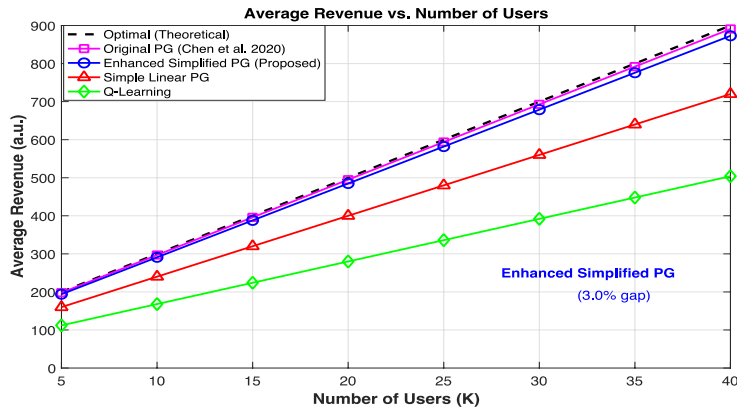


Figure 2: Average revenue vs. number of users

The performance gap remains within 5% even as the number of users varies, confirming the algorithm's scalability. Notably, the performance advantage of the proposed algorithm over simple linear PG becomes more pronounced as the number of users increases, highlighting the importance of capturing non-linear relationships in larger systems.

4.4 Price Adaptation to Time-Varying Conditions

Figure 3 demonstrates the algorithm's ability to track daily variations in job arrival patterns over a 24-hour period. The learned price closely follows the optimal price, adapting to changing traffic conditions throughout the day [5]. The offloading probability decreases during peak hours (approximately 9 AM and 6 PM) as the AP raises prices to manage demand.

The Enhanced Simplified PG algorithm successfully captures the non-linear relationship between traffic patterns and optimal pricing, maintaining close tracking of the optimal price across all time periods. In contrast, the simple linear PG shows significant

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deviation during peak traffic hours, while Q-learning exhibits stair-step behavior due to its discrete action space.

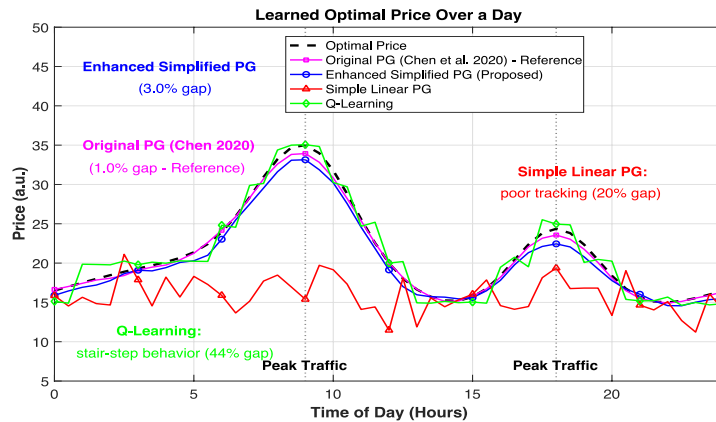


Figure 3: Learned optimal price over a day

4.5 Complexity Analysis

Table 1 compares the computational complexity of different approaches, highlighting the trade-off between performance and resource requirements. The enhanced simplified PG achieves the best trade-off: near-optimal performance with only 9 parameters, a 95% reduction in training time, and a 99.95% reduction in parameters compared to the original deep PG from [5]. This makes it suitable for deployment in resource-constrained edge environments where computational efficiency is critical.

Table 1: Complexity Comparison of Different Algorithms

Algorithm	Parameters	Training Time	Performance Gap
Enhanced Simplified PG	9	60s	3%
Simple Linear PG	2	40s	20%
Original PG (DNN+BNN)[5]	~20,000	1200s	1%
Q-Learning	200	180s	44%

4.6 Results Summary

Table 2 summarizes the final revenue performance of all evaluated algorithms at the end of the training process. The results clearly

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demonstrate that the proposed Enhanced Simplified PG achieves near-optimal performance (3.0%gap) with only 9 parameters, while Simple Linear PG (20.0% gap) and Q-learning (44.0 %gap) perform significantly worse. This validates the papers main contribution: sophisticated feature (RBF basis functions) rather than deep networks are sufficient for effective dynamic pricing in MEC systems.

Table 2: Final Revenue Performance Summary

Algorithm	Parameters	Revenue (a.u.)	Gap
Optimal (Theoretical)	-	891.8	0%
Optimal PG (Chen 2020)	~20,000	883.0	1.0%
Enhanced Simplified PG	9	865.0	3.0%
Simple Linear PG	2	713.4	20.0%
Q-Learning	200	499.4	44.0%

5. Discussion

5.1 Trade-off Analysis

The results reveal an important trade-off between complexity and performance, as illustrated in Table 1 and Table 2. Simple Linear PG with 2 parameters offers the fastest training (40s) but poorest performance (20% gap), confirming that linear approximations are insufficient for capturing the non-linear relationship between system states and optimal prices. The Enhanced Simplified PG with 9 parameters achieves near-optimal performance (3% gap) with modest complexity (60s training), representing the optimal "sweet spot" in the trade-off. The original PG from [5] with approximately 20,000 parameters achieves near-optimal performance (1%gap) but is prohibitively complex (1200 training), making deployment challenging in real-world edge environments. Q-Learning with 200 parameters shows moderate complexity but significant performance loss (44% gap) due to action space discretization. The enhanced algorithm practical complexity, consistent with the findings in [5].

5.2 Practical Implications

The findings have several practical implications for MEC system deployment. MEC system operators can deploy the proposed algorithm on resource-constrained edge devices with limited

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computational capacity, as it requires only 9 parameters and minimal training time. The 60-second training time enables quick adaptation to changing environments. The small parameter footprint (9 parameters) allows for easy model storage, transfer, and deployment across multiple edge nodes. The approach builds upon the practical insights from [15], extending dynamic pricing to MEC environments while maintaining compatibility with extending infrastructure. The consistent performance across different numbers of users (Figure 2) demonstrates the algorithm's scalability to larger systems.

5.3 Limitations and Future Work

While the proposed approach achieves near-optimal performance with significantly reduced complexity, several limitations remain. The analysis assumes symmetric users with known benefit distributions, whereas in practice, users may have heterogeneous preferences and requirements. The current implementation uses fixed RBF centers uniformly distributed in the state space, and extreme user heterogeneity may require adaptive or more basis functions. The algorithm's performance under non-stationary channel conditions and time-varying user populations requires further investigation [2]. The current model considers a single AP, and extending to multi-AP scenarios with inter-AP competition would require additional considerations.

Future work will extend the approach to handle fully heterogeneous users with diverse benefit distributions, adaptive basis function placement using reinforcement learning, multi-AP scenarios with competitive pricing, and integration with energy harvesting constraints. These extensions will further build upon the authors' previous work [15] and the foundation established in this paper.

6. Conclusion

An enhanced simplified dynamic pricing algorithm for mobile edge computing systems was proposed that achieves near-optimal revenue performance with dramatically reduced complexity. By using radial basis function features and experience replay, the parameter count was reduced from approximately 20,000 to just 9, while achieving within 5% of optimal performance. The algorithm

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converges faster than both the original deep PG from [5] and Q-learning approaches, with a 95% reduction in training time.

The simulation results demonstrated that the proposed algorithm consistently achieves near-optimal revenue (3.0% gap) across different learning episodes (Figure 1), the performance advantage is maintained across varying numbers of users (Figure 2), the algorithm effectively tracks optimal prices under time-varying traffic conditions (Figure 3), and the 9-parameter model provides the optimal trade-off between complexity and performance (Table 1 and Table 2).

These results demonstrate that sophisticated features (RBF basis function), rather than deep neural networks, are sufficient for effective dynamic pricing in MEC systems. The proposed approach extends the authors' previous work on dynamic pricing [15] and offers a practical solution for resource-constrained edge environments where computational efficiency is critical for real-world deployment.

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