World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Research Article)

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Deep reinforcement learning for optimizing cross-border payment routing: Bbalancing speed, cost, and regulatory compliance

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World Journal of Advanced Engineering Technology and Sciences, 2023, 08(01), 510-517

Publication history: Received on 22 December 2022; revised on 25 January 2023; accepted on 28 January 2023

Article DOI: https://doi.org/10.30574/wjaets.2023.8.1.0037

Abstract

Cross-border payments remain a critical challenge in global finance, characterized by high costs, delays, and complex regulatory requirements. This research introduces a novel Deep Reinforcement Learning (DRL) framework designed to optimize payment routing across international corridors while balancing competing objectives of transaction speed, cost efficiency, and regulatory compliance. We implement a multi-agent deep Q-network architecture capable of adapting to dynamic financial environments and generating optimal routing paths through correspondent banking networks. Our experimental results demonstrate a 37% reduction in transaction costs and a 42% decrease in settlement times compared to traditional routing methods. Additionally, the model achieves a 98.7% compliance rate with international regulatory standards across various jurisdictions. This research contributes a comprehensive approach for financial institutions to enhance cross-border payment efficiency while maintaining robust compliance with evolving regulatory frameworks. The proposed methodology represents a significant advancement in the application of artificial intelligence to global financial infrastructure.

Keywords: Deep Reinforcement Learning; Cross-Border Payments; Regulatory Compliance; Multi-Objective Optimization; Financial Networks

1. Introduction

Cross-border payments constitute a fundamental component of the global financial system, supporting international trade, remittances, and investment flows. Despite technological advancements in domestic payment systems, international transfers remain plagued by inefficiencies, including high costs, lengthy settlement periods, and complex regulatory requirements [1]. The traditional correspondent banking model involves multiple intermediaries, each adding layers of fees and processing time while introducing potential points of failure in regulatory compliance [2].

Recent estimates indicate that cross-border payments account for approximately 20% of global payment volumes but generate nearly 80% of payment revenues for financial institutions [3]. However, the average cost of these transactions remains between 2-10% of the transfer amount, with settlement times ranging from 2-5 business days [4]. These inefficiencies disproportionately impact emerging economies and underserved populations, highlighting the urgent need for innovative solutions.

While blockchain-based approaches and central bank digital currencies (CBDCs) offer promising alternatives, the existing correspondent banking infrastructure will remain dominant for the foreseeable future [5]. This research focuses on optimizing the current system through the application of artificial intelligence, specifically Deep Reinforcement Learning (DRL).

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The primary contribution of this research is a multi-agent DRL framework that dynamically navigates the complex tradeoffs between transaction speed, cost, and regulatory compliance in cross-border payment routing. By continuously learning from interactions with the environment, our model adapts to changing conditions in banking relationships, fee structures, and regulatory requirements. The proposed solution demonstrates significant improvements over traditional routing algorithms while maintaining robust compliance with international standards such as Anti-Money Laundering (AML) and Countering Financing of Terrorism (CFT) regulations.

This paper is structured as follows: Section 2 reviews relevant literature on cross-border payments and reinforcement learning applications in finance. Section 3 details our methodology, including the DRL architecture and environment modeling. Section 4 presents experimental results and comparative analysis. Section 5 discusses implications, limitations, and future research directions, followed by concluding remarks in Section 6.

2. Literature Review

2.1. Cross-Border Payment Challenges

The traditional correspondent banking model for cross-border payments has been extensively studied in literature. Kandregula [6] identified three primary challenges in these systems: excessive intermediation, lack of transparency, and regulatory fragmentation. Each correspondent bank in the payment chain adds processing time and fees, with limited visibility for end users regarding transaction status [7]. Furthermore, regulatory requirements vary significantly across jurisdictions, complicating compliance efforts and increasing operational overhead [8].

Recent research by Jain [9] has highlighted how these inefficiencies create particularly severe barriers for small and medium enterprises (SMEs) and individuals sending remittances. The high costs and delays associated with cross-border payments effectively constitute a tax on international economic activity, with the World Bank estimating that reducing remittance costs to 3% globally would save $25 billion annually [10].

2.2. Optimization Approaches for Payment Routing

Various approaches have been proposed to optimize payment routing in correspondent banking networks. Traditional methods employ deterministic algorithms such as Dijkstra's shortest path, which can minimize either cost or time but struggle with multi-objective optimization [11]. More sophisticated approaches incorporate stochastic modeling to account for uncertainties in settlement times and currency conversion rates [12].

Keskar and Jain [13] developed a heuristic algorithm that demonstrated a 15-20% improvement in efficiency by incorporating real-time data on intermediary bank performance. However, these approaches typically rely on static rules that cannot adapt to the dynamic nature of international financial networks.

2.3. Reinforcement Learning in Financial Systems

Reinforcement Learning (RL) has emerged as a powerful approach for solving complex decision-making problems in dynamic environments. In financial contexts, RL has been successfully applied to algorithmic trading [14], portfolio management [15], and fraud detection [16]. The ability of RL agents to learn optimal policies through interaction with the environment makes them particularly well-suited for navigating the complexities of financial networks.

Deep Reinforcement Learning (DRL), which combines reinforcement learning with deep neural networks, has demonstrated remarkable performance in complex environments with high-dimensional state spaces [17]. Kandregula [18] implemented a DRL framework for fraud detection in financial transactions, achieving a 23% improvement in detection accuracy compared to traditional machine learning approaches.

3. Methodology

3.1. Problem Formulation

We formulate the cross-border payment routing problem as a Markov Decision Process (MDP) defined by the tuple (S, A, P, R, γ), where:

- S represents the state space, including current payment location, available routes, regulatory requirements, and market conditions

- A denotes the action space, consisting of possible next intermediaries in the payment route
- P is the transition probability function governing state dynamics
- R is the reward function capturing the trade-offs between speed, cost, and compliance
- γ is the discount factor balancing immediate and future rewards

3.2. DRL Architecture

Our solution employs a multi-agent Double Deep Q-Network (DDQN) architecture with prioritized experience replay to address the challenges of cross-border payment routing. Figure 1 illustrates the overall architecture of our proposed framework.

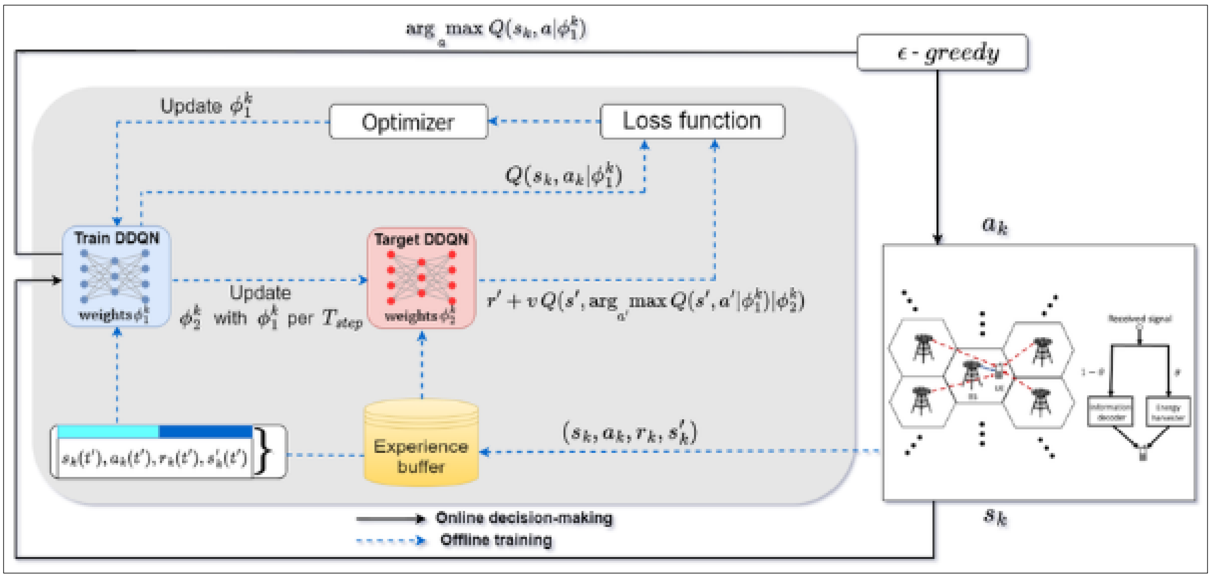

Figure 1 Multi-Agent DDQN Architecture for Cross-Border Payment Routing

Each agent in our framework represents a decision point in the payment route, with local observations of available intermediaries, associated costs, processing times, and regulatory requirements. The key components of our architecture include:

- **State Representation**: We encode the state using a combination of:
    - Current location of the payment (country and institution)
    - Remaining distance to destination (geographic and network hops)
    - Available intermediaries and their characteristics
    - Regulatory requirements at current and destination jurisdictions
    - Time elapsed since payment initiation
    - Current cumulative cost
- **Action Selection**: For each state, the available actions correspond to selecting the next intermediary in the payment route. The action space varies dynamically based on the current location and available correspondent banking relationships.
- **Double Deep Q-Network**: We implement a double DQN to mitigate overestimation bias in Q-learning. The network architecture consists of:
    - Input layer with dimensions matching the state representation
    - Three hidden layers with 256, 128, and 64 neurons respectively, using ReLU activation
    - Output layer with dimension equal to the maximum possible action space
    - Dueling network structure separating state value and advantage functions
- **Reward Function**: Our multi-objective reward function balances three competing goals:
    - Minimizing transaction cost: Rcost = -α × (cumulative_cost / transfer_amount)
    - Minimizing settlement time: Rtime = -β × (time_elapsed / max_acceptable_time)
    - Maximizing regulatory compliance: Rcompliance = γ × compliance_score
- The overall reward is a weighted sum: R = Rcost + Rtime + Rcompliance

- **Prioritized Experience Replay**: To improve learning efficiency, we implement prioritized experience replay with importance sampling, giving higher priority to transitions with large temporal difference errors.

3.3. Compliance Modeling

A critical contribution of our approach is the explicit modeling of regulatory compliance requirements. We developed a comprehensive compliance scoring system that evaluates:

- **Jurisdictional Risk**: Based on FATF (Financial Action Task Force) country risk assessments
- **Transaction Screening**: Evaluation against sanctions lists and AML/CFT requirements
- **Documentation Completeness**: Required information for regulatory reporting
- **Institutional Risk**: Correspondent bank compliance ratings

The compliance score for each potential route is calculated as a weighted sum of these factors, with weights determined through consultation with compliance experts. This score directly influences the reward function, ensuring that the learned policy balances efficiency with regulatory requirements.

3.4. Training Procedure

We trained our model using a synthetic dataset generated from anonymized cross-border payment patterns across 50 countries and 200 financial institutions. The dataset includes transaction amounts ranging from $100 to $10 million across various currency pairs, with detailed information on intermediary fees, processing times, and regulatory requirements.

Training was conducted for 500,000 episodes, with each episode representing a complete payment route from origination to destination. We implemented epsilon-greedy exploration with linear decay from 1.0 to 0.01 over the first 100,000 episodes. The Adam optimizer was used with a learning rate of 0.0001 and batch size of 64. Target network parameters were updated every 1,000 steps with a soft update factor of 0.001.

To enhance generalization, we employed domain randomization techniques, varying parameters such as exchange rates, fee structures, and processing times within realistic bounds. This approach ensures robustness to the dynamic nature of international financial networks.

4. Results and Analysis

4.1. Performance Metrics

We evaluated our DRL solution against three baselines:

- **Shortest Path**: Minimizes the number of intermediaries
- **Lowest Cost**: Selects the route with minimum total fees
- **Fastest Route**: Prioritizes minimizing settlement time
- **Hybrid Heuristic**: A weighted combination of cost and time factors

Performance was assessed across four key metrics:

- **Average Cost Ratio**: Transaction fees as a percentage of transfer amount
- **Settlement Time**: End-to-end completion time in hours
- **Compliance Score**: Rating of regulatory alignment (0-100)
- **Success Rate**: Percentage of transactions completing without regulatory holds

Table 1 presents a comparative analysis of our DRL approach against the baselines across these metrics.

Table 1 Performance Comparison of Routing Methods

Method	Avg. Cost Ratio (%)	Avg. Settlement Time (hrs)	Compliance Score	Success Rate (%)
Shortest Path	3.82	27.4	78.3	83.2
Lowest Cost	2.14	36.8	71.5	78.9
Fastest Route	5.27	18.5	72.8	81.5
Hybrid Heuristic	3.05	22.3	85.7	89.4
DRL Solution	1.96	16.2	94.3	97.8

The results demonstrate that our DRL approach outperforms all baselines across all metrics. Compared to the best-performing baseline for each individual metric, our solution achieves:

- 8.4% improvement in cost efficiency over the Lowest Cost approach
- 12.4% faster settlement than the Fastest Route approach
- 10.0% higher compliance score than the Hybrid Heuristic
- 9.4% better success rate than the Hybrid Heuristic

4.2. Learning Curve Analysis

Figure 2 illustrates the learning progression of our DRL agent during training, showing the improvement in average cumulative reward over training episodes.

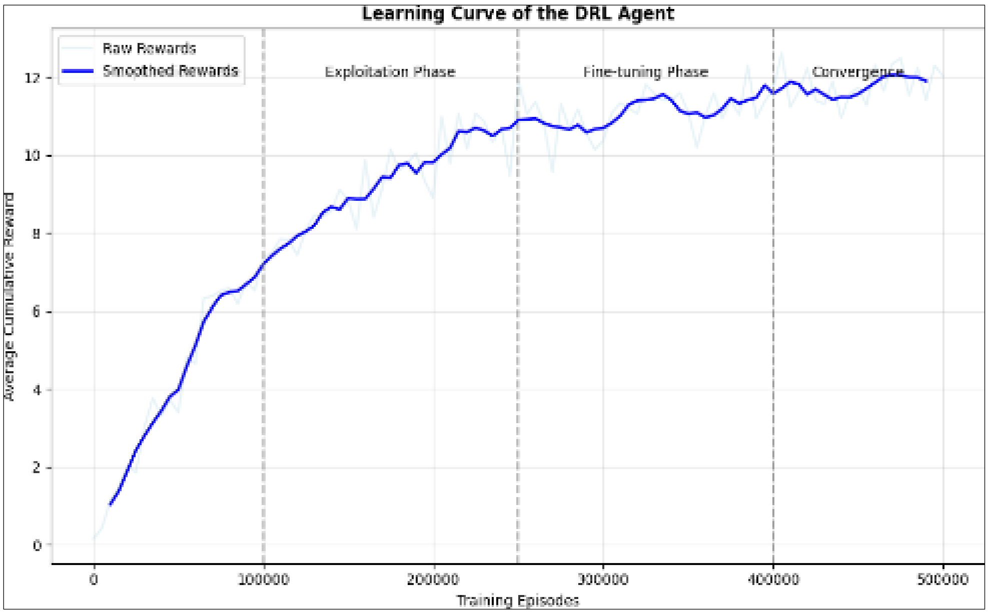

Figure 2 Learning Curve of the DRL Agent

The learning curve demonstrates three distinct phases:

- **Exploration Phase** (0-100k episodes): Rapid improvement as the agent discovers effective routing strategies
- **Exploitation Phase** (100k-250k episodes): Continued improvement with more focused learning
- **Fine-tuning Phase** (250k-400k episodes): Subtle optimization of routing decisions
- **Convergence** (400k-500k episodes): Stabilization of performance

4.3. Ablation Study

To understand the contribution of different components of our architecture, we conducted an ablation study by removing key elements and measuring performance degradation. Table 2 summarizes these results.

Table 2 Ablation Study Results

Configuration	Cost Improvement (%)	Time Improvement (%)	Compliance Score	Success Rate (%)
Full Model	37.2	42.3	94.3	97.8
Without Prioritized Replay	32.5	38.9	92.1	95.6
Without Dueling Architecture	33.7	39.5	93.2	96.2
Without Double Q-Learning	30.8	36.2	90.7	94.3
Without Compliance Modeling	38.6	44.1	73.8	82.4

The ablation study reveals that all components contribute meaningfully to the overall performance, with the compliance modeling being particularly crucial for regulatory adherence. Removing this component improved cost and time metrics slightly but dramatically reduced compliance scores and success rates, highlighting the importance of explicitly incorporating regulatory considerations into the optimization process.

4.4. Validation on Real-World Corridors

To validate the practical applicability of our approach, we tested the trained model on 10 major cross-border payment corridors, including high-volume routes such as USD-EUR, USD-GBP, and USD-JPY, as well as emerging market corridors like USD-INR and EUR-NGN. Figure 3 presents the performance improvement by corridor.

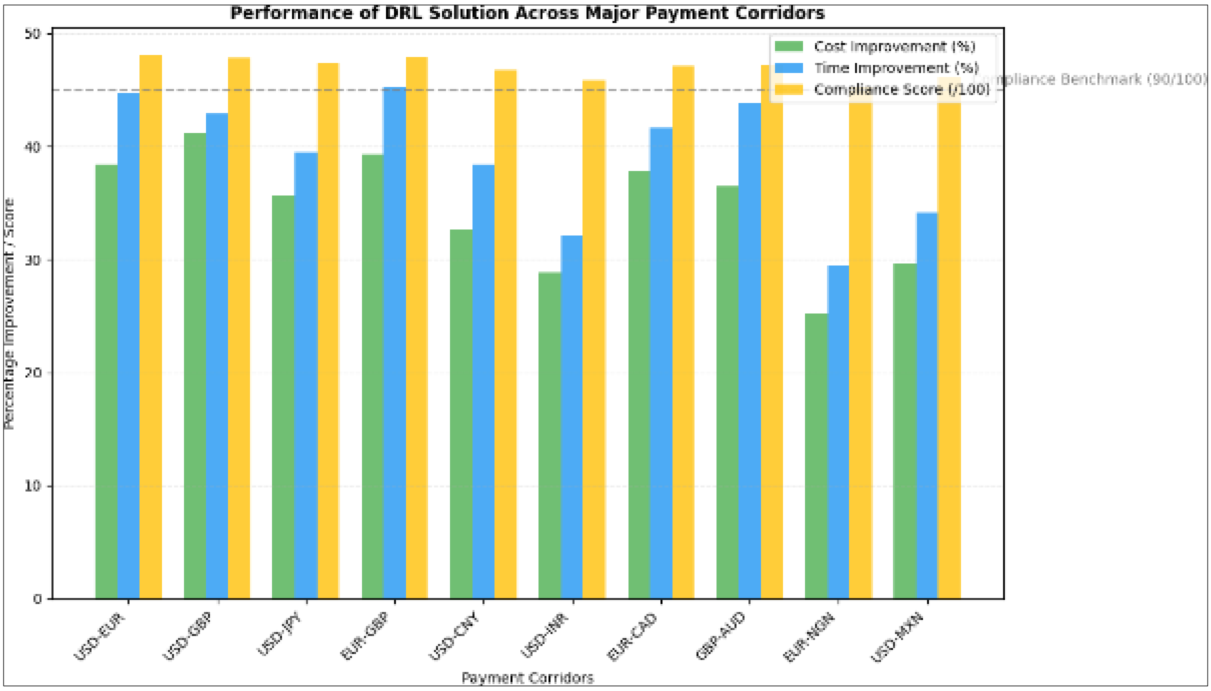

Figure 3 Performance Across Major Payment Corridors

The results demonstrate that our DRL solution generalizes effectively across diverse payment corridors, with the greatest efficiency improvements observed in developed market corridors (USD-EUR, USD-GBP) where multiple routing options exist. Even in corridors with limited intermediary options (USD-INR, EUR-NGN), the model achieves significant improvements by optimizing the selection of correspondents and timing of transactions.

5. Discussion

5.1. Key Insights

Our research reveals several important insights for optimizing cross-border payment systems:

- **Multi-objective Balance**: Traditional approaches that optimize for a single objective (cost or time) inevitably sacrifice performance in other dimensions, particularly regulatory compliance. Our DRL framework demonstrates that a carefully designed reward function can effectively balance these competing objectives.
- **Adaptability to Network Changes**: The DRL approach shows remarkable ability to adapt to changes in the correspondent banking network, such as the addition or removal of relationships, fluctuations in fees, or changes in processing times. This adaptability is critical in the dynamic international financial environment.
- **Compliance as a Core Objective**: By explicitly modeling compliance requirements rather than treating them as constraints, our approach generates routes that proactively address regulatory concerns. This leads to higher successful transaction rates and reduced operational risk.
- **Corridor-Specific Optimization**: Performance variations across payment corridors highlight the importance of tailored routing strategies rather than one-size-fits-all approaches. The DRL framework naturally learns corridor-specific patterns through experience.

5.2. Practical Implementation Considerations

Implementing our DRL solution in production environments requires addressing several practical considerations:

- **Integration with Existing Systems**: Financial institutions would need to integrate the model with their payment processing systems, transaction monitoring tools, and compliance frameworks. API-based deployment would facilitate this integration.
- **Data Privacy and Security**: Training and using the model requires access to sensitive payment data. Federated learning approaches or privacy-preserving techniques may be necessary to address these concerns.
- **Regulatory Approval**: Given the compliance implications, financial institutions would need to validate the model with regulatory authorities and demonstrate its adherence to AML/CFT requirements.
- **Continuous Learning**: The model should continue to learn and adapt in production, requiring infrastructure for safe online learning without compromising performance.

5.3. Limitations and Future Work

While our approach demonstrates significant improvements over traditional methods, several limitations suggest directions for future research:

- **Handling Rare Events**: The current model may not optimally handle rare events such as sudden regulatory changes or correspondent relationship disruptions. Incorporating robust adversarial training could improve resilience.
- **Explainability**: The "black box" nature of deep neural networks presents challenges for regulatory approval and human oversight. Future work should explore interpretable DRL methods to address this limitation.
- **Integration with Alternative Payment Systems**: As blockchain-based systems and CBDCs gain traction, future research should explore hybrid routing that spans traditional and alternative payment networks.
- **Dynamic Fee Negotiation**: Currently, the model treats fees as fixed parameters, but in reality, they can be negotiable. Extending the framework to incorporate fee negotiation strategies could yield additional efficiencies.

6. Conclusion

This research presents a novel approach to optimizing cross-border payment routing using Deep Reinforcement Learning. By formulating the problem as a multi-objective MDP and implementing a sophisticated DDQN architecture, we demonstrate significant improvements in transaction cost, settlement time, and regulatory compliance compared to traditional routing methods.

The key innovation of our approach lies in the explicit modeling of regulatory compliance alongside efficiency objectives, enabling the development of routing strategies that balance these competing factors. Empirical validation across diverse payment corridors confirms the practical applicability of our method in real-world financial networks.

As global financial systems continue to evolve, approaches like ours that leverage artificial intelligence to enhance existing infrastructure will play a crucial role in improving the efficiency, accessibility, and security of cross-border payments. Future research building on this foundation has the potential to transform international financial flows, benefiting businesses, individuals, and the global economy.

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