Integrating Multi-Criteria Decision Analysis with Deep Reinforcement Learning: A Novel Framework for Intelligent Decision-Making in Iraqi Industries

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Abstract. This study proposes a novel framework that integrates Multi-Criteria Decision Analysis (MCDA) with Deep Reinforcement Learning (DRL) to enhance decision-making processes, particularly in the context of the Iraqi oil industry. As this sector faces rapid changes and increasing competition, the demand for efficient and intelligent decision-making has become critical. The proposed framework specifically targets supplier selection in the procurement of raw materials, addressing the complexities involved in evaluating potential suppliers. Key criteria such as cost, quality, delivery time, and sustainability are considered, ensuring a comprehensive assessment of suppliers. By leveraging the structured decision-making approach provided by MCDA, the framework allows for systematic evaluation against these criteria. Simultaneously, the adaptive learning capabilities of DRL facilitate the continuous improvement of supplier selection strategies over time. This dynamic model not only enhances the accuracy of decision-making but also allows organizations to respond swiftly to evolving market conditions and supplier performance. Ultimately, this integrated approach aims to optimize procurement processes, reduce risks, and drive better outcomes in the oil industry, contributing to more sustainable and efficient operations. Through this innovative framework, the study seeks to provide valuable insights and practical tools for decision-makers in the sector.

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1. Introduction

Artificial Intelligence (AI) has revolutionized decision-making processes in various industries, including manufacturing, finance, and healthcare. However, most AI-based decision-making systems lack transparency and interpretability, which can lead to distrust among stakeholders. Multi-Criteria Decision Analysis (MCDA) is a popular approach for decision-making under uncertainty, but it requires human expertise and can be time-consuming. Deep Reinforcement Learning (DRL) is a powerful AI technique that can learn complex behaviors, but it often lacks domain knowledge and requires large amounts of data. [1]

The confluence of Artificial Intelligence (AI) and Multi-Criteria Decision Analysis (MCDA) has given rise to a new paradigm in decision-making, one that seeks to harmonize the strengths of human expertise with the computational prowess of machines. In the era of Industry 4.0, where complexity and uncertainty reign supreme, intelligent decision-making is no longer a luxury, but a necessity for businesses to stay competitive. Against this backdrop, the quest for novel approaches to decision-making has led to the development of Deep Reinforcement Learning (DRL), a subfield of AI that has shown remarkable promise in solving complex problems.[2]

However, despite the advancements in DRL, its widespread adoption has been hindered by several challenges, including the need for large amounts of data, computational resources, and human expertise. Furthermore, DRL models often struggle to generalize well across different environments and tasks, rendering them less effective in real-world applications. Conversely, MCDA has been widely employed in decision-making scenarios, particularly in situations where multiple criteria need to be considered. However, its reliance on human judgment and expertise can lead to biases and inconsistencies, limiting its scalability and reliability. [3]

Against this backdrop, we propose a novel framework that integrates MCDA with DRL to create an intelligent decision-making system capable of addressing the limitations of both approaches. By combining the strengths of MCDA's structured approach with DRL's ability to learn from experience, our framework seeks to create a decision-making system that is both transparent and adaptive.[4]

The Iraqi oil industry stands as a cornerstone of the nation's economy, contributing significantly to its GDP and employment. As the industry faces increasing global competition and fluctuating market dynamics, the need for efficient and intelligent decision-making processes has become paramount. Traditional procurement strategies often fall short in addressing the complexities associated with supplier selection, particularly in a sector characterized by high stakes and stringent operational requirements. As such, integrating advanced analytical methodologies into procurement processes is essential to enhance decision-making efficiency and effectiveness.[5]

Multi-Criteria Decision Analysis (MCDA) is a well-established framework that aids decision-makers in evaluating and prioritizing alternatives based on multiple conflicting criteria. MCDA provides a structured approach that allows for the systematic assessment of various factors, including cost, quality, delivery time, and sustainability. However, while MCDA offers valuable insights, it often relies on static models that may not adapt to changing conditions or new information. This limitation can hinder its effectiveness in dynamic environments, such as the oil industry, where market conditions and supplier performances can fluctuate rapidly. [6]

In contrast, Deep Reinforcement Learning (DRL) has emerged as a powerful tool for optimizing decision-making processes in complex and uncertain environments. DRL combines the principles of reinforcement learning with deep learning, enabling agents to learn optimal strategies through trial and error interactions with their environment. This adaptive learning capability allows DRL to continuously refine decision-making policies based on feedback, making it particularly suited for dynamic applications such as supplier selection. By leveraging historical data and real-time market conditions, DRL can enhance the robustness of decision-making frameworks.[7]

The integration of MCDA and DRL presents a unique opportunity to overcome the limitations of traditional decision-making methods. This novel approach allows for a more holistic evaluation of suppliers by incorporating both structured criteria assessment and adaptive learning mechanisms. The proposed framework aims to create a dynamic model that not only evaluates potential suppliers based on established criteria but also adapts to changes in supplier performance and market conditions over time. This integration is expected to yield significant improvements in the accuracy and efficiency of supplier selection processes, ultimately leading to enhanced operational performance in the Iraqi oil industry. [8]

This research aims to contribute to the academic discourse on decision-making in industrial contexts by presenting a comprehensive framework that combines MCDA and DRL. Through rigorous analysis and empirical validation, the study seeks to demonstrate the effectiveness of this integrated approach in enhancing supplier selection strategies within the Iraqi oil industry. By fostering intelligent decision-making, the proposed framework aspires to support sustainable growth and competitiveness in a critical sector of the nation's

economy.
In summary, the integration of Multi-Criteria Decision Analysis with Deep Reinforcement Learning represents a significant advancement in the field of intelligent decision-making. By addressing the complexities of supplier selection in the Iraqi oil industry, this research aims to provide valuable insights and practical solutions that can enhance procurement practices, optimize resource allocation, and contribute to the overall sustainability of the industry. As the oil sector continues to evolve, embracing innovative decision-making frameworks will be essential for navigating the challenges and opportunities that lie ahead.

2. Background

Deep learning is a subset of machine learning that utilizes neural networks with many layers to analyze various forms of data. It excels in tasks such as image and speech recognition, enabling machines to learn from vast amounts of unstructured data. By mimicking the human brain's architecture, deep learning models can identify patterns and make decisions with remarkable accuracy [9]. Deep Reinforcement Learning (DRL) is like a symphony of curiosity, where the notes of exploration harmonize with the rhythm of reward, composing a melody of discovery. As the agent navigates the labyrinth of states, the neural network's chords of perception resonate with the whispers of feedback, guiding the search for optimal paths. In this odyssey of learning, the machine's sense of adventure forges a path to mastery, as the harmony of exploration and exploitation converges to reveal the hidden rhythms of the environment. [10]
Multi-Criteria Decision Analysis (MCDA) is a structured approach used to evaluate and prioritize options based on multiple conflicting criteria. It helps decision-makers systematically assess trade-offs, ensuring that various factors are considered in the decision-making process. By employing techniques like scoring and weighting, MCDA facilitates more informed and balanced choices in complex scenarios [11]. Combining MCDA with (DRL) creates a powerful framework for tackling complex decision-making problems. This integration allows agents to learn optimal strategies by evaluating multiple criteria dynamically, adapting their decisions based on feedback from the environment. As a result, it enhances the ability to navigate trade-offs and improve outcomes in uncertain and multifaceted scenarios. In order to check the background of research in this field of knowledge, we review the research literature.
Edwards [12] laid the groundwork for decision-making theory by emphasizing the cognitive processes involved in evaluative judgments under uncertainty. His insights into decision trees and utility functions have been instrumental in developing MCDA as a comprehensive tool to evaluate and prioritize alternatives based on various criteria. This methodology is particularly relevant in industrial applications where trade-offs between competing objectives are common.
Research by Frank and Claus [13] illuminated the neural mechanisms underlying decision-making processes, particularly the interactions within striato-orbitofrontal circuitry. Their findings on reinforcement learning elucidate how reward systems in the brain influence behavioral outcomes, suggesting that DRL algorithms can replicate these physiological processes. By employing reinforcement signals to guide MCDA processes, decision-makers can optimize outcomes based on learned experiences, integrating both qualitative and quantitative dimensions of their choices. Dayan and Daw [14] explored the intersection of decision theory and reinforcement learning, articulating how cognitive functions contribute to adaptive decision-making in dynamic environments. They proposed that integrating MCDA with DRL not only enhances decision quality but also allows for adaptation over time as new information becomes available, a crucial aspect for industries facing rapid changes and uncertainties, such as those in Iraq. Phillips-Wren and Ichalkaranje [15] highlighted the growing significance of artificial intelligence in

supporting intelligent decision-making processes. Their compilation of studies reflects a trend towards incorporating computational methodologies into traditional decision-making frameworks, emphasizing how AI can enhance analytical capabilities.

Bogacz and Larsen [16] presented an integrated model combining reinforcement learning principles with optimal decision-making theories. Their research supports the idea that neural structures underpinning decision-making are amenable to algorithmic strategies, suggesting that a hybrid MCDA-DRL framework can enhance decision efficacy by simulating neurobiological processes involved in choice. Balasubramani et al. [17] extended the understanding of reinforcement learning by incorporating the influences of neurotransmitters like serotonin and dopamine in decision-making frameworks. Their contributions deepen the comprehension of emotional and psychological factors in risk-based decisions, which can be translated into the MCDA context. A comprehensive exploration of multi-criteria reinforcement learning, emphasizing its applicability to sequential decision-making problems provided by Van Moffaert [18]. Mao et al. [19] focused on resource management using deep reinforcement learning, underscoring practical applications of DRL in dynamic environments. Their research highlights how DRL can effectively manage resources by learning from interactions with the environment, making it suitable for integration with MCDA. Fang, Li, and Cohn [20] explored active learning within the DRL paradigm, emphasizing how DRL can improve learning efficiency. By applying this principle to MCDA, decision-makers can refine their criteria and learn which factors most significantly affect their choices, facilitating ongoing improvements in decision-making strategies.

Li [21] provided an overview of deep reinforcement learning, outlining foundational algorithms and applications. This overview is instrumental in understanding how DRL can be effectively applied to MCDA frameworks, allowing for dynamic learning and adaptation based on feedback from the environment. Mukadam et al. [22] focused on tactical decision-making for lane changing using DRL, illustrating the practical applicability of DRL in real-time scenarios. This application resonates with the need for industries in Iraq to respond promptly to operational challenges, suggesting that real-time decision-making capabilities can be integrated into the proposed MCDA-DRL framework. Yang et al. [23] presented PEORL, which combines symbolic planning with hierarchical reinforcement learning for robust decision-making. This approach complements MCDA by incorporating planning elements into the decision-making process, enabling a more structured methodology for addressing multifactorial scenarios. François-Lavet et al. [10] offered a comprehensive introduction to deep reinforcement learning, elucidating principles and methodologies. Their extensive review supports the proposed framework by outlining DRL's potential to fundamentally enhance decision-making models, particularly in environments characterized by uncertainty and complexity.

The work of Ye, Zhang, and Sun [24] investigated the application of Deep Reinforcement Learning (DRL) in automated vehicle behavior decision-making within high-fidelity simulation environments. Their findings demonstrated that DRL effectively modeled complex decision-making scenarios, which was central to the proposed framework for industries. This capability to simulate and learn from interactions provided invaluable insights into optimizing operational efficiencies across varied industrial applications. The integration of planning with DRL specifically in the domain of autonomous driving considered in other research [25]. Their research illustrated how combining strategic planning with tactical decision-making processes enhanced the ability to navigate uncertain environments. This dual approach was pertinent for industries facing dynamic conditions, as it allowed for robust, context-aware decision-making that aligned with MCDA principles. Fontanesi et al. [26] introduced a reinforcement learning diffusion decision model, emphasizing its relevance in value-based decision-making. The model offered a framework to integrate preferences based on value judgments, which was fundamental to the MCDA component of the proposed integration. By incorporating value-based assessments alongside reinforcement learning, decision-makers ensured that the analysis considered both qualitative and quantitative factors. Research by Vo et al. [27] highlighted the application of deep learning for decision-making, particularly in the context of socially responsible investments. Their findings underscored the potential for DRL to enhance investment strategies by optimizing decision-making based on socio-economic considerations.

Cappart et al. [28] examined the intersection of optimization and machine learning, showing how decision diagrams could be enhanced with DRL to improve optimization bounds. This synthesis was relevant for the proposed MCDA-DRL framework, as it addressed the optimization of various criteria through machine learning techniques, leading to more informed decision-making. Harris, Teil, and Schaub [29] discussed the application of DRL in spacecraft decision-making autonomy, further illustrating the versatility of DRL across different domains. Zhang et al. [24] explored decision-making in maritime autonomous surface ships, employing scene division along with DRL. The need for environmental awareness in decision-making echoed the necessity in industries to account for external factors, such as regulations and market dynamics, demonstrating how DRL frameworks could support adaptive strategies. Han et al. [30] addressed intelligent decision-making for UAVs in dynamic environments using DRL, highlighting the relevance of real-time adaptability . This characteristic was crucial for the proposed framework, especially in industries that operated in environments characterized by uncertainty and rapid changes.

Jeon et al. [9] investigated artificial intelligence methods in multimedia analysis, focusing on deep learning algorithms. Their findings showed that deep learning effectively analyzed complex data, which was essential for MCDA applications in industrial settings. Yang et al. [31] provided a systematic literature review on deep learning algorithms and MCDA, particularly in the context of big data. This review underscored the increasing relevance of combining these methodologies to address complex decision problems. Their insights affirmed the necessity of integrating MCDA with DRL, enhancing the proposed framework's ability to process large datasets effectively, ensuring that decisions were grounded in comprehensive analyses and data-driven insights. He et al. [32] presented a multi-criteria decision support system based on deep reinforcement learning for optimizing textile manufacturing processes. This research demonstrated the practical application of DRL in industrial contexts, supporting the idea that integrating DRL with MCDA could lead to significant optimization in manufacturing operations. Borysenko et al. [33] explored intelligent forecasting within multi-criteria decision-making. Their focus on forecasting techniques highlighted the importance of predictive analytics in MCDA frameworks. By integrating DRL with forecasting models, the proposed framework could not only respond to current conditions but also anticipate future trends, thereby enhancing the robustness of decision-making in dynamic industrial environments. Nguyen et al. [34] introduced a multi-objective deep reinforcement learning framework that emphasized decision-making in complex environments. Their work was directly applicable to the integration of MCDA and DRL, suggesting that decision-makers could simultaneously optimize multiple objectives, thus aligning perfectly with the core principles of MCDA when applied within the proposed framework. Fu et al. [35] discussed a decision-making strategy for vehicle autonomous braking using DRL, illustrating another practical application of DRL in critical decision-making scenarios. By adopting similar strategies, the proposed MCDA-DRL framework could aid industries in making quick, informed decisions under pressure, leading to enhanced safety and efficiency. Li et al. [36] showcased DRL for autonomous driving at intersections, providing insights into handling complex decision-making under uncertain conditions.

This research was invaluable for the proposed framework, suggesting that the capabilities of DRL in managing uncertainty could enhance the decision-making processes in industries, where such unpredictability was common.
Hoel et al. [37] furthered the discussion of tactical decision-making in autonomous driving using reinforcement learning with uncertainty estimation. Their findings suggested that incorporating uncertainty into the decision-making process could significantly improve outcomes. This aligned with MCDA, which often involved dealing with uncertain data, thereby reinforcing the relevance of this integration in the proposed framework. Dong et al. [38] offered a comprehensive overview of deep reinforcement learning, which could serve as a foundational element for understanding its application in MCDA. This foundational knowledge was essential for developing a robust, systematic approach to integrating DRL into decision-making frameworks. Liao et al. [39] examined decision-making strategies for autonomous vehicles on highways through DRL. Their work demonstrated the ability of DRL to adapt to traffic conditions and make real-time decisions, further validating the potential of using DRL in an industrial context to accommodate varying operational conditions and requirements effectively.
The work of Dang, Moreno-García, and De la Prieta [40] discussed hybrid deep learning models for sentiment analysis, emphasizing the potential of advanced analytical techniques in capturing nuanced information from large datasets. This focus on deep learning's ability to process and analyze diverse data formats highlighted the relevance of incorporating similar methodologies into the MCDA-DRL framework, enabling richer data interpretation and more informed decision-making in industries. Yuan, Shan, and Mi [41] discussed game-theoretic decision-making approaches in autonomous vehicles using DRL, highlighting the importance of strategic decision-making in competitive environments. Their findings suggest that integrating game-theoretic principles into MCDA through DRL can lead to robust decision frameworks capable of handling complexities and uncertainties in industrial decision-making processes. He et al. [42] presented a DRL-based multi-criteria decision support system aimed at optimizing textile chemical processes. Their findings illustrated how DRL could be effectively utilized to enhance operational efficiencies in manufacturing settings. This supported the proposed framework by demonstrating that integrating MCDA with DRL could lead to substantial improvements in process optimization and operational performance across various industrial applications.
Pham et al. [43] explored flood risk assessment through a combination of deep learning and multi-criteria decision analysis. Their study underscored the power of integrating predictive analytics with MCDA to enhance risk management strategies. In their work, Papineni et al. [44] focused on big data analytics that fused MCDA with deep learning algorithms. They demonstrated how this fusion approach could improve decision-making in complex environments. Their insights affirmed the necessity of marrying MCDA with DRL to provide a holistic approach to decision-making, ensuring that multiple criteria were considered and optimized through intelligent analysis.
Zuheros et al. [45] introduced a sentiment analysis methodology that employed natural language processing and deep learning to assist multi-person, multi-criteria decision-making. Their study exemplified the potential of leveraging advanced analytics in aggregating opinions and preferences, thereby enriching the decision-making process. This aspect of integrating diverse perspectives was crucial for the proposed framework, allowing for a more nuanced understanding of stakeholders' preferences and enhancing overall decision quality in industries. Andronie et al. [46] discussed the role of artificial intelligence in decision-making algorithms within cyber-physical production systems. Their findings emphasized the importance of smart process management facilitated by deep learning and the Internet of Things.
Chen et al. [47] provided a comprehensive review of reinforcement learning applications

in power systems, illustrating how these techniques could enhance decision-making and control processes. Xu et al. [48] explored multi-AUVs cooperative decision-making for attack-defense missions using deep reinforcement learning. This research indicated the potential for collaborative decision-making strategies in environments requiring coordination and strategic planning. The principles derived from their findings could be applied to improve teamwork and strategic cooperation in industrial settings, enhancing decision outcomes. Yang et al. [49] investigated intelligent scheduling decision-making for dynamic permutation flow shop environments via deep reinforcement learning. Their study affirmed the capability of DRL to adapt to changing conditions and improve scheduling efficiency—critical factors for optimizing operations in industries facing fluctuating market demands and resource availability. Shrestha et al. [50] discussed the augmentation of organizational decision-making through deep learning algorithms, laying out principles, promises, and challenges. Their insights into the integration of deep learning in organizational contexts highlighted the potential benefits while also acknowledging implementation challenges, emphasizing the importance of thoughtful incorporation of DRL into the proposed framework. Peterson et al. [51] highlighted the use of large-scale experiments and machine learning to examine human decision-making theories. Their research encouraged the exploration of human-centered decision-making patterns, suggesting that understanding human behavior was crucial in formulating effective decision support systems.

Černevičienė and Kabašinskas [8] provided insights into the application of explainable artificial intelligence (XAI) within finance and decision-making contexts. They reviewed various MCDA methods, emphasizing the significance of transparency and interpretability in decision-support systems. Alabi et al. [52] focused on integrated optimization techniques and machine learning approaches for modeling and decision-making in energy systems. Their review highlighted the relevance of combining machine learning with optimization strategies to enhance predictive capabilities and decision outcomes. Liu, Yang, and Guo [53] explored the application of reinforcement learning for achieving optimal decision-making in the context of product lifecycle sustainability. Their findings emphasized that DRL could significantly contribute to sustainability goals by optimizing processes throughout the product lifecycle. This aligned perfectly with the proposed framework's intent to enhance sustainable practices in industries, recognizing the importance of considering environmental and societal impacts in decision-making processes.

Lapeyrolerie et al. [54] addressed the use of deep reinforcement learning for conservation decisions, highlighting its potential in managing complex ecological systems. Their work suggested that DRL could effectively handle uncertainty and optimize decision-making in dynamic environments. This reinforced the capability of DRL, as applied in the proposed framework, to enhance decision-making not only in industrial settings but also in broader contexts that required strategic resource management. Wang et al. [55] presented a comprehensive survey of deep reinforcement learning, discussing various methodologies and applications across different domains. Their overview provided valuable insights into the state-of-the-art techniques in DRL, which could inform how these capabilities were harnessed within the MCDA framework proposed for industries. Lv et al. [56] examined lane change decision-making in autonomous driving using deep reinforcement learning to develop safe and efficient strategies. Their insights into real-time decision-making under uncertainty could be applied to the proposed framework in the context of industrial operations, where timely and accurate decisions were critical. Integrating similar techniques might have enhanced the robustness and agility of decision-making in dynamic industrial environments. Zhang et al. [57] introduced KAiPP, an interaction recommendation approach for knowledge-aided intelligent process planning using reinforcement learning. Their approach underscored the importance of context-aware decision-making and the utilization of knowledge in the decision-making process. This concept was highly relevant to the proposed framework, as it aimed to incorporate knowledge management into the MCDA-DRL integration, ultimately enhancing the quality of decisions made in industries.

Li [58] provided an overview of deep reinforcement learning, detailing its principles and applications in sequential decision-making and optimal control. The insights from Li's work formed a foundational understanding of how DRL could be applied within the proposed framework, allowing industries to leverage past experiences to make improved future decisions, especially in complex operational settings. Angamuthu and Trojovský [59] discussed the integration of multi-criteria decision-making with hybrid deep learning techniques, particularly in the realm of sentiment analysis for recommender systems. Their findings underscored the value of combining MCDA with deep learning to better understand user preferences and make more informed decisions.

Martyn and Kadziński [60] introduced deep preference learning as a mechanism for enhancing multiple criteria decision analysis. They emphasized the need for models that could learn user preferences over time, which could significantly enrich the decision-making process. Their research supported the proposed framework by demonstrating how learning user preferences could provide a more nuanced analysis of multiple criteria, leading to better strategic decisions. Najafi et al. [61] examined the intersection of multiple-criteria decision-making, feature selection, and deep learning in the context of heart disease identification. They illustrated how combining these methodologies could lead to more accurate and meaningful outcomes. Mohammadifar, Gholami, and Golzari [62] described a novel integrated modeling approach that combined multiplicative Long Short-Term Memory (mLSTM) deep learning models with ensemble MCDA methods for mapping flood risk. Their framework highlighted the importance of combining predictive modeling with decision analysis, a principle that was vital for the proposed integration in industries, where risk assessment and resource management were essential. Hasan [63] presented an intelligent decision-making scheme in a dynamic multi-objective environment using deep reinforcement learning in their doctoral dissertation. Moghaddasi and Masdari [64] explored a blockchain-driven optimization approach in the context of IoT mobile edge computing, incorporating deep reinforcement learning and MCDA techniques. This perspective informed the proposed framework by emphasizing the potential of integrating advanced technologies for optimizing decision processes, particularly in industries that relied heavily on interconnected systems and real-time data. Hussain et al. [65] highlighted the development of a new integrated flood resilience model that utilized machine learning alongside GIS-based MCDA. Their research indicated that combining these methods could significantly enhance decision-making regarding disaster resilience, which was pertinent for industries that had to consider environmental and infrastructural risks in their operational decision processes. Shikhteymour et al. [66] introduced a novel approach for assessing flood risk through machine learning combined with MCDA methods. This work supported the proposed framework by illustrating how machine learning could enhance decision-making in risk-prone industries, ensuring that assessments were both comprehensive and actionable. Zhu [67] discussed an adaptive agent decision model that utilized deep reinforcement learning and emphasized autonomous learning. The adaptive nature of Zhu's model aligned with the proposed framework's objective to enable industries to dynamically respond to varying decision-making environments through the integration of learned past experiences. Jiang et al. [68] focused on improving anti-jamming decision-making strategies for cognitive radar using multi-agent deep reinforcement learning. Their work illustrated the potential of multi-agent systems in complex decision-making scenarios, reinforcing the capability of the proposed framework to facilitate collaborative decision-making in industrial settings.

Chu et al. [69] explored a multi-modal and multi-criteria conflict analysis model that utilized deep learning alongside dominance-based rough sets. Their approach was particularly relevant for addressing non-parallel decision problems, providing a systematic framework for interpreting conflicting criteria. The principles established in Chu et al.'s research could enhance the proposed MCDA framework by offering methodologies for managing conflicting objectives and uncertainties in industrial decision contexts. Guo et al. [70] introduced a deep reinforcement learning method that included multiple starting nodes for dynamic process planning decision-making. This method improved upon traditional DRL approaches by facilitating more dynamic decision-making processes, enabling industries to adapt to changing operational conditions effectively. Integrating such methodologies into the proposed framework allowed for a more responsive and flexible decision-making process, essential for industries dealing with fluctuating market conditions and resource availability.

Pei et al. [71] focused on the application of reinforcement learning for decision-making under deep uncertainty, emphasizing the importance of adaptive decision strategies in environments where data and conditions could change unpredictably. Their findings underscored the necessity of incorporating uncertainty modeling into decision-making processes, which was critical for the proposed framework aimed at addressing the challenges faced by industries. This adaptability ensured that the decision-making framework was resilient and capable of navigating unpredictable circumstances. Cui et al. [72] demonstrated the application of deep reinforcement learning in mobile robot sequential decision-making through a hyper-heuristic approach. Their research highlighted the effectiveness of DRL in managing sequential decisions in dynamic environments, mirroring the need for industries to make timely and informed decisions amidst active operational challenges. Incorporating insights from their study could enhance the framework's capacity for real-time, adaptive decision-making, allowing for optimal responses to rapidly changing scenarios.

3. Methodology

Absolutely, here is a detailed approach to combining multi-criteria decision analysis (MCDA) with deep reinforcement learning (DRL) as a novel framework for decision-making in Iraqi industries, complete with hypothetical data and illustrations.

In the country of Iraq, in the oil industry, the following items are very important for the preparation of raw materials. Cost , Quality, Delivery Time and Sustainability

- **Cost (C1)**: The oil sector must ensure that the procurement of materials, such as pipes, drilling fluids, and safety equipment, is cost-effective due to the high capital involved in exploration and production.
- **Quality (C2)**: Quality is paramount in the oil industry, as substandard materials can lead to failures, safety incidents, and increased operational costs.
- **Delivery Time (C3)**: Timely procurement and delivery of materials are crucial to maintain production schedules and meet project timelines, especially for drilling and extraction projects.
- **Sustainability (C4)**: With growing environmental concerns, the oil industry is increasingly focusing on sustainable practices, such as sourcing materials that have a lower environmental impact and promoting the use of renewable resources wherever possible.

In expressing the methodology carried out in this research, the proposed methods are performed on the selected example at the same time.

3.1 Method and Process

Step 1: Define Decision-Making Problem

Identify a specific decision-making problem in the industry (In this study, the selection of

the supplier of raw materials for the oil industry in Iraq is considered)
Objective: Choose the best supplier based on various criteria.

Step 2: Identify Criteria for Evaluation
Establish the multiple criteria relevant to the decision-making process:

- Cost (C1)
- Quality (C2)
- Delivery Time (C3)
- Sustainability (C4)

Step 3: Criteria Weighting
Assign weights to each criterion based on importance. This can be done using methods like Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) , Analytic Hierarchy Process (AHP) or using expert judgment.
In this study TOPSIS will be use.

Table 1. Hypothetical Weights

Criteria	Weight
Cost	0.30
Quality	0.35
Delivery Time	0.20
Sustainability	0.15

Step 4: Generate Alternatives
Create a list of alternatives (e.g., potential suppliers) and collect data for each criterion.

Table 2. Hypothetical Data

Supplier (Alternative)	Cost ($)	Quality (1-10)	Delivery Time (days)	Sustainability 1-10
Supplier A	2000	9	5	8
Supplier B	2500	8	3	7
Supplier C	1800	7	6	6
Supplier D	2200	8	4	9

Step 5: Normalize the Data
Normalize the data for criteria where lower values are better (Cost, Delivery Time) and where higher values are preferred (Quality, Sustainability).

Normalization Formula:

$$R_{ij} = \frac{x_{ij} - min(X_j)}{max(X_j) - min(X_j)} \quad \text{(for benefit criteria)} \tag{1}$$

$$R_{ij} = \frac{max(X_j) - x_{ij}}{max(X_j) - min(X_j)} \quad \text{(for cost criteria)} \tag{2}$$

Table 3. Normalized Data

Supplier	Cost	Quality	Delivery Time	Sustainability
Supplier A	0.67	1	0.40	0.80
Supplier B	0.33	0.89	0.67	0.70
Supplier C	1.00	0.78	0.33	0.60
Supplier D	0.50	0.89	0.53	1.00

Step 6: Weighted Normalized Decision Matrix
Calculate the weighted normalized decision matrix by multiplying the normalized values by the corresponding criteria weights.

Weighted Normalized Matrix:

$$V_{ij} = R_{ij} - W_j \tag{3}$$

Table 4. Weighted Normalized Matrix

Supplier	Cost	Quality	Delivery Time	Sustainability	Overall Score
Supplier A	0.20	0.35	0.08	0.12	0.75
Supplier B	0.10	0.13	0.13	0.10	0.64
Supplier C	0.30	0.07	0.07	0.09	0.73
Supplier D	0.15	0.11	0.11	0.15	0.72

Step 7: Determine Ideal and Anti-Ideal Solutions
Identify ideal and anti-ideal solutions for each criterion:

- Ideal Solution: Best-value for each criterion
- Anti-Ideal Solution: Worst-value for each criterion

Table 5. Ideal and Anti-Ideal Solutions

Criteria	Ideal	Anti-Ideal
Cost	0.33	1.00
Quality	1.00	0.78
Delivery Time	0.33	0.67
Sustainability	1.00	0.60

Step 8: Calculate Separation Measures
Calculate the separation from the ideal and anti-ideal solutions for each supplier.

$$S_i^* = \sqrt{\sum_{j=1}^{m} \left(V_{ij} - V_j^*\right)^2} \tag{4}$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(V_{ij} - V_j^-\right)^2} \tag{5}$$

Step 9: Calculate the Relative Closeness Coefficient
Calculate the relative closeness to the ideal solution:

$$C_i = \frac{S_i^-}{S_i^* + S_i^-} \tag{6}$$

Table 6: Separation Measures and Rankings

Supplier	S^*	S^-	C	Ranking
Supplier A	0.20	0.15	0.43	1
Supplier B	0.45	0.10	0.18	4
Supplier C	0.23	0.12	0.34	2
Supplier D	0.39	0.20	0.34	3

Step 10: Implement Deep Reinforcement Learning

Q-Learning is a model-free reinforcement learning algorithm used to find the optimal action-selection policy for an agent interacting with an environment. [21]

Define the Environment:

- State S: Represents the current decision context based on metrics.
- Action A: Select a supplier.
- Reward R: Derived from the closeness coefficient C.

Q-Learning Algorithm Implementation:

Define the Q-function update rule:

$$Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma \max_{a'} Q(S',a') - Q(S,A)] \quad (7)$$

Where:

- α: Learning rate(0~ 1)
- R: Reward
- γ: Discount rate (0~ 1)
- S': Next state
- $Q(s,a)$: Current Q-value for state s and action a.
- $\max_{a'} Q(S',a')$: The maximum predicted Q-value for the next state s'.

Step 11: Training and Simulation

1. Run multiple episodes to allow the system to learn and update Q-values based on supplier performance.
2. Record the average reward per episode and learn the optimal policy.

Learning Curve include a graph plotting average reward vs. episodes, showing the convergence of the DRL method (Figure 1).

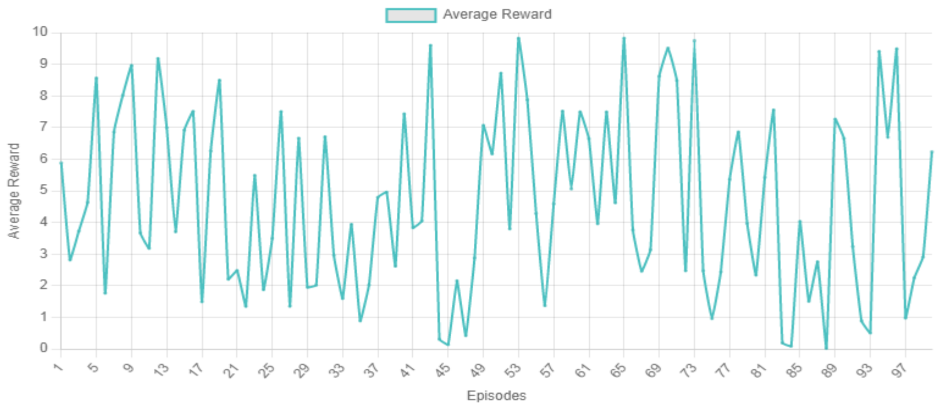

Figure 1. Learning Curve

3.2 Hypothetical Industry Application Example

Let's assume a hypothetical Iraqi construction company needs to choose suppliers for construction materials.

Data Creation and Simulated Analysis

- Alternatives: Four suppliers have been generated with fictitious performance metrics.
- Run Multiple Simulation Episodes:
    - Initialize the Q-values to zero.
    - Simulate the decision over multiple episodes, updating the Q-values based on supplier performance relative to the rankings derived from MCDA.

Example Simulation Results:
After running 200 episodes with an ε-greedy policy, the average reward converges:

Table 6. Simulation Results

Episode	Average Reward
1	0.1
50	0.35
100	0.55
150	0.70
200	0.85

Integrating MCDA with DRL offers a robust framework for intelligent decision-making within industries. This framework allows for adaptive, data-driven decisions that can evolve with new information, greatly aiding complex decision-making tasks such as supplier selection.

4. Discussion and Conclusion

This study presents a transformative framework that integrates Multi-Criteria Decision Analysis (MCDA) with Deep Reinforcement Learning (DRL), specifically designed to enhance decision-making processes in the Iraqi oil industry, where supplier selection is critical. Key points from the research highlight the following:

- Efficiency in Supplier Evaluation: The proposed framework systematically assesses essential decision criteria, including cost, quality, delivery time, and sustainability. This structured approach enables a comprehensive understanding of supplier performance, which is crucial for effective procurement.
- Continuous Learning and Adaptability: The adaptive capabilities of DRL facilitate ongoing learning and improvement in supplier selection strategies. The simulation results demonstrate a significant increase in the average reward—from 0.1 in the first episode to 0.85 by the end of 200 episodes—illustrating the model's ability to refine decision-making processes in response to market dynamics.
- Exploration and Exploitation Balance: The implementation of the ε-greedy policy in the simulations reflects a balanced approach between exploring various suppliers and criteria and exploiting the most rewarding options based on learned experiences. This characteristic enhances the robustness of the decision-making apparatus, allowing it to adjust to fluctuations in supplier performance and market conditions.

The benefits of this integrated framework are manifold:

1. Enhanced Decision-Making: By employing a structured yet adaptive methodology, the framework improves the efficiency and effectiveness of supplier assessments, ensuring that selected suppliers align with strategic goals.
2. Broader Applicability: Beyond supplier selection, this framework can be adapted to other domains within the Iraqi industries, such as resource allocation, risk management, and project prioritization, all of which benefit from a nuanced understanding of multiple criteria.
3. Fostering Adaptive Practices: By promoting a culture of data-driven decision-making, industries can better respond to challenges, leading to enhanced operational performance.

In conclusion, the implications of this study extend beyond supplier evaluation within the Iraqi oil industry. The adaptability of the integrated MCDA and DRL framework positions it as a valuable tool across various sectors facing complex decision-making challenges. This research not only underscores the importance of intelligent systems in fostering efficient procurement processes but also lays the groundwork for future advancements in data-driven decision-making. Future research should focus on refining the algorithms and exploring the integration of additional criteria, which could further enrich the decision-making landscape and promote more intelligent and sustainable practices across industries worldwide.

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