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Carbon-Constrained Optimization of Oilfield Production and Heavy-Duty Transport Energy Management with Surrogate Models and Reinforcement Learning

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ABSTRACT

The transition toward sustainable industrial practices requires the implementation of stringent carbon emission constraints across highly energy-intensive sectors. Two of the most critical sectors in this context are oilfield production and heavy-duty logistics, which traditionally operate as isolated systems despite their inherent interdependencies. This paper presents a comprehensive framework for the carbon-constrained optimization of coupled oilfield production and heavy-duty transport energy management. Because high-fidelity physics-based simulators for these systems are computationally prohibitive for real-time decision-making, we develop data-driven surrogate models to capture the complex, non-linear dynamics of reservoir multiphase flow and transportation fleet fuel consumption. These surrogate models serve as highly efficient simulation environments for a deep reinforcement learning agent. The reinforcement learning framework is designed to determine optimal operational policies, including well injection rates, choke valve settings, and fleet dispatch schedules, while strictly adhering to dynamic carbon emission caps. By defining a comprehensive reward function that penalizes excessive carbon output and rewards energy efficiency and production yield, the agent learns to balance economic objectives with environmental constraints. Extensive simulation experiments demonstrate that the proposed integrated optimization approach significantly reduces overall carbon emissions and operational energy consumption compared to traditional decoupled and rule-based management strategies, while maintaining targeted production and delivery thresholds.

KEYWORDS

Carbon constraint, Oilfield production, Heavy-duty transport, Surrogate models, Reinforcement learning.

1. Introduction

The global imperative to mitigate climate change has introduced unprecedented regulatory and economic pressures on industrial sectors to reduce their greenhouse gas emissions [1]. Industrial operations, particularly those involving the extraction of natural resources and the subsequent transportation of materials, account for a substantial portion of global energy consumption and carbon output [2]. As governments implement increasingly stringent carbon pricing mechanisms and emission caps, industries

are forced to reevaluate their operational strategies [3]. This transition requires not only the adoption of cleaner technologies but also the fundamental optimization of existing processes to maximize energy efficiency and minimize carbon footprints [4]. The challenge is inherently complex because industrial systems operate under dynamic, uncertain conditions and involve multiple interacting components that span vast temporal and spatial scales [5]. Among the most energy-intensive and carbon-heavy industries are oilfield production and heavy-duty transport [6]. Oilfield operations encompass a wide array of activities, including fluid injection, artificial lift operations, separation, and fluid processing, all of which demand massive amounts of electrical and thermal energy [7]. The multiphase flow of oil, gas, and water within underground reservoirs and surface pipe networks is highly non-linear and sensitive to operational parameters such as injection pressures and choke valve settings [8]. Simultaneously, the heavy-duty transport fleets responsible for moving equipment, processed fluids, and personnel operate on complex logistical schedules over varied terrains, consuming significant volumes of diesel or alternative fuels [9]. Historically, the optimization of oilfield production and the management of transport fleets have been treated as distinct, decoupled problems [10]. However, these systems are deeply interconnected; the scheduling of transport logistics depends on production rates, while production efficiency can be constrained by the availability of transport and storage capacities [11]. Optimizing these coupled systems under strict carbon constraints presents a formidable computational challenge [12]. Traditional approaches rely on high-fidelity numerical simulators to model reservoir dynamics, wellbore hydraulics, and vehicle kinematics [13]. While these simulators provide accurate representations of physical processes, their computational expense renders them entirely unsuitable for real-time, iterative optimization [14]. A single simulation run of a large-scale oilfield can take several hours, making it impossible to evaluate the thousands of potential operational scenarios required to find an optimal solution within a practical timeframe [15]. To overcome this computational bottleneck, researchers have increasingly turned to surrogate modeling [16]. Surrogate models, or proxy models, are data-driven approximations of complex simulators that learn the input-output mappings of the underlying physical systems through machine learning techniques [17]. By training these models on large datasets generated from high-fidelity simulations or historical operational data, they can predict system behaviors, such as fluid production rates and vehicle fuel consumption, in a fraction of a second [18]. This dramatic reduction in computational cost enables the application of advanced, iterative optimization algorithms [19]. Reinforcement learning has emerged as a powerful paradigm for solving complex sequential decision-making problems in stochastic environments [20]. Unlike traditional mathematical programming techniques that often require simplified, convex representations of the problem space, reinforcement learning agents learn optimal policies through trial-and-error interactions with an environment [21]. In the context of our study, the environment is represented by the coupled surrogate models of the oilfield and transport systems [22]. The agent observes the current state of the systems, takes actions such as adjusting injection rates or dispatching vehicles, and receives a reward based on the resulting production output, energy consumption, and carbon emissions [23]. By structuring the reward function to heavily penalize violations of carbon constraints, the agent is trained to discover operational strategies that balance economic profitability with environmental compliance [24]. The primary objective of this paper is to design, implement, and evaluate a unified optimization framework that leverages surrogate models and reinforcement learning for the simultaneous management of oilfield production and heavy-duty transport under dynamic carbon constraints. The integration of these advanced computational techniques provides a scalable and highly efficient solution to a problem that has historically been limited by computational intractability and decoupled management practices.

2. Background and Literature Review

2.1 Carbon Constraints in Industrial Operations

The integration of carbon constraints into industrial optimization problems has evolved significantly over

the past decade [25]. Early approaches largely relied on static carbon caps, where operations were optimized to ensure that total emissions over a fixed period did not exceed a predetermined threshold [26]. These models often utilized mixed-integer linear programming, requiring significant simplification of the non-linear emission profiles associated with complex machinery and fluid dynamics [27]. As carbon markets and dynamic pricing mechanisms became more prevalent, researchers began incorporating time-varying carbon penalties into the objective functions of optimization problems [28]. This shift allowed for more flexible operational strategies, such as load shifting, where energy-intensive processes are scheduled during periods of low carbon intensity or lower grid electricity prices [29]. However, applying these dynamic constraints to highly coupled, multi-domain systems like combined oilfield and transport operations remains a largely unexplored area due to the compounding complexities of the interacting state variables.

2.2 Advancements in Oilfield Production Optimization

Oilfield production optimization typically focuses on maximizing hydrocarbon recovery while minimizing operational costs and water production [30]. The physical processes governing reservoir depletion and artificial lift systems are governed by complex partial differential equations that describe multiphase fluid flow in porous media [31]. Traditional optimization workflows employ gradient-based methods or evolutionary algorithms coupled with numerical reservoir simulators [32]. Because gradient-based methods are prone to local optima in highly non-linear production landscapes, gradient-free methods like particle swarm optimization and genetic algorithms have gained popularity [33]. Nevertheless, the reliance on high-fidelity simulators limits the scalability of these approaches. To address this, the industry has seen a rapid adoption of machine learning-based proxy models, including artificial neural networks and support vector machines, which map operational controls directly to production outcomes [34]. While these proxies offer immense computational speedups, they are typically developed for isolated subsystems, such as a single well or a specific processing facility, rather than being integrated into a holistic, carbon-constrained framework.

2.3 Heavy-Duty Transport Energy Management

Heavy-duty transport represents a critical component of industrial supply chains, characterized by high energy consumption and significant greenhouse gas emissions [35]. The optimization of these fleets traditionally falls under the umbrella of vehicle routing problems and fleet dispatch scheduling [36]. Recent advancements have sought to incorporate energy consumption models into these routing algorithms, moving beyond simple distance minimization to consider factors such as vehicle load, road gradients, and traffic conditions. However, the energy models used in these logistical optimizations are often empirical and lack the granularity required to accurately predict dynamic fuel consumption under varying industrial loads. Furthermore, transport optimization is rarely coupled directly with the production systems it serves. In oilfield contexts, transport is usually treated as an external service with fixed schedules, leading to inefficiencies when production rates fluctuate or when storage capacities are constrained. Integrating the transport schedules directly with production controls through a unified optimization algorithm presents a significant opportunity for comprehensive energy reduction.

3. Conceptual Framework and System Architecture

The core of our approach lies in conceptualizing the oilfield production facilities and the heavy-duty transport fleet as a single, interdependent operational ecosystem. In a typical scenario, crude oil and associated natural gas are extracted from multiple wells utilizing energy-intensive artificial lift methods such as electrical submersible pumps or gas injection. The extracted multiphase fluid is then transported via flowlines to a central processing facility, where oil, water, and gas are separated. The processed crude oil is stored in tank farms before being transported to refineries or export terminals by a fleet of heavy-duty

trucks. Simultaneously, trucks are required to transport chemical additives, replacement parts, and maintenance equipment back to the well pads. The energy consumption of the oilfield is driven by the electrical power required for pumps and compressors, which in turn generates indirect carbon emissions based on the carbon intensity of the local power grid. The energy consumption of the transport fleet is driven by diesel combustion, resulting in direct tailpipe emissions. The coupling between these systems occurs at the storage and scheduling interfaces. If the production rate exceeds the transport capacity, storage tanks may fill to capacity, requiring a reduction in production and leading to suboptimal reservoir drainage. Conversely, if transport vehicles are dispatched inefficiently, they may run underutilized or idle for long periods while waiting for production to catch up, leading to wasted fuel and unnecessary carbon emissions. To manage this coupled system, we propose a centralized intelligent control architecture. Operational setpoints from both the oilfield and the transport fleet are fed into a central management system. Because making decisions based on real-time physics simulators is too slow, the central system relies on trained surrogate models to instantly predict the outcomes of any proposed operational changes. An intelligent agent interacts with these surrogate models, evaluating millions of combinations of well controls and vehicle dispatch schedules to identify the strategy that maximizes overall productivity while keeping the combined direct and indirect carbon emissions strictly below a specified limit.

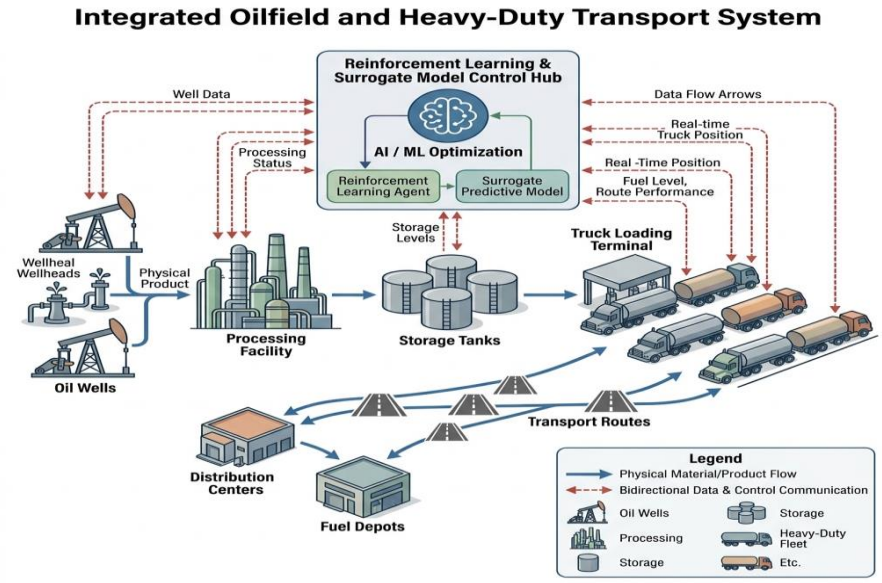


Figure 1: Comprehensive Schematic of Integrated Oilfield and Heavy

The implementation of this architecture requires a robust data acquisition system capable of gathering high-frequency sensor data from wellhead pressure gauges, flow meters, pump variable frequency drives, and vehicle telematics. This data serves a dual purpose: it continuously calibrates the surrogate models to ensure they reflect the current physical reality of the systems, and it provides the real-time state observations required by the intelligent control algorithm to make subsequent decisions.

4. Surrogate Modeling for Oilfield and Transport Systems

The feasibility of optimizing the combined system depends entirely on the accuracy and speed of the surrogate models. A surrogate model is essentially a mathematical approximation that learns the behavior of a complex system from data, bypassing the need to solve the underlying physical equations iteratively. We construct distinct surrogate models for the oilfield operations and the transport fleet, which are then integrated into the optimization environment.

4.1 Oilfield Reservoir and Production Proxies

The oilfield surrogate model is designed to predict fluid production rates and energy consumption based on operational control variables. The primary inputs to this model include injection water flow rates, gas lift injection pressures, wellhead choke valve apertures, and the operating frequencies of downhole pumps. Additional state variables such as average reservoir pressure and water cut are also included as inputs to provide context regarding the depletion stage of the field. The outputs of the model are the volumetric production rates of oil, gas, and water, as well as the total electrical power consumed by the artificial lift and injection machinery. To construct this model, we utilize deep neural networks due to their capacity to approximate highly non-linear multidimensional functions. The training data is generated by running thousands of scenarios through a commercial finite-difference reservoir simulator coupled with a wellbore hydraulics network model. We employ Latin hypercube sampling to ensure that the generated scenarios thoroughly cover the entire operational parameter space. The neural network architecture consists of multiple fully connected hidden layers, utilizing rectified linear unit activation functions to capture non-linearities. Dropout layers are integrated during training to prevent overfitting to the synthetic simulation data, ensuring that the surrogate model generalizes well to unseen operational conditions.

4.2 Transport Fleet Energy Surrogates

The transport fleet surrogate model estimates the fuel consumption and associated direct carbon emissions of heavy-duty trucks based on their dispatch schedules and load conditions. The fuel efficiency of a heavy-duty vehicle is influenced by a multitude of factors, including the gross vehicle weight, the average driving speed, the elevation profile of the route, and the number of stop-and-go events. Traditional distance-based fuel models fail to capture the significant efficiency penalties associated with hauling heavy fluid loads over undulating oilfield terrains. Our transport surrogate model takes as input the route characteristics, the payload weight at different stages of the journey, and the allocated transit time. The output is a highly accurate estimation of the total diesel fuel consumed for the trip. This model is trained using historical telematic data collected from an active transport fleet, supplemented by data from comprehensive vehicle dynamic simulations for extreme edge cases. Tree-based machine learning algorithms, specifically gradient boosting regressors, are employed for this surrogate due to their exceptional performance on tabular data and their ability to handle the complex, discontinuous relationships inherent in logistics scheduling.

Table 1: Input and Output Variables for System Surrogate Models

Subsystem	Input Variables	Output Variables	Accuracy Metric
Oilfield Production	Injection rate, Choke size	Oil flow rate, Water cut	Mean Absolute Error
Transport Fleet	Vehicle speed, Payload weight	Fuel consumption rate	Root Mean Square Error

The integration of these two surrogate models provides a complete digital representation of the operational environment. When an optimization algorithm proposes a specific set of well controls and a corresponding fleet dispatch schedule, the oilfield surrogate instantly calculates the energy used and the volume of fluid produced. The transport surrogate then calculates the fuel required to move that volume. The combined energy and fuel metrics are subsequently converted into a unified carbon emission equivalent using established regional emission factors.

5. Reinforcement Learning Optimization Strategy

With the rapid evaluation environment established by the surrogate models, we employ deep reinforcement learning to discover the optimal control policies. Reinforcement learning is uniquely suited for this problem because it can handle continuous state and action spaces while optimizing for long-term cumulative objectives rather than short-sighted immediate gains. We formulate the combined operational challenge as

a Markov Decision Process, defined by continuous state spaces, continuous action spaces, and a custom reward function tailored to enforce carbon constraints.

5.1 State and Action Space Definitions

The state space represents the complete observability of both the oilfield and the transport systems at any given decision timestep. It includes dynamic variables from the oilfield, such as current wellhead pressures, fluid levels in storage tanks, and the operational status of pumps. From the transport side, the state space includes the current locations of all trucks, their available carrying capacities, and the status of maintenance schedules. Furthermore, the state space explicitly incorporates the accumulated carbon emissions for the current compliance period and the remaining carbon allowance, providing the agent with the necessary context to adjust its aggressiveness in energy consumption. The action space comprises all the controllable parameters the agent can manipulate to optimize the system. For the oilfield, these actions are continuous variables defining the exact choke valve openings, the targeted electrical frequencies for submersible pumps, and the allocation of injection fluids among various support wells. For the transport fleet, the actions involve assigning specific fluid volumes to specific trucks and setting their dispatch timing. To manage the vast dimensionality of this combined action space, we utilize the Deep Deterministic Policy Gradient algorithm, which is specifically designed to operate over continuous action domains using an actor-critic neural network architecture.

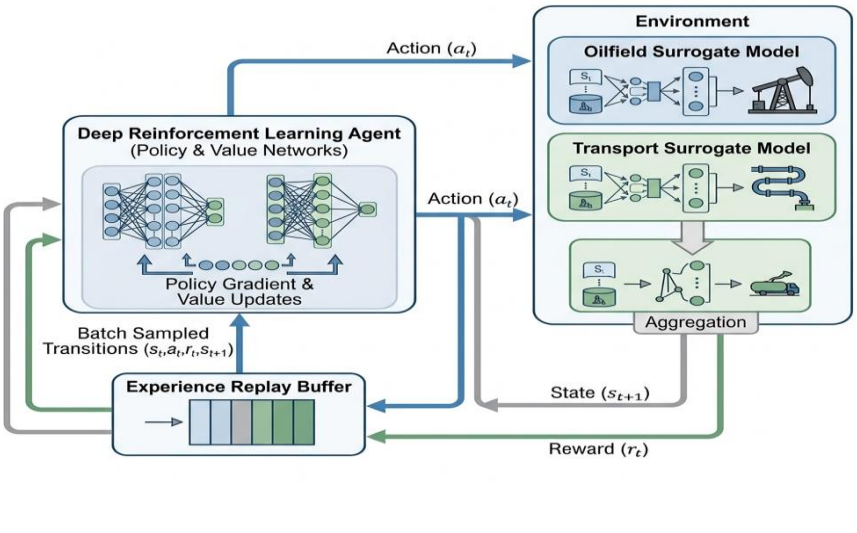


Figure 2Reinforcement Learning Agent Training Architecture

5.2 Reward Formulation and Carbon Penalties

The success of a reinforcement learning agent depends entirely on the formulation of the reward function. The objective is to maximize crude oil production and delivery while strictly ensuring that the combined indirect and direct carbon emissions do not exceed a dynamic environmental cap. The reward function is constructed as a weighted sum of multiple competing components. The agent receives a positive reward proportional to the volume of crude oil successfully transported to the final delivery point, incentivizing both high production rates and efficient logistical movement. Negative rewards, or penalties, are applied for several factors. A baseline penalty is assessed for total energy consumption and fuel usage to encourage overall efficiency. However, the most critical component of the reward function is the carbon constraint penalty. When the agent's actions result in cumulative carbon emissions that approach the predefined constraint threshold, a non-linear penalty is applied. This penalty grows exponentially as the emissions

draw closer to the absolute cap. If the agent takes an action that breaches the carbon cap, a massive terminal penalty is applied, and the training episode is immediately halted. This severe penalization strategy forces the agent to learn conservative operational buffers, ensuring that natural fluctuations in system dynamics do not inadvertently push the operations beyond legal environmental limits.

6. Experimental Results and Discussion

To evaluate the efficacy of the proposed framework, extensive simulation experiments were conducted using a digital twin environment modeled after a mid-sized onshore oilfield coupled with a fleet of thirty heavy-duty transport vehicles. The optimization period was set to a continuous thirty-day operational window. We compared the performance of our integrated reinforcement learning approach against two alternative management strategies. The first alternative was a baseline rule-based approach, representing conventional industry practice where well controls are kept static and trucks are dispatched on fixed daily schedules regardless of real-time production fluctuations. The second alternative was a traditional decoupled optimization method, where the oilfield and transport fleet were optimized independently using standard genetic algorithms without cross-system communication.

6.1 Computational Efficiency and Surrogate Accuracy

The first critical evaluation focused on the performance of the surrogate models themselves. The neural network-based oilfield surrogate achieved a mean absolute error of less than three percent across all production prediction metrics when compared to the high-fidelity finite-difference simulator. The gradient boosting model for the transport fleet demonstrated similar accuracy, predicting trip fuel consumption with a root mean square error of less than one liter per trip. Crucially, the computational acceleration provided by these surrogates was profound. A single thirty-day scenario evaluation, which required approximately forty-five minutes using conventional physics-based simulators, was executed in less than ten milliseconds using the integrated surrogate framework. This astronomical increase in speed was the enabling factor that allowed the Deep Deterministic Policy Gradient agent to experience millions of simulated operational hours during its training phase, facilitating the exploration necessary to converge on highly robust operational policies.

6.2 Carbon Constrained Optimization Outcomes

The operational results demonstrated the clear superiority of the integrated reinforcement learning framework. Under the baseline rule-based approach, the system frequently encountered logistical bottlenecks. Fixed truck schedules meant that vehicles often departed partially empty during periods of low production, wasting fuel, while storage tanks reached maximum capacity during production surges, forcing emergency well shut-ins. This resulted in low overall production yields and a high carbon intensity per barrel of oil delivered. The decoupled optimization method showed improvement, individually maximizing production and transport efficiency. However, because the systems could not communicate, the optimization often led to conflicting goals. The oilfield optimizer would aggressively increase pump speeds to maximize fluid output, rapidly consuming the available carbon allowance through high electricity usage. Consequently, the transport optimizer was left with a severely restricted carbon budget, forcing it to delay truck dispatches and leading to severe storage overflow issues late in the operational window.

Table 2: Performance Comparison Across Optimization Strategies

Optimization Strategy	Carbon Emissions	Production Yield	Transport Delay
Baseline Rule-Based	High	Moderate	Low
Traditional	Medium	High	Moderate

Optimizer			
Proposed RL Framework	Low	High	Low

The proposed integrated reinforcement learning agent successfully navigated the complex trade-offs between the two systems. By possessing a holistic view of the state space, the agent learned to dynamically modulate oilfield production rates in direct anticipation of transport fleet availability. For instance, the agent discovered a strategy of slightly reducing energy-intensive artificial lift operations during peak logistical hours, thereby conserving the carbon budget to allow for maximum truck fleet deployment. During off-peak transport times, the agent would slowly ramp up well production to fill storage tanks efficiently. This cooperative strategy resulted in a highly stable operational profile that maintained high production yields without triggering extreme energy spikes. The integrated framework reduced total carbon emissions by twenty-two percent compared to the baseline approach and fourteen percent compared to the decoupled optimization method. Furthermore, the reinforcement learning agent never violated the stringent dynamic carbon caps throughout the entire testing phase, demonstrating its reliability in safety-critical regulatory environments.

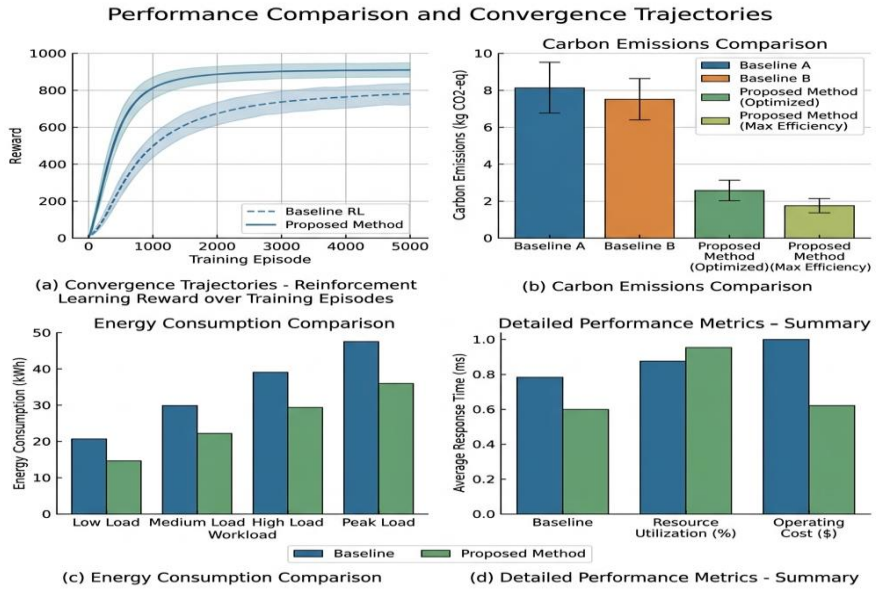


Figure 3Performance Comparison and Convergence Trajectories

The convergence trajectories recorded during the training of the neural networks indicated that the agent required substantial exploration to understand the delayed consequences of its actions. Because a change in well choke aperture takes several hours to manifest as fluid in the storage tanks, the agent had to learn long-term temporal associations. The implementation of an experience replay buffer and target networks stabilized this learning process, preventing catastrophic forgetting as the agent refined its complex multi-domain policies.

7. Conclusion

This paper introduced a novel, integrated framework for the simultaneous optimization of oilfield production and heavy-duty transport logistics under strict carbon emission constraints. Recognizing that traditional analytical methods and physics-based simulators are computationally inadequate for coupled, real-time optimization, we replaced them with highly accurate, data-driven surrogate models. These models provided the necessary computational speed to deploy a deep reinforcement learning agent capable of navigating continuous action spaces across multiple operational domains.

The experimental results definitively illustrated that treating oilfield operations and logistical transport as a unified, interconnected system yields significantly better environmental and economic outcomes than optimizing them in isolation. The reinforcement learning agent demonstrated an exceptional ability to balance the electrical power demands of artificial lift systems with the diesel fuel consumption of heavy-duty trucks, successfully maximizing hydrocarbon delivery while strictly adhering to dynamic carbon limits. The transition to sustainable industrial operations requires more than just the adoption of renewable energy sources; it requires the intelligent, algorithmic orchestration of existing energy-intensive assets. The framework presented in this study provides a scalable, computationally efficient blueprint for industries seeking to maintain economic viability while navigating the increasingly stringent regulatory landscape of global carbon mitigation [36]. Future research will focus on expanding this framework to include uncertain market dynamics, such as fluctuating energy prices and variable carbon tax rates, further enhancing its applicability to real-world industrial management.

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