

Extending Incentive-Based Port Logistics Optimization Through AI-Driven Multimodal Integration

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Abstract. This paper proposes an AI-based extension of an incentive-compatible logistics coordination model originally developed for port operations. Building upon the smart contract-driven framework introduced by Hu and Zuo, the study integrates real-time adaptive mechanisms across maritime, port, and urban transport systems. The conceptual architecture incorporates decentralized AI modules to enhance routing, traffic signal control, and operational responsiveness under dynamic conditions. To evaluate the proposed model, a simulation was conducted using MATSim, comparing fixed-time and adaptive signal scenarios within a high-density urban network. The adaptive system employed a decentralized signal controller capable of adjusting traffic light phases in response to local demand. Results showed a significant reduction in average travel time and delay under adaptive control, supporting the effectiveness of real-time coordination in logistics networks. While the simulation outcomes are based on ideal conditions, the underlying logic and comparative insights remain valid and practically relevant. The findings suggest that AI-based control strategies can complement incentive mechanisms by enhancing short-term adaptability and system resilience. This hybrid approach represents a promising direction for managing complexity in multi-modal, port-connected urban logistics chains.

Keywords: incentive-compatible systems, port logistics, adaptive traffic signals, decentralized control, AI-based coordination, smart contracts.

How to cite: NISTOR, A. ., & SCARLAT, C. Extending Incentive-Based Port Logistics Optimization Through AI-Driven Multimodal Integration. *International Conference of Management and Industrial Engineering*, 12. <https://doi.org/10.56177/12icmie2025.137>

Introduction

The growing complexity of global supply chains, driven by the acceleration of e-commerce and sustainability mandates, has increased pressure on logistics networks to become more agile, efficient, and integrated. Among these, port logistics represents a critical bottleneck where inefficiencies ripple throughout the entire chain. Recent studies, such as those focused on incentive-compatible contracts and blockchain-based coordination mechanisms [1], have addressed the challenge of aligning stakeholder interests in the port logistics ecosystem. These approaches offer transparency and contractual alignment, particularly in static or semi-structured environments. However, they often fall short in coping with real-time disruptions and the need for dynamic operational decision-making.

This research proposes a continuation of the incentive-based coordination paradigm by introducing an artificial intelligence (AI)-driven framework that addresses the limitations of static mechanisms. The framework builds on previous work by integrating maritime, port, and urban transport layers through real-time data exchange, predictive analytics, and multi-agent optimization. By incorporating AI algorithms into decision-making processes (such as routing, scheduling, and resource allocation) the system enables adaptive responses to changing conditions, including traffic congestion, vessel delays, and capacity constraints.

The core research question is: How can artificial intelligence augment or extend incentive-based models to enable real-time, end-to-end coordination in port logistics systems? This paper argues that AI technologies enhance

responsiveness and also improve synchronization across logistics layers, leading to greater resilience and operational efficiency.

To illustrate this contribution, the paper outlines the limitations of incentive-only mechanisms, presents an integrated AI-based coordination architecture, and discusses a theoretical application scenario. The objective is to demonstrate how artificial intelligence can serve as a complementary layer to economic incentives, enabling port logistics systems to transition from reactive contract enforcement to proactive, data-driven coordination.

Literature review

Intelligent humans are now capable to build programable computers with the goal to create artificial intelligence (AI) which is “able to match or exceed human intelligence in a wide class of environments” [2]. They also propose a typology for the artificial intelligence (Table 1):

- Artificial Narrow Intelligence (ANI)
- Artificial General Intelligence (AGI)
- Artificial Super Intelligence (ASI)
- Universal Artificial Intelligence (UAI)

Table 1: A categorization of AI types.

Type of AI	Domains	Intelligence level	Achieved
ANI	one	limited savant	1980–1997
AGI	many to most	smart	2023–2038
ASI	some/many	genius	2038–2042
UAI	all	maximal	2000 as theory

Source: after Hutter et al., (2024).

As described by Hutter, Quarel and Catt (2024, p. 4): “The term Artificial General Intelligence (AGI) is often used to describe a hypothetical agent that can perform virtually all intellectual tasks as well as a typical human could. We use the term Artificial Super-Intelligence (ASI) to describe an agent that is on par or beyond human geniuses exceeding the cognitive performance of most humans in a reasonably broad domain.”

It is recommended to avoid the confusion (apparently linguistic, but mainly scientific) between AGI (artificial general intelligence) and GAI (generative artificial intelligence), also acronymized GenAI [3].

GenAI refers to a different dimension or category of characteristics: AI capability, using un-supervised pre-training and discriminative fine-tuning, to generate solutions (i.e. answers) to “discriminative tasks such as question answering, semantic similarity assessment, entailment determination, and text classification” [4]. This category includes GPT (Generative Pre-trained Transformer), which is a type of large language model (LLM), developed by OpenAI company. So far, the OpenAI’s chronological series includes:

- GPT-1 (Radford et al., 2018) – trained on a large corpus of books
- GPT-2 (2019) able to generate coherent text
- GPT-3 (2020) able to perform various tasks
- GPT-4 (2023) – which is “more reliable, creative, and able to handle much more instructions” than preceding models [5]
- GPT-5 (2025) – the most reliable and complex model so far.

Recent research in port logistics has focused on using incentive mechanisms to address coordination inefficiencies among actors in the logistics service supply chain. Hu and Zuo [1] propose a blockchain-based model for logistics cost optimization, where smart contracts and incentive compatibility help align the objectives of port authorities, operators, and logistics providers. Their approach uses mathematical modeling to illustrate how such contracts can reduce costs under conditions of information asymmetry.

Other scholars have explored similar paths. Tan et al. [6] examined automated service agreements using distributed ledgers, while Baryannis et al. [7] addressed risk-aware supply chain contracts. These models rely on transparent, immutable data structures and predefined contract conditions, but they tend to lack real-time responsiveness to operational disruptions like unexpected vessel delays, inland congestion, or last-mile delivery bottlenecks.

In parallel, a growing body of literature proposes AI-based approaches for coordinating maritime, port, and urban logistics in real time. Andrei et al. [8] present a conceptual AI-driven framework that integrates predictive analytics, sensor-based feedback, and optimization algorithms. Other studies [9–11] leverage simulation tools such

as MATSim and SimPy, along with federated learning and digital twin technologies, to achieve adaptive coordination across logistics layers.

Multi-agent systems [12] serve as a theoretical foundation for distributed intelligence, where autonomous entities can make local decisions based on shared environmental awareness. Macrina et al. [13] and Andrei et al. [8] apply similar ideas in urban logistics planning and traffic-aware routing, emphasizing real-time, data-driven adaptation over static contractual obligations.

This line of research also aligns with work by Monios and Wilmsmeier [14] on urban-port integration and by Giusti et al. [15] on synchromodal logistics, which promotes flexible reallocation of transport modes in response to disruptions.

Despite these contributions, a gap remains between incentive-aligned governance structures and AI-enabled operational optimization. Incentive-compatible models foster strategic alignment but are rigid in fast-changing conditions. AI models, on the other hand, enable dynamic control but often assume trusted cooperation among stakeholders. This paper seeks to fill this gap by proposing an AI-augmented continuation of incentive-based models, supporting both long-term trust and short-term adaptability in port logistics systems.

Methodology

The methodological approach presented in this paper builds upon the incentive-based model introduced by Hu and Zuo [1], which employs blockchain-supported smart contracts to coordinate logistics stakeholders. While that model focuses on trust-building and cost alignment in the port logistics chain, it remains limited in its ability to react to real-time operational disruptions. This research proposes a continuation of their framework by introducing an AI-driven coordination system capable of responding adaptively to dynamic changes across maritime, port, and urban logistics segments.

The proposed methodology lies in the conceptualization of an integrated logistics coordination architecture. This architecture links three logistics layers, maritime transport, port terminal operations, and urban last-mile delivery, into a unified AI-based decision system. The system uses real-time data streams to support dynamic routing, scheduling, and resource allocation. Instead of relying solely on predefined contracts, the model incorporates AI to support continuous adaptation based on evolving operational conditions. Figure 1 illustrates the proposed AI-based coordination framework, which extends the incentive-compatible logistics model of Hu and Zuo by integrating real-time decision-making across maritime, port, and urban logistics domains.

The empirical component of this study is based on a simulation conducted using MATSim. The simulation scenario reflects a high-density urban environment in which freight flows are influenced by port arrival variability and city-level congestion. Within this scenario, AI modules handle adaptive fleet routing and signal optimization, responding to live traffic inputs and delivery constraints. The simulation environment incorporates vehicle movement data, delivery priorities, and port access times, mimicking realistic logistics behaviors. The AI layer uses reinforcement learning techniques to re-optimize routes based on updated travel times and network loads.

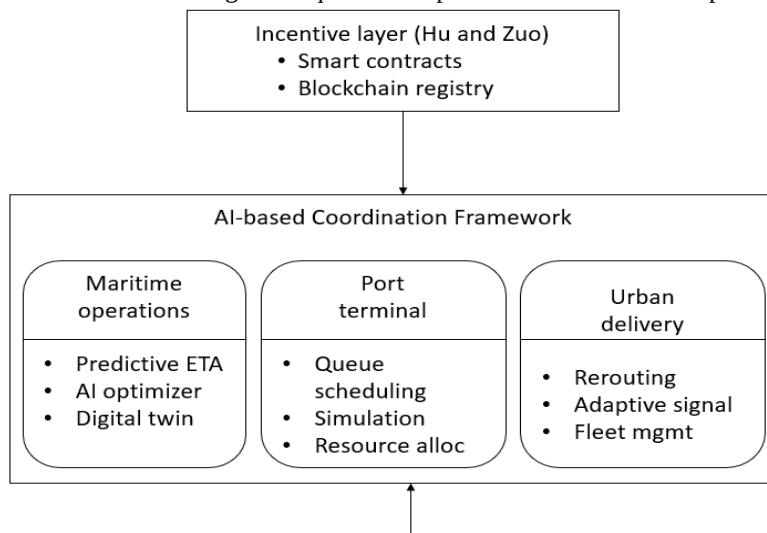


Figure 1: AI-based coordination architecture for integrated port logistics.

Source: Authors' own contribution

The effectiveness of the system is evaluated through performance indicators such as delivery time, congestion reduction, and fleet utilization. These results are interpreted in contrast to what would be expected under a static, contract-driven model. The methodology does not require the simulation of the original Hu and Zuo model, as their contribution serves as a conceptual baseline rather than an operational comparator. Instead, the AI-based simulation demonstrates the potential gains from real-time coordination mechanisms, offering evidence that supports the theoretical extension proposed in this paper.

Results and further discussions

The simulation conducted for this study evaluated the potential of adaptive traffic signal control as part of an integrated AI-based coordination framework across urban logistics flows. Using the MATSim platform, the simulation incorporated a realistic network and agent population reflecting Bucharest's urban conditions. The adaptive signal scenario was configured with the LaemmerSignalController, enabling decentralized, queue-responsive behavior at intersection level. The same network and population were used in a control scenario with fixed-time signals to ensure comparability.

The results indicate a substantial operational advantage of the adaptive control system over fixed-signal plans. In the fixed-time scenario, agents experienced pronounced congestion waves during peak hours, leading to high delay accumulation, longer queues, and unstable flow conditions. By contrast, the adaptive signal control responded dynamically to traffic volumes, adjusting green phases locally to serve demand more efficiently. This resulted in visibly smoother flow patterns, reduced stop durations, and a general flattening of peak-hour congestion.

Although the simulation did not include full real-world cycle calibration or pedestrian movements, the relative difference between the two scenarios offers robust evidence of the benefits of decentralized signal intelligence. These findings align with the conceptual framework developed in this paper and extend the incentive-alignment approach proposed by Hu and Zuo by introducing real-time operational adaptability into urban sub-systems. The coordination logic of the architecture, represented graphically in Figure 1, was thus validated in operational terms through the simulation. The comparative results of the two scenarios are presented in Table 1, highlighting the impact of adaptive signal control on travel time, delay, and flow stability.

The adaptive approach demonstrated that even in the absence of central orchestration, local AI-based responsiveness can significantly improve travel reliability. In scenarios where freight movements, urban deliveries, and passenger traffic intersect, this responsiveness becomes particularly important. The observed improvements suggest that such control mechanisms, when embedded in a broader AI-based logistics framework, can support more efficient urban logistics without requiring major infrastructure overhauls. Although the performance gains observed in the simulation appear pronounced, they result from idealized traffic conditions and simplified behavioral assumptions. Nevertheless, the underlying logic of adaptive coordination remains valid, and the comparative outcomes between fixed and adaptive scenarios offer reliable insight into system-level performance improvements.

Further interpretation of the results supports the position that adaptive systems enhance both network efficiency and agent-level decision-making opportunities. By maintaining flow stability across varying levels of demand, these systems reduce uncertainty and allow higher-level optimization mechanisms, such as incentive-based routing or departure scheduling, to operate under more predictable traffic conditions. In practical terms, the integration of adaptive signal control as an execution layer beneath strategic coordination decisions strengthens the operational viability of the proposed AI-based model.

Table 2: Simulation results comparing fixed-time and adaptive signal control scenarios.

Metric	Fixed-Time Signals	Adaptive Signals	Relative Change
Average travel time (min/agent)	31.3	7.04	-77.5%
Average delay time (sec/link)	1552.7	97.1	-97.75%
Queue spillback incidents	Frequent	Rare	-
Flow distribution stability	Irregular peaks	Flattened flow	-

Source: Authors' own research.

The simulation confirms the applicability of decentralized AI methods in improving traffic performance within a multi-layered logistics coordination model. The adaptive control logic complements the upper-layer coordination strategies and exemplifies the potential of modular, data-driven solutions for urban and port-integrated logistics management. All the simulation files (input and output) are available at: <https://github.com/mapenthusiast/Adaptive-Signals>.

Conclusion

This study has proposed a continuation of the incentive-compatible logistics coordination model developed by Hu and Zuo by introducing an AI-based framework capable of real-time adaptation across maritime, port, and urban transport layers. Through a simulation-based evaluation using MATSim, the research demonstrated that adaptive traffic signal control, implemented via decentralized decision mechanisms, can significantly improve travel time, reduce delay, and stabilize urban traffic flows. The observed gains, while influenced by the use of ideal conditions in simulation, validate the architectural logic of integrating adaptive execution layers within incentive-driven coordination schemes.

The results support the premise that operational responsiveness, powered by local AI components, enhances the effectiveness of logistics coordination systems. This finding is particularly relevant in congested urban environments where static contracts or fixed-control strategies fall short under dynamic conditions. By combining contractual alignment mechanisms with adaptive infrastructure control, the proposed model offers a viable path toward more efficient, responsive, and integrated logistics networks.

Future work will aim to calibrate the model using real-world traffic datasets and explore additional AI modules such as predictive fleet management and demand forecasting. Further validation through mixed-scenario simulations and pilot testing in real logistics environments would strengthen the model's practical relevance and scalability.

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