Using AI for Container Port Infrastructure Development: Alternative Multisolving Strategies

Naoum Tsolakis [a,b,*], Nitin Joglekar [c]

[a] *Department of Supply Chain Management, School of Economics and Business Administration, International Hellenic University (IHU), Thessaloniki 570 01, Greece, ntsolakis@ihu.gr*

[b] *Centre for International Manufacturing, Institute for Manufacturing (IfM), Department of Engineering, School of Technology, University of Cambridge, Cambridge CB3 0FS, United Kingdom, nt377@cam.ac.uk*

[c] *Questrom School of Business, Boston University, Boston, MA, United States, joglekar@bu.edu*

[*] Corresponding Author

Abstract

Container port ecosystems and allied infrastructure play a central role in global trade, with the efficiency of the involved supply networks and logistics, along with potential bottlenecks, being central themes in disciplines such as Operations Management. We conduct a literature review to show that, notwithstanding a plethora of approaches towards calculating the optimal operations performance in container port terminals, the involvement of multiple stakeholders (e.g., inland carriers, customs, and advocates for sustainable transportation) with conflicting interests have not been investigated from an integrated perspective. Motivated by the container handling operations at the port of Thessaloniki, Greece, this research applies Systems Thinking to investigate the complex interconnections and feedback loops associated with Artificial Intelligence (AI) driven infrastructure on operations efficiency and environmental sustainability of container ports under a "multisolving" perspective. We find that AI can catalyze infrastructure development and balance the associated multiple trade-offs in container port systems at the short- and long-term horizon. We also find that multisolving in such a system can be implemented across two alternative strategies: (i) adjusting the input resources to control key stocks; or (ii) altering the weight on decisions that are critical in influencing the outcome trade-offs.

Keywords: Artificial Intelligence; Container Ports; Infrastructure; Multisolving; Systems Thinking

Introduction

Maritime transport and container ports have a pivotal role in the global economy, with international maritime trade flows amounting to 11.0 billion tons in 2021, demonstrating an annual growth of 3.2%, almost reaching the pre-pandemic levels (UNCTAD, 2022). Specifically, containerized trade volume declined by 1.3% in 2020 and rebounded in 2021, reaching 165 million 20-foot Equivalent Units (TEUs) (UNCTAD, 2022). Amid the container volume increases and inbound/outbound flow imbalances, port operations must accommodate the oft-conflicting interests of multiple stakeholders, e.g., terminal operators, drayage carriers, railroads, longshore labor, and governmental authorities (Maloni and Jackson, 2005).

Notwithstanding a plethora of studies focusing on optimizing container port operations for improved efficiency in terms of cost and time constituents, research evidence investigating the associated emissions and energy consumption is limited (Okşaş, 2023). Maritime transport accounts for 3.5-4% of all climate change emissions, primarily carbon dioxide (Walker et al., 2019). Indicatively, in 2021, container ships spent 13.7% longer waiting time in ports (compared to 2020) due to aggravating delays, while the total greenhouse gas (GHG) emissions attributed to the world fleet increased by 4.7% (UNCTAD, 2022). Furthermore, coastal cities harness the economic benefits stemming from the hosted port operations (Tanner et al., 2020). At the same time, they directly experience the associated environmental ramifications (Aguilera et al., 2023). To this end, the International Maritime Organization (IMO) has set a strategy to reduce by 50% the GHG emissions from international shipping activities by 2050, compared to 2008 emissions (IMO, 2020). The required carbon emissions reduction, in tandem with the diverging objectives of stakeholders, requires that port authorities adopt digital technologies to deploy short- and long-term plans to improve the sustainable performance of container port terminal operations (Lam and Li, 2019; Okşaş, 2023).

Container ports are complex ecosystems involving multiple stakeholders with coexisting and often conflicting interests (Ha et al., 2019), spanning the economic, environmental, and social sustainability pillars. Therefore, multiple perspectives are required to understand the dynamics of port operations and the associated sustainability impact. Arguably, "multisolving" approaches may help nullify the myopic views of any one stakeholder by exploring policies or interventions to tackle multiple problems, from efficiency to environmental to healthcare issues (Milstein et al., 2022; Multisolving Institute, 2022). Multisolving is defined as: "*The pooling of expertise, funding, and political will to solve multiple problems with a single investment of time and money*" (Sawin, 2018). In a container port ecosystem, multisolving can offer the capability to regard the complex and interlinked social and environmental challenges associated with operations. Multisolving decisions hinge on the choice of system boundary and the underlying trade-offs that these decisions must address within such a system. In this regard, data are central in informing decision-making to precipitate the well-being of people, places, and profit (Corbett, 2018), in conjunction with disruptive technology platforms and allied Artificial Intelligence (AI) algorithms (Sunar and Swaminathan, 2022). Demonstrating the role of AI in socially relevant, effective, and inclusive management prompts a nascent research field in container port ecosystems. Reconciling the multiple interests of diverse port stakeholders for spillover beneficial outcomes is an emerging subject area (Ha et al., 2019; Lam et al., 2013). Given these goals, our research embarks on analyzing the container port ecosystem from a multisolving perspective and attempts to address the following research question: *How can we integrate AI into multisolving approaches to container port management*?

As with multisolving problems, there are multiple stakeholders (e.g., port platform owner, ship owners, city), each of whom values different objectives (e.g., platform owner wants to maximize port premium, ship owners want to improve efficiency and reduce congestion, the city wishes to have a cleaner and more sustainable footprint). We address this research query, initially by exploring the extant literature to comprehend the dynamics in a container port and its impact on the surrounding ecosystem. Systematic search and taxonomy are used with reference to multicriteria analyses and AI applications in container ports. Since we seek to access “best-quality evidence” (Tranfield et al., 2003), the literature search and taxonomy were limited to peer-reviewed journal articles written in English. Second, the study leverages primary evidence from the case of the Thessaloniki container port in Greece. Owing to the city’s geographical location and its extensive road links and train connections, the container port of Thessaloniki is the largest transit-trade port in Greece, and it is considered the gateway port to the Balkans and Southeast Europe (ThPA S.A., 2022). Third, the study adopts Systems Thinking as a theory-building approach to explore the underpinning interconnected cause-effect relationships and feedback mechanisms to derive a pertinent mental model (Meadows, 2009). Systems Thinking has been used in container port management to assess the impact of capacity and transportation planning policies on financial outcomes (Bahadir and Camgöz Akdag, 2019). In addition, a systems perspective has been applied to investigating infrastructure and organizational issues toward mitigating port congestion (Xu et al., 2021).

We find that AI can catalyze infrastructure development and balance the associated multiple trade-offs in container port systems at the short- and long-term horizon. We also find that multisolving in such a system can be implemented across two alternative strategies: (i) adjusting the input resources to control key stocks; or (ii) altering the weight on decisions that are critical in influencing the outcome trade-offs. Theory and practice implications of these findings are discussed in closing.

Decision-making in Container Ports

Container ports play a critical role in global trade, as they handle most of the world’s merchandise (over 80% of global trade volume) by facilitating the movement of goods from one location to another, using various modes of transportation such as ships, trucks, and trains (UNCTAD, 2022). In essence, container ports provide a crucial link between manufacturers and consumers, enabling the efficient movement of goods across local and national borders (European Commission, 2020). Contemporarily, most container ports are characterized by proximity or embeddedness in urban settings, impacting multiple and diversified stakeholders (Merk, 2013). The latter stakeholders extend from the logistics sector to local authorities and communities, demonstrating varied necessities and priorities. Therefore, the management of container port operations needs to embrace decision-making approaches to address multiple challenges simultaneously and sustainably (rather than solving each problem in isolation), with multisolving providing such a perspective.

Within the context of container ports, multisolving could involve addressing challenges related to environmental sustainability, economic development, and social equity (Figure 1). For example, a container port could exploit renewable energy sources to reduce GHG emissions (Ballester et al., 2020). Furthermore, digitalization and innovation in port operations can foster long-run growth, create job opportunities for local communities and improve access to goods and services for underserved populations (Bottalico et al., 2022). Adopting a multisolving lens, container ports can simultaneously achieve multiple benefits, leading to more sustainable and equitable outcomes. In particular, AI-driven multicriteria analyses can inform operations and infrastructure investments for achieving balanced outcomes.

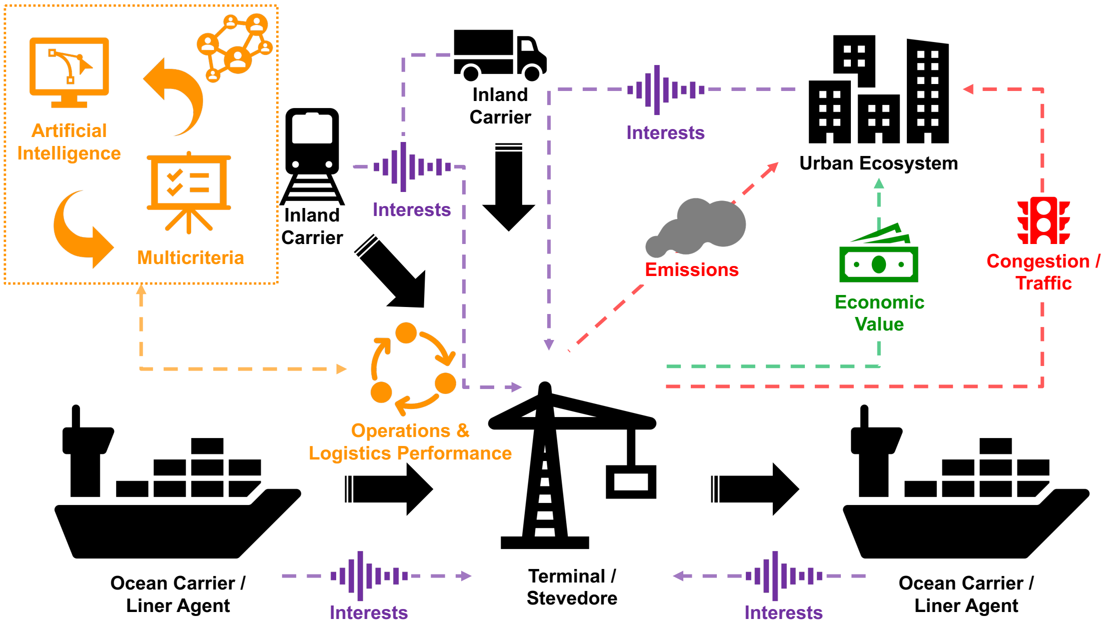

Figure 1. Deployment of AI-based Multicriteria Decisions in Container Port Ecosystem.

Outcome Balance: Multicriteria Analysis in Container Ports

The basis for our literature review for multicriteria analyses in ports is the structured literature search in the Scopus database using the query: {(TITLE-ABS-KEY("container port") AND TITLE-ABS-KEY(multicriteria)) AND (LIMIT-TO(DOCTYPE, "ar"))}. We retrieved and reviewed seven articles to cover the multicriteria analysis topic in container ports. The content of every identified published article was studied carefully to validate its eligibility and relevance to the scope of this research.

Multicriteria decision-making methods have been applied for evaluation purposes of container ports. To begin with, multicriteria analysis has been used to decide on alternative locations for developing a hub port in South Africa (Notteboom, 2011). The main criteria in this specific analysis model concerned the attractiveness to the shipping lines (e.g., capacity, productivity, and information technology systems), the terminal operators/investors (e.g., profitability, connectivity to land infrastructure, and expansion possibilities in TEU capacity), and the community (e.g., economic benefits, energy use, and carbon footprint). The selection of the best performer location was based on meeting the objectives of the terminal operators and the sustainable development of the community in South Africa and Sub-Saharan Africa.

Furthermore, research studies have applied Analytical Hierarchy Process to evaluate and select the most attractive container port in West Africa, considering multiple criteria across four perspectives, including: (i) infrastructure; (ii) port location; (iii) port charge; and (iv) port administration/port efficiency (Gohomene et al., 2016). Empirical-driven findings indicate that port infrastructure is the most crucial criterion for port attractiveness in West Africa, followed by port draught and political stability (Gohomene et al., 2016). In this context*, infrastructure denotes the number and quality of container berths, cranes, tugs, and terminal areas and the effectiveness of information and control systems*. Multicriteria and multivariate analysis has also been used to evaluate the performance of major Brazilian container port terminals from 2006 to 2009 (Madeira Jr. et al., 2012). In particular, the movement factors in the port, port productivity, and container status were considered goals. The findings of this analysis verified the need for infrastructure investments (e.g., in portal gantry cranes, rubber tire gantry cranes, rail-mounted gantry cranes, reach stackers, construction of new berths, development of yards and warehouses, adoption of new digital-enabled processes) towards the selected goals.

Container port competitiveness is generally strongly associated with well-developed infrastructure. In tandem with improved cargo handling capabilities, modernized facilities, improved service coverage, and direct and indirect connectivity to more countries have been proven to be catalytic in transitioning towards new hubs. Specifically, the connectivity of ten major ports in Southeast Asia was evaluated, revealing the pivotal role of favorable geographic locations in connectivity (Nguyen and Woo, 2022). Further, the Technique for *Order of Preference by Similarity to Ideal Solution* analysis helped rank these ports' competitiveness based on the categories of port facilities, cargo volumes, and connectivity; no environmental sustainability factors were considered.

Similarly, Teng et al. (2004) have utilized Grey Relation Analysis (GRA). This analysis calculates the grey relational degree and determines the contribution measure of the main behavior of the system or the influence degree between the system factors. The authors ranked eight East Asian container ports by considering thirty-one factors from their internal and external environment spanning from labor quality and ship mean time in port to political and economic stability. The study findings indicated the significance of political, social, and economic stability in establishing port competitiveness.

Methodologically, these studies have explored the suitability of hybrid multicriteria decision-making models for selecting container ports. Specifically, two Multi-Criterial Decision Models (MCDMs) have been developed for assessing the operational performance of container seaports in the Black Sea region for 2018, namely: (i) the Entropy and Operational Competitiveness Rating Analysis technique; and (ii) the Entropy and Efficiency Analysis Technique With Output Satisfying methods (Görçün, 2021). The analysis was based on input (e.g., number of staff, port infrastructure in terms of quay length, depth, total storage area, port area, and container handling capacity) and output (e.g., number of arrivals, annual income, throughout) factors. The validated findings demonstrated the pertinence of hybrid methods for solving decision-making problems in the maritime industry and highlighted that output factors are more important than input factors.

Finally, research evidence across fourteen major container ports in Greater China concerned the impact of climate change on port operations, highlighting the need for adaptation (Yang et al., 2018). Specifically, improving transport infra- and superstructures have been found to ensure cost-effective long-term resilience to natural catastrophes (e.g., flooding).

Table 1 offers a taxonomy of existing MCDM studies in container ports as these are mapped on the relevant environmental, economic, and social sustainability pillars. Moreover, references to public policy and infrastructure were considered.

Table 1. Multicriterial Decision-making in Container Ports.

Study	Sustainability Pillar				AI
	Env.	Econ.	Soc.	Pub. Pol. & Infr.	
▪ Gohomene et al. (2016)		X		X	No
▪ Görçün (2021)		X		X	No
▪ Madeira Jr. et al. (2012)		X		X	No
▪ Nguyen and Woo (2022)		X		X	No
▪ Notteboom (2011)	X	X	X	X	No
▪ Teng et al. (2004)		X	X	X	No
▪ Yang et al. (2018)		X		X	No

Symbol: Env. for 'Environmental', Econ. for 'Economic', Soc. for 'Social', Pub. Pol. & Infr. for 'Public Policy & Infrastructure', AI for 'Artificial Intelligence'.

This taxonomy in Table 1 demonstrates that extant multicriteria analyses for container ports have largely overlooked multisolving perspectives, merely focusing on balancing outcome performance. However, energy consumption, emissions, and social impact on the local and regional settings are critical aspects of container ports. Moreover, AI-driven implementations in MCDM studies are lacking, thus demonstrating an evident gap in the extant body of research. Consequently, the literature taxonomy leads to the realization that different weights are put on outcomes.

Allocation Balance: Artificial Intelligence to Inform Infrastructure Investments in Ports

In the second half of our review, we looked at seven articles that were retrieved based on the Scopus query search: {(TITLE-ABS-KEY("container port") AND TITLE-ABS-KEY("Artificial Intelligence")) AND (LIMIT-TO(DOCTYPE, "ar"))}.

AI and Machine Learning have been used to conduct benchmarking studies of the operational performance of container ports by considering the allocation balance across several inputs. For example, Data Envelopment Analysis has been used for calculating the container throughput of seventy-seven world container ports in 2007 via utilizing input data related to the available infrastructure (i.e., the capacity of cargo handling machines, number of berths, terminal area, storage capacity) (Wu et al., 2010). Notwithstanding the scientific analyses leveraging intelligent algorithms for ports' evaluation, the evidence has demonstrated the potential benefits of implementing AI in container port operations by improving efficiency, reducing costs, and enhancing security (Wu et al., 2010).

Fast vessel turnaround time and high berth productivity are key performance factors in container terminals to ensure competitive advantage. To this end, implementing intelligence and improving learning capabilities are paramount to the decision-making process in container port terminals' complex and dynamic environments (Lokuge and Alahakoon, 2004). Investigating dynamic vessel scheduling scenarios with hybrid 'Beliefs, Desires and Intention' intelligent agent architecture at the Jaya container terminal port of Colombo demonstrated improved vessel scheduling efficiency (Lokuge and Alahakoon, 2007). In essence, AI-driven scheduling allows the effective utilization of the available capacity while, at the same time, mitigating the risk of paying high penalties for operational delays at berths (Lokuge and Alahakoon, 2007).

In the same vein, regarding operations on the berthing side, research has explored the role of AI in allocating quayside cranes for servicing inbound container ships, considering the available infrastructure and the shipping timetable. Indicatively, evidence from a container terminal company in Busan, Korea, demonstrated the tepid processing performance of quayside cranes, amounting to 50% of the installed capacity (Chatterjee and Cho, 2022). Corresponding simulation modeling analysis incorporating AI and Machine Learning techniques indicated the potential improvements in terminal operations performance.

Furthermore, an evident operations challenge pertinent to container ports is the autonomous routing of container trucks considering container ports' complex and unknown construction environment. To this effect, algorithmic approaches have been proposed to achieve optimal path planning of container trucks while ensuring safe collision evasion and dead ends avoidance. Indicatively, simulation experiments of an improved ant colony optimization algorithm based on a rolling window demonstrated a potential improvement of 22% in the distance traveled by an autonomous container truck (Huang and Zheng, 2016).

Algorithmic-driven and intelligent planning is even more prominent in the key yet mostly manual container stacking operations at the terminal yard. Efficiency challenges emerge due to the necessary relocations/reshuffles of containers to ensure easy access to outbound containers at the expected transfer time. The container stacking problem has been investigated from the AI perspective, with pertinent modeling efforts combining the 'Enforced Hill-Climbing' with a standard 'A search'. The calculated plan minimized the number of necessary reshuffles to allocate selected containers at the top of the stacks or below other selected containers so that no reshuffles are needed to load the outgoing containers (Salido et al., 2009).

To a greater extent, scientific evidence have demonstrated the enabling role of AI and data analytics in the operations efficiency and productivity of potential Automated Guided Vehicles in the port of Piraeus, Greece (Tsolakis et al., 2021). The respective simulation study quantified the environmental benefits of intelligent routing scenarios of alternative types of Automated Guided Vehicles for shoreside container handling operations at freight ports.

Table 2 presents a comprehensive synopsis of the matching of the relevant research efforts with the sustainability pillars and the implementation of AI. Consistent with the multicriteria taxonomy in the previous section, public policy, and infrastructure were considered in this analysis.

Table 2. AI Applications On Input Allocations in Container Ports.

Study	Sustainability Pillar				AI
	Env.	Econ.	Soc.	Pub. Pol. & Infr.	
▪ Chatterjee and Cho (2022)		X			Yes
▪ Huang and Zheng (2016)		X			Yes
▪ Lokuge and Alahakoon (2007)		X		X	Yes
▪ Lokuge and Alahakoon (2004)		X			Yes
▪ Salido et al. (2009)		X			Yes
▪ Tsolakis et al. (2022)	X	X		X	Yes
▪ Wu et al. (2010)		X		X	No

Symbol: Env. for 'Environmental', Econ. for 'Economic', Soc. for 'Social', Pub. Pol. & Infr. for 'Public Policy & Infrastructure', AI for 'Artificial Intelligence'.

In summary, our investigation of the efficiency gain literature on deploying AI infrastructure in container ports has underscored the role of algorithmic implementations towards input allocation, i.e., better planning and scheduling of the physical infrastructure for harnessing the capacity utilization potential. Especially, AI can inform sustainable environmental operations by resolving issues related to tepid performance in container handling. The literature in Table 2 supports the notion that different weights are assigned to inputs.

Overall, our literature taxonomy efforts on multicriteria analyses and AI in container ports demonstrate the research gap in adopting data-driven intelligence in operations. The latter observation supports the need for targeted research in the field, in alignment with a similar need in the manufacturing domain (Chien et al., 2020). Notably, we observed that AI could be applied to putting different weights on the input *and* output sides in container port systems. In a complex feedback system, as in container ports, these choices may have a significant impact; hence, we conducted a stylized case study to examine such simultaneous multisolving opportunities.

Case Study

This study leverages evidence from decision-making at the container port in the city of Thessaloniki, Greece, managed by the Thessaloniki Port Authority S.A. (https://www.thpa.gr/index.php/en/). The port of Thessaloniki serves the transit trade of Central and Southeastern Europe, with the quays being connected to the European Railway network. The container handling area is in Pier 6, covering a surface area of 254,000 m^2. The port can accommodate vessels with a draught of up to 12 meters with an on-site storage capacity of 5,000 TEUs in ground slots. The container terminal is equipped with modern container handling equipment. Four cranes (deploying post-Panamax technology) are used for container loading-unloading services.

Within the Systems Thinking concept, this research employs Systems Dynamics as a modeling approach for analyzing complex dynamic systems characterized by causal relations and feedback loops (Forrester, 1961; Sterman, 2000). Specifically, a causal loop diagram (CLD) is proposed that supports the visualization of the system and its variables' interrelations. Figure 2 illustrates the CLD map that captures the nexus of AI, container ports performance, and multisolving. Our field studies inform the nature of the causal relationships.

Focusing on the port capacity (reinforcing 'Capacity Loop, R1'), an increase in the "*Physical Platforming Degree Using Conventional Infrastructure*" augments the "*Available Capacity (TEUs)*". As the container handling capacity grows, the related "*Traffic*" congestion will be lower than it would have been. However, as more inland and marine carriers decide to collaborate with the port and the traffic increases, the "*Port Congestion*" becomes higher. High congestion, though, decreases the "*Port Attractiveness (for shipping lines)*", negatively impacting, in turn, the contractual agreements and "*Port Connectivity*". As "*Port Connectivity*" increases, the "*Payoff from Contractual Agreements (P)*" increases, which fosters investments in improving the "*Physical Platforming Degree Using Conventional Infrastructure*".

At the same time, an increase in the "*Payoff from Contractual Agreements (P)*" increases the "*Physical Platforming Degree Using Conventional Infrastructure*" and thus the respective "*Port Connectivity*" (reinforcing 'Economic Gain Loop, R2'). However, increased "*Port Connectivity*" may lead to more "*Payoff from Contractual Agreements (P)*" while enhancing the "*Physical Platforming Degree Using Conventional Infrastructure*" but leads to a greater "*Carbon Footprint (C)*". As "*Physical Platforming Degree Using Conventional Infrastructure*" and "*Carbon Footprint (C)*" increase (e.g., emissions increase by the development and increased utilization of conventional infrastructure), the "*Willingness to Increase Congestion*" decreases to comply with the environmental sustainability targets set by the IMO. Decreased "*Willingness to Increase Congestion*", in turn, limits the "*Available Capacity (TEUs)*". As the container handling capacity is reduced, the "Traffic" increases due to the less availability of infrastructure to accommodate the container flow needs. The less the "*Traffic*", the less the observed "*Port Congestion*" that increases the "*Port Attractiveness (for shipping lines)*" due to the expected short waiting and service times, thus enhancing "*Port Connectivity*", ultimately creating a balancing loop (balancing 'Pressure to Reduce Congestion Loop, B1').

The more extended the "*Port Connectivity*", the greater the accumulation on the "*Stock of Knowledge in Digital Platform*", which in turn enhances the "*Ability to Learn Using*

AI". The more advanced the "*Ability to Learn Using AI*" leads to better operations performance, mitigating "*Port Congestion*". Reduced "*Port Congestion*" then increases the "*Port Attractiveness (for shipping lines)*" that expands "*Port Connectivity*", eventually forming the reinforcing 'AI Adoption Loop, R3'.

Concerning carbon emissions, the role of the port's Terminal Operating System (TOS) that manages the movement of containers could be catalytic. In particular, by the "*Application of TOS to Footprint*", the planning, scheduling, and execution of container handling operations improve, hence reducing the "*Carbon Footprint (C)*". Reduced "*Carbon Footprint (C)*" demotivates the "*Search for New Physical Technologies*", which then, after a certain delay, increases the "*Ability to Learn Using AI*". However, the greater the "*Ability to Learn Using AI*", the more effective the "*Application of TOS to Footprint*", hence leading to the foundation of the reinforcing loop 'Longer Term Information Leverage (R4)'.

In addition, increased "*Ability to Learn Using AI*" decreases "*Port Congestion*". Thereafter, decreased "Port Congestion" elevates the "Port Attractiveness (for shipping lines)", hence increasing "*Port Connectivity*" and subsequently the "*Payoff from Contractual Agreements (P)*". Augmented income leads to investments that increase the "*Physical Platforming Degree Using Conventional Infrastructure*", which then leads to a greater "*Carbon Footprint (C)*". The more the "*Carbon Footprint (C)*", the more the need and willingness to "*Search for New Physical Technologies*" that then limits the "*Ability to Learn Using AI*". Typically, there is a delay between the monitoring of "*Carbon Footprint (C)*" and the "*Search for New Physical Technologies*". Ultimately, the balancing loop 'Longer-term Solution as Multisolving, B2' is generated that promotes multisolving.

Finally, the larger the "*Stock of Knowledge in Digital Platform*", the more effective the "*Application of TOS to Footprint*", which then decreases "*Carbon Footprint (C)*". Increased "*Carbon Footprint (C)*" motivates the "*Search for New Physical Technologies*", which deteriorates the "*Ability to Learn Using AI*". The limited use of AI increases "*Port Congestion*", which in sequence limits "*Port Attractiveness (for shipping lines)*" and "*Port Connectivity*". On the other end, increased "Port Connectivity" increases the "*Stock of Knowledge in Digital Platform*". This reinforcing loop ('Platforming Loop as Short-term Leverage, R5') highlights the role of AI as a short-term approach to multisolving.

The described feedback loops are consistent with the fundamental structural mechanisms underpinning the system that we have observed in the Port of Thessaloniki. Even with simplifications through the aggregation of constructs, the current CLD comprises seven key stocks (i.e., "*Ability to Learn Using AI*", "*Carbon Footprint*", "*Level of Port Congestion*", "*Level of Port Connectivity*", "*Level of Payoff from Contractual Agreements*", "*Platforming Degree (Level) using Conventional Infrastructure*", and "*Stock of Knowledge in Digital Platforms*"), integrated through seven key loops (as shown in Figure 2). We analyze the multisolving trade-offs in the next section.

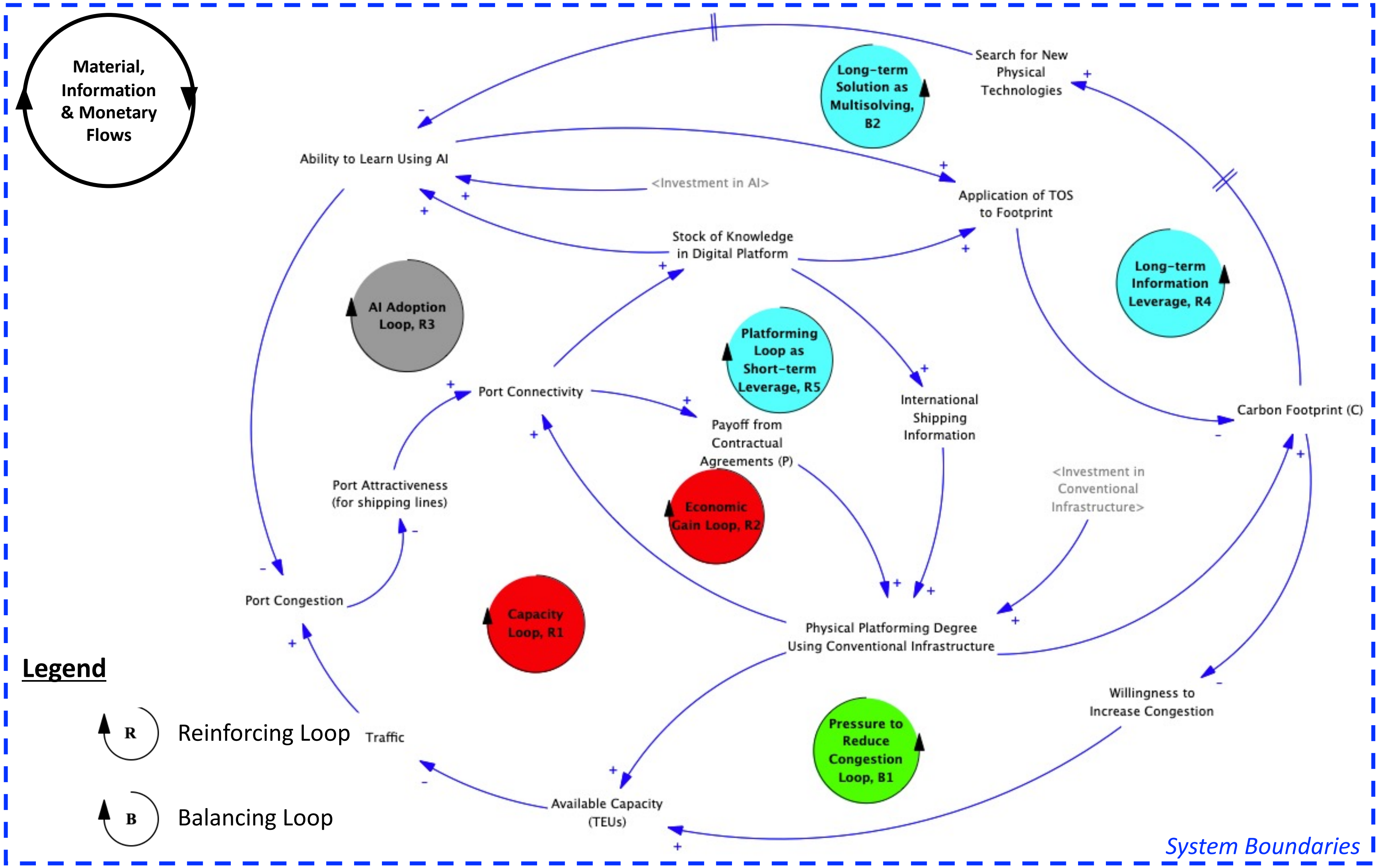

Figure 2. AI and Multisolving Trade-offs in Container Port Systems CLD.

Discussion

In terms of outcome (Figure 3a), the "*Payoff from Contractual Agreements (P)*" and the "*Carbon Footprint (C)*" are the key variables from a multisolving perspective. The outcome can be expressed as in Equation 1:

$$\text{Outcome} = W_p \times P - W_c \times C \qquad \text{Equation (1)}$$

where:

W_p : "*weight on Payoff from Contractual Agreements (W_p)*"
W_c : "*weight on Carbon Footprint (W_c)*"

Assigning weights on either of these key variables is a theme that is aligned with the incentives of the different stakeholders involved in the container port ecosystem. Moreover, over the long haul, the outcome from Figure 3a informs the availability of input resources needed to tackle any prevalent challenges (Figure 3b). The allied allocation mechanism for input resources that shapes the investments is also shown in Figure 3b. In our case, "*Input Resource (I)*" is considered as the capital available for investments.

On the one end, in the case under study, AI can help tackle short-term multisolving challenges by ensuring increased operations efficiency (e.g., optimal routing of transfer trucks transporting the containers in the port yard area). On the other end, physical infrastructure developments (e.g., new quay cranes) are an appropriate multisolving approach for the long-term horizon. Assigning weights on either of these key variables is a theme that is also aligned with the incentives of the different stakeholders involved in the container port ecosystem. The investment in "*Input Resource (I)*" is based on Equations 2 and 3:

$$\text{Investment in Conventional Infrastructure} = W_{ci} \times I \qquad \text{Equation (2)}$$

$$\text{Investment in AI} = W_{ai} \times I \qquad \text{Equation (3)}$$

where:

W_{ci} : "weight on *Conventional Infrastructure (W_{ci})*"
W_c : "*weight on AI (W_{ai})*"

In our casework, we have observed that assigning weights (and allied debates regarding getting stakeholder buy-in) in input resources is relatively straightforward compared to assigning weights to outcomes that drive investments. Overall, both these sets of weights are shaped by the behavioral biases of the stakeholders. Furthermore, in general, the time lag associated with the gathering of outcome data and the following on input into investments makes managing such biases and resolving debates a tricky problem. The goal of this modeling approach is to decipher the leverage points that identify alternative multisolving strategies.

The seven different loops give us different trajectories in terms of which stakeholders influence the choice of weights in their decision-making process. The gains associated with these loops will alter the balance. We leave the calibration of an underlying System Dynamics model and assessment of the loop gains as a follow-on exercise.

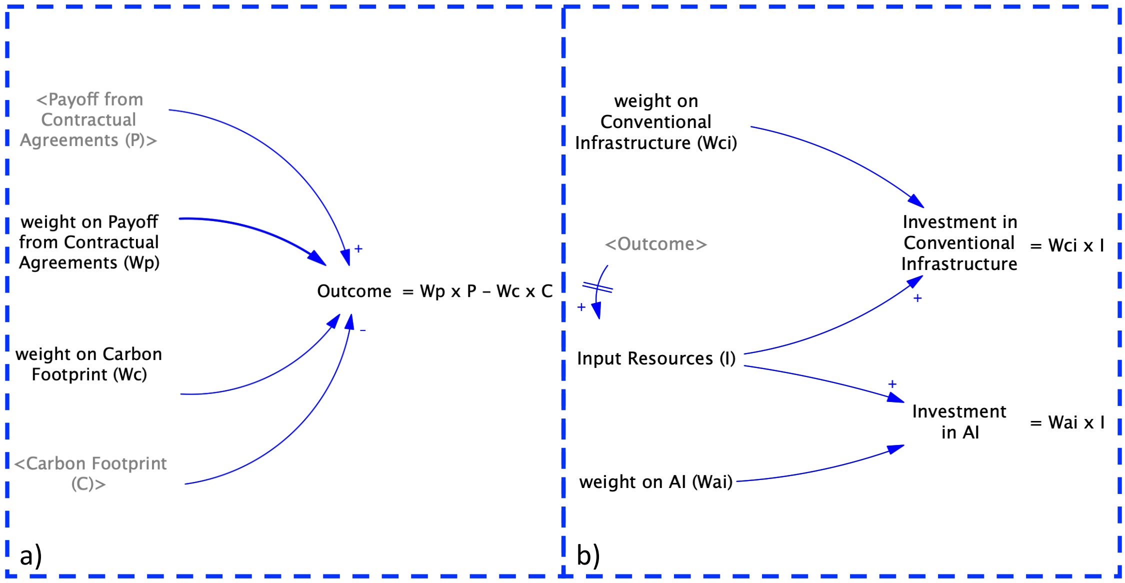

Figure 3. Multisolving Outcome and Input Interrelation.

Even without a fully calibrated model, the short- and long-term multisolving trade-offs associated with using AI in container port systems can be summarised in terms of alternate strategies, as shown in Table 3. The analysis underlying this table suggests that AI can help tackle operational efficiency and performance challenges in the short term but would require corresponding development in physical infrastructure to ensure the viability of port competitiveness.

Specifically, AI investments can lead to immediate observable operations efficiency gains that can help reduce emissions and traffic caused by inland carriers in a regional setting. However, optimized container handling processes and matching supply and demand at the terminals cannot ensure eminent short-term regional economic growth.

Nevertheless, physical infrastructure developments demotivate operations optimization to foster economic growth and sustain a container port's competitive advantage due to the excessive installed capacity, leading to increased emissions. However, infrastructure investments fuel regional economic growth and help address regional traffic issues. Finally, combining investments ensures balanced development with desirable outcomes for all multisolving constituents.

Table 3. Multisolving Trade-offs based on Alternative Strategies

Strategy	Time Horizon	Port Operations Performance	Level of Regional Emissions	Regional Economic Growth	Regional Traffic
Alter Input Weights (Assuming $W_{ai} > W_{ci}$)	Short-term	↑	↓	⟷	↓
Alter Outcome Weights (Assuming $W_p > W_c$)	Long-term	↓	↑	↑	↑
Alter Combination Weights ($W_{ai} > W_{ci}$) AND ($W_p > W_c$)	Both	↑	↓	↑	↓

Symbol: "⟷" – neutral effect; "↑" – increased performance; "↓" – decreased performance.

Conclusions

Multicriteria decision-making methods are often used in evaluating and selecting outcomes in container port systems due to the numerous factors that need to be considered. We have retrieved fourteen articles on this theme based on a structured literature search.

Multicriteria-based methods enable decision-makers to consider various criteria and weight them according to their relative importance in deciding. Multicriteria decision-making methods can be helpful in container port selection as they provide a structured and systematic approach to decision-making. They also enable decision-makers to reflect upon multiple criteria and weight them according to their relative importance, which can help ensure that all relevant factors are considered.

Moreover, the multidimensional role of AI in container ports, particularly while establishing input priorities, involves improving efficiency, safety, security, decision-making, and inventory management. AI can optimize the flow of containers, reduce waiting times, and improve overall efficiency. It can also improve security and safety by detecting threats and unauthorized access. Furthermore, AI can manage the movement of vehicles within the port, reduce congestion, improve safety, and provide real-time data and insights to assist decision-making. Lastly, inventory management can be enhanced by monitoring inventory levels and automatically reordering supplies when necessary, improving efficiency and reducing waste. Overall, AI plays a critical role in optimizing container port operations. Even though the literature is small, it underlines trends in multicriteria decision-making and the use of AI. This is a limitation of our work, but we hope that our research will draw attention to follow-on work.

This research contributes to the Systems Thinking field by proposing a framework for architecting an AI tool to leverage uncertainty and develop multisolving capability in container ports. Deciding on the allocation of available resources to achieve desired outcomes is challenging due to the often-conflicting objectives of the multiple stakeholders involved in container port systems and the time horizon where certain outcomes need to be achieved. Our study indicates that multisolving in a container port system can manifest itself in alternative strategies: (i) adjusting the input resources to control key stocks; or (ii) altering the weight on decisions that are critical in influencing the outcome trade-offs or a combination of these leverage points. Our work has been informed by key multisolving studies in the healthcare sector (Milstein et al., 2022). However, such approaches are yet to see multiple multisolving strategies, particularly while deploying calibrated System Dynamics models. We hope our study will become a part of the burgeoning literature on multisolving using System Dynamics models.

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