Cooperative Logistics: Can Artificial Intelligence Enable Trustworthy Cooperation at Scale?

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Abstract

Cooperative Logistics studies the setting where logistics companies pool their resources together to improve their individual performance. Prior literature suggests carbon savings of approximately 22%. If attained globally, this equates to 480,000,000 tonnes of CO_2-eq. Whilst well-studied in operations research – industrial adoption remains limited due to a lack of trustworthy cooperation. A key remaining challenge is *fair* and *scalable* gain sharing (i.e., how much should each company be fairly paid?). We propose the use of deep reinforcement learning with a neural reward model for coalition structure generation and present early findings.

1 Introduction

The transportation industry[1] emitted 7.1 billion tonnes of CO_2 ($GtCO_2$) globally in 2020 [1, p. 64], or 13% of global greenhouse gas emissions [2]. To limit the global average temperature increase to 1.5°C, the Intergovernmental Panel of Climate Change (IPCC) states that the transportation industry must decrease their CO_2 emissions to 2.6 $GtCO_2$ by 2050 [3].

Road freight transportation emitted 2.2 $GtCO_2$ globally in 2020[2]. Yet, under currently implemented and announced policies, the International Transport Forum expects road freight transportation emissions to *increase* to 2.5 $GtCO_2$ in 2050 – single-handedly exhausting almost all of the transportation industry's carbon budget. In addition, road freight transportation is seen as one of the most difficult industries to decarbonise [5]. This is due to the sheer weights and distances travelled. In 2020, global road freight activity was at 26.8 trillion tonne-kilometers[3]. This is expected to double by 2050 due to an increasing global population and global economic growth [1].

One approach to decarbonise road freight transportation is through cooperation. Cooperative vehicle routing studies the setting where delivery companies share their delivery information and perform deliveries on behalf of one another. An illustration can be found in Figure 1. Cooperative vehicle routing has been studied in operations research for at least two decades, with estimated cost savings between 4-46% [6, 7, 8, 9, 10]. Cooperative vehicle routing results in reduced distance travelled by trucks, thus reducing carbon emissions and road congestion. In addition, delivery companies can increase their revenue, improve customer service, and gain market share [9]. Surprisingly, despite the abundance of perceived benefits, cooperative vehicle routing has still not seen widespread industrial traction [8].

We argue that this is due to a lack of *fair* and *scalable* algorithms for gain sharing, i.e., if two or more companies cooperate, how much should everyone be fairly paid? Fairness is important to

[1] Transportation involves the movement of people and goods across air, road, rail and water.

[2] Due to COVID-19, global freight activity dropped by 4%, but global freight emissions only dropped by 1% due to increased urban deliveries [4, p. 194].

[3] A tonne-kilometer is when a tonne of goods is transported one kilometer.

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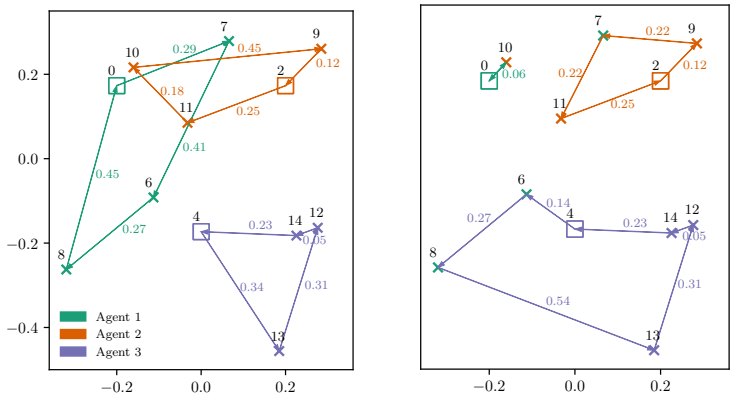

(a) Before cooperation
Total Cost = 3.35

(b) After cooperation
Total Cost = 2.47

Figure 1: An example of three companies (denoted by colours) before and after cooperation. Through cooperation, the companies are able to attain more efficient routes, reducing total cost by 0.88 or 26%. Squares denote depots. Crosses denote customer locations. Node indices (arbitrary) are denoted in black, with route costs given along edges.

ensure trustworthy cooperation. Cooperative game theory allows us to study fair gain sharing in a principled manner and has been widely applied to cooperative logistics [6, 11]. The Shapley value is widely considered as a fair solution concept; however, computing this value for cooperative vehicle routing involves solving 2^n vehicle routing problems, each of which is NP-hard. Consequently, the prior literature on fair cooperative vehicle routing usually studies settings with at most 6 agents [10]. However, scalability is particularly important as the logistics industry is highly fragmented. In the UK, there are 60,000 registered carriers in 2022 [12]. In the EU, there are 1 million registered carriers in 2020 [13]. Moreover, prior literature establishes that the network exteralities[4] are significant and carbon reduction of 22.1% could be achieved [14]. How can we compute fair gain allocations at a global scale? We propose to pose the problem as a coalition structure generation problem (which is rooted in cooperative game theory). A prior method proposes the use of a supervised-learning-based algorithm to perform coalition structure generation which is able to scale to 1,000 companies [14]. However, to obtain the scalability, their heuristic requires $\mathcal{O}(n^2)$ forward passes of a neural network and is based on empirically observed correlation. Instead, we investigate whether the use of transformers, which allows us to attend over all the information in the state space, would eliminiate this reliance on empirical correlation and result in higher performance. We propose the use of reinforcement learning (RL) which presents two key challenges: (1) the high dimensional state space, and (2) generating experience is expensive, requiring many NP-hard vehicle routing problems to be solved. Our contribution is that we pose coalition structure generation as a machine learning problem. As explained in Section 2, the number of possible coalition structures is the Bell number, B_n, where $B_{1000} = 2.98 \times 10^{1927}$. We argue that the characteristic function is not required (which most prior literature assumes oracle access to). Instead, we can implicitly reason about the values of each coalition through simply knowing the delivery requests that each company possesses, coupled with the use of high capacity neural networks. This work is important as coalition structure generation can be applied to the wider cooperative logistics and cooperative supply chain settings, as well as to autonomous sensors [15]; power plants [16]; and radio networks [17].

2 Problem Formulation and Experimental Setup

We wish to solve the problem with a set $N = \{1, \ldots, n\}$ companies cooperating, where in our setting we hope to ultimately scale to at least $n = 1000$ companies. A *coalition* C is a subset of the agents (or companies) N, i.e., $C \subseteq N$. A *coalition structure* CS over N is a collection of coalitions $CS = \{C^1, \ldots, C^k\}$ such that $\cup_{j=1}^{k} C^j = N$ and $C^i \cap C^j = \varnothing$ for any $i, j \in \{1, \ldots, k\} : i \neq j$

[4]Network externalities, or the network effect, is where the value of a good or service increases with an increasing number of users, such as social media platforms.

[18]. The *characteristic function* $v : 2^N \rightarrow \mathbb{R}_{\geq 0}$ maps each coalition $C \subseteq N$ to a real number $v(C)$ which is called the *value* of the coalition C. In Figure 1, $v(\{1, 2, 3\}) = 3.35 - 2.47 = 0.88$. Note, to compute the value of a single coalition involves solving a multi-depot vehicle routing problem (NP-hard). The *social welfare* is the sum of the value of each coalition in the coalition structure, i.e. $\sum_{C \in CS} v(C)$. Coalition structure generation aims to find the coalition structure CS that maximises social welfare. Note that the number of possible coalition structures is the Bell number [19], B_n, where $B_{1000} = 2.98 \times 10^{1927}$. To manage this complexity, as well as to enable tractable gain sharing, we enforce that each coalition has size $|C| = M$, in our case, $M = 3$. After a coalition structure is obtained, each of the (much smaller) sub-coalitions would perform individual fair gain sharing. To calculate the Shapley value without coalition structure generation would require solving 2^{1000} NP-hard VRPs. Using coalition structure generation, this can be seen as a hierarchical approach and now "only" requires $\lfloor \frac{N}{M} \rfloor \cdot 2^M$ NP-hard VRPs to be solved where $M << N$. Alternatively, each sub-coalition could have multi-agent reinforcement learning agents bargain with each other to agree on a fair gain share, resulting in significantly reduced run-times [20, 21, 22].

Data and Experimental Setup: We follow the same experimental setup as in [14] and compare our RL approach to theirs. We collaborate with industry to gather real-world data from the Food & Beverages industry in the UK. The dataset describes 34,692 shipments with 6 unique warehouses (origins) and 976 unique customer locations (destinations) which occupy a varying number of pallets q in a truck. Each truck is assumed to have a capacity Q of 12 pallets. Each shipment also has a price p which the carrier receives for performing that delivery. A training instance is procedurally generated by sub-sampling from the dataset. Each truck is randomly assigned m shipments, in our case $m = 4$. Note that due to the capacity Q, each truck may not necessarily be able to satisfy all four shipments and some shipments may need to be dropped. Thus, the state space has $m \times n$ rows (or shipments), with 10 features to describe each shipment. Due to the large state space, flattening the state and using multi-layer perceptrons is not scalable. In addition, there is permutation invariance in the state, which we can leverage through the use of transformers [23].

At each timestep t, the RL agent selects M companies to form a coalition. We apply invalid action masking to mask out previously selected companies. The value of those M selected companies, $v(C^t)$, is estimated via a neural reward model. This allows for large batch sizes to be used in addition to generating large volumes of training experience, avoiding the explicit calculation of NP-hard VRPs. An episode continues until all companies are assigned to a coalition and a feasible coalition structure is obtained. The total (discounted) return the RL agent receives is thus the social welfare, which it aims to maximise. We use Proximal Policy Optimisation (PPO) [24] which we implement in TensorFlow [25]. We compare our approach against the previous state of the art [14] and also compare against an agent that selects coalitions uniformly at random.

Neural Reward Model: To calculate the value of a coalition $v(C)$ requires solving a multi-depot vehicle routing problem either exactly or approximately, with solvers such as Gurobi or Google OR Tools. However, to train our RL agent would require a large volume of training examples, especially when using on-policy policy gradient methods. Furthermore, due to the high variance in RL, larger batch sizes are preferable. Using traditional solvers would not be able to generate sufficient volumes of training data. Instead, we train a neural network to predict the value of a coalition $v(C)$. We sub-sample from our real-world dataset and select coalitions C uniformly at random. We then train a transformer to predict the value of a coalition $v(C)$. We find that multi-task learning also helps in this scenario. To calculate $v(C)$ also requires knowing the revenues, costs, profits and distances travelled for each agent before and after cooperation. Therefore, we predict these auxiliary targets as well and minimise mean squared error on all heads. We suspect that the learnt representation would also be more robust. The benefit is that large batch sizes and ample, high-quality training experience can now be generated with relative ease.

3 Results and Discussion

The primary metric we train the agent to optimise is the (monetary) social welfare. In Table 1, we present the results of our RL agent trained on instances with 6, 9, 12 and 15 companies as this is early work in progress. Future work will of course investigate additional opportunities to improve performance and scale to the real-world size of at least 1,000 companies. For 6 and 9 agents, our RL method is able to outperform the previous state of the art [14] with statistical significance. For 12 agents, our RL method performs on par with the prior method; however, for 15 agents, our RL method

Table 1: Comparison of methods on 1,000 test instances (extended table in Appendix B)

Method	Social welfare for n agents			
	$n = 6$	$n = 9$	$n = 12$	$n = 15$
Random Agent	1057.2	1590.3	2123.5	2641.6
Anonymous et al. [14]	1101.9	1659.6	2234.1	**2800.1****
RL Agent (Ours)	**1142.0*****	**1705.0*****	**2236.9**	2759.0

H_0: difference in performance between RL agent and Anonymous et al. [14] is 0.
*** = significant at 0.001 level. ** = significant at 0.01 level.

performs worse than previous state of the art. We further present results for the carbon reduction in Appendix A due to space limitations. Surprisingly, even in the 6 and 9 agent setting, in Table 2 we accept the null hypothesis that our RL agent saves as much carbon emissions as prior state of the art, even though RL outperforms in terms of social welfare. It is important that future work is cognizant that solely optimising for social welfare may not directly translate to carbon emissions. However, this should not be interpreted as a disadvantage of our proposed method. Cooperation is highly desirable to reduce carbon emissions, yet has seen limited success to date. With increased social welfare, this presents increased opportunities to further incentivise cooperation. Future work should investigate the most suitable approach to balance social welfare with our international climate objectives.

There is also ample opportunity to improve our method. Firstly, we believe that the nature of this problem is highly amenable to curriculum learning. We hypothesise that, due to our deliberate neural network architecture, a transformer-based agent trained on e.g. $n = 6$ agents should generalise well, and learn useful representations that positively transfer out of distribution to settings with more (or less) agents. We see evidence for this in similar work to ours [26, 27]. Secondly, whilst we train our agents tabula rasa, it may be desirable to pre-train the agents on similar tasks. For example, the learnt representations from our neural reward model may have learnt useful features that could be transferable to the RL setting. Whilst not as elegant, this is commonplace in supervised learning, and used in most of the large-scale RL successes [28, 29, 30]. This direction seems to be garnering interest as "reincarnating" RL [31]. Furthermore, search-based methods could help significantly guide exploration. Finally, this problem setting is interesting due the order invariance of the actions: it does not matter in which order the coalitions are selected in a coalition structure. How can we leverage this invariance?

4 Conclusion and Future Work

Our initial findings suggest that the use of deep reinforcement learning, transformers, and a neural reward model for coalition structure generation to be effective in small scale scenarios, outperforming previous state of the art. We believe this is due to the transformer's ability to attend over the entire state space without losing information, which was required in prior literature. Clearly, one direction for future work is to improve our approach to scale to real-world settings.

However, even if we obtain an algorithm to perform coalition structure generation at global scale, there still remains ample future work. Firstly, cooperative game theory currently assumes that cooperation only occurs once. In the real world, cooperation involves repeated interactions throughout time. If a company tries to take (unfair) advantage over its competitor, this may affect its *reputation*. Moreover, not all companies are equal – some have more market power than others. How do we account for these power dynamics? And then what does fairness even mean in this setting? Can Explainable AI help explain why proposed profit allocations are fair? We believe there is a vast array of interesting algorithmic challenges remaining within cooperative logistics and cooperative supply chains in general and believe that cross-fertilisation of AI and these fields to be highly fruitful.

Time is ticking to tackle climate change. Road freight transportation is certainly not on track to meet international climate objectives [1]. Industry, government and academia already acknowledge the benefits of cooperative logistics [10]. But trustworthy cooperation between competitors is not easy, both algorithmically and in practice. Can AI enable trustworthy cooperation at scale?

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A Carbon Emissions Calculations and Results

The UK's Department for Energy Security and Net Zero, and Department for Business, Energy & Industrial Strategy estimates that the average laden (loaded) heavy goods vehicle, averaged across all types of heavy goods vehicles emits 107.5 gCO_2-eq per tonne kilometer [32]. Since we know the weight of each shipment, combined with the distances travelled, we can estimate the CO_2 emissions before cooperation and after cooperation, resulting in the below table. Of interest, note that the CO_2 reduction in general increases with the number of cooperating companies, thus demonstrating the network externalities present in this system. Thus, it is desirable to obtain an algorithm that can scale to a large number of companies. In the work of [14], they show that in a system with 1,002 companies, a carbon reduction of 22.1% could be achieved.

Table 2: Comparison of methods on 1,000 test instances

	$n = 6$		$n = 9$		$n = 12$		$n = 15$	
Method	CO_2 Reduction (%)	95% CI	CO_2 Reduction (%)	95% CI	CO_2 Reduction (%)	95% CI	CO_2 Reduction (%)	95% CI
Random Agent	9.12	[7.52, 10.7]	8.64	[7.36, 9.92]	8.77	[7.70, 9.85]	8.48	[7.48, 9.49]
Anonymous et al. [14]	10.8	[9.23, 12.4]	**12.9**	[11.6, 14.2]	**14.5*** **	[13.4, 15.6]	**14.6*** **	[13.7, 15.6]
RL Agent (Ours)	**11.1**	[9.45, 12.7]	12.2	[10.9, 13.5]	11.7	[10.6, 12.8]	11.2	[10.2, 12.1]

H_0: difference in performance between RL agent and Anonymous et al. [14] is 0.
*** = significant at 0.001 level. ** = significant at 0.01 level.

B Extended Data Table

Data was first tested for normality using the Anderson-Darling test and visual inspection. A paired t-test was then carried out with the null hypothesis being that the difference in performance between the RL agent and the previous state of the art [14] was 0. Boldface text simply denotes the column-wise argmax. If asterisks are present, the null hypothesis is rejected at the corresponding significance level and we conclude the difference in performance is non-zero.

Table 3: Comparison of methods on 1,000 test instances

	$n = 6$		$n = 9$		$n = 12$		$n = 15$	
Method	Social Welfare	95% CI	Social Welfare	95% CI	Social Welfare	95% CI	Social Welfare	95% CI
Random Agent	1057.2	[1031.9, 1082.5]	1590.3	[1558.8, 1621.7]	2123.5	[2087.2, 2159.9]	2641.6	[2601.2, 2682.0]
Anonymous et al. [14]	1101.9	[1077.5, 1126.3]	1659.6	[1629.6, 1689.6]	2234.1	[2199.2, 2268.9]	**2800.1****	[2762.2, 2838.1]
RL Agent (Ours)	**1142.0*****	[1116.6, 1167.4]	**1705.0*****	[1673.8, 1736.3]	**2236.9**	[2200.1, 2273.6]	2759.0	[2718.2, 2799.8]

H_0: difference in performance between RL agent and Anonymous et al. [14] is 0.
*** = significant at 0.001 level. ** = significant at 0.01 level.

C Waterfall Chart and Locations of Warehouses and Shipments

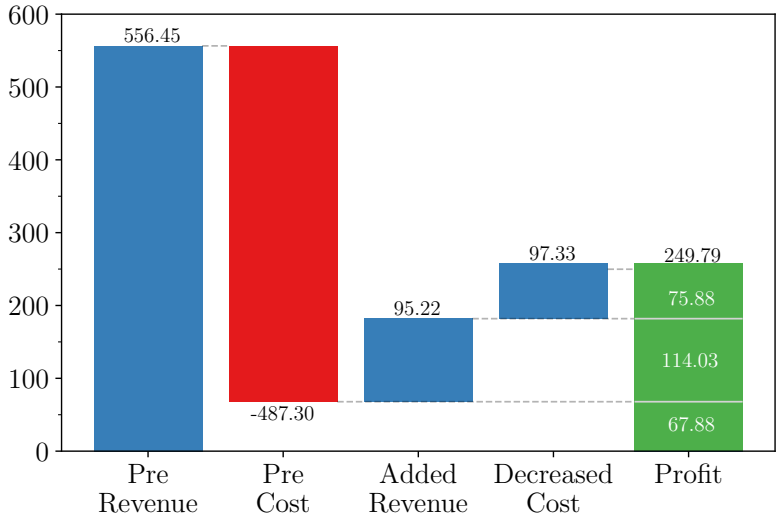
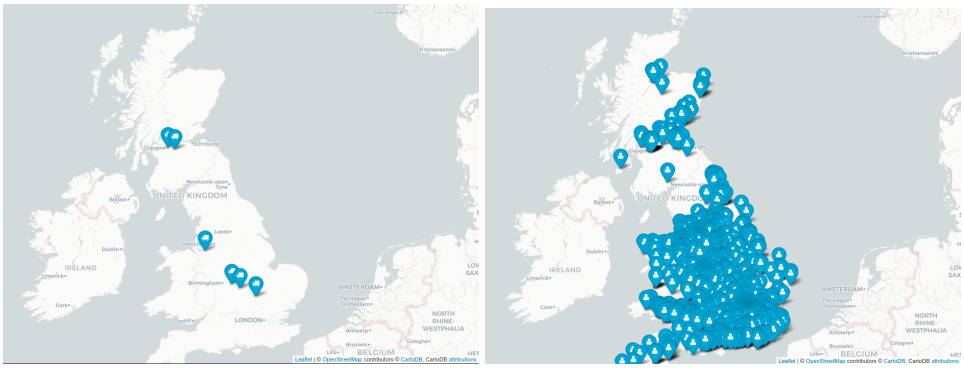


Figure 2: A waterfall chart showing the revenues and cost before cooperation for 6 agents. After cooperation (with the coalition structure generated by our RL method), each truck can on average generate £95.22 extra revenue with a decrease in cost of £97.33. Each company's profits before cooperation consequently raises from £67.88 a day to £249.79 a day.



(a) Locations of Warehouses (origins) (b) Locations of Customers (destinations)

Figure 3: Visualisation of the geographic locations of both warehouses and customers across the UK.