A Meta-heuristic based Multi-Agent Approach for Last Mile Delivery Problem

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Keywords: Horizontal Collaboration, Multi-Agent System, Logistics, Last Mile Delivery Problem, Egalitarianism.

Abstract: e-Commerce has become a primary part of any country's economy, and seeking maximum efficiency and level of service is an essential concern for any corporation in order to stay in business. Logistics has a significant impact on the efficiency of online transactions, especially with the increasingly competitive domain with minimal profit margin-left. Thus, the collaboration between many logistics service providers (LSPs) at different levels has become a desirable approach to reduce the overall costs and increase the utilization level of their resources. In this work, we propose a domain-independent multi-agent framework that allows different LSPs to plan their operations jointly. The system considers the individual satisfaction of LSPs and their profits in an egalitarian manner while trying to achieve an overall benefit. We use different search strategies for every agent as the underlying solving method, and investigate to what level taking the personal interest of participants will affect the overall shared/ common goal.

1 INTRODUCTION

e-Commerce has grown remarkably over a short period of time and become an essential part of the industry (Chatterjee et al., 2016). In order to guarantee the success of an enterprise, companies need to preserve their reputation and trust of their customers and increase the quality of service they provide. In this matter logistics, or what is called the Last Mile Delivery LMD, plays the most significant role as it refers to the last step in the supply chain (Holdorf and Haasis, 2014), in which the items are carried from the fulfillment centers to the customers within the specified delivery period. It forms the most important stage in the purchase process as it adds up nearly to 30% of the total cost. Thus, making this stage most effective is a critical issue in e-commerce transactions (Chinh et al., 2016).

Recently, all aspects of what is expected from logistics have changed, the competition became high, and profit margins declined to a deficient level. This urged many companies and carriers to collaborate on different levels and form partnerships in order to manage the transportation of their goods effectively (Ouhader and El Kyal, 2017); horizontal collaboration is a form of collaboration between parties that belong to the same level of the supply chain (all carriers or all suppliers). Collaborative routing helps to reduce the overall transport costs and to increase the customer satisfaction and utilization level of the logistics and human resources. Hence, it provides better performance from an economic and environmental perspective. For example, the collaboration between different LSPs can save them millions out of the total travel costs by sharing the logistics resources and thereby solving the empty load problem caused by the large number of vehicles that travel long distances underutilized (Chinh et al., 2016). This, in turn, reduces congestion levels on the roads, the possibility of accidents and harmful emissions, respectively (Ouhader and El Kyal, 2017). Figure.1a shows an example of independent routing of two LSPs in LMD where every LSP has one deposit. Meanwhile, Figure.1b shows a collaborative routing that utilizes the resources of each LSP to deliver the packages of all collaborators. It leads to overall shorter trips and lower costs.

As the transportation field is dynamic, complex and consists of many features and constraints, it makes the agent-based paradigm a quite suitable and exciting research method to solve famous problems in this field (Martin et al., 2016). Multi-agent frameworks are powerful in modeling complex problems of distributed nature and can efficiently represent the complicated relationship among the entities in an independent and autonomous way (Czarnowski et al.,

Hasan, M. and Niyogi, R.
A Meta-heuristic based Multi-Agent Approach for Last Mile Delivery Problem.
DOI: 10.5220/0009349004980505
In *Proceedings of the 22nd International Conference on Enterprise Information Systems (ICEIS 2020) - Volume 1*, pages 498-505
ISBN: 978-989-758-423-7

(a) Individual Routing (b) Collaborative Routing

Figure 1: Last mile delivery scenario of two LSPs.

2013). A multi-agent system consists of a set of entities (agents) that interact with each other in some environment through predefined means of communication in order to accomplish some given goal(s) (Czarnowski et al., 2013). Agent-based paradigm increases the computational power and speeds up the performance as it enables parallel task executions; cooperation among the agents allows efficiency, reliability, and robustness. Thus, it is ideal for solving different complex optimization problems such as our last mile delivery problem.

Since most researches on horizontal collaboration focused solely on utilitarianism, which mainly gives importance to overall benefit (Cruijssen et al., 2007), (Lahyani et al., 2015), and since real-life collaborators mostly care about their profits and interests rather than the overall goal, our main contribution is to consider the satisfaction of individual participants in an equal manner and to investigate how this affects the global goal of reducing costs. For this purpose, we propose a domain-independent multi-agent framework in which each LSP agent represents a collaborator and manages a different search strategy to solve the LMD problem from its perspective while cooperating with other agents to combine and improve solutions of all agents. This paper is organized as follows; Section II presents a literature review of collaborative and multi-agent approaches to the problem of last mile delivery. Section III presents problem formation while Section IV explains the proposed framework. Section V discusses the results obtained; Section VI states the conclusion reached.

2 LITERATURE REVIEW

LMD can be considered as a Vehicle Routing Problem (VRP), which is a significant NP-hard that was first introduced in 1959 (Lahyani et al., 2015). It is concerned with finding the most cost-effective set of routes starting from a single distribution center to different customers spreading on a large geographic area while satisfying constraints (Kumar and Panneerselvam, 2012). Different versions of the problem were proposed in the literature under various complexities and constraints; (Kumar and Panneerselvam, 2012) and (Lahyani et al., 2015) present helpful surveys. Various methods have been proposed by researchers to solve the problem, starting with exact methods (Mingozzi et al., 2013), and heuristics and meta-heuristics that find near-optimal solutions (Clarke and Wright, 1964) to hybrid meta-heuristics such as hybridized genetic algorithm (Cattaruzza et al., 2014).

2.1 Horizontal Collaboration

With the increasing market demands and high customer expectations, horizontal collaborative routing has been studied to provide efficient routing with lower total operational costs (Chinh et al., 2016). Different methods were presented through time starting with centralized approaches where a centralized entity solves the optimization problem on behalf of collaborating LSPs with different levels of coordination (Chinh et al., 2016). However, in most cases, there is less willing of different participants to share their full customers' details with a central authority; thus decentralized approach was presented in the literature to provide more compatibility with these privacy concerns such as request exchange and auction-based methods. The work (Wang and Kopfer, 2015) proposed two distributed request exchange mechanisms to solve the dynamic routing problems to provided stable performance. While in (Wang and Kopfer, 2014), a route-based exchange mechanism between collaborating LSPs that do their own planning independently and then send the planned routs to a groupage system (GS) which regenerates routes to reduce the overall costs. Meanwhile, auction-based trading is presented in (Dai and Chen, 2011) to allow the participating LSPs to negotiate and express their preference and the profit margin in a multi-round fashion. Another auction-based clustering method was proposed in (Schwind et al., 2009), where a request is exported based on its cost-reduction probability using a convex hull method with a distance-based cost estimator. Meanwhile, our proposed method is decentralized and allows LSPs to jointly plan their pre-defined outsourcing requests and continuously exchange existing solutions between computing agents to improve the final solution.

As the works mentioned above considered achieving a global goal of reducing overall cost, other work in (Zhou et al., 2013) focuses on load balancing in terms of the tour distance among the moving vehicle as a global goal; wherein (Schwarze and Voß, 2013), they examined effective resource utilization using a minmax model to minimize the maximal vehicle trip length. In our work, we consider the satisfaction of individual participants in an equal manner while achieving total cost reduction.

2.2 Agent-based Approaches

Agent-based systems have contributed to collaborative routing solving because of its autonomous, distributed characteristics and its native support for a dynamic environment (Czarnowski et al., 2013). Several domain-specific multi-agent architectures were proposed in the literature, such as in (Baykasoğlu and Kaplanoğlu, 2015), where the architecture of three types of agents (order, truck, dispatcher) was proposed to obtain effective scheduling under dynamic environment's conditions through negotiation. Also, in (Kalina et al., 2015), they provided a multi-agent system consists of a set of customer agents, route agents, and a central planner. The planner used a local heuristic search to solve the routing problem with time windows. In contraction, our work will not be dedicated only to LMD domain as our agents will be optimizing agents that able to work on any optimization problem. An example of earlier population-based, cooperative multi-agent system was proposed in (Barbucha, 2014); where a multi-phase execution is carried out and different search meta-heuristics are executed at each phase simultaneously while exchanging information about the agents' states and performance at the end of each phase. In (Martin et al., 2016), they proposed a general multi-agent approach where agents periodically exchange parts of their solutions that have potentials to be good edges to guide the search of other agents in a valuable direction. Also, the work (Chatterjee et al., 2016) included public transportation system in their multi-agent framework to plan small-size orders delivery in aim to reduce costs and co_2 emissions.

The work in (Barbucha, 2012) used different synchronization modes in their proposed multi-agent system, and used a learning mechanism to adapt the behavior of the agents to new states of the environment while solving the optimization problem. Meanwhile, the work (Souza et al., 2012) used particle swarm optimization (PSO), where each particle is considered as autonomous agents and represented as a solution in the search space. Otherwise, our proposed multi-agent framework consists of a group of optimization agents exploring different areas of the search space simultaneously, producing a higher level of diversity and mature solutions.

Although collaborative routing has been studied in past years, there are fewer studies in the literature as far as we know that use a multi-agent paradigm to solve a multi-deposit VRP version that considers the personal interests of participants in an equal manner along with a global goal. The main contributions are as follows; we implement a multi-agent framework that supports the collaboration between different LSPs to serve their customers jointly. Our framework is domain-independent, which can be used to solve any optimization problem in contrast to (Baykasoğlu and Kaplanoğlu, 2015), (Kalina et al., 2015). Agents will regularly exchange the best solutions among themselves to combine and improve the solutions.

3 PROBLEM DEFINITION

Last Mile Delivery Problem can be presented as a vehicle routing problem. It aims to create a set of paths to satisfy the delivery of n packages, from distribution center (s) to specified delivery locations satisfying some constraints ex. capacity and time, while minimizing a cost function. Each Logistic Service Provider LSP has a set of distribution centers DCs which contains numerous different-size packages to be distributed to many geographically scattered customers within a city. Each package has a weight demand Dem_j. A distribution center has a set of vehicles V used to complete the delivery tasks, each of these vehicles $v \in V$ has a capacity Q_i that specify the maximum load a vehicle can carry at once.

Here we present the notations of the problem; given a undirected graph G=$< V, E >$, the set of vertices V represents the customers, and the set of edges E determines the existence of a direct road between the adjacent customers; D: set of distribution centers $D = \{1, 2, 3, \ldots, m\}$; C: set of customers $C =$

$\{1,2,3,\ldots,n\}$; K is the total count of vehicles existing in all of the distribution center.

V_{DC}:	sets of vehicles presented in the distribution center DC.
d_{ij}:	euclidean distance between customer i & j.
$MaxDis_i$:	maximum length of a tour a vehicle can do.
y_{ij}^k:	current weight of vehicle k while traversing from customer i to j.
t_{ij}^k:	time consumed by the vehicle k to traverse from customer i to j.
$[ET_i, LT_i]$:	time window of package i.
ET_i:	earliest time at which a package i can be delivered to its owner.
LT_i :	latest time at which a package i is allowed to be delivered to its owner.
Sk_i:	service time needed to deliver the package to the customer i by the vehicle k.
A_i :	arrival time to customer i.
D_i:	leaving time from the customer i.
FC_v:	fixed cost of the vehicle v.
$VarC_v$:	variable cost of a vehicle v within a distance unit (ex: power supply cost).
x_{ij}^{mk}	represent a decision variable.

$$x_{ij}^{mk} = \begin{cases} 1, & \text{if a vehicle } m \text{ of a distribution center } k \\ & \text{can travel directly from } i \text{ to } j. \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

3.1 The Objective Function

1. Minimize the cost of the tour

$$\sum_{k\in V_m}\sum_{j\in D\cup C}\sum_{i\in D\cup C} FC_k * x_{ij}^{mk} + \sum_{k\in V_m}\sum_{j\in D\cup C}\sum_{i\in D\cup C} d_{ij} * x_{ij}^{mk} * VarC_k \tag{2}$$

Subject to these constraints:

(a) Maximum Distance Constraint: the length of the tour taken by a vehicle can not exceed the maximum length tour that is specified for it (due to the fuel or energy supply)

$$\sum_{j\in D\cup C}\sum_{i\in D\cup C} d_{ij} * x_{ij}^{mk} \leq MaxDis_k (k \in V_{DC}, m \in D) \tag{3}$$

(b) Capacity Constraints:
the load of any vehicle k traversing from a customer i to j can not exceed the maximum capacity of that vehicle.

$$0 \leq y_{ij}^k \leq Q_k \ (k \in V_m, m \in D, i, j \in C) \tag{4}$$

(c) Time Constraints: each customer's package i is usually attached with a time window $[ET_i, LT_i]$ that specify the time period in which the customer i is expecting to receive his package, not before the earliest time ET_i or after the latest time LT_i. We can conclude with it the following information The arrival time A_j to customer j from i.

$$A_j = D_i + t_{ij}^k \tag{5}$$

The departure time D_i from customer i

$$D_i = A_i + S_i^k \tag{6}$$

We should attain the following constraints

$$ET_i \leq A_i \leq LT_i \forall (i \in C, k \in V_{DC})$$
$$ET_i \leq S_i^k + A_i \leq LT_i \forall (i \in C, k \in V_{DC})$$
$$A_j \leq LT_j + S_j^k \forall (j \in C, k \in V_{DC}) \tag{7}$$

(d) Precedence Constraints: in case of multi deposit scenarios, we need to guarantee that a customer will not be visited before his provider:

$$D_s \leq D_d \ (s \in D, d \in C) \tag{8}$$

(e) Each customer can be served by single vehicle only

$$\sum_{m\in D}\sum_{k\in V_m}\sum_{i\in D\cup C} x_{ij}^{mk} = 1 \ \forall j \in C \tag{9}$$

(f) The tour of each vehicle must start from a distribution center and finish at the same center.

$$\sum_{i\in D\cup C} x_{ij}^{mk} = 1 \ \forall \ (j, m \in C, k \in V_m) \tag{10}$$

(g) Path Contentiousness: every vehicle must leave a customer location only after reaching and serving that customer.

$$\sum_{i\in D\cup C} x_{iq}^{mk} = \sum_{j\in D\cup C} x_{qj}^{mk} \ \forall \ (\ q \in D\cup C,\ m \in D,\ k \in V_m) \tag{11}$$

2. Penalty for the Undelivered Packages: it is required that all packages get delivered, we use a penalty for undelivered packages. We express the penalty through the package's priority $prio(m)$.

$$\sum prio(m) \ \forall \ (m \text{ not delivered successfully }) \tag{12}$$

So, the final objective function is to minimize

$$\alpha * \sum_{k\in V_m}\sum_{j\in D\cup C}\sum_{i\in D\cup C} FC_k * x_{ij}^{mk} + \sum_{k\in V_m}\sum_{j\in D\cup C}\sum_{i\in D\cup C} d_{ij} * x_{ij}^{mk} * VarC_k + \beta * \sum prio(m) \ \forall \ (m \text{ not delivered }) \tag{13}$$

Where α, β, are weight constants to weightage the function's value are in the overall objective function.

4 PROPOSED MULTI-AGENT FRAMEWORK

Multi-agent approach provides speedup and computation efficiency as it supports exploring different areas of the search space simultaneously, producing a higher level of diversity and mature solutions (Czarnowski et al., 2013).

One of the important multi-agent paradigms is A-Team (Asynchronous Team) that was first proposed in (Talukdar et al., 2003) that describes a set of asynchronous independent software agents that communicate to jointly solve complex problems that can not be solved by single agent alone. A central memory stores a population of initial solutions that will be continuously modified by the software agents.
We will build the proposed distributed framework based on A-Team architecture. It consists of two types of agents, computing agents, each of which represents a logistic service provider and can run on any machine, and a coordinator agent, which is responsible for maintaining the central memory, and managing the communication between computing agents. Figure.2 shows the architecture of our proposed framework. Now we discuss the types of agents included.

4.1 Types of Agents

1. The Coordinator Agent:
   It is a single agent in the proposed architecture that manages a pool of initial valid solutions to the collaborative problem. It receives requests from every participating LSP agent to send it a subset of the available solutions to use it as initial solutions in its computation method. The coordinator agent is considered a synchronizing entity in the system since it manages the communication between different LSPs agents and is kept up to date about their latest status through message passing.

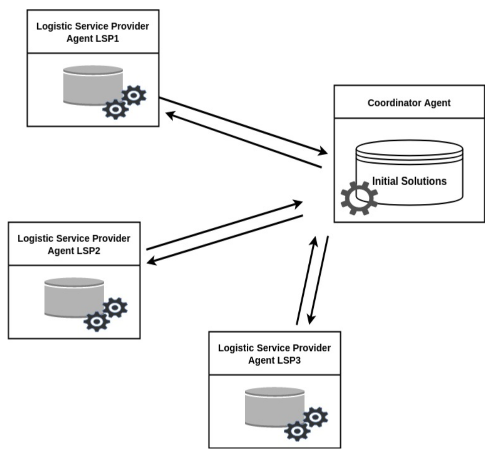

Figure 2: A-Team based multi-agent framework for LMD problem.

2. Logistic Service Provider Agent LSP:
   Each logistic provider is represented in the problem-solving process by an LSP agent that operates on their behalf. The LSP agents do not interact together directly; they exchange information about their state and found solutions through the coordinator agent. In this work, every LSP agent runs a meta-heuristic strategy that is different from the other agents and solves the given problem instance from its perspective and according to its personal priorities and goals, such as following potential SLA agreement. LSP agent finds the best solution and delivers it to the coordinator agent to be evaluated and possibly added to its pool of solutions replacing the worse existing solutions there. The coordinator may then resend the solution to other LSP agents in the next computation round in order to redirect their search to a potentially better region.

4.2 Communication between Agents

1. 2-way Handshake:
   Before starting the computations, every LSP agent registers itself with the coordinator to enable sending and receiving computation messages from the coordinator. This process starts with a SUBSCRIBE message sent by LSP agent to the coordinator, indicating that it is ready to participate in the computation and start its tasks. Then, the coordinator registers the LSP in the coalition and sends back a CONFIRM message to the LSP agent so it can be prepared to the next phase, the message contains the expected number of computation rounds that every LSP shall execute. Once the coordinator agent successfully receives the SUBSCRIBE message from all expected LSPs agents, the computation rounds start. Figure 3 shows the sequence of messages between the agents in the handshake phase.
2. Computation Messages:
   After all LSPs have registered with the coordinator, the coordinator initializes a collection of random feasible solutions to the collaborative problem. Periodically, every LSP agent sends a REQUEST message to the coordinator asking for a subset of the solutions from its pool, so the agent uses it as initial solutions in its solving method. The coordinator reply with an INFORM message containing a random subset of solutions. After receiving the initial solutions by the LSP agent,

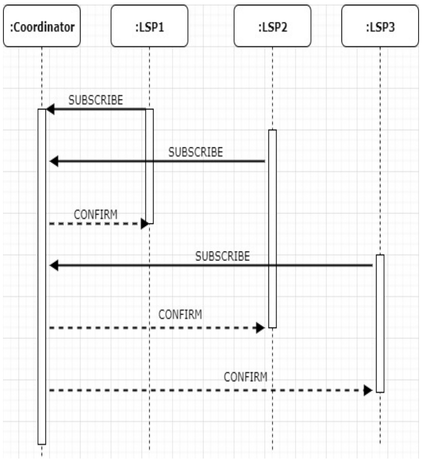

Figure 3: Message exchange between different agents in the 2-way Handshake stage.

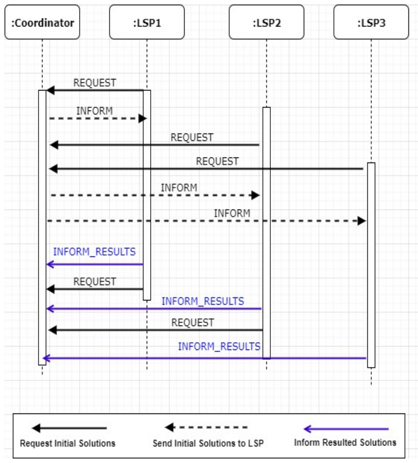

Figure 4: Messages exchange between different agents in the computation phase.

it starts running its search strategy to find the best possible solution. When the search ends, the LSP agent sends the best solution as an INFORM message to the coordinator, which in turn compares the solution's quality, in terms of overall cost-minimizing, to the existing solutions in the pool. If its quality is better, the new solution is added to the pool, replacing a less quality solution. Figure.4 shows messages exchange between the agents in the computation phase.

4.3 Search Strategies

Different search strategies for every agent are carried out in the proposed approach. Each LSP agent uses an adaptive large neighborhood search method (ALNS) as the underlying search method (Pisinger and Ropke, 2007). ALNS is a local search that is based on ruin and recreate principle that was proposed in(Schrimpf et al., 2000). It uses optimization techniques like threshold accepting and simulated annealing to partially destroy and repair the solutions. There are several strategies for the ruin phase, namely, radial ruin, random ruin, and cluster ruin (Pisinger and Ropke, 2007). A feasible solution is obtained by excluding a set of customers. In the recreate phase, all excluded customers are reintroduced to the solution wisely to minimize their effect on the complete solution. Some of the most widely used techniques are greedy and regret insertion methods.

4.4 Gain Assignment

In real-life collaboration, participants of any coalition mostly care about their profits and interests rather than the overall gain. Therefore it is crucial to estimate the individual gain for every participant in the coalition. In this paper, we will use two gain assignment methods. The first method is the Shapley value, which is a concept that was first presented in cooperative game theory as one way to distribute the total gain of a coalition N among the participants in a fair manner. It captures the marginal contribution made by a participant i over all permutation $S \subseteq N$ (Ouhader and El Kyal, 2017).

$$\phi_N(i) = \frac{1}{N!} \sum_{S \subseteq N \setminus \{i\}} k * (cost(S \cup i) - cost(S)) \quad (14)$$

Another method is a proportional method, a demand-based proportional gain assignment that depends on the demands of the participant served by the coalition. Let $cost(s)$ be the cost of the best solution found by given coalition s. Then, the proportional assignment of the participate i is given as :

$$cost(i) = \varphi_i * cost(s) \quad (15)$$

where φ_i is the demand-based factor.

We explore two collaborative scenarios. First, we consider a full collaboration level where the goal is to achieve the minimum cost possible.

Table 1: Characteristics of participating LSPs and the costs of non-collaborative routing.

	No.of orders	No. of vehicles	Demands	Individual routing	
				Cost	No. of vehicle
LSP1	82	13	3591	2469.3	9
LSP2	90	13	4478	2644.4	10
LSP3	77	13	4037	2467.6	9
Total	249	39	12106	7581.3	28

Whereas in the second scenario, personalized collaboration is considered as every LSP agent works accord-

Table 2: Cost reduction in collaborative scenarios and the satisfaction level of the participants.

	Best solution		Overall reduction		Individual satisfaction		
	Cost	No. of vehicle	Cost	No. of vehicle	LSP1	LSP2	LSP3
Full collaboration	4142.1	26	45.3%	7.1%	5.0	6.0	5.5
Personalized collaboration	4588.9	26	39.5%	7.1%	5.67	5.7	5.4

Table 3: The routing cost allocation of LSPs under collaborative scenarios.

	Best solution		Cost share / Shapley value			Proportional cost		
	Total cost	No. of vehicle	LSP1	LSP2	LSP3	LSP1	LSP2	LSP3
Full collaboration	4142.1	26	1312.0	1419.7	1410	1228.6	1532.1	1381.2
Personalized collaboration	4588.9	26	1465.1	1539.6	1577.5	1361.2	1697.4	1530.2

ing to its personal goals while minimizing the overall cost. We take, as an example of LSP's personal goal, its desire to serve its own packages first before the others. To measure the satisfaction level of every participant, we use the average index of its packages' delivery in the found routes. The smaller the value is, it indicates that its packages are often delivered in the early stage with a minimum value of 1 when its packages are delivered first by every vehicle.

5 EXPERIMENTS AND RESULTS

To implement our proposed architecture, we used JADE framework (Java Agent DEvelopment), which supports FIPA specifications. We created a system consisting of one coordinator agent and three LSP agents representing three different logistics service providers in the industry. In our experiment, ALNS algorithm is used as the primary method, along with different ruin and recreate strategies for every LSP agent. LSP1 agent uses ALNS with random ruin strategy and regret/best insertion, LSP2 agent uses radial ruin strategy, and regret insertion, while LSP3 uses cluster ruin strategy and regret/best insertion. The coordinator agent maintains a pool of 20 initial solutions which will be continuously updated. We consider a multi-depot vehicle routing problem MDVRP; we use a dataset derived from famous Cordeau datasets (Cordeau et al., 1997) with few adjustments to fit the collaborative scenario. We will evaluate the proposed approach based on its performance in solving this problem.

Table.1 shows the characteristics of participating LSPs and the cost and vehicles needed for their individual routing, where every LSP uses its resources to serve its own customers only with no collaboration. Table.2 shows the cost of the best solution for collaborative routing scenarios using our proposed framework. We calculate the overall cost reduction of collective routing as the marginal percentage of $(Total\ Cost_{no\_collaboration} - Total\ Cost_{collaboration}) / Total\ Cost_{no\_collaboration} * 100$. Thus, we found that full collaboration between LSPs reduced the total costs of a margin of 45% with an almost varied level of satisfaction for the participants in terms of the average index of delivered packages since the overall cost reduction was the only goal. In the second scenario, when considering personal goals and interests, a decrease in total savings is observed compared to the first scenario, along with an increase in participants' satisfaction levels to almost equal value as every agent works to achieve its personal goal first. Table.3 shows the cost allocation for every participant LSP in both collaboration scenarios calculated by methods mentioned in Eq.14 and Eq.15 respectively. The overall results show that participants' satisfaction levels can be increased by tolerating some loss in profits.

6 CONCLUSIONS

We have presented a multi-agent framework that supports the collaboration between different LSPs in the logistics level serving their customers jointly. The proposed framework is domain-independent and can be used for different cooperation scenarios in problem-solving. Furthermore, it is computationally efficient and scales to large size problems as it exploits exploring different areas of the search space simultaneously, and produce diverse and mature solutions. When the overall benefit is prioritized, some unintended biases to one of the participants may happen, and that will affect the trust in the coalition. Therefore, we examined when participants work to achieve objectives according to their preferences instead of focusing on the unified objective. We noticed that collaboration could achieve a cost reduction of near 45% compared with individual routing, along with different satisfaction levels. However, when personalized goals are considered, the overall saving is comparatively reduced, but better levels of satisfaction are obtained. Therefore, considering the egalitarian approach that guarantees an equal level of service and satisfaction may encourage different LSPs to work towards further collaboration on several levels.

REFERENCES

Barbucha, D. (2012). Search modes for the cooperative multi-agent system solving the vehicle routing problem. *Neurocomputing*, 88:13–23.

Barbucha, D. (2014). A cooperative population learning algorithm for vehicle routing problem with time windows. *Neurocomputing*, 146:210–229.

Baykasoğlu, A. and Kaplanoğlu, V. (2015). An application oriented multi-agent based approach to dynamic load/truck planning. *Expert Systems with Applications*, 42(15-16):6008–6025.

Cattaruzza, D., Absi, N., Feillet, D., and Vidal, T. (2014). A memetic algorithm for the multi trip vehicle routing problem. *European Journal of Operational Research*, 236(3):833–848.

Chatterjee, R., Greulich, C., and Edelkamp, S. (2016). Optimizing last mile delivery using public transport with multi-agent based control. In *2016 IEEE 41st Conference on Local Computer Networks Workshops (LCN Workshops)*, pages 205–212. IEEE.

Chinh, N. Q., Kim, H. C., Siwei, J., and NengSheng, Z. (2016). Collaborative vehicle routing problem for urban last-mile logistics. In *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 001531–001536. IEEE.

Clarke, G. and Wright, J. W. (1964). Scheduling of vehicles from a central depot to a number of delivery points. *Operations research*, 12(4):568–581.

Cordeau, J.-F., Gendreau, M., and Laporte, G. (1997). A tabu search heuristic for periodic and multi-depot vehicle routing problems. *Networks: An International Journal*, 30(2):105–119.

Cruijssen, F., Bräysy, O., Dullaert, W., Fleuren, H., and Salomon, M. (2007). Joint route planning under varying market conditions. *International Journal of Physical Distribution & Logistics Management*, 37(4):287–304.

Czarnowski, I., Jędrzejowicz, P., and Kacprzyk, J. (2013). *Agent-based optimization*. Springer.

Dai, B. and Chen, H. (2011). A multi-agent and auction-based framework and approach for carrier collaboration. *Logistics Research*, 3(2-3):101–120.

Holdorf, S. and Haasis, H.-D. (2014). Last mile delivery concepts in e-commerce an empirical approach. In *The 8th International Conference on Software, Knowledge, Information Management and Applications (SKIMA 2014)*, pages 1–6. IEEE.

Kalina, P., Vokřínek, J., and Mařík, V. (2015). Agents toward vehicle routing problem with time windows. *Journal of Intelligent Transportation Systems*, 19(1):3–17.

Kumar, S. N. and Panneerselvam, R. (2012). A survey on the vehicle routing problem and its variants. *Intelligent Information Management*, 4(03):66.

Lahyani, R., Khemakhem, M., and Semet, F. (2015). Rich vehicle routing problems: From a taxonomy to a definition. *European Journal of Operational Research*, 241(1):1–14.

Martin, S., Ouelhadj, D., Beullens, P., Ozcan, E., Juan, A. A., and Burke, E. K. (2016). A multi-agent based cooperative approach to scheduling and routing. *European Journal of Operational Research*, 254(1):169–178.

Mingozzi, A., Roberti, R., and Toth, P. (2013). An exact algorithm for the multitrip vehicle routing problem. *INFORMS Journal on Computing*, 25(2):193–207.

Ouhader, H. and El Kyal, M. (2017). Combining facility location and routing decisions in sustainable urban freight distribution under horizontal collaboration: how can shippers be benefited? *Mathematical Problems in Engineering*, 2017.

Pisinger, D. and Ropke, S. (2007). A general heuristic for vehicle routing problems. *Computers & Operations Research*, 34(8):2403–2435.

Schrimpf, G., Schneider, J., Stamm-Wilbrandt, H., and Dueck, G. (2000). Record breaking optimization results using the ruin and recreate principle. *Journal of Computational Physics*, 159(2):139–171.

Schwarze, S. and Voß, S. (2013). Improved load balancing and resource utilization for the skill vehicle routing problem. *Optimization Letters*, 7(8):1805–1823.

Schwind, M., Gujo, O., and Vykoukal, J. (2009). A combinatorial intra-enterprise exchange for logistics services. *Information Systems and E-business Management*, 7(4):447–471.

Souza, G. R., Goldbarg, E. F., Goldbarg, M. C., and Canuto, A. M. (2012). A multiagent approach for metaheuristics hybridization applied to the traveling salesman problem. In *2012 Brazilian Symposium on Neural Networks*, pages 208–213. IEEE.

Talukdar, S., Murthy, S., and Akkiraju, R. (2003). Asynchronous teams. In *Handbook of Metaheuristics*, pages 537–556. Springer.

Wang, X. and Kopfer, H. (2014). Collaborative transportation planning of less-than-truckload freight. *OR Spectrum*, 36(2):357–380.

Wang, X. and Kopfer, H. (2015). Rolling horizon planning for a dynamic collaborative routing problem with full-truckload pickup and delivery requests. *Flexible Services and Manufacturing Journal*, 27(4):509–533.

Zhou, W., Song, T., He, F., and Liu, X. (2013). Multiobjective vehicle routing problem with route balance based on genetic algorithm. *Discrete Dynamics in Nature and Society*, 2013.