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A Novel Air Delivery Approach Using Crowdshipping and Commercial Flights

Chefi Triki[a,*], Sarah Hassaan[b]

[a]*Kent Business School, Canterbury, CT27FS, UK. *Email: C.Triki@kent.ac.uk*
[b]*Hamad Ben Khalifa University, Doha, Qatar*

Abstract

In this paper, we propose a crowdshipping application that focuses on using commercial airlines as a mean of transportation to reduce worldwide air-fuel consumption by using the available resources. We achieve this by creating a generic crowdshipping business model that reflects all the domains needed for a successful application. A process flow and two mathematical models were developed: Integer Programming (IP) to ensure the customers-travelers matching and Goal Programming (GP) to investigate the effect of relaxing some the constraints. The work was tested on the North African countries region which are characterized by a variety in travelers, airports, and airport distributions. It was shown that the greater the ratio of travelers to the customers, the fewer deviations were needed and the higher the packages distribution among the travelers is achieved. This study demonstrates that as the network becomes broader, big data analytics and faster matches are required to secure the scalability of the application.

Keywords: Crowdshipping; Matching Models; Goal Programming

1. Introduction

Globalization and digitalization have hand in hand developed the socialization between individuals, paving the way towards an efficient shared economy society. With various businesses creating their online presence to sell their goods abroad, big tech companies, and presently existing social sites allowing direct business transactions, multiple freight forwarding fleets, cargo fleets, and private fleets emerged to encounter the uncertain consumer demand. This was evident with the surge of delivery requests during the Covid-19 pandemic, which created a competitive atmosphere between organizations to reach same-day deliveries. However, striving for fast deliveries requires a considerable investment to coordinate fleets, scheduling fleet deliveries, fuel, maintenance costs, etc. To invent solutions to these

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problems, companies are divulging into the shared economy to outsource their delivery and create collaborative opportunities to crowds, expanding their businesses at cheaper costs. Through the evolution of the IC T, along with the development of advanced optimization tools, businesses are creating application platforms to link delivery requests with crowd members willing to carry out the delivery. This type of community service has been called "crowdshipping", delivering packages to the desired destination with the logistical support of occasional delivers.

Focusing on transportation applications that deliver through air mediums, the fuel consumption in 2019 by commercial airlines alone amounted up to 95 billion gallons (Statista, 2022), and that does not account for cargo air freight shipments, military aircraft consumptions, and jet fuel consumptions. As commercial airlines are already set on routes to transport people, companies can utilize the same transportation medium to deliver small packages to different regions to reduce the delivery load on air cargo shipments such as documents, clothes, and other small items. This research proposes an E-business model that addresses the requirements to create a successful crowdshipping application based on a matching algorithm to complete successful assignments between users. A mathematical formulation is developed to focus on the utilization of commercial airlines to deliver small packages. Two different linear programming techniques are used: IP and GP, to produce the optimal global matches and identify whether the constraint relaxation through the GP yields better outcomes. Throughout this paper, we refer to the: (i) travelers (or crowds) as those providing the delivery services, (ii) customers as those requesting the delivery services and (iii) platform the application allowing an efficient travelers/customers communication as well as the payment of the service. The interaction between the customers and travelers through the application is schematized in Figure 1.

It is worth noting that the security aspect related to any delivery is the responsibility of the traveler who should make sure that the parcel to be transported respects all the rules imposed by the concerned parties, including the airline and the airport authorities. The customer should not pack his parcel before allowing the traveler to check its content.

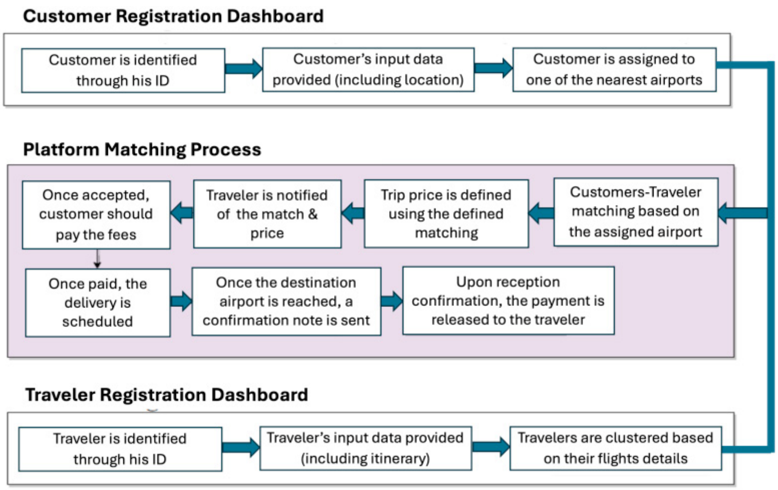


Fig. 1: Crowdshipping delivery application flow

In the remainder of this paper we provide aa literature review discussion in Section 2. Afterwards, Section 3 is devoted to describing our crowdshipping application together with the IP and GP models. Our experimental results are discussed in Section 4. Finally, the last section concludes the paper and covers the limitations and future work.

2. Literature Review

The general concept behind crowdshipping applications is to select a traveler that matches the customer's requirements. Customers' requirements such as parcel's weight, size, location, and delivery time should all be considered in the matching process to select the fittest traveler (Le and Ukkusuri, 2019; Inoue et al., 2023). Many existing crowdshipping systems are not automated and depend on manual customer and traveler communications, where they negotiate requirements and expectations (Le et al., 2019; Fessler et al., 2024). As the number of customers and travelers increases, the crowdshipping models become challenging and the use of optimization becomes essential to solve the arising problems (Hosseini et al., 2014). We employ here the matching models to determine the optimal assignments between customers and travelers. Matching models are a consolidated optimization technique in the literature of mathematical programming but that emerged nowadays as an efficient modelling basis for several shared economy application such as ridesharing (Triki et al., 2021a), carpooling (Tamannaei and Irandoost, 2019) or last-mile delivery (Pourrahmani and Jaller, 2021). As Figure 2 shows, several matching models can be defined over a bipartite graph with customers shown on the left-hand side and the travelers shown on the right-hand side. In this work we will mainly focus on one-to-one and many-to-one matching models, but other variants can be easily implemented within our application as well (Klaus and Walzl, 2008).

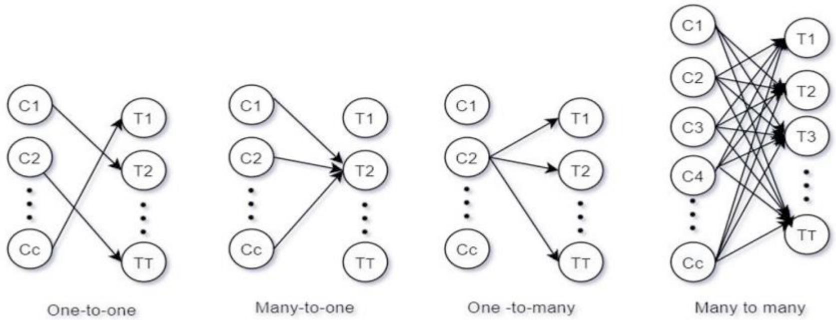


Fig. 2: Different matching models

Crowdsourcing is a multidisciplinary domain that covers multiple ways of utilizing the crowd. Crowdshipping delivers packages by using occasional travelers as the deliverers in front of a small reward (Bathke and Münch, 2024). This opens a new endeavor for businesses, individuals, and governments alike to outsource their transportation needs and reduce the cost of maintaining their transportation fleets. With the increase of retail stores and customer demands, logistic service providers must adhere and adapt to offer competitive prices and deliver in the least amount of time. These delivery services range from road deliveries, covering urban and first and last mile delivery services, to overseas delivery covering air and sea freight. Therefore, logistic providers need often to invest in more transportation facilities to sustain their status in the market, which increases their overall expenses and carbon footprint. By outsourcing some transportation needs to those with available capacity, logistic service providers can delegate work to travelers, reducing the need to increase their transportation fleets (Yang et al., 2024). For a comprehensive study on the advantages and shortcomings of crowdshipping, interested readers are directed to the recent reviews such as that of Peng et al. (2024). However, based on our literature review we can claim that, to the best of our knowledge, a crowdshipping system based on the employment of commercial flights has never been developed and this study represents an attempt to fill in this gap and to layout the basis towards a successful business.

3. Matching Models

We start by defining an IP model that ensures the matching between the available travelers and the customers' requests, then develop a GP model to deduce if relaxing the constraints and creating a multi-objective function allow better matches. The optimization is based on selecting the closest airport to the customer which allows to only focus on travelers available at the specific needed airport. The following notation will be used along this Section:

i	Index of customers (i=1 … n)
j	Index of travelers (j=1…m)
AI_{ij}	Distance of the departure airport of both customer and traveler
AF_{ij}	Distance of the arrival airport for both recipient and traveler
TI_{ij}	Time between the customer availability and traveler departure (in hours)
TF_{ij}	Time between the traveler arrival and recipient departure (in hours)
W_{ij} / V_{ij}	Weight/Volume difference of customer and travelers (in grams)
WT_j	Free weight of each traveler (in grams)
H_i / L_i / W_i	Height/Length/Width of the customer's package (in inches)
VT_j	Free volume of each traveler (in inches)
X_{ij}	Binary decision variable equals 1 if the customer i is assigned to the traveler j, 0 otherwise.

Thus, the developed IP model having $X_{ij} \in \{0,1\}$ as decision variables, can be summarized as follows:

$$\min z = \sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij} * (AI_{ij} + AF_{ij} + TI_{ij} + TF_{ij}) \quad (1)$$

Subject to:

$$\sum_{j=1}^{m} X_{ij} = 1 \quad \forall i \quad (2)$$

$$\sum_{i=1}^{n} X_{ij} \leq 3 \quad \forall j \quad (3)$$

$$\sum_{i=1}^{n} X_{ij} * W_{ij} \leq WT_j \quad \forall j \quad (4)$$

$$\sum_{i=1}^{n} X_{ij} * V_{ij} \leq VT_i \quad \forall j,\ H_i \leq 22,\ L_i \leq 14,\ W_i \leq 9 \quad (5)$$

The objective function (1) minimizes the distance between the departure airports and arrival airports for all customers and travelers. It also minimizes the time gap (or waiting time) for all the users of platform. Constraint (2) ensures that each customer is assigned a maximum of one traveler, the nearest traveler that matches the customer's needs. Constraint (3) assigns at most three customers to the available travelers, giving way for a many-to-one matching, if needed. Constraints (4) and (5) ensure that the availability of weight and volume of each traveler are greater or equal to the customers' requests. Abnormal sized parcels will result in the issue of no-delivery occurrence. The above formulation is a binary model whose size increases remarkably with the number of travelers and customers.

Our preliminary experiments have shown that some of the above constraints can be too restrictive so that some of the requests remain unserved. For this purpose, we developed an alternative formulation that allows a controlled level of constraints relaxation through introducing some deviation variables and also objective function alterations (Uddin et al., 2021). The resulting goal programming model has three different objective functions that minimize the undesirable deviation with respect to the right-hand-side values. Subsequently, weights were introduced to create a single objective function that can be solved by any commercial software package. The purpose of the deviations and their weights is to reflect how much allowance is possible to reach a compromised solution for each of these objectives. The first weight, W1, refers to the deviation of the objective function on time. The second weight, W2, is for the deviations on the customer and traveler's desired weights, while the third weight, W3, is for deviation of the volume of the package and the volume allowed on the commercial plane. The deviations are in pairs, with each constraint having a positive and negative deviation. They are set as decision variables and will result in real non-negative numbers to show how much over or under the constraint's limit we have to achieve a common goal. More specifically, the following additional notation is introduced:

$W1$	Weight value for deviation s_1^{∂}
$W2$	Weight value for deviation s_2^{∂}
$W3$	Weight value for deviation s_3^{∂}
$s_1^{\partial+}$	Positive deviation for goal 1 (s_1)
$s_1^{\partial-}$	Negative deviation for goal 1 (s_1)
$s_2^{\partial+}$	Positive deviation for goal 2 (s_2)
$s_2^{\partial-}$	Negative deviation for goal 2 (s_2)
$s_3^{\partial+}$	Positive deviation for goal 3 (s_3)
$s_3^{\partial-}$	Negative deviation for goal 3 (s_3)

The GP model that, besides X_{ij}, has all the non-negative deviational quantities as decisions variables, is:

$$\min z = W1 * s_1^{\partial+} + W2 * s_2^{\partial-} + W3 * s_3^{\partial-}$$

Subject to:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij} * (AI_{ij} + AF_{ij}) + X_{ij} * (TI_{ij} + TF_{ij} + s_1^{\partial+} + s_1^{\partial-}) = 0 \quad \forall\, i, \forall\, j$$

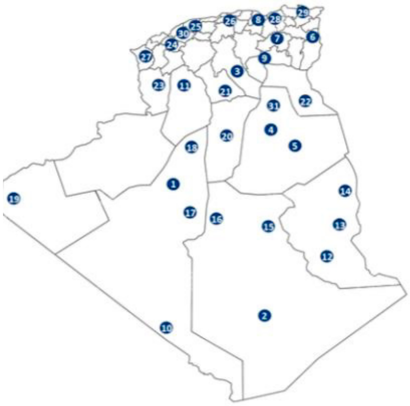
$$\sum_{i=1}^{m} X_{ij} * Wt_{ij} + s_2^{\partial+} + s_2^{\partial-} = WT_j \quad \forall\, j$$

$$\sum_{i=1}^{n} X_{ij} * V_{ij} + s_3^{\partial+} + s_3^{\partial-} = VT_{i.} \quad \forall\, j, H_i \leq 22, L_i \leq 14, W_i \leq 9$$

The new objective function minimizes the deviations introduced in the constraints to achieve the required goals. From each pair of deviations introduced in the constraints, only the deviation that negatively affects the boundary of the constraint goal is selected and placed in the objective function. The target is to reduce the violation of the constraint as much as possible. Weights are assigned to each selected deviation to rank the significance of each of the goals. High values of the weights state the importance of satisfying this goal with minimal violations. The weights are usually subjective to the management's needs and can be altered accordingly. The constraints are similar to those introduced in the IP case, with the clear difference of the deviational variables added in the three constraints.

4. Experimental Results

Data was collected from the Algerian network of 31 airports, whose locations are shown in figure 3, and used to validate the models and to investigate the effect of GP relaxation. In the same figure the airports names, flights per day and number of travelers registered are also reported for the same case-study.



	Airport Name	Flights/Day	Traveler/Day
1	Benina	7	35
2	Airport Brač	1	5
3	Ghadames	1	5
4	Kufra	1	5
5	Al-Marj	1	5
6	Al Khadim	1	5
7	Al Abraq	2	10
8	Marsa Brega	1	5
9	Sebha	1	5
10	Ghat	1	5
11	Misrata	3	15
12	Mitiga	6	30
13	Tripoli	1	5
14	Zuwarah	2	10
15	Zintan	1	5
16	Ain Salah	2	10

	Airport Name	Flights/Day	Traveler/Day
17	Reggane	1	5
18	Timimoun	1	5
19	Tindouf	2	10
20	El Meniaa	1	5
21	Hassi R'Mel	2	10
22	El Oued	1	5
23	Mecheria	2	10
24	Ghriss	1	5
25	Chlef	2	10
26	Houari Boumediene	22	110
27	Messali Hadj	5	25
28	Jijel Ferhat Abbas	1	5
29	Rabah Bitat	2	10
30	Mostaganem	2	10
31	Touggourt	1	5

Fig. 3. Airport locations and flight details in Algeria.

Since the number of customers is an uncertain input data, a scale of 100 to 500 inclusive will be used with 100-unit intervals to conduct the sensitivity analysis to reflect the customer changes against the overall travelers. The customers were assigned randomly to each airport, and an array was formed to deduce the distance between the customers and the airports. It was assumed that a total of 5 travelers would be registered in the crowdshipping application for each flight that departed from any airport. Once the departure airports were assigned to customers and travelers, the arrival airports were randomly assigned to each party depending on the available airports in the country. The departure time was randomly assigned to customers and travelers between 1-12 hours, whereas the arrival time was randomly chosen between 13-24 hours. This was to ensure that no duplicates occur during randomization. The weight and volume were also randomly assigned, but care was taken not to exceed the limit set by the model assumptions.

For the GP model, greater importance was given to the weight deviation with a value of 3 given the major restriction the air companies put on the weight limitations. The time was ranked second in importance and given a weight of 2 since we want to satisfy the consumer demand and hence the arrival time of the traveler to the airport is crucial. Minor importance was placed on the volume as travelers can often provide alternative solutions at no extra charge to accommodate slightly voluminous packages. The models were run using CPLEX 12.10.0. Overall, running the programs on Cplex was deemed non particularly challenging when the number of customers and travelers is kept small. As the collected and randomized data increased and the instances become relatively of large-scale, the Cplex took longer to find a global solution (few minutes). Based on the statistics of the model runs, as the numbers of travelers and customers got higher, the model became larger, and the number of binary variables increased. For the Algerian case-study, for example, for 500 customers and 1,525 travelers, resulted in 762,500 binary variables being defined. Such an increase resulted to be significantly more remarkable in the case of the GP model due to the additional floats in the deviations.

Figure 4 shows that both the IP and GP models produce substantially similar results. Both the programming models show a decrease in the resulting matches suggesting that given the limited number of travelers available, results in fewer packages distribution that can occur. When the number of customers increase remarkably no additional requests can be satisfied and, thus, the number of matches vanishes. Both the models start by ensuring several one-to-one matchings but make then recourse to many-to-one matching as the number of requests increase. On the other hand, as the right-hand-side sketch shows, the number of employed travelers reaches its saturation value not only through one-to-one matching but even with many-to-one matching.

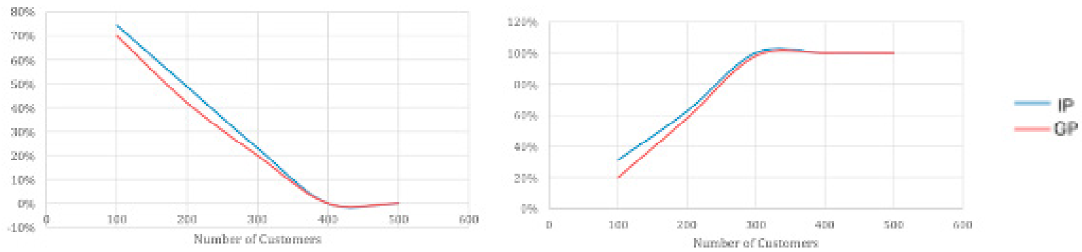


Fig. 4. Percentage of matching (left) and rate of travelers utilization (right) for Algeria

A slightly different behaviour can be observed when considering Morocco as a second case-study (whose input details are omitted here for the sake of brevity). In this case, the number of travelers is high enough to allow very high number of one-to-one matchings (see Fig. 5). Indeed, no clear superiority of any of the models outcomes (i.e. IP nor GP) with respect to the other one can be observed. However, the same figure highlights how the travelers utilization rate results to be significantly lower in the case of the GP model as the number of customers increases. This is a clear evidence of the success of the GP in activating more many-to-one matchings and, thus, in optimizing better the resources utilization, that never reach the saturation in this case.

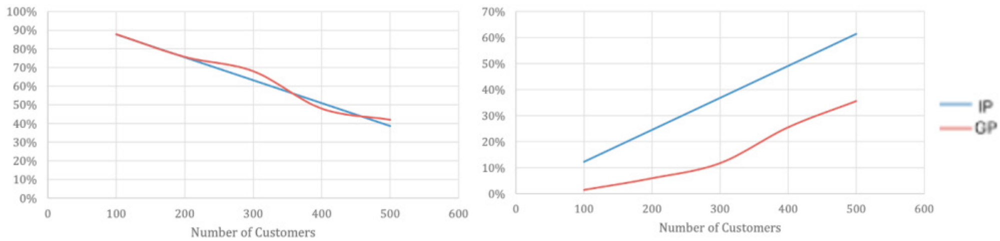


Fig. 5. Percentage of matching (left) and rate of travelers utilization (right) for Morocco

For comparison and sensitivity analysis purpose, we also solved additional test problems related to other countries in the same region, namely Egypt, Sudan, Libya, Morocco, and Tunisia. The aim is to compare the deviations of the GP model among these countries that have different characteristic, even though we omit to report here the detailed results for every country for the sake of brevity.

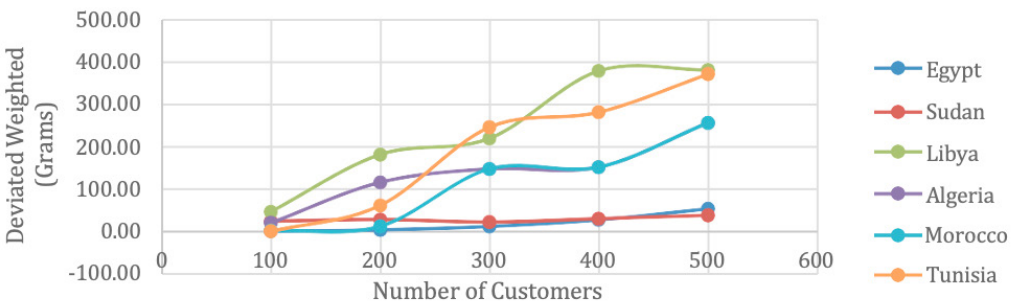


Fig. 6. Comparison of the extent of weight deviation for all the 6 countries in the region

As shown in figure 6 those busy airports in highly populated areas had little to no deviation. The deviation in this scene conveys that those travelers have to carry extra weights to be successfully matched. Egypt and Sudan presented the slightest deviations to achieve the target goals. As the number of customers increased, the deviations increased sluggishly, meaning that abundant travelers were situated in the customer's airport. Tunisia and Libya showed the most significant deviations as they both had the lowest number of airports compared to the other regions, and not many travelers were situated in these airports.

4. Concluding Remarks

The main focus of this study was to create an advanced application interface that connects travelers and customers based on matching models that select the best fit, as this is where the primary decision-making lies. Two different programming strategies were used to identify the effect of relaxation of the constraints on the percentage of matches. It can be seen that when the number of travelers is greater in ratio to the number of customers, there is a higher expectation of more matches to occur with the least concern on the traveler's scarcity. Hence there is a greater reliance on one-to-one matches. However, once the number of customers is equal to or greater than the number of travelers, the system favours the many-to-one matching scheme to account for the customers' requirements. This was also an issue in the GP outcomes as the weight deviations assigned customers over their free weight to ensure suitable matches. Many other aspects clearly also affect the results, such as the closeness of the airports, the density of the customers in the populated regions, etc. Those areas with a higher population tended to have successful matches despite the low numbers of travelers.

As bigger countries are considered, and the number of participants grows, using the Cplex software becomes challenging and time consuming. In this case, the application will need more specialized approaches to solve the large-scale matching instances to ensure prompt outcomes. The shift in the software package will also pave the way to consider dynamic programming paradigms where customers and travelers are assigned as they log into the system on a real-time basis. Finally, the pricing aspect can be considered by implementing, for example, an advanced auction mechanism (Triki et al., 2021b). These aspects are left as a possible venue for future investigations.

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