

## Pickup and delivery problem in the collaborative city courier service by using genetic algorithm and nearest distance

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### ABSTRACT

One problem in collaborative pickup delivery problem (PDP) was excessive outsourced jobs. It happened in many studies on the collaborative PDP. Besides, the revenue sharing in it was unclear although important. This work aimed to propose a novel collaborative PDP model which minimizes total travel distance while maintains low outsourced jobs. It proposed several contributions. First, it prioritized internal jobs first rather than full collaborative model. Second, it proposed new revenue sharing model. It adopted cluster-first route-second and mixed pickup and delivery. It was developed by combining the genetic algorithm and nearest distance algorithm where the genetic algorithm was used in the clustering process and the nearest distance was used in the routing process. The simulation result shows that the proposed model was better than the comparing models: (1) combined K-means and genetic algorithm model (KMGA) and (2) combined simulated annealing and last-in first-out (SNLIFO) model. When the number of orders was high (300 units), the total travel distance of the proposed model was 37 percent lower than the KMGA model and 30 percent lower than the SNLIFO model. In average, the outsourcing rate of the proposed model was 70 percent lower than the previous models.

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## 1. INTRODUCTION

Logistic service becomes more popular due to the increasing of the e-commerce [1]. This condition is also boosted by the COVID-19 pandemic which forces people to stay at home. It shifts some offline transactions to the online one. People have become more familiar with mobile based transactions. This phenomenon is also popular in the food delivery business because dine-in activity is restricted. Besides food, people also utilize mobile transactions to purchase products from the mall or other stores in the city due to the lockdown. This circumstance benefits the city courier services, such as Go-Jek and Grab in Indonesia. The business model of the city courier service can be modeled as a pickup and delivery problem (PDP). PDP is a derivative of the capacitated vehicle routing problem [2], [3]. PDP is widely used in reverse and forward logistics [3], [4]. Reverse logistics is the practice of managing the return of products from the customers to the manufacturer for disposal, repair, recycling, and so on [4]. A request is executed by picking up a stuff from a pickup location and then delivering it to the destination location. In the capacitated vehicle routing problem (CVRP) context, the vehicle can only carry products up to its maximum capacity [5].

There are three types of PDP models: backhauling; mixed deliveries and pickup, and simultaneous delivery and pickup [3]. In the backhauling model, all deliveries must be executed first before pickup begins [3]. It means the vehicles depart from the depot with the load to be delivered. After all-carried loads have

been delivered completely, the vehicle starts to pick up loads from customers. In the mixed delivery and pickup model, pickup and delivery can be conducted in any order [3]. In the simultaneous delivery and pickup, vehicle conducts both delivery and pickup in a single stop [3]. When a vehicle visits a customer, it can pick up products from the customer and deliver them to the customer.

One derivative of the PDP is collaborative PDP or PDP with resource sharing [6], [7]. It is usually implemented in a multi provider environment. In it, the environment consists of a certain number of logistic providers or depots. A provider has several vehicles and orders. In the non-collaborative model, each provider manages its own vehicles and orders. There are several inefficiencies in this non-collaborative model. First, the number of vehicles a provider has limited [7]. Second, an order may be too far away from the provider, and it is nearer to the other providers (cross delivery) [7]. Third, in a multi-product system, different types of products should be delivered simultaneously, and other providers can serve better [7]. This circumstance may increase the travel time, cost, lateness, and decrease the unexecuted orders and service level. On the other hand, the collaborative model can solve these problems. In the context of the city courier service, implementing the collaborative model means orders that are received by a provider can be outsourced to or executed by other providers which can serve better due to their fleet availability or distance factor. Moreover, the collaborative model has the potential for customer demand splitting. In this case, a customer can be visited several times [8]. Below are several studies in PDP with their objectives, circumstances, and methods.

Several studies were conducted on order splitting and transshipment. Perez and Gonzalez [8] developed a PDP model for single commodity. The environment was the self-service bike sharing system. In the night, the bicycles were collected and reallocated to certain locations in the city. Its objective was to minimize the cost. The problem was formulated using mixed integer programming (MIP), and the branch-and-cut algorithm was used as a solution. The orders consisted of picking up the load from a certain location, and then delivering it to a certain location. A vehicle could handle several orders simultaneously. This combined load might not surpass the vehicle's maximum capacity. Due to the excessive load, an order could be split into several trips. Wolfinger and Salazar-Gonzalez [2] developed the PDP model where the load can be split and transferred to other vehicles (transshipment). Its objective was to minimize the transshipment and travel costs. The problem was formulated by using MIP and branch-and-cut algorithm was used as the solution. This word assumed that each customer could be visited more than once.

Fazi *et al.* [9] developed a simultaneous PDP model which was implemented in the inland container-shipping activity. Its environment was a dry-port system in Port of Rotterdam which handled export and import containers. Its objective was to minimize the number of trucks, barge utilization, traveling distance, and achieve the economics of scale. This model used the hybrid local search metaheuristic and branch-and-cut algorithm. The capacity restriction and the on-time delivery guarantee became constraints. Bruni *et al.* [10] developed profitable PDP model for multiple vehicles. The process was transporting products from the suppliers (pickup) to the customers (delivery). Its objective was to maximize net profit. The net profit was calculated by subtracting the collected revenue with the cost. This work used mixed integer linear programming (MILP) to formulate the problem, and graph searches as solution. There were two types of customers: mandatory (had to be picked up) and optional (could be picked up whether profitable).

Mahjoob *et al.* [11] developed green PDP model for a flour industry in Teheran. The process was distributing the flour among bakeries. Its objective was to minimize cost (inventory, transportation, delivery, and receiving). The vehicles were heterogeneous in capacity. Order delivery could be split so that a customer could be visited by several vehicles. It used MILP to formulate the problem and Pareto solution. Andriansyah *et al.* [12] developed PDP problem to be implemented in courier service. Its objective was to minimize total travel time and number of unserved customers. The simulated annealing was used as solution. The last-in first-out (LIFO) was implemented. LIFO is usually implemented for dangerous, heavy, or fragile goods and the vehicle has only a single door [13]. All orders were picked up first, and then the delivery process ran. The constraints were the number of vehicles, time window, and travel duration.

Puspita *et al.* [14] developed PDP model for garbage transportation in Palembang, Indonesia. The process was transporting garbage from the temporary waste disposal to the final waste disposal. Like the bicycle problem, this work was also a single commodity problem. The system was multi-depot system. Its objective was to minimize the travel distance and travel time. The branch-and-bound algorithm was used as a solution. The deadline and time window became constraints. Phuc and Thao [1] developed PDP model for e-logistics service providers. The environment consists of e-commerce merchants/warehouses and customers. The vehicle visited some pickup nodes and then delivered the products to the customers. Its objective was to minimize the total travelling cost. The solution was developed based on the ant colony optimization. The vehicles were heterogeneous. The constraints were limited time window and travel duration.

Yuan *et al.* [15] developed multi objective PDP model with grey time window. The model consisted of two types of time window: hard time window and soft time window. Its objectives were minimizing distribution cost and maximizing customer satisfaction. The customer satisfaction was related to the delivery

time within time window. Each customer was served by one vehicle and order could not be split. The solution was developed by using quantum evolution algorithm. Wang *et al.* [6] developed multi-depot PDP model where resource sharing is allowed. The system consisted of several logistic service providers. The logistic service providers consisted of multiple distribution centers, multiple pickup centers, and multiple customers. Each logistics facility handled several trucks. Due to a resource sharing mechanism, the clustering and routing processes were centralized. This model was not simultaneous. Each truck handled one role only: pickup or delivery. Its objective was to minimize the logistic cost and number of vehicles. The K-means method was used in the clustering process and non-dominated sorting algorithm (NSGA II) and Clark-Wright algorithm were used in the routing process.

Ju *et al.* [16] developed PDP model for transporting military personnel. The environment was a wartime area. The activities should be efficient and time saving. Its objective was to minimize the completion time of the troop movement. In this work, the ant colony optimization was used as the solution. There were two types of vehicles. The first vehicle was used for the reconnaissance activities to visit the destination location. The second vehicle was used for transporting the troops by picking up the troops from the origin to the destination. Sze *et al.* [17] developed a simultaneous PDP model. Its objective was to minimize the travel distance. The variable neighborhood search was used as the solution. The vehicle departed from and returned to the depot. The total payload could not surpass the vehicle's maximum capacity. The vehicle departed from the depot with some payload to be delivered to the customers. Meanwhile, during the trip, vehicles also picked up payloads from the customers to be delivered to the depot. When the vehicle's capacity was full, it should return to the depot.

Alhujaylan and Hosny [18] developed a profitable PDP model. It was a selective PDP which was a derivative of the classic PDP. Due to limited resources, some nodes might not be visited. The system might prioritize nodes based on the profitability of visiting or not visiting them. The system consisted of a central depot, a set of vehicles, and a set of orders. The vehicles and products were homogeneous. Profit (revenue) could be generated from the orders. There was a limitation in the vehicle travel time. The vehicle travel time could not exceed the maximum daily travel time. Vehicle started and ended with empty load. Its objective was to maximize profit which was the reduction between revenue and cost. The greedy randomized adaptive search problem (GRASP) was used as a solution.

Collaborative PDP model can be found in several studies as follows. Deng *et al.* [7] developed a collaborative PDP model for system that consists of multiple distribution centers. Its objective was to minimize the total cost and the number of vehicles. The grid particle swarm optimization was used as the solution. In this work, there are two types of collaboration (resource sharing). First, resource sharing occurred among vehicles within the distribution center among different service periods. Second, vehicles could be shared among distribution centers. Wang *et al.* [19] developed a collaborative multi period PDP model. This work referred to the logistics service providers in Chongqing City, China. The shared resources included customer information, service facilities, and vehicles. It was a multi-objective model that its objectives were to minimize the total operational cost, waiting time, and the number of vehicles. The improved multi-objective particle swarm optimization (MOPSO) was chosen for the solution. The profit sharing was conducted based on the cost saving rather than the revenue sharing.

Several points can be summarized based on the analysis of these previous works. First, PDP can be implemented in the logistics service providers which conducts reverse and forward logistics, especially in the city courier service where the vehicle conducts both pickup and delivery. Second, the collaboration among city courier providers promises to improve efficiency (travel time, cost, and so on). Ironically, the revenue sharing model has not been explored yet because studies in the collaborative PDP focused on minimizing the total cost of the entire system. On the other hand, revenue sharing among city courier providers is critical for the system stability because the provider generates revenue from its customers. This revenue must be shared when these orders are outsourced to other providers so that providers in the system still have the willingness to receive outsourced orders. Meanwhile, collaborative model among city courier services may trigger new problem. First, the increasing of the outsourcing rate may reduce the customers' trust in the city courier providers due to the fleet reliability, so that the outsourcing rate must be maintained low.

Based on this problem, this work aims to develop a collaborative PDP model that can be implemented in the system or environment that consists of multiple city courier providers. Its objective is to minimize total travel distance and maintain a low outsourcing rate. This model adopts cluster-first route-second approach. The genetic algorithm is chosen to solve the clustering process while the nearest neighbor method is chosen to solve the routing process. The genetic algorithm is a well-known combinatorial optimization method and is widely used in the VRP studies. The contributions of this work are as:

- This work proposes a novel collaborative PDP model which focuses on minimizing the total distance while maintaining a low outsourcing rate.

- This work embeds the revenue sharing mechanism in the proposed model, which is not explored clearly in the existing collaborative PDP model, despite that it is important and critical in the collaborative city courier services.

The rest of this paper is organized as; the proposed collaborative PDP model is explained in the second section. The simulation that was conducted to evaluate the performance of the proposed model; the simulation result, and the findings due to the simulation result are discussed in the third section. The conclusion and the future research potential are explained in the fourth section.

## 2. RESEARCH METHOD

This collaborative PDP model is developed based on the collaborative city courier service system. This work adopts mixed PDP where a vehicle conducts both activities: pickup and delivery. In this system, there is certain number of city courier service providers (providers). Each provider has its own fleet. The fleet consists of certain number of motorcycle-based vehicles. The fleet size can be different among providers. The capacity of each vehicle is limited. Assumptions used in this model are as:

- The number of vehicles is predetermined [20].
- The orders are predetermined (pickup and destination location) [5].
- Order is picked up at the certain location and delivered to its destination [21].
- All vehicles and orders are ready at time zero [5], [10].
- All vehicles are identical in capacity [18], [21].
- All orders must be picked up and delivered [17].
- Overload is forbidden [18], [21].
- Each order/customer is served once [20], [21].
- Order cannot be split [17].
- Every vehicle departs and returns to its own depot (home) [17], [21].
- Provider does not have dedicated centralized depot.
- Every vehicle has a single trip [22].
- The travel duration and time window are unlimited.
- The distance between two points is measured by using Euclidean distance [23], [24].

This collaborative PDP model is developed based on the cluster-first route-second method. In this approach, the orders are clustered first based on the vehicle before they are routed [23]. The number of clusters represents the number of vehicles. Orders in the same cluster are executed by the same vehicle. The clustering process is conducted by using genetic algorithm. This algorithm is a well-known algorithm that has been used in many VRP and PDP studies [4], [20], [24]. As a population-based optimization algorithm which adopts evolution mechanism, its process consists of reproduction, cross-over, and mutation [25]-[28]. After the clustering process, the second step is routing. The routing process is conducted by using nearest neighbor method. The nearest neighbor algorithm is chosen because it has been used in several VRP studies and it is proven lightweight in the computation process [29]-[31]. Due to its simplicity, nearest neighbor algorithm was combined with other algorithms, such as Tabu search [32]. Moreover, as a heuristic method, the nearest neighbor is proven better than other heuristic methods [33], more realistic in solving real world problem [34], and widely used in many travelling salesman problem applications [35]. By using this method, the next destination of the vehicle is the nearest unvisited node from its current location.

There are several notations used in this work. These notations are as:

$c$	: courier service company (provider)
$c_o$	: company who owns the order
$c_e$	: company who executes the order
$C$	: set of providers
$d$	: distance
$d_p$	: pickup distance
$d_t$	: travel distance
$d_{tt}$	: total travel distance
$l_p$	: order pickup location
$l_d$	: order destination location
$l_{cv}$	: vehicle current location
$l_{dv}$	: vehicle depot (home) location
$n_{imax}$	: maximum number of iterations
$o$	: order
$o_m$	: mutating order
$O$	: set of orders

$p_c$	: vehicle current payload
$p_{max}$	: vehicle maximum payload
$r_r$	: travel cost rate
$r_t$	: travel cost
$r_{tt}$	: total travel cost
$r_{er}$	: revenue rate
$r_d$	: delivery revenue
$r_{dt}$	: total delivery revenue
$s$	: solution or individual
$S$	: set of solutions
$st_o$	: order's status (-1=has not been picked up, 0=has not been delivered, 1=accomplished)
$t$	: time
$t_t$	: total time
$tr_{mu}$	: mutation threshold
$v$	: vehicle
$v_m$	: mutating vehicle
$V$	: set of vehicles
$x$	: target node
$X$	: set of target nodes
$X_{up}$	: set of pickup target nodes
$X_{ud}$	: set of delivery target nodes

The first step is clustering orders to the vehicle. The initial population is generated randomly. A population consists of solution which is the list of vehicles and their orders list. It can be modeled as a two-dimensional array. The first dimension represents the vehicle, and the second dimension represents the orders list that will be executed by every vehicle. This genetic algorithm is shown in algorithm 1.

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**Algorithm 1: genetic-algorithm-based orders clustering**

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1  generate initial population ( $S$ )
2   $i = 1$ 
3  route
4  calculate  $d_{it}$  for every individual
5  sort the population based on  $d_{it}$ 
6  choose the best half of population as new generations
7  mutate the new generations
8   $i++$ 
9  if  $i < n_{imax}$  go to step 3, else go to step 10
10 stop

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The clustering or allocation mechanism consists of two processes. The first process adopts non-collaborative approach. Its objective is to minimize the outsourced jobs. In the first process, orders are allocated to any available vehicles with the same providers. The second process is conducted to allocate orders that are unallocated in the first process. The second process adopts collaborative approach. In the second process, the unallocated orders are allocated to any available vehicles in the system. Its objective is to minimize the unexecuted orders. The available vehicle is vehicle which its current payload is less than its maximum payload.

The initial vehicle selection mechanism is formalized by using (1) and (2). In (1) shows that the vehicle for an order is selected randomly among the vehicles where their owner is equal to owner of the order and its current capacity is still less than the maximum capacity. Meanwhile, (2) shows that in the second process, the vehicle is selected randomly among vehicles whose current capacity is less than the maximum capacity and the ownership constraint is ignored.

$$v_{sel}(o) = U(V), c(o) = c(v) \wedge p_c(v) < p_{max} \quad (1)$$

$$v_{sel}(o) = U(V), p_c(v) < p_{max} \quad (2)$$

After the initial population is set, the next process is the routing process. This routing process uses nearest neighbor method. It means, the vehicle's next point is nearest location that must be visited by the vehicle. This routing process adopts the mixed pickup and delivery approach. It means, the vehicle's next point can be pickup location or destination location. This routing process is formalized by using (3) to (7).

$$l_{cv}(0) = l_{dv} \quad (3)$$

$$l_{cv}(v, t + 1) = \begin{cases} l_{dv}, \forall st_o(v, t) = 1 \\ \min(d(l_{cv}(v, t), x)), x \in X(v, t) \wedge \exists st_o(v, t) \neq 1 \end{cases} \quad (4)$$

$$X(v, t) = X_{up}(v, t) \cup X_{ud}(v, t) \quad (5)$$

$$X_{up}(v, t) = \{l_p(o) | v_{sel}(o) = v \wedge st_o(t) = -1\} \quad (6)$$

$$X_{ud}(v, t) = \{l_d(o) | v_{sel}(o) = v \wedge st_o(t) = 0\} \quad (7)$$

The explanation of (3) to (7) is as; (3) declares that the vehicle's initial location is its depot or home, (4) shows that when all orders have been delivered, the vehicle will return to its depot. Else, the vehicle's next location is its nearest target node, (5) shows that vehicle's target nodes are the joint of pickup target nodes and delivery target nodes, (6) shows that the vehicle's pickup target nodes are all of vehicle's order pickup location where these orders have not been picked up, (7) shows that the vehicle's delivery target nodes are all of vehicle's order delivery locations where these orders have been picked up but have not been delivered.

The next process is calculating the fitness function. The fitness parameter is the total travel distance. It is obtained by aggregating all vehicle's travel distances. This process is formalized by using (8) and (9). In (8) shows that the total travel distance in a solution or individual is the accumulation of all vehicles' travel distance. In (9) shows that the vehicle's travel distance is the aggregation of the distance of all links that this vehicle routes.

$$d_{tt} = \sum_v d_t(v) \quad (8)$$

$$d_t(v) = \sum_{t=1}^t d(l_{cv}(v, t - 1), l_{cv}(v, t)) \quad (9)$$

After the total travel distance of all individuals has been calculated, the next process is sorting the population based on their fitness ascendingly. Individuals with smaller fitness will get a better rank. This rank is then used to generate new individuals. The number of the new individuals is a half of the previous population. These new individuals are copied from the half best individuals. The half worst individuals in the population are replaced by the new individuals. Hereafter, the new generations begin to mutate. This mutation occurs by interchanging orders between two vehicles with the same provider. The objective is maintaining the outsource rate. This process is conducted for entire vehicles with the certain probability which is determined by the mutation threshold. This mutation process is formalized by using (10) to (13).

$$a = \begin{cases} \text{mutation}, U(0,1) < tr_{mu} \\ \text{do nothing}, \text{else} \end{cases} \quad (10)$$

$$a = \text{switch}(o_m(1), o_m(2)), p(o_m(1)) = p(o_m(2)) \quad (11)$$

$$o_m = U(o(1), o(n(O, v_m))) \quad (12)$$

$$v_m = U(v(1), v(n(V), c)) \quad (13)$$

The explanation is as: (10) shows that mutation occurs only when the generated uniform random number is less than the mutation threshold, (11) shows that the mutation is conducted by switching two orders. The mutating order is selected by choosing the order inside the vehicle randomly. The mutating vehicle is selected by choosing a vehicle among vehicles with the same provider. The outsourcing rate and the total vehicles' revenue also become the evaluation parameters in this work. These parameters are formalized by using (14) and (15). Meanwhile, the revenue calculation is formalized by using (16) to (18), and the cost calculation is formalized by using (19) and (20).

$$r_o = \frac{n(O_o)}{n(O)} \quad (14)$$

$$O_o = \{o | o \in O \wedge p_o(o) \neq p_e(o)\} \quad (15)$$

$$r_{dt} = \sum_{\forall v} r_d(v) \quad (16)$$

$$r_d(v) = \sum_{\forall o} r_d(o), v_{sel}(o) = v \quad (17)$$

$$r_d(o) = \begin{cases} \left( \left( \text{int} \left( d \left( l_p(o), l_d(o) \right) \right) + 1 \right) \cdot r_{er}(c_e(o)), c_e(o) = c_o(o) \right. \\ \left. \left( \left( \text{int} \left( d \left( l_p(o), l_d(o) \right) \right) + 1 \right) \cdot (r_{er}(p_e(o)) \cdot 0.5), c_e(o) \neq c_o(o) \right) \end{cases} \quad (18)$$

$$r_{tt} = \sum_{\forall v} r_t(v) \quad (19)$$

$$r_t(v) = (\text{int}(d_{tt}(v)) + 1) \cdot r_r \quad (20)$$

### 3. RESULTS AND DISCUSSION

This proposed model is then implemented into the simulation application so that its performance can be analyzed. The environment is Bandung city in Indonesia which its size is approximately 167 kilometers square. The main observed parameter is total travel distance as it has been used in many PDP studies [13], [17]. The second observed parameter is the outsourcing rate which value is obtained by using (14). The third observed parameter is the total net profit which is obtained by reducing the total revenue and the total cost. In this simulation, this proposed model is compared with the existing PDP models. The first compared model was acronymized as KMGMA because it used K-means clustering and non-dominated sorting genetic algorithm (NSGA II) [6]. This model conducted resource sharing method. In this simulation, the NSGA II is modified into classic GA because of the single objective model. The second model is acronymized as SNLIFO because this model used the combined simulated annealing algorithm and LIFO [12]. In this simulation, this algorithm is transformed into collaborative model. The proposed model is acronymized as GAND.

This simulation consists of one adjusted parameter and several static parameters. The number of orders becomes the adjusted parameters. It ranges from 100 to 300 orders with the step size is 20 orders. Meanwhile, the static parameters include: the number of providers, the number of vehicles, and the average provider's revenue rate. The number of providers is 5 providers. The number of vehicles is 20 units. The average provider's revenue rate is 1,500 rupiah per kilometer. The travel cost rate is 200 rupiah per kilometer. Several variables are set randomly. The provider's revenue rate follows normal distribution. The vehicle's home, pickup, and destination locations follow uniform distribution. The result is shown in Table 1 and visualized in Figure 1.

Table 1. Relation between the number of orders and the observed parameters

Number of orders (unit)	Total travel distance (kilometer)			Outsourcing rate			Total net profit (Million rupiah)		
	GAND	KGMA [6]	SNLIFO [12]	GAND	KGMA [6]	SNLIFO [12]	GAND	KGMA [6]	SNLIFO [12]
100	784	720	781	0.26	0.80	0.78	0.84	0.53	0.54
120	894	910	927	0.25	0.79	0.79	1.06	0.67	0.67
140	979	1,082	1,073	0.24	0.81	0.81	1.29	0.79	0.80
160	1,073	1,231	1,206	0.23	0.81	0.81	1.44	0.87	0.86
180	1,144	1,392	1,339	0.24	0.81	0.79	1.63	0.98	1.00
200	1,215	1,650	1,509	0.27	0.80	0.81	1.74	1.05	1.07
220	1,300	1,785	1,637	0.22	0.79	0.80	2.12	1.23	1.27
240	1,366	1,942	1,808	0.22	0.80	0.80	2.22	1.29	1.32
260	1,419	2,116	1,939	0.21	0.80	0.80	2.30	1.30	1.35
280	1,492	2,331	2,140	0.20	0.79	0.79	2.66	1.53	1.56
300	1,547	2,449	2,223	0.19	0.80	0.79	2.93	1.67	1.72

The explanation of Figure 1 is as; Figure 1(a) shows that the total travel distance is proportional to the number of orders. This relation occurs in all models. Comparing among models, the proposed model is the best model in creating low total travel distance rather than the previous models, the KMGMA model [6] and SNLIFO [12]. This condition occurs in almost all number of orders, although in the beginning, the total travel distance of the proposed model is little bit higher than the previous models. When the number of orders is high (300 units), the total travel distance of the proposed model is 37 percent lower than the KMGMA model

[6] and 30 percent lower than the SNLIFO model [12]. Figure 1(b) shows that the number of orders does not have relation to the outsourcing rate for the previous models [6], [12]. Meanwhile, the number of orders is reverse proportional to the outsourcing rate for the proposed model with small gradient. Comparing among models, the proposed model performs the best by creating the lowest outsourcing rate among the previous models. In average, the outsourcing rate of the proposed model is 70 percent lower than the previous models. Meanwhile, the outsourcing rate between the previous models is almost equal. Figure 1(c) shows that the orders processors' total net profit is proportional to the number of orders. It occurs in all models. Comparing among models, the proposed model performs as the best model by creating the highest net profit for the order's processors rather than the previous models [1], [12]. When the number of orders is high (300 units), the total processors' net profit of the proposed model is 76 percent higher than the KGMA model [6] and 70 percent higher than the SNLIFO model [12].

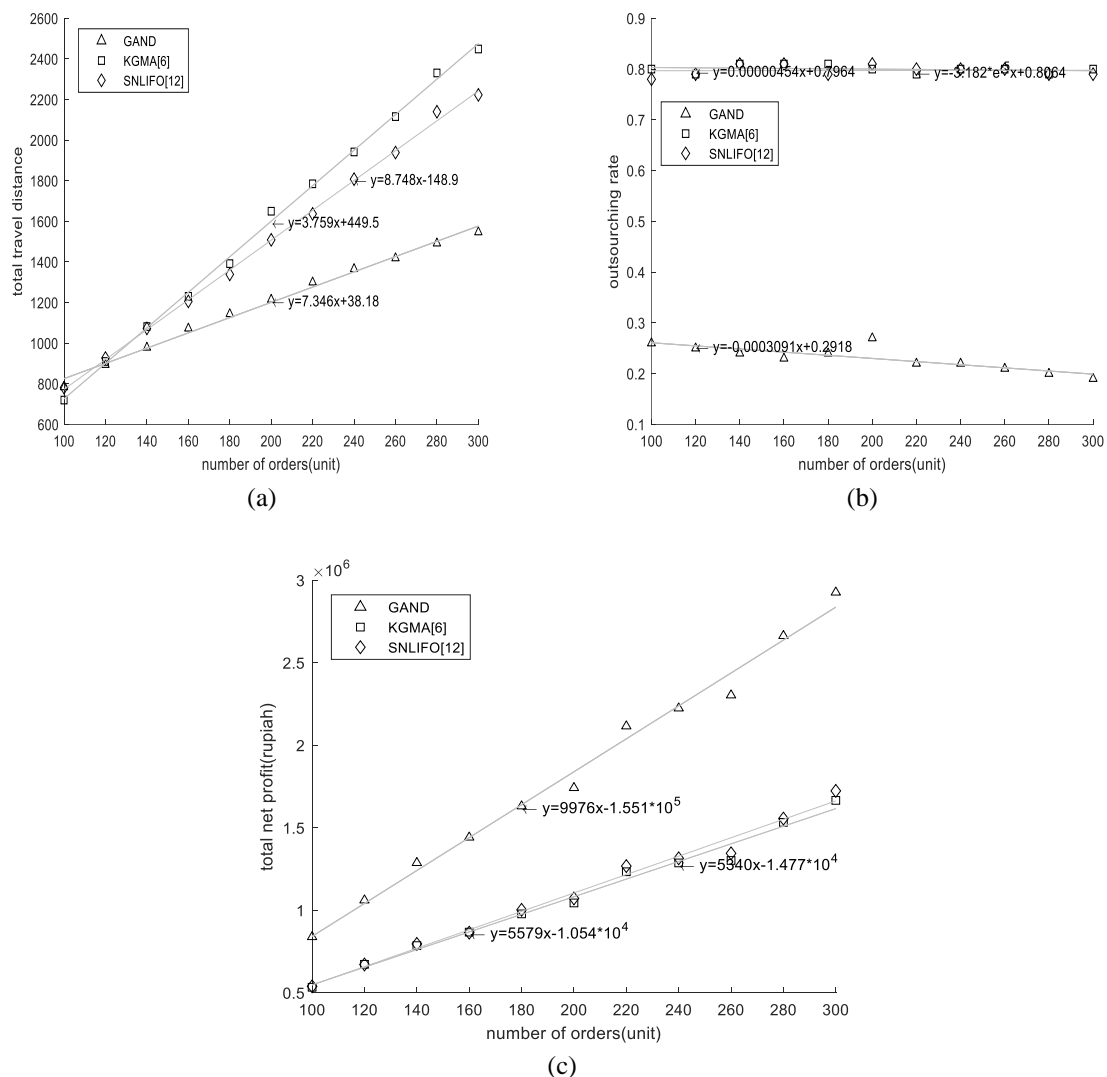


Figure 1. Relation between the number of orders and the observed parameters; (a) total travel distance, (b) outsourcing rate and (c) net income

Data in Figure 1 is also enriched with linear regression to observe the trend. The analysis of linear regression can be represented in Table 2. It shows the characteristic of linear regression (R Square, coefficient, and P-value) for each model. The R square is high while the P-value is low, indicating that the linear regression model can explain the variability of total travel distance and total net profit. Additionally, the coefficients are positive, indicating the positive correlation between number of orders to total travel distance and total net profit, respectively. Meanwhile, the linear regression is insufficient for representing the



variability of outsourcing rate. Through regression model, if the number of orders changes, we can still forecast the number of observed parameters.

Table 2. Characteristic of linear regression for GAND, KGMA [6], SNLIFO [12] model

Model	Total travel distance			Outsourcing rate			Total net profit		
	R Square	Coefficients	P-value	R Square	Coefficients	P-value	R Square	Coefficients	P-value
GAND	0.99519	3.62091	1.40E-10	0.67166	-0.000296	0.0020	0.9898	9975.70	2.82E-10
KGMA [6]	0.99822	8.74818	1.09E-13	0.05588	-0.000023	0.4840	0.9860	5339.59	1.17E-09
SNLIFO [12]	0.99853	7.34636	4.60E-14	0.00589	-0.000011	0.8225	0.9871	5579.39	8.04E-10

There are several findings due to the simulation result above. These findings and the simulation results are then analyzed deeper in this section. The motivation is to explore the findings by tracking back the method that has been used by each model, the proposed model and the compared existing models [6], [12], to find the reasoning of these phenomena. The first finding is that the proposed model is very effective when the number of orders is high. The gap between the proposed model and the compared models, both the KGMA model [6] or the SNLIFO model [12] is wide. The key reason is that the proposed model does not separate the pickup process and delivery processes into two distinct sub processes as it is conducted in the compared models, both the KGMA model [6] or the SNLIFO model [12]. By adopting the pickup-first delivery-later approach [12], these models are like the VRP with backhaul approach [3], but in the opposite order. The concept is still the same which is separation between the pickup and delivery. Meanwhile, the proposed model adopts the mixed pickup and delivery [3] so that both pickup and delivery activities are not separated. Action is taken as long as it is the nearest distance. In the separated approach, the vehicle still chooses to pick up the next order, during the pickup sub process, although there is delivery point which is nearer to it or creates lower total travel distance. On the other side, the vehicle still chooses to deliver the next order, during the delivery sub process, although there is pickup point which if this action is taken, will create lower total travel time. In general, it can be said that the mixed pickup and delivery approach is better than the backhaul approach in minimizing the total travel time.

The second finding is that the proposed model creates lower outsourcing rate rather than both existing models [6], [12] and the number of orders does not affect the outsourcing rate. The reasoning behind this circumstance is that in the proposed model, the outsourcing mechanism occurs only when it is needed. In the first round, system tries to dispatch orders to the vehicle with same owner. Outsourcing only occurs when there is not any vehicle with the same owner can pick up these orders. It is different from the existing models which does not concern the orders ownership. The orders can be dispatched to any vehicles in the system if the maximum capacity constraint is not surpassed.

The third finding is that the proposed model creates higher net profit for the order processors rather than the existing models [6], [12]. This finding is correlated with the first and second findings. Net profit comes from two aspects: revenue and cost. By creating lower outsourcing rate as it is demonstrated in the second finding, the proposed model creates higher revenue by minimizing the revenue that must be shared between the order owner and the order processor. On the other hand, the proposed model creates lower travel cost by minimizing the total travel distance.

#### 4. CONCLUSION

This work has demonstrated that the proposed model has met its objectives in: (1) developing collaborative PDP model that minimizes the travel distance and maintain low outsourcing rate, and (2) proposing revenue sharing model in this collaborative PDP model. When the number of orders is high (300 units), the total travel distance of the proposed model is 37 percent lower than the KGMA model and 30 percent lower than the SNLIFO model. In average, the outsourcing rate of the proposed model is 70 percent lower than the previous models. When the number of orders is high (300 units), the total processors' net profit of the proposed model is 76 percent higher than the KGMA model and 70 percent higher than the SNLIFO model. These advantages come from the mixed pickup and delivery approach and same owner prioritization. This model still has limitations that can be improved in the future works. For example, this work ignores the time window, penalty, maximum travel duration, and so on. Besides, this work assumes that all vehicles are identical which is different from the real condition. So, this model can be improved by including these aspects in the future works.

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