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Trucks Pooling and Allocation in TSE Concept Using GIS Spatial and Novel FFOA

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ABSTRACT: Strategic system logistics business entails the importance of regulating truck pooling facilities and allocating the trucks for cost optimization goals. Regulators and investors must consider spatial constraints such as the supply-demand gap and service distance. Little attention has been paid to developing decision logistics models, particularly truck pooling and allocation decisions. In this study, the FFOA and GIS were used to determine the spatial component of truck pooling decisions, providing a scenario for origin pooling and delivery distance. The model evaluates truck allocation to each city, a distance vector, a spatial factor, and city demand are used for the cost optimization goal. The results show that the FFOA model successfully defines the optimal truck allocation for each truck pooling site with a cost. The managerial implication in developing a sharing economy concept for truck logistics is to use the study's framework model result to solve challenges in truck logistics.

Keywords: Trucks Pooling, Trucks Allocation, FFOA, GIS, Spatial, Optimization.

INTRODUCTION

In the trucking business, truck pooling is one of the important operation factors which necessitates the truck owner to send the trucks to one of the site locations due to the concurrent need for truck sharing in specific areas (Bouchery et al., 2022; Marukawa, 2017; Marzano et al., 2022). As demonstrated by some truck companies, the system's environment requires operation management to conduct truck pooling in the truck sharing economy, abbreviated as TSE, in this study (Moeckel & Donnelly, 2016; Standing et al., 2019). Some trucks participate in the truck pooling process based on order volume, distance traveled by the logistics company, and spatial considerations such as road conditions and infrastructure readiness (Abdelazim et al., 2022).

In this study, we emphasize the significance of the sharing economy application for its collaborative benefit among truck players, sometimes enabled by system information technology (Abdelmagid et al., 2022; Akter & Hernandez, 2022; Osieczko et al., 2021). The truck owner must decide whether to invest the vehicles in a specific location based on the contracts TSE concept or to pool the trucks as in the traditional approach based on profitability and other factors (Islam et al., 2019). It is difficult for the owner or regulator of trucks based on the sharing economy concept to analyze such concerns holistically without a rigorous approach and preliminary environmental observation research (Küffner, 2022).

In this regard, three critical points should be discussed: First, from the distance variable, the truck sharing economy collaborators, in this case, truck owners, will discuss the availability of trucks to be pooled in a specific location. On the other hand, owners of certain trucks must monitor their utilization to make investment decisions. Thus, the distance between the truck pooling site and the owner-based company location significantly impacts how willing the owner is to invest in their trucks to meet the needs of the truck-sharing concept in this case. Second, the collaborators must evaluate the logistical coverage of services. To ensure that trucks are used efficiently and profitably, collaborators and truck owners must evaluate how the sharing economy concept should deliver services. Third, the truck pooling locations that will be selected are closely related to the logistics demand in a specific area. The greater the demand in a given area, the more trucks should be assigned to meet that demand. Thus, to evaluate those three dimensions holistically, field observation requires significant financial and time resources.

Furthermore, companies may have logistics expertise, such as demand data owned by specific trucking companies, which will be critical in determining the coverage area. However, gathering this information presents some challenges. Furthermore, combining that data into meaningful insights for strategic truck pooling allocation hints at technical challenges, such as a lack of trust between companies and a severe mental model of competition (Islam et al., 2019). A rigorous method system will be required to define agreement amongst collaborators on allocating trucks and how many trucks should be pooled in a specific location. The Fruit Fly Optimization Algorithm, proposed in this study for allocating trucks in the sharing economy concept in order to determine the most profitable allocation (W. T. Pan, 2012). Because a recent study by Siahaan found that the existing body of literature has largely ignored common trucking problems such as empty trips, developing a novel truck allocation model could benefit both an academic and practical standpoint (Siahaan et al., 2021).

Furthermore, the optimization mindset is frequently associated with resource reduction and pursuing the lowest possible cost. In other words, achieving operational effectiveness and efficiency while running a business is possible. Aside from gaining efficacy and efficiency as the sharing economy concept matures, the concept of a TSE has not been extensively formed or represented in a rigorous business model, which is unfortunate. As was the case in this study, the operationalization aspects of truck pooling have received little attention concerning the truck sharing economy concept. Thus, this study aims to simulate a truck pooling allocation to potential service node cities to contribute to the concept's maturity. This model study is advantageous for sharing economy regulators because it allows them to evaluate resources efficiently by adapting a novel algorithm to estimate the lowest logistics costs. There are numerous uncertainties when it comes to logistics delivery, and not just truck logistics. The fierce competition for the silo mental model among players has hampered information sharing and data dissemination (Islam & Olsen, 2014). This study attempted to address the scarcity of data by incorporating simulation through modeling and implementing a newly developed novel algorithm known as FFOA. This model framework will help regulators evaluate potential allocations when distance data becomes available. The study findings may persuade industry participants to gather missing data on the evaluated variable through collective information sharing.

A. Problem Description

This study applies the sharing economy concept to the truck logistics business, which is referred to as the truck sharing economy, abbreviated as TSE. The issues in the logistics trucks identified are as follows: in the trucking industry, determining the truck pooling facility position is difficult due to a lack of data and coordination among truck owners. Information on centralized location points is also unavailable to decide on the best truck pooling location. Thus, to determine the pooling point position, city node, demand, and cost are required variables in this study. Furthermore, a company-wide managerial decision typically determines the allocation of trucks to a pool. However, truck allocation is frequently determined by decisions that are not optimized. The primary consideration is meeting customer needs at the lowest possible cost.

Thus, this study aims to figure out how many trucks to assign to a truck pooling position with the minimum cost. The study's delimitation and scope are that it provides a decision-making model based on FFOA in the TSE concept. The results section demonstrates the cost optimization difference between FFOA and manual allocation. However, we need to clarify that this study is not a comparative study that shows how optimal the FFOA algorithm is but how to apply FFOA to assist managerial decisions as a result of this paper in the form of an application model. Thus, this study summarizes three research questions: first, how to determine the truck pooling position; second, how to determine truck allocation; and third, what is the cost impact of manual allocation versus FFOA allocation?

B. Research Novelty and Purpose

This research aims to determine the truck pooling position based on each province's selected case's demand centrality factor. In this study, we used ArcGIS Spatial Software to determine the truck pooling position by analyzing the spatial situations, such as city nodes, centrality, and calibration distance. Another goal of this research is to determine the truck allocation for each pooling position. Several factors are considered in this study: the city node, the distance of the truck pooling to the city node, the logistics demand, and delivery costs. The third goal is to compare the cost impact of truck allocation based on the FFOA algorithm to manual allocation. This study, however, does not include determining how optimal the FFOA algorithm is.

This study aims to demonstrate how spatial analysis with ArcGIS and the FFOA Algorithm can aid operational decisions such as location and allocation strategies for cost optimization based on truck logistics demand. Our review of the literature reveals that much comparative research on the benefits of FFOA has been conducted. Therefore, the purpose of this study is not to demonstrate how optimal FFOA is - but how FFOA applications can be used in the context of business truck logistics. The comparison of manual allocation and FFOA in this study is presented to help readers understand how the benefits of FFOA can be used if the allocation strategy is optimized with a specific algorithm.

In summary, the structure of this paper is as follows: The first section serves as an introduction and provides context. The second section examines the FFOA literature, discusses its application, and summarizes the study's research, contribution, and innovation. The third section describes the technique, including an overview of the FFOA application, how to use and briefly explain the GIS tool, and how to configure the simulation, boundary, and data collection. The fourth section discusses the study's findings, such as manual vehicle pooling to city node service businesses, FFOA truck allocation, cost comparison, and discussion of the findings. The fifth section delves into the study's conclusion, limitations, and business implications.

LITERATURE REVIEW

Fruit fly optimization (FFOA), a newly developed algorithm, has recently received much attention, discussion, and popularity because of its fast and clever computations (Karkalos et al., 2019; R. Y. Wang et al., 2022; Xing & Gao, 2014). According to the research, major conventional algorithms such as linear programming, particle swarm optimization, genetic algorithms, and other well-known algorithms outperformed the optimization method (Cheng & Shi, 2022; Geruna et al., 2017; Yang Li & Xu, 2022). The foraging food behavior of fruit flies was adopted for the insect species best known for its ability to sense and see food even from 40 kilometers away (W. T. Pan, 2012; Zhao et al., 2021). Algorithms and fast computations have been widely disseminated in recent years due to their ease of application to optimization problems (Mahmoodabadi et al., 2018; Sun et al., 2022; Xing & Gao, 2014). Furthermore, several algorithm reviews have also emerged, such as comparing the original FFOA to ten different chaotic maps adapted as CFOA (Mitić et al., 2015). The other study uses the Cluster Head Algorithm to improve the FFOA (Poluru & Kumar R, 2021). Specific study problem solving, such as the use of FFOA to solve an antenna design problem (Polo-López et al., 2018), and numerous other studies related to the emerging FFOA either for improving, adapting, or proposing FFOA uses (Dai et al., 2014; Iscan & Gunduz, 2014; Yancang Li & Lian, 2018; Q. K. Pan et al., 2014; Wu et al., 2015).

Several studies have applied the concept algorithm to vessel control, data mining, the knapsack problem, power load forecasting, allocation, and flow control, as mentioned in a study review of FFOA (Xing & Gao, 2014). Furthermore, a comparative study on the application of FFOA to the economic dispatch problem, demonstrated the benefit of FFOA (Geruna et al., 2017). The use of FFOA in logistics has also been considered which evaluates modified FFOA for logistics storage selection with the goal of cost optimization (W. T. Pan et al., 2017). In further studies, the researchers considered using FFOA for vehicle routing, despite research on allocation in the context of trucks and warehouse logistics problems. The use of FFOA in the context of truck logistics, particularly TSE, has been limited or non-existent (Mousavi et al., 2017; C. L. Wang & Li, 2018).

Furthermore, the importance of optimization in logistics, particularly trucking logistics, a multibillion-dollar industry, cannot be overstated. The investigation of logistics allocation, particularly in trucks, will impact cost-cutting measures (Ta et al., 2005). Incorporating optimization problems into trucking also helps to alleviate concerns about truck utility. The best solution for trucks would be to reduce empty trips using the proposed shared economy concept (Islam et al., 2019). Although there have been studies on truck allocation, none have proposed a model for TSE based on the concept of a novel optimization algorithm. The sharing economy is well-known for alleviating the problem of idle resources or low resource utility (Eckhardt et al., 2019; Miller, 2015), resource utilization issues such as energy sharing and food sharing (Boyko et al., 2017), cost savings, and climate benefits associated with collaborative transportation use (Islam & Olsen, 2014). Furthermore, sharing economy is advantageous for empty trips, such as when applied to trucks (Islam, 2018). As a result, our research goal aligned with the advancement of the current body of knowledge gaps.

The study's focus on TSE application, the emerging concept of "sharing economy," and the lack of policy development have all contributed to a significant gap in the study's context. Using a novel optimization algorithm to propose simulation aspects to address uncertainties in defining the truck pooling model allocation could thus benefit academics, especially in developing the sharing economy. Following the completion of this study's literature review, conclusions can be drawn: While optimization in logistics operations has received considerable attention in various research designs, there have been very few studies on truck logistics in the context of the sharing economy concept. The implementation of truck pooling has also been ruled out. Second, while mathematical methods have been considered for optimization, the use of an algorithm that has been shown to increase computation speed has not been considered. An algorithm such as the Novel Fruit Fly Optimization Algorithm represents an excellent opportunity to contribute to the logistics sector's knowledge gap, particularly in areas such as the truck sharing economy, which has been overlooked.

There is a growing tendency to pay more attention to gaps in logistics research, particularly those related to the development of the sharing economy concept (Siahaan et al., 2021). This study covers topics such as the study's setting and primary themes and the methodology for conducting studies on the sharing economy concept, specifically in the trucking industry. As a result, recommendations based on literature reviews will be useful in various ways, including suggestions from the previous study (Siahaan et al., 2021), which was part of the motivation for conducting this study. In conclusion, the likelihood of demonstrating the benefits of the sharing economy concept in terms of increasing logistics mode utilization is high. Any study design that perfects the concept can contribute significantly to the study area under consideration. As a result, the development of this study adds to the literature by providing a concept development design in the context of truck logistics optimization.

METHOD

This section will explain how this research method is used. In general, the research was carried out with three main goals: first, determining the location of truck pooling using ArcGIS; second, determining truck allocation using FFOA; and third, demonstrating the cost impact by comparing costs and allocations from non-optimized allocation versus allocation with FFOA. Figure 1. depicts a summary of the research methodology.

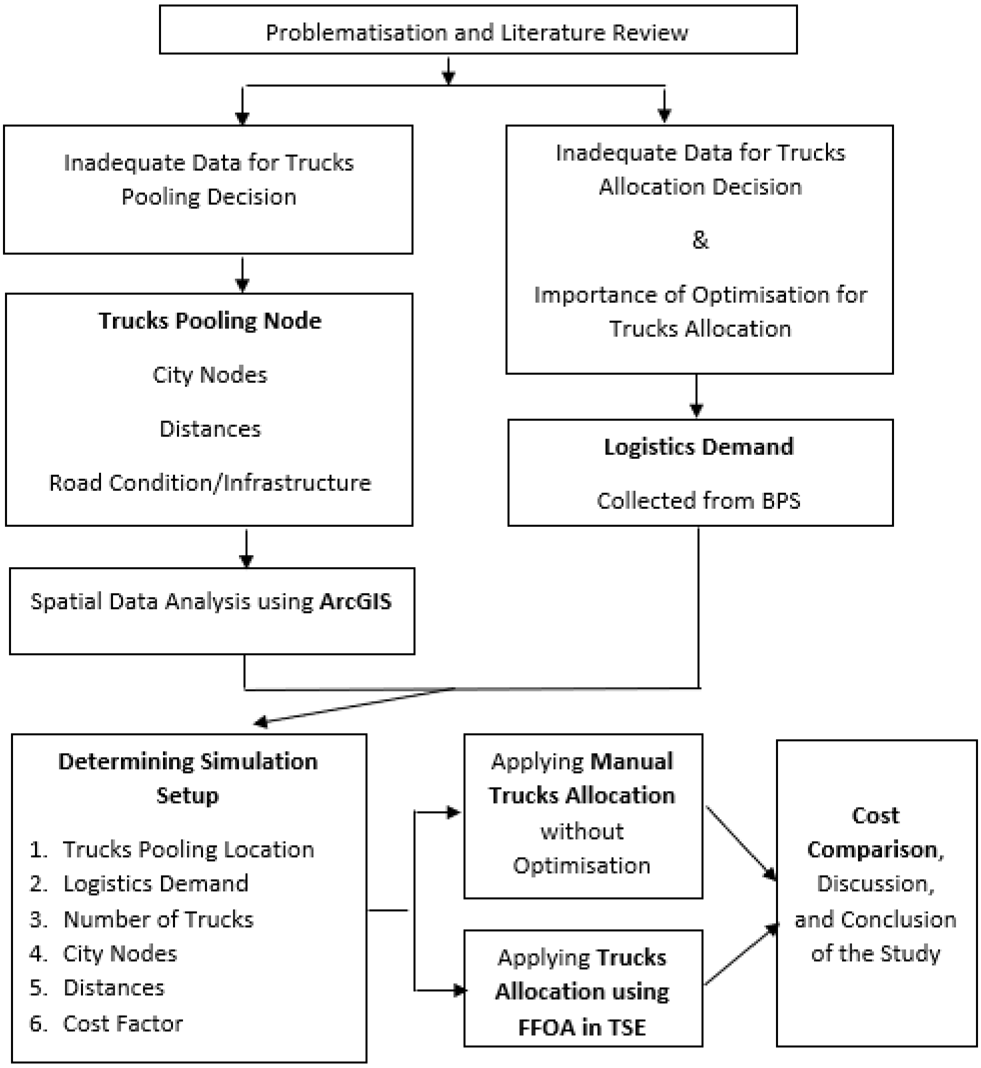

Figure 1. Research Approach

A. Trucks Pooling Location Selection

In this study, we looked at six provinces on the Indonesian island of Java. The unique characteristics of Indonesia's archipelago provide a distinct and novel setting for this logistics allocation. Java Island is also the most populous region in Indonesia, and it is home to the country's capital, Jakarta, which is also located on the island of Java. Java has been a crossroads for politics and commerce for more than a century. As a result, the site's characteristics contributed to the complexity of logistics in this area, as the variables chosen for this research include the distance between node cities, the spatial condition of the node cities, and the demand for the node cities.

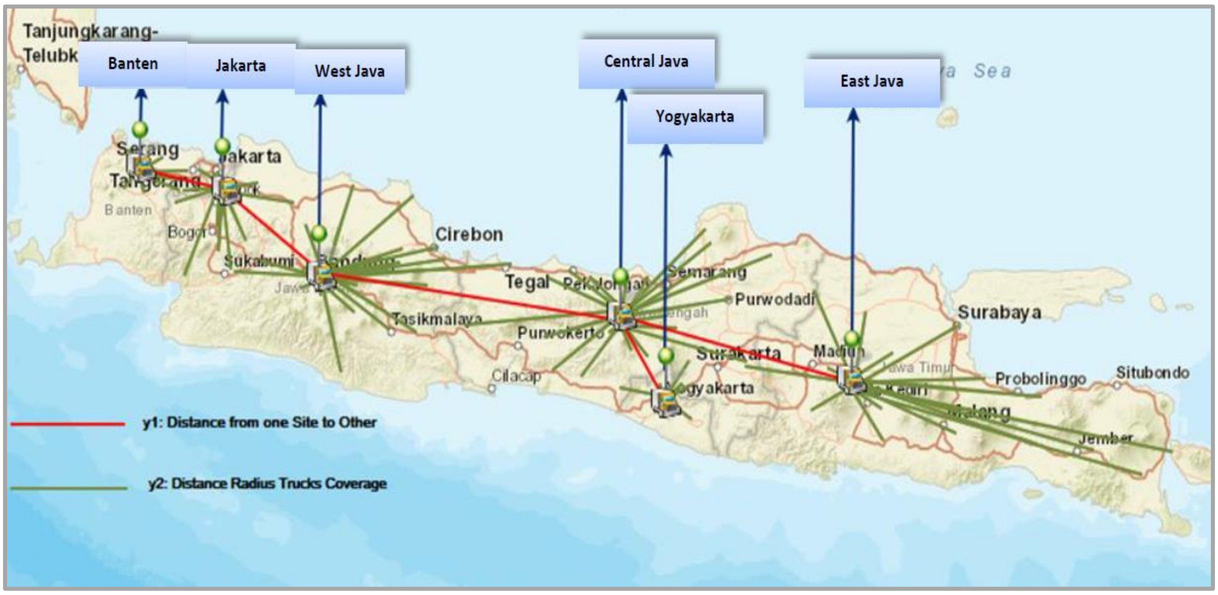

Figure 2. Trucks Pooling Location Selection

Using ArcGIS, we can determine the truck pooling location in Figure 2. based on the centrality of each province's radius. Satellite calibration can also determine the data node cities from each truck pooling point.

B. Spatial Analysis using ArcGIS

We collected data for this study from two distinct categories. A radius of truck service to city nodes is determined by the location of the truck pooling point. Second, the distances for service in each province. In this case, we use the capital city of each province as a reference point to locate the truck pooling sites and then calibrate the GIS with a 50-kilometer satellite view. Each city depicted on the map will generate a line radius by pooling the locations. As a result, this information was collected as the first type of data called *Distances*. The distances explain how far is a certain city node from a truck's pooling.

Using a mapping approach with a specific tool is extremely useful in establishing the context of a service area, which in this case is related to the location of truck pooling location and the coverage of logistics. This study uses ArcGIS software to evaluate potential cities based on satellite images captured with a certain range of calibration by the application. In this study, we used a calibration distance of 50 kilometers from the satellites. We considered the cities on the ArcGIS Geographic Information System as the truck pooling node cities. The site selection process was depicted in Figure 2. based on the provinces' centrality in ArcGIS; we also evaluated the potential coverage of the truck services. We evaluate city appearances at 50km distances by calibrating nodes using ArcGIS software; furthermore, the green line in the figure represents radius coverage, with detailed distances for each line provided.

Furthermore, the variable "spatial factor" is one of the focus of the simulation component. The road, infrastructure differences, and other factors such as the possibility of an accident on the road, the rate of traffic jams, and uncertainty factors such as theft and even disasters all impact the route from trucks pooling location to city nodes. We simulate all of those factors in a range of percentages because collecting the entire logistics aspect of those factors in the field is difficult without adequate resources and manpower. The "Spatial Factor Variable" represents all the uncertain characteristics of the infrastructure condition mentioned above.

Furthermore, regarding the road condition, a "cost factor" evaluation component is determined based on a spatial factor, distance, and demand. Road conditions and distance, which were collected using ArcGIS, are simplified measures as it is extremely difficult to estimate the possibility of road damage and road quality in actual situations. Thus, in this simulation, road conditions are assigned at random to each road by trucks pooling positions to a certain city node. We view that when distance and demand are not the only determinants of real logistics service costs, rationalization may be beneficial in improving logistics service cost accuracy.

We defined a "spatial factor" range of 0.1 to 0.5: The best rate is 0.1, the second-best rate is 0.2, the good/normal rate is 0.3, the bad rate is 0.4, and the worst rate is 0.5. We used the spatial factor rate to convert the cost in the FFOA simulation; the lower the spatial factor rate, the better the spatial factor, simplifying the complicated factors in this study such as road conditions, infrastructure conditions, traffic, and miscellaneous. A road with a spatial factor of 0.1, for example, may represent a good road with little traffic congestion and a low risk of an accident. It is opposed to a city node destination with a spatial factor of 0.5.

C. Trucks Logistics Demand

The other important data set is logistics demand in each province's assessed area. We use data from the Badan Pusat Statistics Indonesia's most recent official statistics publication (BPS Indonesia). We believe that the more available data, the more accurate truck pooling allocation forecasting will be. Based on the BPS Indonesia publication, we compiled published data in Ton and converted it to an initial forecast of total truck demand. According to the official website of BPS Indonesia, there are four major business production sectors in Indonesia: livestock farming, fruit and vegetable farming, maritime and sea capture, and fish cultivation.

Additional significant industries include forest, oil, gas, cement, and retail, all of which incorporate the demand for logistics, particularly truck logistics. However, the lack of data on oil and gas and other industries specific to each province within the study's boundary has played a role in the decision to exclude those data and establish them as the study's boundary and limitation. Furthermore, this study does not include industries such as the forest industry located on islands outside Java like Borneo and Kalimantan.

D. Fruit Fly Optimisation Algorithm

Pan discovered the algorithm, which adapts to the foraging behavior of fruit flies in evaluating food positions, as shown in figure 3 (W. T. Pan, 2012). When fast computing is required, then the use of FFOA is extremely beneficial. The use of FFOA in this study is critical for several reasons. First, the data city nodes in this study have implications for the simplest point value. Second, city nodes can be interpreted as a customer position point, a customer pick-up point, or a delivery point for a delivery order, thus parameter and its adequacy can be obtained (Shudapreyaa & Subramanian, 2016). Rapid computing is required as each of these points has the potential to reach millions of data points. As FFOA is known for its reputation for very fast computing speeds, as suggested in the previous study (Geruna et al., 2017), the use of FFOA for this study is very beneficial.

After defining the truck pooling location, city nodes, logistics demand, and spatial factors, the next step is allocating trucks. In manual allocation, the number of trucks to allocate is determined by a company's logistics network coverage and infrastructure readiness by using historical data or any other factors deemed appropriate by the company. However, in the FFOA, the setup simulation depicts the number of trucks required based on demand and optimal cost. Furthermore, in this simulation, we set a limit of 5.5 service orders per day per business entity, with around 2000 orders per year. We calculated the manual allocation using that number. With that allocation of trucks, we could calculate the total cost for each year using the previously mentioned assumptions.

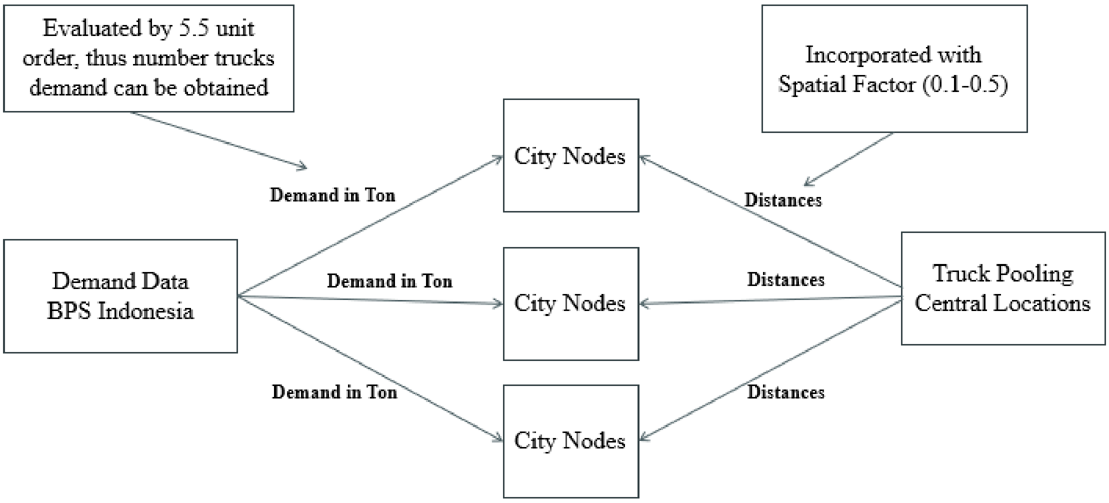

Figure 3. FFOA Simulation Components

The goal of implementing FFOA is to ensure that enough trucks are allocated to meet the demand for logistics trucks to deliver goods from truck pooling to city nodes. The number of trucks to be allocated must consider all factors, including demand, distance, and spatial factors, translated into costs, as shown in Figure 4. As a result, when the allocation is made, FFOA must be able to present the number of truck allocations in a pooling truck at the lowest possible cost.

Table 1. Sample of Data: Case of Banten Provinces

Cities Node	Distance in km	Spatial Factor	Demand in Ton
1	23	0.4	3100000
2	41	0.2	1262424
3	33	0.1	900000
4	38	0.3	3420000
5	17	0.3	1100000
6	18	0.2	730000
7	8	0.4	2234000
8	15	0.5	5300000

Note: Data compiled by the Author references from “Badan Pusat Statistik Indonesia” and ArcGIS.

Table 1 shows that city node 1 has a delivery distance of 23 km from trucks pooling, with a spatial factor of 0.4, which describes the quality of the road and the possible conditions for traffic jams, and accidents, which are quite high, so that the cost factor becomes higher. Furthermore, Table 1 shows the coverage area of the city node of demand. Using this information, FFOA will focus not only on demand but also on all other aspects.

RESULT AND DISCUSSION

According to the results of the FFOA, the allocation has the lowest cost in each comparison. As shown in Table 2, the model allocation for each city node can be calculated after applying FFOA (W. T. Pan, 2012), to the data collected through ArcGIS. Furthermore, a comparison was made between the FFOA Algorithm allocation and the manual allocation. The FFOA allocation could save 25302.1-factor costs in the long run. Following the evaluation of the FFOA result, the allocation decision is made using the optimized algorithm, which considers the factors of distance and spatial factor, with the latter indicating a more optimal allocation at a lower cost for each allocation decision.

Table 2. Result of FFOA Allocation Compared to Non-Optimized Allocation

Cost Unit/ Truck Delivery	Manual Truck Allocation	Manual Total Cost Factor	FFOA Truck Allocated	FFOA Total Cost Factor
9.2	1550	14260	595	5474
8.2	631	5174.2	969	7945.8
3.3	450	1485	2599	8576.7
11.4	1710	19494	986	11240.4
5.1	550	2805	942	4804.2
3.6	365	1314	1302	4687.2
3.2	1117	3574.4	756	2419.2
7.5	2650	19875	874	6555

Figure 3 also depicts a side-by-side comparison of the costs associated with allocating trucks to city nodes in each province. For the truck sharing concept, the FFOA algorithm is superior at allocating complex decision-making regarding demand data and spatial factors. Figure 4 also depicted the study's optimization iteration for achieving the lowest cost for each province throughout the iteration. The Fruit Fly optimization algorithm was modified to evaluate potential cost estimates, with the algorithm comparing costs in each iteration until the goal was reached.

One of the study's motivations is to map the city nodes and the number of possible cities covered. We simplified the cities covered in this study because the study's primary contribution is a novel adaptation of an algorithm for evaluating the optimal allocation model. However, the evaluation application is much broader and more complicated than the evaluation of this study; for example, using ArcGIS with a lower calibration will increase the number of cities that can be covered, which in this term could range from hundreds to thousands and even millions. As a result, finding an optimal algorithm with rapid computation is critical.

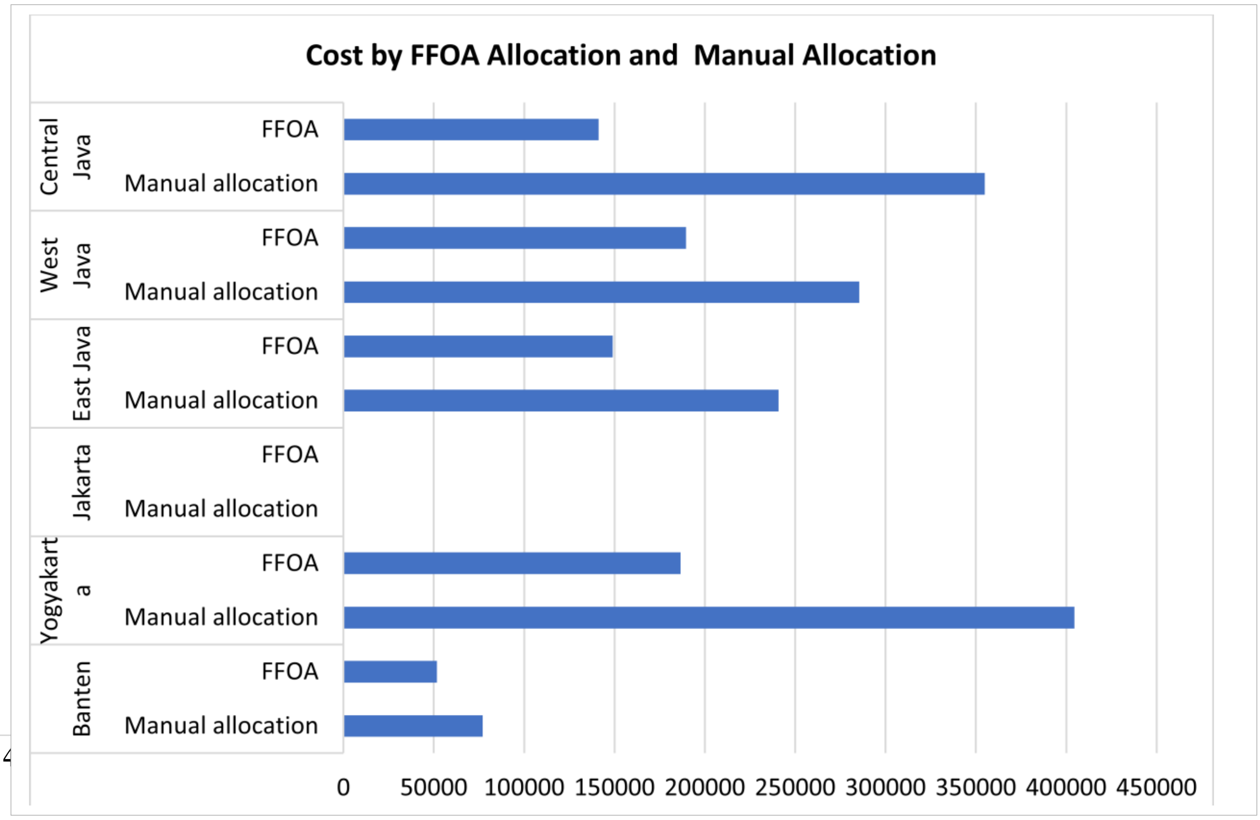

Figure 4. Cost for manual and FFOA allocation.

Comparing the manual implementation of truck pooling to the FFOA implementation is illustrated in Figure 4. The significance of the results can be determined by examining the simulation's use of predetermined rates on a scale of 0.1–0.5. Environmental variables such as road conditions, infrastructure, and other variables were predetermined, thus scale becomes pivotal. Additionally, ArcGIS can calculate the distance between two points on a map. The newly developed Fruit Fly algorithm outperforms commonly used algorithms such as Genetic Algorithms and Linear Programming (Geruna et al., 2017). Thus, the Fruit Fly algorithm's benefits, particularly in terms of allocating thousands of cities for cost estimation based on the availability of demand data and spatial factors, could be obtained by applying the framework model of this study.

FFOA is effective when allocating a pool of trucks based on available data (environmental factors, distance, and logistical demand data). Manual allocation is based solely on the availability of data and the proximity of information; for instance, truck owners will prioritize previously completed orders. FFOA, on the other hand, allocates trucks only when the cost reaches optimization through the iteration. By conducting simulations for logistics demand data in six Java provinces using FFOA, we could evaluate the position of FFOA and its methods in cost optimization.

There is a component of the evaluation called the "cost factor," determined by road conditions and the distance between the truck pool's location and the destination city. As discussed in the methodology section, the Spatial Factor and distance calculated using ArcGIS are simplified. The simplification is applied because of the possibility of road damage and road quality, which are extremely difficult to determine in real field data. This condition is randomly assigned to each road lane based on the World Ranking Statistics for Logistics' ranking data for the quality of road infrastructure in Indonesia. Indonesia's infrastructure Simplifying is beneficial for improving cost accuracy in situations where distance and demand are not the only determinants of actual logistics service costs.

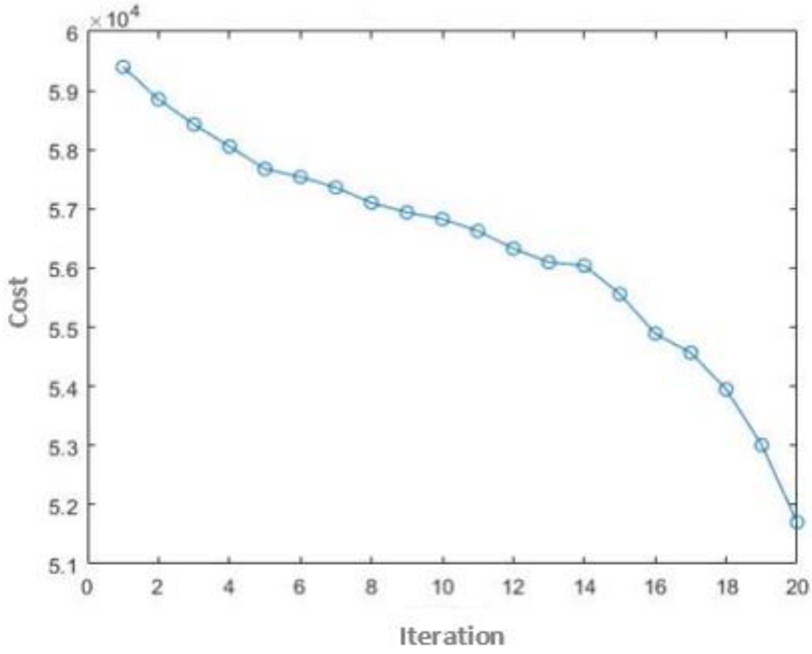

Figure 5. Example of FFOA iteration achieving optimal cost on one province

Furthermore, in this results section, we can show iterations of FFOA achievement towards the lowest price as in Figure 5. In this process, each truck allocation in a certain city from truck pooling, along with the number of cargo orders, is carried out to achieve a condition called the lowest possible cost based on the criteria of cost factor, spatial distribution, and number of demands. In the FFOA algorithm, just like the concept of foraging food on the fruit fly, the objective function of using FFOA here is to find the lowest price with the best allocation in the city destination from truck pooling.

In this allocation, a process is carried out to determine the best allocation of trucks at known demand and the best number of trucks at the lowest cost. The process is usually done by the logistics business operator manually using the company's historical data. For example, a request for some goods with certain logistical needs based on previous transactions. With FFOA, the business can execute computations looking for truck allocation possibilities with the concept of cost optimization and run them in the context of a truck-sharing economy. This process can occur with iterations to reach the lowest price, as shown in Figure 5.

The optimization of FFOA shows the scalability and capability of the algorithm's ability to achieve the objectives of the problem of this study. In all cases in this study province, we evaluate each iteration's optimization location and time. The detailed movement of each iteration to achieve cost optimization can be seen in Figure 5. The difference in iteration movement can be noticed, assessed, and contrasted based on the complexity of the data.

On the graph of Figure 5, it can be observed that early optimization happens with the fewest iterations in the Jakarta example compared to other situations with similar data complexity. Unlike the other case cases in this study, Jakarta is the simplest. In the instance of Banten, it is obvious that optimization occurs on a constant and stable basis. The results demonstrate that the potential of FFOA could provide the benefits of its use in more complex scenarios, such as field data from a considerably greater number of cities, which can be evaluated using a very large number of iterations at a low computing cost.

CONCLUSION

We demonstrate the advantages of employing the FFOA algorithm, the relevance of our scenario study model, and the outcomes of the algorithm simulation, which demonstrate an important practical business managerial impact in our conclusions. In this study, we discovered that we could optimize allocation by comparing the cost factor based on our model of the simulation setup boundary. The entire case examined area truck pooling distribution based on demand data and distance factors simulated by adding spatial elements, resulting in cost savings via FFOA application rather than predicting based on the number of common delivery orders.

Furthermore, the optimization problem concerns the optimal allocation of resources to maximize or decrease certain characteristics of the research's objective function. In this scenario, the study's objective is to provide a framework model of allocation that accounts for uncertainties or to avoid utilizing conventional techniques such as assigning delivery based on unverified cost estimates based on coverage service experience.

The underlying concept is the availability of demand data; the prediction of resources, which in this case is the number of trucks; and the availability of known factors to estimate costs, which we refer to as "spatial factors" in our model, all of which are dependent on the availability of demand data. These aspects of the sharing economy business model should be taken into consideration by policymakers. In situations where relevant data is available, and the logistics of viable service coverage are known, this model allows for the application of FFOA.

This study implies that the usage of a study framework can be beneficial for the practical component. Regarding data demand, a common example would be the delivery of common trucking services by a certain corporation. Companies may have such demand data, which may also be related to real spatial factors such as road conditions for cost estimation purposes if it is decided to cover the service area. This information may also be available based on previous service coverage experience if the service area has been covered. The more complete the data, particularly in this case related to mapping demand data and collecting geographical factor data to estimate cost, the more likely companies will use the Fruit Fly method for allocation and optimization decision-making.

The limitation of this study is that it analyzed the framework for geographical area allocation in six major provinces on Indonesia's Java Island. However, in defining the site locations and destinations for truck pooling city nodes, a lack of and inadequacy of spatial condition data collection, such as road and infrastructure conditions, traffic congestion, accident rates, and miscellaneous aspects such as theft rate, compelled this study to use simulation. Thus, the study's primary finding is not to propose a numerical value for the city nodes collected in ArcGIS. The primary objective is to recommend truck allocation in city nodes using a unique algorithm to minimize logistics costs while maximizing profitability.

Furthermore, this study focused on the simulation aspect of the city node coverage with a small number for evaluation. The city nodes that could be covered by service would increase from hundreds to thousands if the study looked at a broader aspect of the business, such as using ArcGIS with a closer calibration (i.e., 5km). For example, suppose a company, regulator, or actors who regulate a sharing economy contract must allocate based on distance, spatial distance estimation, and cost. In that case, the optimization algorithm is necessary to find the most optimal solution. The results of this study indicate that the FFOA is a good fit in this situation.

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