SELECTION OF CENTRAL WAREHOUSE LOCATION USING CO_2 EMISSION SIMULATION

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ABSTRACT

Central warehouse is a strategic component in logistics operations, and selection of its location in the era of Industrial Revolution 4.0 has been increasingly supported by software tools. Software equipped with GIS maps can be utilized not only to determine optimal locations but also to accommodate the principles of the Sustainable Development Goals (SDGs), particularly those related to responsible production and consumption. This concept is highly relevant in Bali Island that relies heavily on cultural tourism, making it essential to consider environmental factors when selecting the central warehouse location. This study employs AnyLogic-based software to support the selection of central warehouse location, using CO_2 emissions as a key factor. The emission calculation is based on the amount of CO_2 released by fleet trucks during logistics operations. Simulation results indicate that Gianyar is the most favorable location, as it produces the lowest CO_2 emissions among other alternatives.

Keywords: central warehouse; CO_2 emissions; GIS map; simulation

INTRODUCTION

Warehouses in logistics processes serve various functions, such as being a place for receiving commodities, processing them to add value, functioning as a dry port, serving as storage facilities, and acting as dispatch points for commodities (Politeknik Transportasi Darat Bali, 2020). In logistics, the role of warehouses has evolved into distribution centre or central warehouse, which generally functions as a transit point for commodities en route to branch locations. Theoretically, a central warehouse can serve as the focal point for commodity movement, the main processing site, a container operation hub, as well as a storage and distribution center (Qian et al., 2017). In this context, the role of a central warehouse is considered vital, as commodities typically stop there before reaching consumers. This vital role necessitates the strategic selection of the central warehouse's location, ensuring it can minimize transportation distances and optimizing logistic costs (Alkaabneh et al., 2014; Liu & Lan, 2013).

The selection of central warehouse locations in the Industrial Revolution 4.0 is supported by software with high computational capabilities, the utilization of large volumes of data—commonly referred to as Big Data—and internet-based technologies. Consequently, decision support systems to determine location are shaped by the availability of extensive datasets and the computational algorithms embedded within the software. Such decision support systems do not necessarily require costly applications or prolonged analytical processes. One effective solution presented as a decision support tool is modeling and simulation (Grigoryev, 2018). In addition to enhancing efficiency, modeling also helps for handling any disruptions occurred in business.

Central warehouse selection is a systematic and logical effort aimed at cost efficiency within business analysis that prioritizes trade-offs (Rushton et al., 2014). Given that business processes are generally stochastic in nature, as noted by Wagner & Taudes (1987), it is therefore logically sound to model these processes through simulations that include uncertainty (Borshchev, 2013). Such stochastic models involve the use of random numbers—commonly referred to as seeds—and statistical distribution concepts such as the normal distribution or exponential distribution.

This approach can yield different outcomes compared to deterministic models, thereby offering alternative insights for business decision-making.

Beyond evaluating costs and benefits, modern organizations are increasingly confronted with environmental issues such as global warming and pollution. The concept of the Sustainable Development Goals (SDGs), as introduced by the United Nations, clearly articulates one of its key objectives: responsible production and consumption that remains mindful of environmental impacts (UNCTAD, 2017). This concept being adapted in Indonesia to what is now known as green economy, or sustainable development with an environmental perspective (Makmun, 2011).

Bali Island is one of Indonesia's premier tourist destinations, primarily relying on cultural tourism. Cultural tourism is inherently linked to the community's awareness and concern for the environment. This environmental consciousness also influences business processes—particularly logistics—which serves as a key support system for cultural tourism in Bali Island. According to Adekunle et al. (2022) there is a positive correlation between carbon emissions, economic activities and environmental degradation. In line with the concept of sustainable development, the selection of a central warehouse location must not only consider travel time but also include calculations of CO_2 emissions produced by the transportation fleet. To perform these calculations, we employ a modeling software known as AnyLogic, which features an integrated GIS (Geographical Information System) mapping capability. Using AnyLogic, the author constructs a model based on a distribution scenario that generates outputs in the form of CO_2 emission data. These outputs can then serve as a consideration in determining the best location for the central warehouse.

METHOD

GIS or Geographic Information System is a computer based system that make it possible to enter, manipulate, analyze and display data or information that is tied to a location on the earth's surface (Ali, 2020). In addition, GIS may be described as an integrated system of cooperating computer components, whose operations include positional data analysis and storage (Sánchez Lozano et al., 2015). Given its usefulness in simulations, several software, such as AnyLogic, have incorporated GIS features to support work in areas such as urban transportation analysis, the placement of buildings and public facilities, parking area determination, logistics routing, and more (Li et al., 2011).

The development of AnyLogic modeling emerged from the rise of object-oriented programming languages such as Java, along with improvements in hardware performance. What was once merely a conceptual approach on paper has evolved into a practical reality after the year 2000 (Grigoryev, 2018). In object-based modeling—more commonly referred to as agent-based modeling—researchers make an approach to a system by analyzing the behavior of individual agents. Each object or agent within the system is governed by specific behavioral rules, allowing a comprehensive understanding of the overall system to be constructed. It is essential that the configuration of these objects or agents aligns with existing data or conceptual frameworks established in prior study or derived from other credible data sources.

Agents within a modeling framework may represent various real-world entities such as commodities, transporters, investments, processing times, and more. By assigning distinct behavioral attributes—such as communication behavior—agent-based modeling can yield a diverse range of outcomes. Consequently, careful consideration is required in configuring each

agent and its corresponding behavior. This study employs AnyLogic, a modeling platform built upon a dialect of the Java programming language, to facilitate such configurations.
We design a tool to determine optimal locations for central warehouse in Bali Island, based on CO_2 emission calculations. This study utilizes simulation via AnyLogic to model the underlying business processes. The expected outcome is a detailed calculation of CO_2 emissions from each city or regency appointed as a potential central warehouse's location. The area with the lowest emissions is identified as the most viable candidate for recommendation. This study contributes to incorporating environmental and sustainable development considerations into the decision-making process for an appropriate central warehouse location. This environmental perspective is important given that previous study rely on transportation parameters such as distance, travel time, average speed, and fuel costs.

Several previous studies have provided conceptual frameworks for this study. Ramadhan et al. (2020) used AnyLogic to model the supply chain of Honda automobile commodities. In this business process model, three entities were used: the factory, the warehouse, and the dealership. The simulation method was discrete-event simulation, which was further enhanced with a GIS map to determine the location of entities, and statecharts to model the behavior of each entity. The distribution process, as depicted in the statechart, involved statistical distribution calculations and random number generation to represent stochastic conditions. The study evaluated the performance of the automobile supply chain based on the average time each vehicle spent within the system, marking a development from previous study that assessed performance based on the total distance traveled by the vehicle transport units.

Qian et al. (2017) utilized a combination of life-cycle analysis, carbon emission indices, cost calculations, and linear programming. In their model, the authors estimated carbon emissions from four stakeholders—suppliers, logistics service providers, manufacturers, and distribution centers—considering two types of commodities. Carbon emissions were calculated based on the quantity of goods transported and the distance covered, under the assumption that emission rates per transport unit remained constant. Such an approach is categorized as a deterministic calculation. The study yielded outputs in the form of total logistics costs, incorporating carbon emission costs, transportation costs, and fixed costs. The most cost-efficient scenario involved operating three out of the four planned logistics centers—specifically centers 2, 3, and 4—while center 1 remained non-operational.

This study is a continuation of the model in Gautama et al. (2023), which determined the central warehouse location in Bali Island based on the total traveling distance of the entire transportation fleet during the distribution process. Using a modified GIS map, the study concluded that Mangupura was the most optimal location for the central warehouse due to the minimum of total traveling distance. This study aims to compare the results while we run the model with a CO_2 emissions calculation instead of traveling distance.

RESULT AND DISCUSSION

The primary data used in this study are coordinate points on a GIS map, obtained through field surveys. These points were subsequently filtered, and only the selected points were displayed on the AnyLogic GIS map. This selection process was carried out to prevent the transport units moving in straight lines, which may occur when AnyLogic fails to recognize the provided coordinates. The movement of transport units is expected to follow the road network on the map to better reflect real-world conditions. The GIS map used in this study is shown in Figure 1.

The modeling design begins with the design of simulation scenario. The frequency of orders placed by branches is between one and four times per week. These orders are automatically generated by AnyLogic using a random number facility, rather than a seed-based as in previous studies. The seed method produces a reproducible sequence of random numbers that can be used in other models for comparative purposes. In contrast, with purely random numbers, researchers typically uses replications to obtain average values as output(Borshchev, 2013).

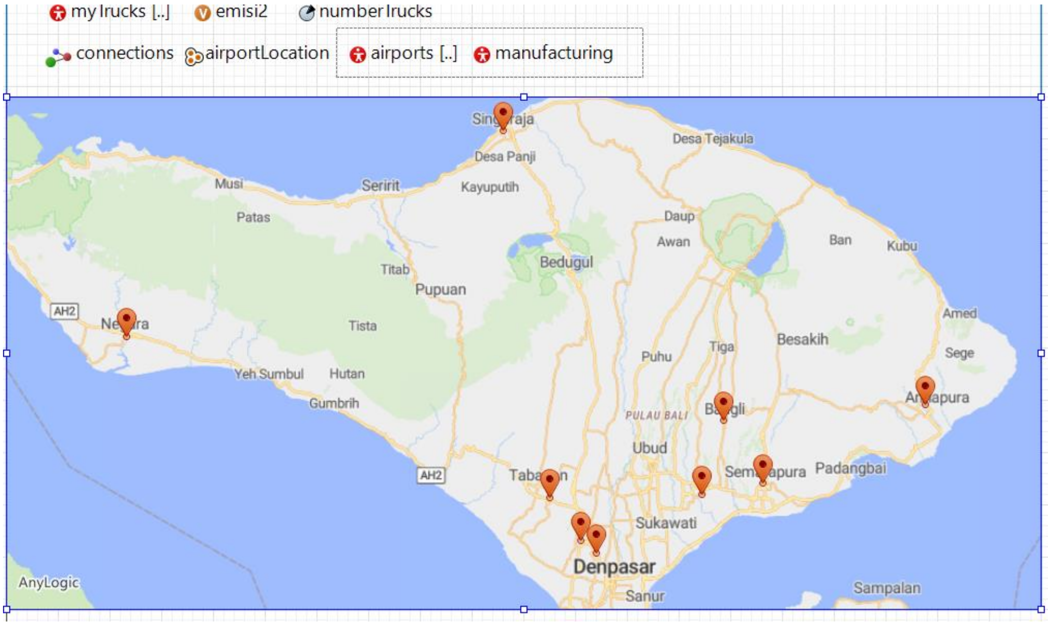

Figure 1. GIS Map of Bali Island

The variables used in the business process are divided into two categories: input and output variables. On the input side, the business process begins when the central warehouse receives orders from each branch, represented by agents which we called *Order*. Upon receiving this order, the central warehouse dispatches a truck unit to the ordering branch. In this business process, an exchange of information occurs at the central warehouse between the *Order* agent and the warehouse's truck agent, ensuring that the truck is directed to the correct branch. The movement of the truck then triggers carbon dioxide (CO_2) emissions. The calculation of CO_2 emissions is based on an estimation that involves the amount of fuel consumed and the corresponding emission factor (Boer et al., 2012). The equation used for calculation of CO_2 exhaust emissions is expressed in equation (1):

$$CO2\ Emission = \sum\nolimits_a \quad BB_a\ Consumption \times FE_a \tag{1}$$

with BB refers to fuel type which is diesel fuel and FE is the emission factor of diesel fuel, while a denotes index. To calculate BBa consumption, we use equation (2):

$$BB_a\ Consumption = consumption\ volume \times heat\ value \tag{2}$$

The volume of diesel fuel consumption in equation (2) can be derived from the travel distance calculated by the model. The consumption volume can then be estimated from number of MPG (miles per galon). Meanwhile, the energy content of diesel fuel (heat value) is set at 0.037 TJ/kL. The emission factor (FE) is based on the default values provided in the 2006 IPCC Guidelines, as shown in Table 1. For diesel fuel, the emission factor is 72,600 kg/TJ for the lower value, 74,800 kg/TJ for the upper value, and a default value of 74,100 kg/TJ. Given that the emission factor is expressed as a range or interval, the calculation of CO_2 emissions no longer follows a deterministic value.

In studies involving deterministic calculations, the default emission factor of 74,100 kg/TJ is commonly used for each truck movement. Therefore, the central warehouse with the farthest location will generate the highest carbon emissions. In this study, due to the random nature of order and the use of a range-based emission factor (FE), the CO_2 emission values will vary.

Table 1.
The Emission Factor of CO_2 in Road Transportation

Fuel type	*Default* (kg/TJ)	*Lower*	*Upper*
Motor Gasoline	69,300	67,500	73,000
Gas/Diesel Oil	74,100	72,600	74,800
Liquefied Petroleum Gases	63,100	61,600	65,600
Kerosene	71,900	70,800	73.700
Compressed Natural Gas	56,100	54,300	58,300
Liquefied Natural Gas	56,100	54,300	58,300

Source: Boer, et al. (2012)

The output data in AnyLogic is calculated through the following steps:

1. Calculation of total travel distance for all truck using the getDistance() function, with the output in kilometers.
2. Conversion from travel distance to diesel fuel volume, based on an estimate of 1 liter per 8 kilometers, equivalent to 18 miles per gallon (Salatigaweb, n.d.; Fitzgerald, 2024). Then we convert this value to consumption volume in kiloliters (kL).
3. Conversion of fuel volume to energy consumption, using heat value of 0.037 TJ/kL. The resulting value represents fuel consumption in terajoule (TJ).
4. CO_2 emission calculation is carried out using Equation (1), with the emission factor (FE) modeled using a triangular distribution. The CO_2 emission values are expressed in kilograms (kg).
5. A total of 9 trucks are available at the central warehouse to serve all branch's order. This setup anticipates the possibility of simultaneous orders from all branches. In previous trials, an error message appeared when orders arrived but no trucks were available, causing the simulation to terminate automatically. The simulation is set to run for a total of 50 days.
6. Order frequency from branches is determined randomly, ranging from a minimum of once to a maximum of four times per week.

Considering the use of random numbers, we conduct repeated simulation runs (replications) with the same parameters over time. A total of 5,000 replications were performed, in accordance with the recommendation by Grigoryev (2018).

The first step is adding a Collection representing the locations of branches and central warehouse which we use in the simulation. This Collection is an ArrayList with the data type of GISPoint. A GISPoint refers to a point on the GIS map, which is a built-in feature in AnyLogic. One of the main advantages of using an ArrayList is its flexibility in size, allowing elements to be added or removed dynamically as needed. The next step was to configure the conditions for each branch unit according to the statechart shown in Figure 2.

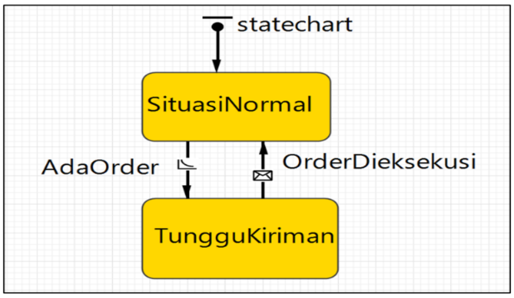

Figure 2. Statechart in every branch

The default condition assigned to each branch is *SituasiNormal*. In this state, each branch awaits the occurrence of a transition (*AdaOrder*), which is triggered randomly between 1 to 4 times per week. Once *TungguKiriman* is reached, the branch waits for the next trigger, *OrderDieksekusi*. This trigger is activated when the central warehouse dispatches a truck, and it arrives at the ordering branch respectively.

This experiment combines discrete-event simulation with agent-based modeling. The agents in this simulation represent trucks, branch locations, and the central warehouse, reflecting real-world entities. A total of nine trucks are deployed to prevent runtime errors. Such errors occur when a branch places an order, but the Central Warehouse is unable to fulfill it due to an insufficient number of trucks. The decision to allocate nine trucks is based on the maximum expected number of orders per day, which is eight, and from the fact that order fulfillment does not require a full day. We integrate carbon emission calculation, by adding a command line as shown in Figure 3, to the truck movement component. The resulting emission values are then accumulated within the Main(). This Main() serves as the parent structure in the AnyLogic model, and equipped with variable named *emisi2*.

```
double
emisi1=2*distanceByRoute(agent.customer)/8*0.037*triangular(72600,
74800,74100)/1000000;

main.emisi2 += emisi1;
```

Figure 3. Code for Emission Calculation

To verify the simulation result, first we have to do the emission calculation manually. The following is a manual calculation example for a scenario in which the branch located in Singaraja—assumed to be 88 km from the central warehouse (Gianyar)—places an order. This example illustrates the CO_2 emissions resulting from a single order by one branch. The first manual calculation, using the minimum value of the triangular distribution (72,600), is as follows:

Emissions = 2 x 88,000 / 8 x 0.037 x 72,600 / 1,000,000
Emissions = 59.09 kg

Using the same method, the emission values for the triangular distribution's mode (74,100) and maximum (74,800) are 60.32 kg and 60.88 kg, respectively.

One of the simulations result in AnyLogic has a total CO_2 emissions of 2,031.07 kg. This result derived when Gianyar is set as the central warehouse location. This value represents the accumulated emissions generated by all trucks fulfilling orders from each branch. A rough verification can be made by assuming the average distance from Gianyar to each branch is 44 km. Thus, the CO_2 emissions from a single round trip would be around 30 kg. If each of the 8 branches places only one order per week, or 7 orders during a 50-day cycle, the lower bound for total CO_2 emissions can be roughly estimated as:

Emissions = 30 kg x 8 x 7 = 1,680 kg of CO_2

For the upper bound, assuming that each branch places 4 orders per week (28 orders per cycle), the estimated emissions are:

Emissions = 30 kg x 8 x 28 = 6,272 kg of CO_2

Based on these rough estimates, the total of 2,031.07 kg falls within the acceptable range between the lower and upper bounds. Subsequent experiments has been done using different central warehouse locations, with each location replicated by as many as 5,000 times. To perform these simulation replications, this study utilized the Parameter Variation feature in AnyLogic. The settings applied are as follows:

1. Random seed is enabled so that each simulation is based on stochastic/random values.
2. Replications are set to a fixed number of 5,000.

The next phase involves performing the same emission calculations using alternative central warehouse locations. The results of all experiments, covering 9 predefined locations in GIS Map, are shown in Table 2.

Table 2.
Result of CO_2 Emission Calculation

Central Warehouse Location	Average CO_2 Emission (kg)
Amlapura	4,781.95
Denpasar	2,822.73
Negara	5,771.37
Tabanan	2,414.87
Semarapura	2,507.11
Bangli	2,448.03
Singaraja	4,263.47
Mangupura	2,335.04
Gianyar	2,285

Based on the simulation results, the selected location with the lowest CO_2 emissions is Gianyar. The conclusion for the central warehouse location in Bali Island varies depending on the scenario applied. Gautama N. W. (2022) employed traveling distance as the primary parameter, using 10 different scenarios (*seed* 1–10) for each location. After 100 days of simulation, the chosen warehouse location was determined as Gianyar. In contrast, Gautama et al. (2023) extended the simulation period to 365 days, also using traveling distance as the key parameter. Under these conditions, the selected central warehouse location was Mangupura.

CONCLUSION

Based on the simulation method for calculating CO_2 emissions, it can be concluded that Gianyar is the most suitable location for the Central Warehouse in Bali Province. Future research may incorporate additional factors such as land rental costs, population density, and travel time to provide a more comprehensive analysis.

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