# An Integrated Inventory Model with Electric Vehicles, Freight Costs, and Stochastic Lead-time

**Ivan Darma Wangsa, Iwan Vanany, and Nurhadi Siswanto**
Department of Industrial and Systems Engineering, Institut Teknologi Sepuluh Nopember,
Surabaya, Indonesia, Kampus ITS,
Sukolilo, 60111, Indonesia
ivan.darma.wangsa.idw@gmail.com, vanany@ie.its.ac.id, siswanto@ie.its.ac.id

## Abstract

In this paper, we study an integrated inventory model for a single-vendor and a single-buyer considering environmental issues. The carbon emissions generated by both parties and involving the third-party logistics (TPL). A TPL collects the product in the vendor's warehouse and sends to the buyer's warehouse using an electric vehicle. The lead-time depends on the time of production, transportation, loading-unloading, and in-transit. We adopt Wangsa et al. (2020)'s algorithm to find the optimal decision variables, i.e., the order quantity, number of shipments, safety factor, lead-time, and total emission quantity. We construct and compare two cases, namely the fossil fuel-equipment based on model of Wangsa et al. (2020) and the electric-powered model in the numerical example section. From the comparison of the result, we conclude that the integrated total cost under the electric-powered is lower than the fossil fuel-equipment with cost saving around 13-14%.

## Keywords
Inventory, Electric Vehicles, Freight Cost, Stochastic Lead-time, and Carbon Emissions.

## 1. Introduction

The issue of climate change has become a highlight issue for countries, academicians, and non-profit organization in various sectors. Carbon emissions are a type of emission resulting from the burning process of fossil fuels and caused the climate change. This impact will affect the sustainability of eco-systems in the next future. In the Industry 4.0 era, various technologies have developed, such as electric vehicles (EVs), drone, and robotic technology, which have helped many people do work. Unlike conventional vehicles that still use fossil fuels, the types of EVs (trucks, vans, and motorbikes) that use electric-powered are environmentally friendly (low emissions). The disadvantage of using EVs is the very high initial investment cost for the fleet (Bahnke, 2019). In addition, due to EVs have to recharge and need to visit the charging stations and the actual shipping weight is smaller (Breunig et al., 2019).

Recently, some researchers have investigated the inventory management considers the environmental and carbon emission cost. Wangsa (2017) investigated the impact of carbon penalty and incentive on vendor-buyer inventory model. Tiwari et al. (2018) developed a vendor-buyer inventory model considering carbon emissions, deteriorating and imperfect quality items. Jauhari et al. (2018) investigated the impact of stochastic demand, defective items, and carbon emissions cost on a two-echelon inventory model. Daryanto et al. (2019) examined a three-echelon inventory model considering emissions from the transportation, warehousing, and disposal activities. A two-echelon inventory considering GHG emissions, energy usage, and imperfect production was studied by Marchi et al. (2019). Wangsa et al. (2020) investigated the emissions impact of the production, transportation, and warehousing activities on a single-vendor and a single-buyer system with considers the freight cost and stochastic lead-time. Green technology strategy to reduce carbon emission can be seen the researchers such as Datta (2017) and Huang et al. (2020). Several studies for modeling EVs can be seen in Schneider et al. (2014) and Breunig et al. (2019). Based on the best of our knowledge, in the literature review some of EVs models are still limited to the two-echelon vehicle routing problems (VRP).

The integrated inventory model for vendor-buyer supply chain system with EVs has not been studied comprehensive in the previous study. In reality, the impact of EVs should be considered by the model due to the environmental concern and including lot quantity, lead-time, carbon emissions, actual shipment, number of shipments, and safety factor. We extend the freight cost model of Wangsa et al. (2020) by considering EVs as a freight cost using electricity costs. Since we considered EV's in our proposed model, we modified the buyer's emission of Wangsa et al. (2020). The main objective of the proposed model is to reduce carbon emissions, lead-time, and total cost.

## 2. Notations and Assumptions

**Decision variables:**

$Q$ = lot quantity (units);
$m$ = the number of shipments (times);
$k$ = safety factor (times);
$L(Q)$ = total lead-time (days);
$TE(Q,m)$ = total carbon emission quantity (ton $CO_2$).

The following **notations** are used in this paper:

| Parameter | Description |
|---|---|
| $D$ | Demand rate of the product (units/year) |
| $\sigma$ | Demand standard deviation (units/year) |
| $A$ | Ordering costs ($) |
| $h_{b1}$ | In-house holding cost ($/unit/year) |
| $h_{b2}$ | In-transit holding cost ($/unit/year) |
| $\pi$ | Backorder cost ($/unit) |
| $C_{GHG}$ | Carbon emission cost ($/ton $CO_2$) |
| $\Delta_{b1}$ | Buyer's indirect emission factor (ton $CO_2$/liter) |
| $\Delta_{b2}$ | Buyer's direct emission factor (ton $CO_2$/lb) |
| $F_x$ | The freight rate for a full truckload (FTL) ($/lb/mile) |
| $F_y$ | The freight rate for a less-than-truckload (LTL) ($/lb/mile) |
| $w$ | Weight of a product(lbs/unit) |
| $\theta$ | The surcharge cost per shipment for the pick-up policy ($) |
| $W_x$ | The shipping weight of a full truckload (FTL) (lbs) |
| $W_y$ | Actual shipping weight (lbs) |
| $\alpha$ | Discount factor for LTL shipments, $0 \leq \alpha \leq 1$ |
| $t_s$ | In-transit time (years) |
| $\delta$ | Worldwide diesel fuel price($/liter) |
| $\tau$ | Electricity cost ($/kWh) |
| $d_v$ | Distance from the vendor to TPL (miles) |
| $d_b$ | Distance from the TPL to buyer (miles) |
| $d_f$ | Distance from the shipping and receiving facilities to a vehicle (miles) |
| $v_t$ | Average speed of the vehicle (mph) |
| $\gamma_{t1}$ | Fuel consumption of a vehicle (liters/mile) |
| $\gamma_{t2}$ | Electricity consumption of the electric truck (kWh/hr) |
| $c_f$ | Forklift load capacity (lbs) |
| $v_f$ | Forklift travelling speed (mph) |
| $\gamma_{f1}$ | Fuel consumption of the forklift (liters/hour) |
| $\gamma_{f2}$ | Electricity consumption of the electric forklift (kWh/hr) |
| $P$ | Production rate (units/year) |
| $S$ | Setup cost ($) |
| $h_v$ | Vendor's holding cost ($/unit/year) |
| $e_{co}$ | Electricity energy consumption (Kwh) |
| $s_{co}$ | Steam energy consumption (Kwh) |
| $h_{co}$ | Heating energy consumption (Kwh) |
| $c_{co}$ | Cooling energy consumption (Kwh) |
| $L_r$ | Energy loss rate (%) |
| $\Delta_{v1}$ | Vendor's indirect emission factor (ton $CO_2$/Kwh) |

| Parameter | Description |
|---|---|
| $\Delta_{v2}$ | Vendor's direct emission factor (ton $CO_2$/unit) |
| $ITEC(Q,k,m)$ | Integrated total electric-powered cost ($/year) |

The following **assumptions** are used in our model which are the same as those in Wangsa et al. (2020):

1. The observed system consists of a single vendor-buyer system considering a TPL.
2. The demand is assumed follows a normal distribution with mean and standard deviation.
3. The vendor produces the product with a limited production and higher than buyer's demand.
4. This model is not considered visits to charging station.
5. The linear distance is assumed as total distance of the firms.

## 3. Model Formulation

### 3.1 Total Lead-time Function

We assume the lead-time is stochastic and dependent on the order size $(Q)$. The buyer orders a lot size of $Q$ to the vendor and adopts the pickup policy with incorporates the TPL. Based on the policy, the buyer will request to the TPL to pick the items and delivers to the buyer with the transportation time by the truck. After receiving request to pick from the buyer, the items will be handled by the forklift and calculates the material handling time. The lead-time consists of the production time, material handling time, transportation time and in-transit time (Wangsa et al., 2020).

$$L(Q) = \frac{Q\left(c_f v_f + 4Pwd_f\right)}{Pc_f v_f} + \frac{(2d_v + d_b)}{v_t} + t_s \tag{1}$$

### 3.2 Total Carbon Emission Function

By adopting the carbon emission model of Wangsa et al. (2020), the vendor, TPL, and the buyer emit the carbon emissions. The emissions are classified into the production emission, warehouse emission, and transportation emission. The emissions are also classified to indirect and direct emissions (Wangsa, 2017 and Wangsa et al., 2020).

$$TE(Q,m) = \Delta_{b1}\left[\gamma_{t1}(2d_v + d_b) + \frac{4\gamma_{f1}d_f}{v_f}\right] + \Delta_{b2}wQ + \Delta_{v1}(e_{co} + s_{co} + h_{co} + c_{co})L_r + \Delta_{v2}mQ \tag{2}$$

The above formulation indicates that there are many practical impacts of the equipment (the truck and forklift) fuel-based on the total emission quantity in the real world (Wangsa et al., 2020). In recent year, the electric-powered equipment has evolved to address the increasing worldwide diesel fuel costs and stricter GHG emissions from the transportation and warehousing. To evaluate the long-term impact then the electric equipment does not generate any harmful emissions into the air. Therefore, the Eq. (2) can be modified:

$$TE(Q,m) = \Delta_{b2}wQ + \Delta_{v1}(e_{co} + s_{co} + h_{co} + c_{co})L_r + \Delta_{v2}Qm \tag{3}$$

### 3.3 Buyer's Total Cost Function with Fossil-fuel Equipment

The buyer's total cost includes the ordering $(OC_b)$, shortage $(SC_b)$, in-house holding cost $(IHC_b)$, in-transit holding cost $(THC_b)$, surcharge cost $(PC_b)$, material handling cost $(LUC_{b1})$, freight cost $(LC_{b1})$, and carbon emission cost $(CE_{b1})$. The buyer's total cost function based on fossil-fuelled equipment (Wangsa et al., 2020):

$$TC_{b1}(Q,k) = \frac{D\begin{bmatrix} A + \theta + \pi\sigma\psi(k)\sqrt{L(Q)} + h_{b2}Qt_s \\ +(2d_v + d_b)[\alpha F_x W_x + \gamma_{t1}(\delta + \Delta_{b1}C_{GHG})] + \dfrac{4\gamma_{f1}d_f(\delta + \Delta_{b1}C_{GHG})}{v_f} \end{bmatrix}}{Q} + h_{b1}\left[\frac{Q}{2} + k\sigma\sqrt{L(Q)}\right] + D[(1-\alpha)F_x w(2d_v + d_b) + \Delta_{b2}wC_{GHG}] \tag{4}$$

### 3.4 Buyer's Total Cost Function with the Electric-powered Equipment

In this subsection, we improve the previous model with considers the electric-powered for the electric equipment (the truck and forklift). The buyer's total cost includes the ordering cost, shortage cost, in-house holding cost, in-transit holding cost, surcharge cost, material handling cost for the electric forklift $(LUC_{b2})$, freight cost for the electric truck $(LC_{b2})$, and buyer's direct carbon emission cost. Therefore, the buyer's total cost function based on electric-powered equipment is given by:

$$TC_{b2}(Q,k) = \frac{D\left[A+\theta+\pi\sigma\psi(k)\sqrt{L(Q)}+h_{b2}Qt_s+(2d_v+d_b)\left(\alpha F_x W_x+\frac{\tau\gamma_{t2}}{v_t}\right)+\frac{4\gamma_{f2}d_f\tau}{v_f}\right]}{Q} + h_{b1}\left[\frac{Q}{2}+k\sigma\sqrt{L(Q)}\right]+D[(1-\alpha)F_x w(2d_v+d_b)+\Delta_{b2}wC_{GHG}] \tag{5}$$

### 3.5 Vendor's Total Cost Function

During production process, the vendor produces a batch size of $mQ$ and delivers equally to the buyer. The vendor's average inventory level can be determined by subtracting accumulated consumption of the buyer from the vendor's accumulated production. The vendors' inventory per unit time is given by:

$$I_v(Q,m) = \frac{\left[mQ\left(\frac{Q}{P}+(m-1)\frac{Q}{D}\right)-\frac{m^2Q^2}{2P}\right]-\left[\frac{Q}{D}\left(1+2+\cdots+(m-1)\right)Q\right]}{mQ/D} \tag{6}$$

$$I_v(Q,m) = \frac{Q}{2}\left[m\left(1-\frac{D}{P}\right)-1+\frac{2D}{P}\right]$$

The vendor's total cost per unit time including the holding cost $(HC_v)$, setup cost $(OC_v)$, and indirect and direct carbon emission cost $(CE_v)$ is given below:

$$TC_v(Q,m) = HC_v + OC_v + CE_v \tag{7}$$

$$TC_v(Q,m) = \frac{h_vQ}{2}\left[m\left(1-\frac{D}{P}\right)-1+\frac{2D}{P}\right]+\frac{D[S+\Delta_{v1}(e_{co}+s_{co}+h_{co}+c_{co})L_rC_{GHG}]}{Qm}+D\Delta_{v2}C_{GHG}$$

### 3.6 Integrated Electric-powered Total Cost Function

Integrated electric-powered total cost formulation for a single-vendor and a single-buyer system with freight forwarder can be determined by adding of the buyer's total cost with the electric equipment (Eq. 5) and the vendor's total cost (Eq. 7) which is given by:

$$\begin{aligned}\text{Min } & IETC(Q,k,m) \\ &= \frac{D}{Q}\left[A+\theta+\pi\sigma\psi(k)\sqrt{L(Q)}+h_{b2}Qt_s+(2d_v+d_b)\left(\alpha F_xW_x+\frac{\tau\gamma_{t2}}{v_t}\right)+\frac{4\gamma_{f2}d_f\tau}{v_f}\right. \\ &\qquad \left.+\frac{[S+\Delta_{v1}(e_{co}+s_{co}+h_{co}+c_{co})L_rC_{GHG}]}{m}\right]+h_{b1}k\sigma\sqrt{L(Q)} \\ &\qquad +\frac{Q}{2}\left\{h_{b1}+h_v\left[m\left(1-\frac{D}{P}\right)-1+\frac{2D}{P}\right]\right\} \\ &\qquad +D[(1-\alpha)F_xw(2d_v+d_b)+(\Delta_{b2}w+\Delta_{v2})C_{GHG}]\end{aligned} \tag{8}$$

### 3.7 Solution Methodology

The integrated electric-powered total cost in Eq. (8) is formulated as a function of $(Q,k,m)$. First, for fixed of $m$, the partial derivatives of Eq. (8) with respect to $(Q,k,m)$ and by setting the result to zero then the formulations are shown below:

$$Q^* = \left[ \frac{2D \left\{ \begin{array}{c} A + \theta + (2d_v + d_b)\left(\alpha F_x W_x + \frac{\tau\gamma_{t2}}{v_t}\right) + \frac{4\gamma_{f2} d_f \tau}{v_f} \\ + \frac{[S + \Delta_{v1}(e_{co} + s_{co} + h_{co} + c_{co}) L_r C_{GHG}]}{m} - \pi\sigma\psi(k)\left[\frac{Q\left(c_f v_f + 4Pwd_f\right)}{2Pc_f v_f \sqrt{L(Q)}} - \sqrt{L(Q)}\right] \end{array} \right\}}{\frac{h_{b1} k\sigma\left(c_f v_f + 4Pwd_f\right)}{Pc_f v_f \sqrt{L(Q)}} + \left\{h_{b1} + h_v\left[m\left(1 - \frac{D}{P}\right) - 1 + \frac{2D}{P}\right]\right\}} \right]^{1/2} \quad (9)$$

$$\Phi(k^*) = 1 - \frac{Q h_{b1}}{D\pi} \quad (10)$$

To solve the above problem and find the optimal solutions, an algorithm is adapted based on Wangsa et al. (2020).

## 4. Results and Discussion

Let us consider the data for numerical example used in Wangsa et al. (2020) and they are divided into three parts: **General data:** $D$ = 10,000 units/year; $P$ = 60,000 units/year; $\sigma$ = 300 units/year; $A$ = \$50; $S$ = \$1400; $h_{b1}$ = \$10/unit/year; $h_{b2}$ = \$1/unit/year; $h_v$ = \$3/unit/year; $\pi$ = \$200/unit; $F_x$ = \$0.000040217/lb/mile; $w$ = 22 lbs/mile; $\theta$ = \$14; $W_x$ = 46,000 lbs; $\alpha$ = 0.11246; $t_s$ = 1 day; $\tau$ = \$0.10/kWh; $v_t$ = 20 miles/hr; $\gamma_{t2}$ = 6 kWh/hr; $c_f$ = 3300 lbs; $v_f$ = 6 miles/hr; $\gamma_{f2}$ = 2.092 kWh/hr. **Emission data:** $C_{GHG}$ = \$10/ton $CO_2$; $r$ = 0.20/\$/year; $a$ = 3500; $\Delta_{b2}$ = 0.00250-ton $CO_2$/lb; $\Delta_{v1}$ = 0.02264-ton $CO_2$/kWh; $\Delta_{v2}$ = 0.00965-ton $CO_2$/unit; $e_{co}$ = 154,556 kWh; $s_{co}$ = 115,917 kWh; $h_{co}$ = 38,639 kWh; $h_{co}$ = 77,278 kWh; $L_r$ = 1%. **Distance data:** $d_v$ = 50 miles; $d_b$ = 600 miles; $d_f$ = 0.015 miles.

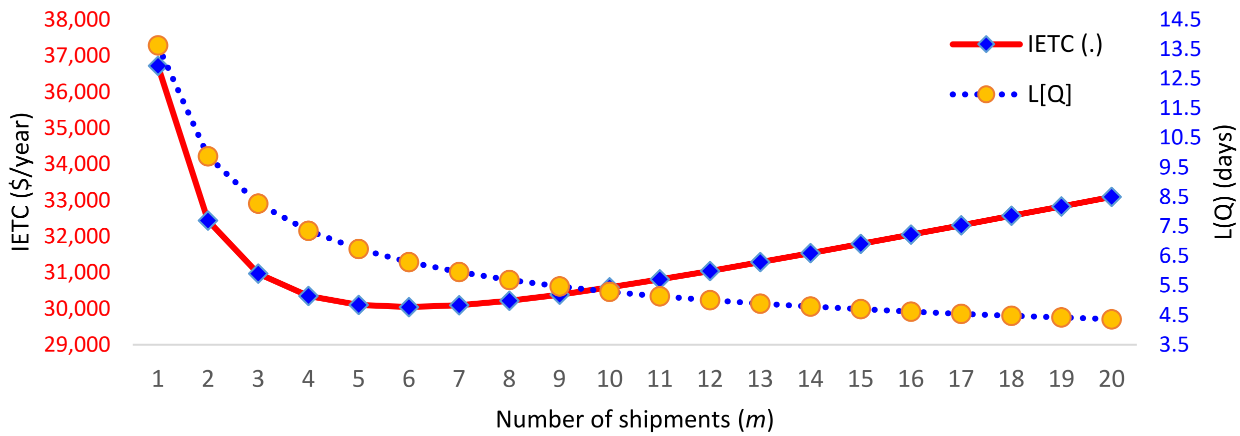


Figure 1. Graphical representation of total cost and lead-time with respect to number of shipments ($m$)

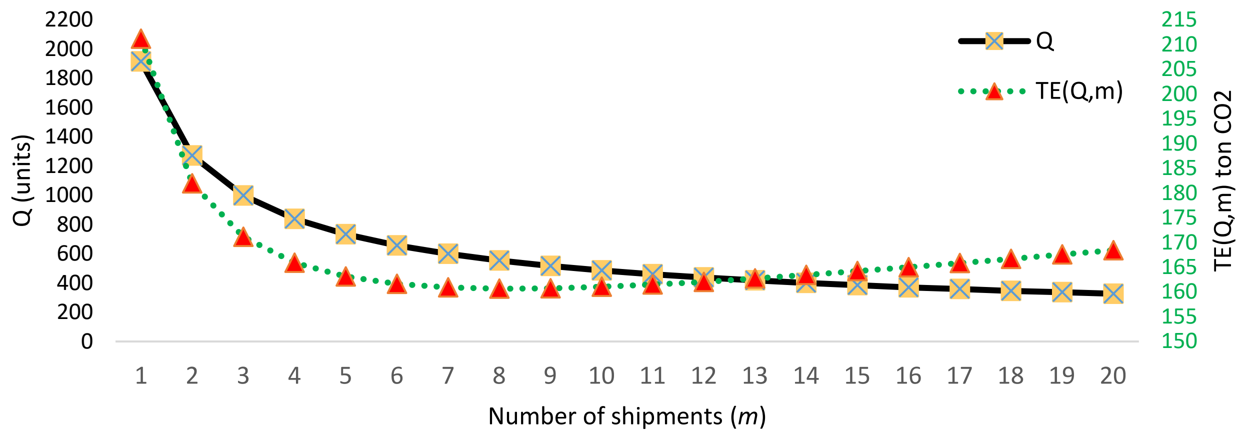


Figure 2. Graphical representation of total emission and order quantity with respect to number of shipments (*m*)

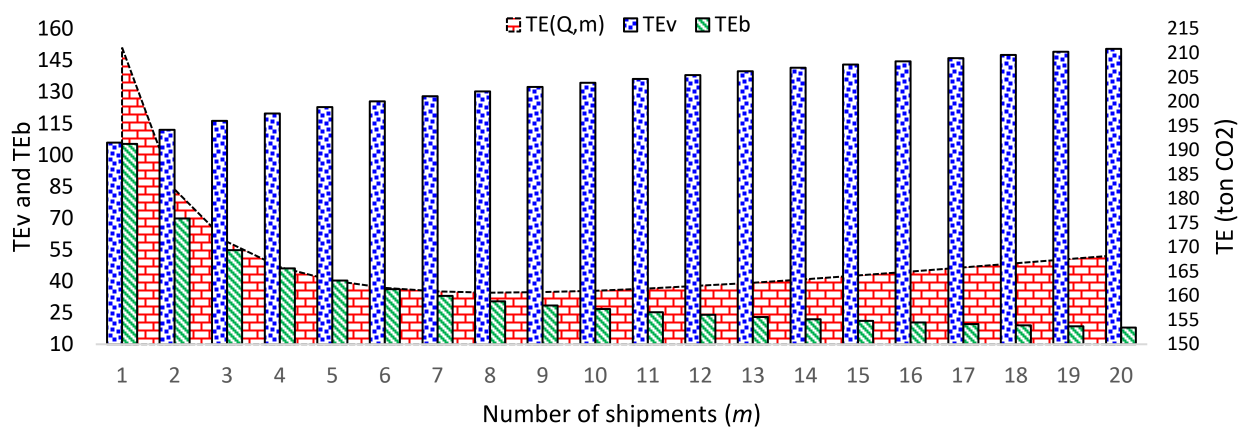


Figure 3. Total emission with respect to number of shipments (*m*)

Figure 1 represents that the optimal of $IETC(\cdot)$ when $m^* = 6$ (red line) and the lead-time decreases (blue dot-line) as the number of shipments decreases. Figure 2 shows that the optimal total emission $TE(Q^*, m)$ at point $m^* = 8$ (green line) and the $(Q^*)$, black line, decreases as the parameter $m$ increases. Figure 3 portrays that the vendor's total emission $TE_v(Q^*, m)$ increases as the parameter $m$ increases which is influenced by the optimal vendor's batch size, $(Q^*m)$. The buyer's total emission $TE_b(Q^*)$ decreases as the number of shipments increases. The results show that $Q^* = 656.89$ units, $k^* = 2.72$, $W_y^* = 14{,}451.54$ lbs., $m^* = 6$ times, $[L(Q^*)] = 6.29$ days, $TE_v(Q^*, m^*) = 125.51$-ton $CO_2$ and $TE_b(Q^*) = 36.13$-ton $CO_2$ with the $IETC(\cdot) = \$30{,}043.03$/year.

Table 1. The comparison of the results

| | **Fossil-fuel cost model (Wangsa et al., 2020)** | **Proposed model (electric-powered cost)** |
|---|---|---|
| Order quantity (units) | 1,371.18 | 656.89 |
| Actual shipping weight (lbs.) | 30,165.95 | 14,451.54 |
| Safety factor (times) | 2.46 | 2.72 |
| Number of shipments (times) | 3 | 6 |
| Lead-time (days) | 10.46 | 6.29 |
| Vendor' total emission (ton CO2) | 127.17 | 125.51 |
| Buyer's total emission (ton CO2) | 81.06 | 36.13 |

| | **Fossil-fuel cost model (Wangsa et al., 2020)** | **Proposed model (electric-powered cost)** |
|---|---|---|
| **Total emission (ton CO2)** | **208.23** | **161.64** |
| Vendor' total cost ($/year) | 10,265.74 | 11,006.40 |
| Buyer' total cost ($/year) | 24,579.49 | 19,036.63 |
| **Integrated total cost ($/year)** | **34,845.23** | **30,043.03** |

We compare and analyze the results of the proposed model and the results of the fossil-fuel based on that is developed by Wangsa et al. (2020). In this comparative analysis, assuming some of the data, the fuel price $1.02/liter, the fuel consumption of the truck = 0.63569 liters/mile, and the fuel consumption of the forklift = 3 liters/hr. In Table 1, the proposed model provides a lower emissions 46.660-ton $CO_2$ (22.38%), lead-time 4.17 days (39.86%) and saving cost by $4,802.20/year (13.79%).

## 6. Conclusion

This paper presents a sustainable integrated inventory for a two-echelon by considering EVs. The emission quantity can be reduced by considering EVs and this will affect on the lot size. From the numerical example, we can obtain the amount of cost saving ranging from 13% to 14% and the amount of significant emission reduction around 22% to 23%. The model can be developed further by investigating the investment of the green technology and considering the drone for the last mile.

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## Biographies

**Ivan Darma Wangsa** is a first-year Ph.D. student in the Department of Industrial and Systems Engineering at the Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia. Ivan D. Wangsa has 10 years of work experience and consulting in HSSE Department at the State-owned Enterprise of Indonesia. His doctoral is focused on investigates the inventory models on the last-mile logistic systems. He received B.Eng. in Industrial Engineering at the Universitas Islam Indonesia (UII) in Indonesia. He obtained his M.Sc. degree in Industrial Engineering and Management from the Institut Teknologi Bandung (ITB) in Indonesia. He also holds Certified Professional in Logistics Management (CPLM) from ISCEA (USA) and Certified Associates in Supply Chain (CASC) from ISCQA. His research interests include inventory modeling, logistics and supply chain management, sustainable management, and safety engineering. He can be contacted at ivan.darma.wangsa.idw@gmail.com.

**Iwan Vanany** is a Professor in the Department of Industrial and Systems Engineering at Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia. His research interests are in food supply chain management, business process management, and halal operations dan supply chain. He has published in International *Journal of Information System and Supply Chain Management*, *Meiji Business Journal*, *Supply Chain Forum: An International Journal, International Journal Logistics Systems and Management*, *Journal of Islamic Marketing*, *International Journal of Lean Six Sigma*, *British Food Journal*, and *Food Control*. He teaches business process reengineering, supply chain management, enterprise resources planning (ERP), logistics system, productions and planning control, transportation, and warehouse management, and purchasing management. He can be contacted at vanany@ie.its.ac.id.

**Nurhadi Siswanto** is a faculty member and the Head of Department of Industrial and Systems Engineering at Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia. He earned his bachelor's degree in Industrial Engineering from Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia, a master's degree in industrial engineering from Purdue University, West Lafayette, IN, USA and a PhD from University of New South Wales, Canberra, Australia. His research interests include operation research, large-scale optimization, simulation, vehicle routing, inventory routing and modeling of maritime transportation. He has taught courses in Operations Research, Decision Analysis, Discrete Event Simulation, Simulation Modeling and Quantitative Modeling. He can be contacted at siswanto@ie.its.ac.id.