# Impact of Electric Trucks and Setup Cost Reduction Investment on a Two-tier Supply Chain

**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

This research develops a joint optimization model for a two-tier supply chain by involving a manufacturer and a retailer. We investigate the impact of investment in setup cost reduction and electric-powered equipment such as electric forklifts and trucks on the joint total cost. $CO_2$ emissions are produced by both parties and transportation activities involving a logistics provider. The products at the manufacturer's warehouse are collected by a logistic provider and delivered to the retailer's warehouse by using the electric truck. We consider the lead-time that depends on the production time, transportation time, material handling time, and in-transit time. The goal is to minimize the joint total cost, which is to obtain the decision variables, such as the lot size, factor of safety, and the number of batches. A numerical example is provided to demonstrate the application of the proposed model. The result shows that the proposed model compared with Wangsa et al. (2020) can significantly affect cost-saving, increase service level, short lead-time, and reduce carbon emissions levels by 24.42%; 0.36%; 41.03%; and 29.41%, respectively.

## Keywords
Two-tier supply chain, electric vehicles, setup cost reduction, stochastic lead-time, and carbon emissions.

## 1. Introduction
In the last decade, research on sustainability issues has grown rapidly in various countries. One of them is the problem of greenhouse gas emissions. The greenhouse gas that has the greatest impact on air quality is carbon emissions, one of which is carbon dioxide ($CO_2$) emissions. This pollutant is a greenhouse gas that is a major cause of global warming and climate change. Recently, climate change that has occurred is the effect of global warming caused by the increase in greenhouse gases in the atmosphere. Global warming now has clear evidence of natural damage and disasters that have hit various parts of the world, including degradation, hail, floods, earthquakes, and tsunamis. These impacts will affect the sustainability of ecosystems in the future. In the era of Industry 4.0, a variety of emerging technologies, such as electric vehicles, drones, and robotics have emerged to help many people work. Unlike traditional vehicles that still use fossil fuels, the types of electric vehicles (trucks, vans, and motorcycles) that run on electricity are environmentally friendly (low emissions). The disadvantage of using an electric vehicle is the very high initial investment cost of the equipment (Bahnke, 2019). In addition, the electric vehicle needs to be recharged and the charging station needs to be visited, resulting in lower actual shipping weight (Breunig et al., 2019). Lead-time is one concern for coordinating in the supply chain system between a supplier and a retailer. Lead time and setup cost reductions are key business parameters, as order size, service levels, and $CO_2$ emissions are directly or indirectly affected by this concern. In practice, setup costs investment can be reduced by training workers, changing procedures, and purchasing special equipment (Tiwari et al., 2018b).

Currently, almost all activities that occur in the supply chain area (such as storage, production, and transportation) have an impact on carbon emissions (Benjafaar et al., 2012). However, transportation activities produce the most carbon emissions among other activities (The US EPA, 2021). Several researchers have studied inventory control with the costs of carbon emission. Wangsa (2017) studied the effect of penalties incentives of carbon for a single vendor-buyer system. Tiwari et al. (2018a) modeled an integrated inventory model that considers carbon emissions, deterioration of items, and product defects. An integrated production-inventory model to reduce controllable lead times, order costs, and setup costs was developed by Tiwari et al (2018b). The effect of probabilistic demand, reject products, and costs of carbon emission on an integrated inventory model was investigated by Jauhari et al. (2018). Daryanto et al. (2019) investigated a three-tier supply chain model that considers the emissions from multi-activities such as transport, storage, and disposal. A two-echelon inventory model by considers greenhouse gas emissions, energy consumption, and production defects was carried out by Marchi et al. (2019). Finally, Wangsa et al. (2020) formulated an integrated inventory model by considering the emissions of production, transportation, and storage activities for a single-vendor and a single-buyer system as well as considering transportation costs and stochastic lead-time. The model considers the diesel truck mode from a single vendor to a single buyer. Sarkar et al. (2015a) developed an EOP/EPQ model by considering the probabilistic demand, quality improvements, reduced setup costs, and service level constraints. Then, Sarkar et al. (2015b) developed a JELS model involving setup costs reduction and unequal lot sizes. An integrated lot size model for the imperfect production process by considering the quality improvement and setup cost reduction was developed by Guchhait et al. (2020). Tiwari et al. (2020) extended model of Tiwari et al. (2018b) considers inspection errors and backorder discounts. Green technology strategies to reduce CO2 emissions were included by Datta (2017) and Huang et al (2020). Some electric vehicle modeling studies are still limited to the vehicle routing problem such as the study of Schneider et al. (2014) and Breunig et al. (2019).

To solve this problem, we proposed a two-echelon supply chain integrated inventory model with a single manufacturer and a single retailer system that considers electric trucks and accommodates investments to reduce setup costs. As far as we know, the impact of reducing electric vehicles and setup costs on total cost has not been extensively considered in previous studies. By extending the model of Wangsa et al. (2020) considering transportation costs are still based on fossil fuels, the main objective of this study is to reduce $CO_2$ emissions, lead time, and total costs as well as improve customer service levels. The difference between the proposed model, Wangsa et al. (2020), Guchhait et al. (2020), and Tiwari et al. (2020) is shown in Table 1.

Table 1. The comparison of the model

| **Characteristic** | **Guchhait et al. (2020)** | **Tiwari et al. (2020)** | **Wangsa et al. (2020)** | **This study** |
|---|---|---|---|---|
| System | Two-echelon | Two-echelon | Two-echelon | Two-echelon |
| Carbon emissions | No | No | Yes | Yes |
| Lead-time | No | Controllable | Stochastic | Stochastic |
| Optimum service level | No | No | No | Yes |
| Setup cost reduction | Yes | Yes | No | Yes |
| Transportation mode | Not considered | Not considered | Diesel truck | Electric truck |

## 2. Notations and Assumptions

In this section, we present the notations (decision variables, dependent variable, objective function, and parameters) and assumptions used in this study.

**Decision variable:**

$Q$ = lot size (units)
$m$ = number of batches (times)
$k$ = safety factor (times)
$S$ = setup cost ($)

**Dependent variable:**

$W_y$ = Total shipping weight (kg)
$SL$ = Service level (%)
$L(Q)$ = lead-time (days)
$TE(Q,m)$ = total carbon emission (ton $CO_2$)

**Objective function:**

$ITC(Q,k,S,m)$ = Integrated total cost ($/year).

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

| **Parameter** | **Description** |
|---|---|
| $D$ | Average of demand (units/unit-time) |
| $\sigma$ | Standard deviation of demand (units/unit-time) |
| $A$ | Cost of ordering ($) |
| $h_{r1}$ | Holding cost of in-house ($/unit/year) |
| $h_{r2}$ | Holding cost of in-transit ($/unit/year) |
| $\pi$ | Cost of shortage ($/unit) |

| **Parameter** | **Description** |
|---|---|
| $C_{GHG}$ | The cost of carbon (\$/ton $CO_2$) |
| $\Delta_r$ | Retailer's emission factor (ton-$CO_2$/kg) |
| $F_x$ | Freight rate for a FTL (\$/kg/km) |
| $F_y$ | Freight rate for an LTL (\$/kg/km) |
| $w$ | Weight of product (kg/unit) |
| $\theta$ | Additional cost per delivery (\$) |
| $W_x$ | Shipping weight of a FTL (kg) |
| $\alpha$ | Discount factor for LTL shipments, $0 \leq \alpha \leq 1$ |
| $t_s$ | Time of in-transit (unit-time) |
| $\tau$ | Cost of electricity (\$/kWh) |
| $d_v$ | Distance of a single manufacturer – a single provider (km) |
| $d_b$ | Distance of a single provider – a single retailer (km) |
| $d_f$ | Distance of material handling facilities (km) |
| $v_t$ | Electric truck speed (mph) |
| $\gamma_t$ | Electricity consumption of the truck (kWh/hr.) |
| $c_f$ | Load capacity of the electric forklift (kg) |
| $v_f$ | Speed of the electric forklift (mph) |
| $\gamma_f$ | Forklift electricity consumption (kWh/hr) |
| $P$ | Rate of production (units/year) |
| $S_0$ | Initial setup cost (\$) |
| $h_m$ | Holding cost of manufacturer (\$/unit/year) |
| $e_{co}$ | Consumption of electricity (kWh) |
| $s_{co}$ | Consumption of steam (kWh) |
| $h_{co}$ | Consumption of heating (kWh) |
| $c_{co}$ | Consumption of cooling (kWh) |
| $Y$ | Annual fractional cost of capital investment (/\$/unit-time) |
| $I(S)$ | Capital investment in setup cost reduction (\$) |
| $\xi$ | The percentage decrease in $S$ per dollar increase in $I(S)$ |
| $L_r$ | Loss rate of energy (%) |
| $\Delta_{m1}$ | 1st manufacturer's emission factor (ton $CO_2$/kWh) |
| $\Delta_{m2}$ | 2nd manufacturer's emission factor (ton $CO_2$/unit) |

The following **assumptions** are used in our model:

1. The system consists of a single manufacturer and a single retailer with a provider.
2. This study assumes a normal distribution of retailer demand with the mean and standard deviation.
3. The manufacturer produces the product with limited production and higher than the retailer's demand.
4. The electric truck in this model is not considered a visit to the charging station.
5. Linear distance is assumed to be the total distance of the companies.
6. The capital investment $I(S)$ in reducing the manufacturer's setup cost is a logarithmic function of the setup cost, $S$. That is, $I(S) = B \ln\left(\frac{S_0}{S}\right)$ for $0 < S \leq S_0$ where $B = \frac{1}{\xi}$. (Sarkar et al., 2015a; 2015b; Guchhait et al., 2020; Tiwari et al., 2018b; 2020).

## 3. Model Formulation

### 3.1 Total Lead-time Function

Firstly, we formulate a stochastic lead-time that depends on the retailer's lot size $(Q)$. The retailer orders a lot size of $Q$ to the manufacturer and applies a pickup policy with involves the logistics provider. The policy requires the provider to ask the manufacturer to pick the goods and sends to the retailer with the time of transport by the electric truck mode with total distance, $\rho = (2d_v + d_b)$. Then, the retailer warehouse receives the goods and immediately handles it with a forklift and calculates the material handling time. This study considers the stochastic lead-time which consists of production time, material handling time, transportation time, and transit time (Wangsa et al., 2020).

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

## 3.2 Total Carbon Emission Function

Second, in modeling carbon emissions for this study, we use the carbon emission model developed by Wangsa et al. (2020). Carbon emissions are emitted from the production process at the manufacturer and inventory at a retailer. In this study, we have considered electric trucks and forklifts (zero emission). Therefore, the formulation of total carbon emissions is as follows:

$$TE(Q,m)=\Delta_r wQ+\Delta_{m1}(e_{co}+s_{co}+h_{co}+c_{co})L_r+\Delta_{m2}Qm \tag{2}$$

## 3.3 Total Cost Function

In this subsection, we formulate the total cost of the retailer, manufacturer, and joint total costs. The average inventory level at retailer and safety stock are $\frac{Q}{2}+k\sigma\sqrt{L(Q)}$, respectively, then the expected holding cost for the retailer per year is given by $h_{r1}\left[\frac{Q}{2}+k\sigma\sqrt{L(Q)}\right]$. The expected of the number of shortages for the retailer per year can be formulated by considering the replenishment per year, $D/Q$, the number of shortages, $\sigma\psi(k)\sqrt{L(Q)}$, therefore the expected shortage cost is given by $D/Q\left(\pi\sigma\psi(k)\sqrt{L(Q)}\right)$. Next, we consider transportation cost and material handling by considering the electric vehicle and electric forklift. The transportation cost and material handling cost per year are $D/Q\left[\rho\left(\alpha F_x W_x+\frac{\tau\gamma_t}{v_t}\right)\right]+D(1-\alpha)F_x w(2d_v+d_b)$ and $D/Q\left(4\gamma_f d_f\tau/v_f\right)$, respectively. Here, we also consider the carbon emissions resulted from warehouse activity at retailer. The carbon emission is given by $D\Delta_{b2}wC_{GHG}$. Thus, the retailer's total cost function based on electric-powered equipment consisting of the cost of ordering $(OC_r)$, cost of shortage $(SC_r)$, holding cost of in-house $(IHC_r)$, holding cost of in-transit $(THC_r)$, additional cost $(PC_r)$, material handling cost for the electric forklift $(LUC_r)$, transport cost for the electric truck $(LC_r)$, and retailer's direct carbon emission cost $(CE_r)$ is given by:

$$\begin{aligned}TC_r(Q,k)=&\frac{D\left[A+\theta+\pi\sigma\psi(k)\sqrt{L(Q)}+h_{r2}Qt_s+\rho\left(\alpha F_x W_x+\frac{\tau\gamma_t}{v_t}\right)+\frac{4\gamma_f d_f\tau}{v_f}\right]}{Q}\\&+h_{r1}\left[\frac{Q}{2}+k\sigma\sqrt{L(Q)}\right]+D[(1-\alpha)F_x w(2d_v+d_b)+\Delta_r wC_{GHG}]\end{aligned} \tag{3}$$

The manufacturer makes a batch size of $mQ$ during production and distributes it equally to the retailer. By deducting the retailer's cumulative consumption from the manufacturer's cumulative production, we can calculate the manufacturer's average inventory level. The manufacturer's annual inventory level is provided by:

$$I_m(Q,m)=\frac{\left[mQ\left(\frac{Q}{P}+(m-1)\frac{Q}{D}\right)-\frac{m^2Q^2}{2P}\right]-\left[\frac{Q}{D}\left(1+2+\cdots+(m-1)\right)Q\right]}{mQ/D} \tag{4}$$

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

One of the best ways to reduce the manufacturer's overall cost is thought to be through capital investments that lower setup costs. In this study, we assume that the capital investment $I(S)$ in reducing the manufacturer's setup cost is a logarithmic function of the vendor's setup cost and optimizes the initial setup cost $(S_0)$ (Sarkar et al., 2015a; 2015b; Guchhait et al., 2020; Tiwari et al., 2018b; 2020).

$$I(\mathrm{S})=B\ln\left(\frac{S_0}{S}\right) \tag{5}$$

Subject to: $0<S\le S_0$; where $B=\frac{1}{\xi}$; $\xi$ is the percentage decrease in S per dollar increase in $I(\mathrm{S})$. If $Y$ is the manufacturer's fractional setup cost technology investment, then the formulation is:

$$ISC_m=YI(\mathrm{S})=YB\ln\left(\frac{S_0}{S}\right) \tag{6}$$

The manufacturer's total cost per year involving the cost of holding ($HC_m$), cost of initial setup ($OC_m$), cost of carbon emission ($CE_m$), and investment for reducing setup cost ($ISC_m$) is given below:

$$TC_m(Q,S,m) = HC_m + OC_m + CE_m + ISC_m \tag{7}$$

$$TC_m(Q,S,m) = \frac{h_m Q}{2}\left[m\left(1-\frac{D}{P}\right)-1+\frac{2D}{P}\right] + \frac{D[S+\Delta_{m1}(e_{co}+s_{co}+h_{co}+c_{co})L_r C_{GHG}]}{Qm} + D\Delta_{m2}C_{GHG} + YB\ln\left(\frac{S_0}{S}\right)$$

Finally, the mathematical model of the integrated total cost for a single-manufacturer and a single-retailer system with a logistics provider can be determined by adding the retailer's total cost with the electrical equipment (Eq. 3), investment in reducing setup cost (Eq. 6), and the manufacturer's total cost (Eq. 7) which is given by:

$$\begin{aligned}\text{Min } & ITC(Q,k,S,m) \\ &= \frac{D}{Q}\left[A+\theta+\pi\sigma\psi(k)\sqrt{L(Q)}+h_{r2}Qt_s+\rho\left(\alpha F_x W_x+\frac{\tau\gamma_t}{v_t}\right)+\frac{4\gamma_f d_f \tau}{v_f} + \frac{[S+\Delta_{m1}(e_{co}+s_{co}+h_{co}+c_{co})L_r C_{GHG}]}{m}\right] + h_{r1}k\sigma\sqrt{L(Q)} \\ &+ \frac{Q}{2}\left\{h_{r1}+h_m\left[m\left(1-\frac{D}{P}\right)-1+\frac{2D}{P}\right]\right\} + YB\ln\left(\frac{S_0}{S}\right) \\ &+ D[(1-\alpha)F_x w(2d_v+d_b)+(\Delta_r w+\Delta_{m2})C_{GHG}]\end{aligned} \tag{8}$$

## 3.4 Solution Methodology

The total cost is formulated as shown in Eq. (8). The equation is a function of $(Q,k,S,m)$. First, for fixed of $m$, the partial derivatives of Eq. (8) with respect to $(Q,k,S)$ which satisfies $\partial ITC(Q,k,S,m)/\partial Q = 0$, $\partial JTC(Q,k,S,m)/\partial k = 0$, and $\partial ITC(Q,k,S,m)/\partial S = 0$, simultaneously and setting the result to zero then the formulations are shown below:

$$Q^* = \left[\frac{2D\left\{\begin{gathered}A+\theta+\rho\left(\alpha F_x W_x+\frac{\tau\gamma_t}{v_t}\right)+\frac{4\gamma_f d_f\tau}{v_f}\\ +\frac{[S+\Delta_{m1}(e_{co}+s_{co}+h_{co}+c_{co})L_r C_{GHG}]}{m}-\pi\sigma\psi(k)\left[\frac{Q(c_f v_f+4Pwd_f)}{2Pc_f v_f\sqrt{L(Q)}}-\sqrt{L(Q)}\right]\end{gathered}\right\}}{\frac{h_{r1}k\sigma(c_f v_f+4Pwd_f)}{Pc_f v_f\sqrt{L(Q)}}+\left\{h_{r1}+h_m\left[m\left(1-\frac{D}{P}\right)-1+\frac{2D}{P}\right]\right\}}\right]^{1/2} \tag{9}$$

$$\Phi(k^*) = 1-\frac{Qh_{r1}}{D\pi} \tag{10}$$

and

$$S^* = \frac{mQYB}{D} \tag{11}$$

We modified Wangsa et al. (2020)'s algorithm to address the proposed model and find the optimal solutions. An iterative procedure for this problem is shown as follows:

**Step 1** Start with $m$ = 1, $S = S_0$ and all other parameters value into initial lot size ($Q_0$).

$$Q_0 = \sqrt{\frac{2D\left\{\begin{gathered}A+\theta+\rho\left(\alpha F_x W_x+\frac{\tau\gamma_t}{v_t}\right)+\frac{4\gamma_f d_f\tau}{v_f}\\ +\frac{[S+\Delta_{m1}(e_{co}+s_{co}+h_{co}+c_{co})L_r C_{GHG}]}{m}\end{gathered}\right\}}{h_{r1}+h_m\left[m\left(1-\frac{D}{P}\right)-1+\frac{2D}{P}\right]}}$$

**Step 2** Compute $k_i$ and $S_i$ by substituting $Q_0$ into Eq. (10) and Eq. (11).

**Step 3** Compute $Q_1$ from Eq. (9).

**Step 4** Check the actual shipping weight; if $(Qw > W_x)$ is not satisfied then revise the lot quantity $\left(Q_{i1} = \frac{W_x}{w}\right)$ and go to the next step. Otherwise, $(Qw \leq W_x)$, we go on to the next step.

**Step 5** Compute the value of $\Phi(k_{i2}) = 1 - \frac{Qh_{r1}}{D\pi}$ and $S_{i2} = \frac{mQYB}{D}$.

**Step 6** Repeat Steps (2) - (5) until no change in the value of $(Q_i, k_i, S_i)$.

**Step 7** Compare the decision variables of $S_i$ and $S_0$.

i). If $S_i < S_0$ then the optimal solution by $(Q_i{}^*, k_i{}^*, S_i{}^*)$.

ii). If $S_i \geq S_0$ then we set $S_i{}^* = S_0$ and utilize Eqs. (9) and (10) to determine the new $(Q_i{}^*, k_i{}^*)$ by the same Steps (2)-(4) then the result is denoted $(Q_i{}^*, k_i{}^*, S_i{}^*)$.

**Step 8** Calculate $JTC$ using Eq. (8).

**Step 9** If $JTC\left(Q^*_{(m)}, k^*_{(m)}, m, S^*_{(m)}\right) \leq JTC\left(Q^*_{(m-1)}, k^*_{(m-1)}, m-1, S^*_{(m-1)}\right)$, then set $m = m + 1$, and repeat Steps 2. Otherwise, go to Step 10.

**Step 10** The optimal decision variables, $(Q^*, k^*, m^*, S^*) = \left(Q^*_{(m-1)}, k^*_{(m-1)}, m-1, S^*_{(m-1)}\right)$, then $(Q^*, k^*, m^*, S^*)$ is the optimal solution.

## 4. Results and Discussion

Let us consider a supply chain inventory model involving a single manufacturer and a single retailer and consider the e-trucks and e-forklifts used in Wangsa et al. (2020). We categorize the data into three sections, namely: 1) **General data:** $D$ = 10,000 units/year; $P$ = 60,000 units/year; $\sigma$ = 300 units/year; $A$ = \$50; $S$ = \$1400; $h_{r1}$ = \$10/unit/year; $h_{r2}$ = \$1/unit/year; $h_m$ = \$3/unit/year; $\pi$ = \$200/unit; $F_x$ = \$0.000040217/kg/km; $w$ = 22 kg/km; $\theta$ = \$14; $W_x$ = 46,000 kg; $\alpha$ = 0.11246; $t_s$ = 1 day; $\tau$ = \$0.10/kWh; $v_t$ = 20 mph; $\gamma_t$ = 6 kWh/hr; $c_f$ = 3300 kg.; $v_f$ = 6 mph; $\gamma_f$ = 2.092 kWh/hr, $Y$ = 0.10/\$/year; and $B$ = 3500. 2) **Emission data:** $C_{GHG}$ = \$10/ton $CO_2$; $\Delta_r$ = 0.00250-ton $CO_2$/kg; $\Delta_{m1}$ = 0.02264-ton $CO_2$/kWh; $\Delta_{m2}$ = 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%. 3) **Distance data:** $d_v$ = 50 km; $d_b$ = 600 km; $d_f$ = 0.015 km. By employing the above algorithm, we obtain the following results. The optimal lot size, number of batches, safety factor, setup cost, total shipping weight, service level, lead-time, total emission are 635.83 units; 4 times; 2.73 times; \$89.02/setup; 13,988.32 kg.; 99.68%; 6.17; 146.99-ton $CO_2$, respectively. The cost incurred by the vendor, buyer and whole of system are \$7,297.86/year; \$19,039.64/year; and \$26,337.50/year, respectively.

We analyzed the results of the proposed model and the results of Wangsa et al. (2022) which is a fossil-fuel model and an electric-powered model without investment in reduced setup cost. In this analysis, we assume data such as the initial setup cost \$1,400/setup, fuel price \$1.02/liter, truck's fuel consumption = 0.63569 liters/km, and forklift's fuel consumption = 3 liters/hr. Table 2 shows if the proposed model is compared to Wangsa et al. (2020)'s model, we have lower emissions of 61.24-ton $CO_2$ (29.41%), lead-time 4.30 days (41.01%), service level increase by 0.37%, and saving cost by \$8,507.74/year (24.42%). In the same table, if we compared electric-powered with setup cost reduction and without setup cost reduction, we got a lower emission of 14.65-ton $CO_2$ (9.07%), lead-time faster than 0.13 days (1.96%), service level increase 0.01% and saving cost by \$3,705.53/year (12.34%).

Table 2. The comparison of the results

| | **Wangsa et al. (2020)'s model** | **Electric-powered model w/o setup cost reduction** | **Proposed model (electric-powered with setup cost reduction)** |
|---|---|---|---|
| Lot size | 1,371.18 units | 656.89 units | 635.83 units |
| Total shipping weight | 30,165.95 kg | 14,451.54 kg | 13,988.32 kg |
| Number of batches | 3 | 6 | 4 |
| Safety factor | 2.46 | 2.72 | 2.73 |
| Setup cost optimal | \$1,400/setup | \$1,400/setup | \$89.02/setup |
| Service level | 99.31% | 99.67% | 99.68% |
| Lead-time | 10.46 days | 6.29 days | 6.17 days |
| Manufacturer' emission | 127.17-ton $CO_2$ | 125.51-ton $CO_2$ | 112.02-ton $CO_2$ |
| Retailer's emission | 81.06-ton $CO_2$ | 36.13-ton $CO_2$ | 34.97-ton $CO_2$ |
| **Total emission** | **208.23-ton $CO_2$** | **161.64-ton $CO_2$** | **146.99-ton $CO_2$** |
| Manufacturer's cost | \$10,265.74/year | \$11,006.40/year | \$7,297.86/year |
| Retailer's cost | \$24,579.49/year | \$19,036.63/year | \$19,039.64/year |
| **Integrated total cost** | **\$34,845.23/year** | **\$30,043.03/year** | **\$26,337.50/year** |

Figures 1-4 illustrate the impact of changes in number of batches on total cost, lead-time, carbon emissions, and service level. The figures also show a comparison between Wangsa et al. (2020)'s model, an electric-powered model without reduced setup costs, and a proposed model that considers electric-powered technology and reduced setup costs. Figures 1-3 show that the total cost, carbon emissions, and lead time of the proposed model are smaller than the electric-powered model without reduced setup costs and Wangsa et al. (2020)'s models. In contrast to the service level, the proposed model provides the highest service level compared to other methods (Figure 4). Figures 2 and 4 show that the lead time decreases, and the service level increases as the number of batches increases.

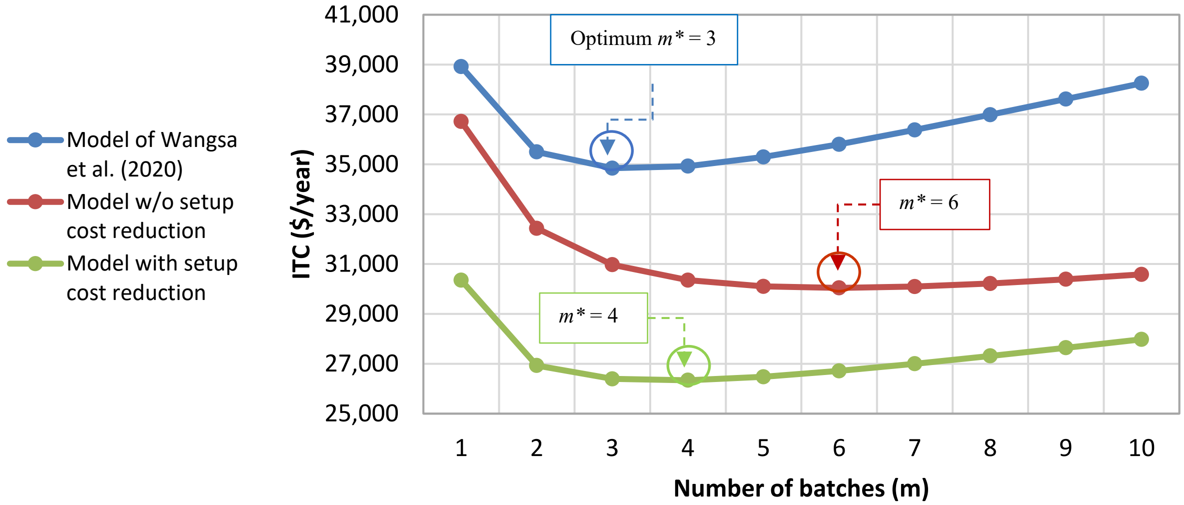


Figure 1. Joint total cost with respect to number of shipments ($m$) for each model

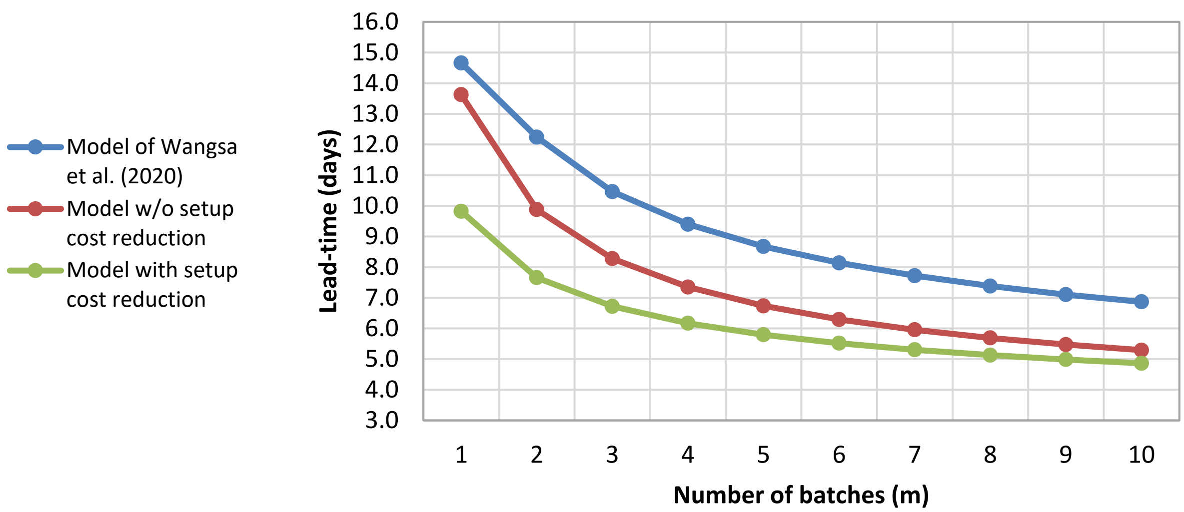


Figure 2. Lead-time with respect to number of shipments ($m$) for each model

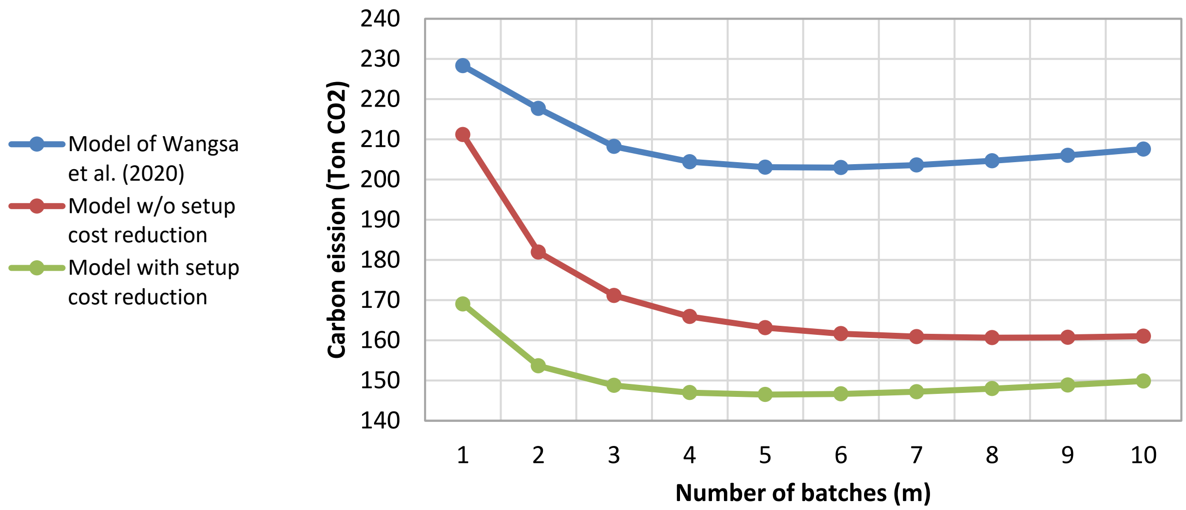


Figure 3. Total carbon emission with respect to number of shipments (*m*) for each model

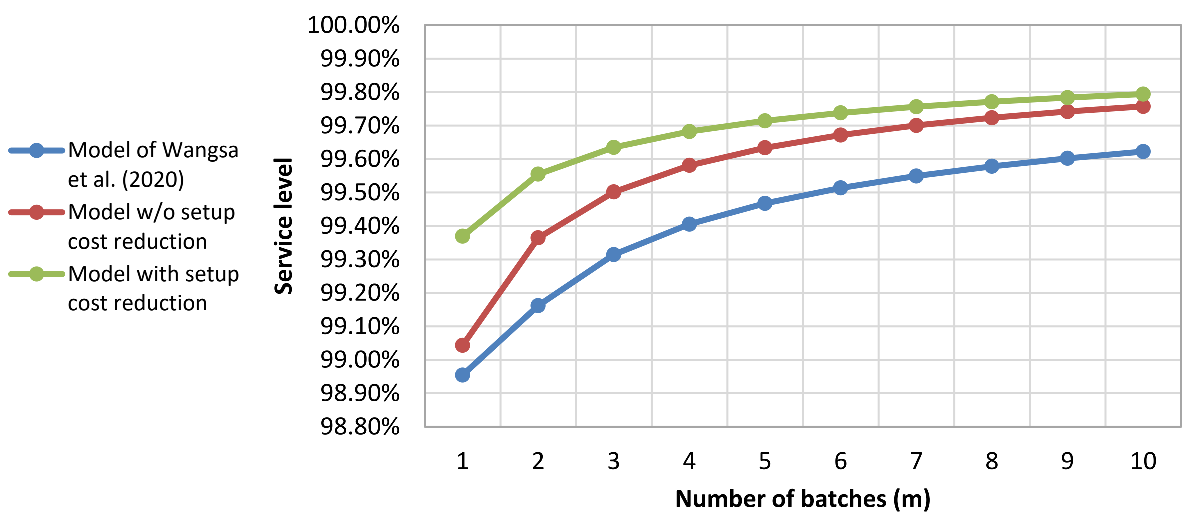


Figure 4. Service level with respect to number of shipments (*m*) for each model

## 5. Conclusion

This study develops a sustainable integrated inventory model for a two-tier supply chain by involving electric trucks. We consider a probabilistic demand, stochastic lead-time, carbon emission, service level, and setup cost reduction. Stochastic lead-time includes the production time, transportation time, loading-unloading time, and in-transit time. The carbon emission can be reduced especially transportation emissions by considering electric trucks. The emissions will affect the lot size and lot production. From computation analysis, we obtain a total cost savings of 25%, a significant total emission reduction of about 30%, a lead-time reduction of 41%, and an increase in service level of 0.36%. The proposed model can guide managers to determine the optimum lot size, safety factor, number of batches, customer service level, carbon emissions, and lead-time. Further study could be by investigating the green technology investment and considering the drone for the last mile system. The production and truck capacities constraint would be considered in further research. Furthermore, the other possibility is considering rework in the manufacturing production process.

## References

Behnke, M., Recent Trends in Last Mile Delivery: Impacts of Fast Fulfillment, Parcel Lockers, Electric or Autonomous Vehicles, and More. In *Logistics Management*, pp. 141-156, Springer, Cham, 2019.

Benjaafar, S., Li, Y., & Daskin, M., Carbon footprint and the management of supply chains: Insights from simple models. *IEEE transactions on automation science and engineering*, *10*(1), 99-116, 2012.

Breunig, U., Baldacci, R., Hartl, R. F., and Vidal, T., The electric two-echelon vehicle routing problem. *Computers & Operations Research*, vol. 103, pp. 198-210, 2019.

Daryanto, Y., Wee, H. M., and Astanti, R. D., Three-echelon supply chain model considering carbon emission and item deterioration. *Transportation Research Part E: Logistics and Transportation Review*, vol. 122, pp. 368-383, 2019.

Datta, T. K., Effect of green technology investment on a production-inventory system with carbon tax. *Advances in operations research*, 2017.

Guchhait, R., Dey, B. K., Bhuniya, S., Ganguly, B., Mandal, B., Bachar, R. K., ... & Chaudhuri, K., Investment for process quality improvement and setup cost reduction in an imperfect production process with warranty policy and shortages. *RAIRO-Operations Research*, *54*(1), pp. 251-266, 2020.

Huang, Y. S., Fang, C. C., and Lin, Y. A., Inventory management in supply chains with consideration of Logistics, green investment and different carbon emissions policies. *Computers & Industrial Engineering*, vol. 139, pp. 106207, 2020.

Jauhari, W. A., A collaborative inventory model for vendor-buyer system with stochastic demand, defective items and carbon emission cost. *International Journal of Logistics Systems and Management*, vol. 29, no. 2, pp. 241-269, 2018.

Marchi, B., Zanoni, S., Zavanella, L. E., and Jaber, M. Y., Supply chain models with greenhouse gases emissions, energy usage, imperfect process under different coordination decisions. *International Journal of Production Economics*, vol. 211, pp. 145-153, 2019.

Sarkar, B., Chaudhuri, K., & Moon, I., Manufacturing setup cost reduction and quality improvement for the distribution free continuous-review inventory model with a service level constraint. *Journal of Manufacturing Systems*, *34*, pp. 74-82, 2015a.

Sarkar, B., Saren, S., Sinha, D., & Hur, S., Effect of unequal lot sizes, variable setup cost, and carbon emission cost in a supply chain model. *Mathematical Problems in Engineering*, Article ID 469486, 2015b.

Schneider, M., Stenger, A., and Goeke, D., The electric vehicle-routing problem with time windows and recharging stations. *Transportation Science*, vol. 48, no. 4, pp. 500-520, 2014.

Tiwari, S., Daryanto, Y., and Wee, H. M., Sustainable inventory management with deteriorating and imperfect quality items considering carbon emission. *Journal of Cleaner Production*, vol. 192, pp. 281-292, 2018a.

Tiwari, S., Kazemi, N., Modak, N. M., Cárdenas-Barrón, L. E., & Sarkar, S., The effect of human errors on an integrated stochastic supply chain model with setup cost reduction and backorder price discount. *International Journal of Production Economics*, 107643, 2020.

Tiwari, S., Sana, S. S., & Sarkar, S., Joint economic lot sizing model with stochastic demand and controllable lead-time by reducing ordering cost and setup cost. *Revista de la Real Academia de Ciencias Exactas, Físicas y Naturales. Serie A. Matemáticas*, vol. 112, no. 4, pp. 1075-1099, 2018b.

The US Env Protection Agency, Sources of Greenhouse Gas Emissions. Retrieved from https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#colorbox-hidden, August 8, 2021.

Wangsa, I. D., Greenhouse gas penalty and incentive policies for a joint economic lot size model with industrial and transport emissions. *International Journal of Industrial Engineering Computation*, vol. 8, no. 1, pp. 453-480, 2017.

Wangsa, I. D., Tiwari, S., Wee, H. M., and Reong, S., A sustainable vendor-buyer inventory system considering transportation, loading and unloading activities. *Journal of Cleaner Production*, vol. 271, pp. 122120, 2020.

## Biography

**Ivan Darma Wangsa** is a 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.